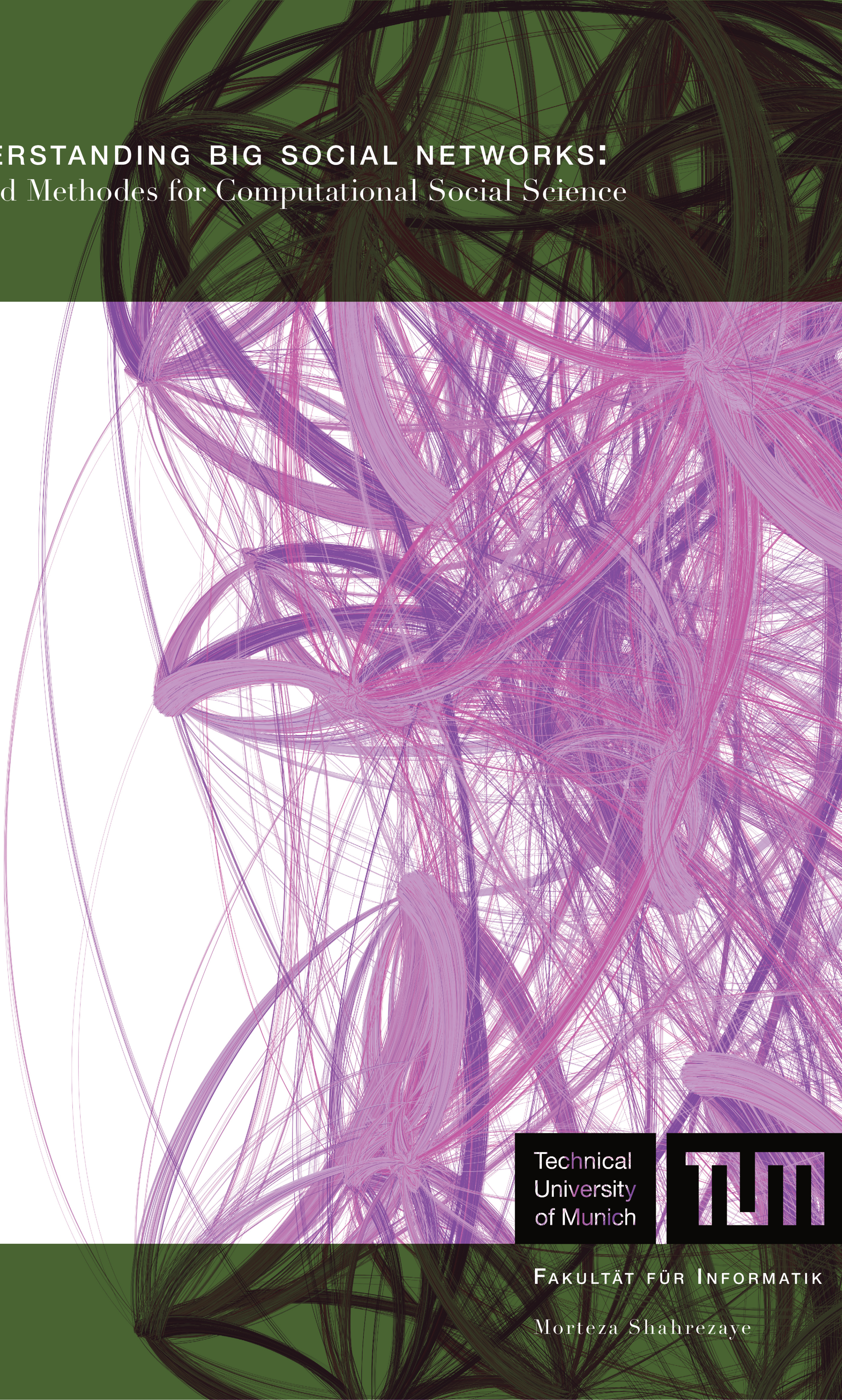
Understanding big social networks: Applied Methodes for Computational Social Science



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Understanding Big Social Networks: Applied Methods for Computational Social Science

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Abstract

The burst of Web 2.0 services during the early years of the 21^{st} century has resulted in the generation of a long list of online social media platforms, cultivating an online participatory culture. Approximately 69% of the adult Americans used at least one major online social media platform in 2018. The online social media platforms gather and store different kinds of data, for example, concerning the interaction of users with their platforms as well as the communication patterns among various users. This renaissance of big data, which is a term that refers to the explosion of available data, is characterized by the continuous production of high dimensional and unstructured data collected on an unprecedented scale with a relatively low cost. The collected data offers social scientists with novel opportunities to study the behavior of humans in massive scales. However, analyzing this data is highly challenging because this data is high dimensional and has large amount of noise, incidental endogeneity, and spurious correlations. It is crucial for social scientists to be equipped with field knowledge related to modern machine learning techniques, computer science, statistics, and mathematics to exhaust potential opportunities and to discover the complex patterns embodied in this data.

The focus of this dissertation is to generate political knowledge from the huge amounts of data being generated on the online social media platforms. The first part of this dissertation serves as a general introduction to social big data, the opportunities for its political exploration, and the challenges associated with it. Additionally, a general framework is introduced to continuously store raw social media data on scalable distributed databases. In the second part, the theoretical basis for efficiently analyzing the data is described, based on which proper quantitative tools are developed for generating knowledge.

For the theoretical part of this thesis, a wide range of algorithms are developed, all of which have to fill the theoretical gap between the different aspects of social sciences and computational sciences. The main two studies constituting this dissertation are based on state-of-the-art network theory tools. In Shahrezaye et al. [139], efficient algorithms are developed based on metric learning and harmonic functions to efficiently estimate the political orientation of mass Twitter users using less than 50 training observations per class. Shahrezaye et al. [140] measures the overall efficiency of communication in social networks which have a positive-degree correlation between neighboring vertices, the so-called networks with assortative mixing. Additionally, a polarization index is derived/defined, which can be used to measure the the level of political polarization between the sub-clusters of online social networks. In Papakyriakopoulos et al. [120] hyperactive users are theoretically and mathematically defined. It is subsequently shown that hyperactive users can become opinion leaders on online social platforms and that they affect the political discourse on these platforms.

Zusammenfassung

Mit der rasanten Entwicklung von Web 2.0-Diensten in den frühen Jahren des 21. Jahrhunderts entstand eine große Anzahl von sozialen Netzwerken, die die Entstehung einer Online-Beteiligungskultur ermöglichten. So nutzten zum Beispiel schon circa 69% der erwachsenen Amerikaner im Jahr 2018 mindestens eine der wichtigsten Social Media Plattformen im Internet. Diese sammeln und speichern dabei verschiedene Arten von Daten, zum Beispiel über die Interaktion der Nutzer mit den Plattformen sowie über deren Kommunikation untereinander. Diese Renaissance von Big Data - ein Begriff, der sich auf den explosionsartigen Anstieg verfügbaren Daten bezieht - ist gekennzeichnet durch die kontinuierliche Generation von hochdimensionalen und unstrukturierten Daten, die in einem beispiellosen Umfang und mit relativ geringen Kosten erhoben werden können. Diese Renaissance bietet Sozialwissenschaftlern neue Möglichkeiten, das Verhalten der Menschen in großem Maßstab zu untersuchen. Die Analyse dieser Daten ist jedoch aufgrund ihrer hohen Dimensionalität und Ungenauigkeit, der zufälligen Endogenität und auch wegen häufig auftauchenden, falschen Korrelationen sehr schwierig. Um die Potenziale vollständig zu erschließen und komplexe Muster in den Daten zu erkennen, ist es entscheidend, dass Sozialwissenschaftler mit den modernen Methoden des maschinellen Lernens ausgestattet sind und sich in der Informatik, Statistik sowie Mathematik auskennen.

Der Schwerpunkt dieser Dissertation liegt auf der Generierung von politischem Wissen aus den riesigen Datenmengen, die auf Social Media Plattformen erzeugt werden. Der erste Teil der Dissertation dient hierbei als allgemeine Einführung in Social Big Data, die Möglichkeiten ihrer politischen Erforschung und den damit verbundenen Herausforderungen. Zusätzlich werden allgemeine Methoden zur kontinuierlichen Speicherung von Social Media-Rohdaten auf skalierbaren verteilten Datenbanken eingeführt. Der zweiten Teil beschreibt den theoretischen Rahmen für die effiziente Analyse der Daten, auf dessen Grundlage die quantitativen Werkzeuge zur Generierung von Wissen entwickelt werden.

Für den theoretischen Teil dieser Arbeit wird eine breite Palette von Algorithmen entwickelt, mit dem Ziel, die theoretische Lücke zwischen den verschiedenen Aspekten der Sozial- und Informatikwissenschaften zu schließen. Die beiden Hauptveröffentlichungen dieser Dissertation basieren auf modernsten netzwerktheoretischen Methoden. In Shahrezaye et al. [139] werden effiziente Algorithmen, basierend auf Methoden des metrischen Lernens und mit Hilfe harmonischer Funktionen, entwickelt, um die politische Orientierung von Twitter-Massenbenutzern mit weniger als fünfzig Trainingsbeobachtungen pro Klasse effizient einschätzen zu können. Shahrezaye et al. [140] messen die gesamte Kommunikationseffizienz in sozialen Netzwerken, welche eine positive Korrelation zwischen benachbarten Knoten aufweisen, den sogenannten Netzwerken mit assortativer Mischung. Des

Weiteren wird ein Polarisationsindex definiert, mit dem der Grad der politischen Polarisierung zwischen den Unterclustern von sozialen Online-Netzwerken gemessen werden kann. In Papakyriakopoulos et al. [120] sind die sogenannten *hyperactive users* sowohl theoretisch als auch mathematisch definiert. Abschließend wird gezeigt, dass diese *hyperactive users* zu Meinungsbildern auf den sozialen Netzwerken werden und somit den politischen Diskurs beeinflussen können.

List of Publications

This dissertation, "Understanding Big Social Networks: Applied Methods for Computational Social Science", constitutes a cumulative doctorate dissertation based on three peer-reviewed publications that are presented in Table 1. The main author of this work, Morteza Shahrezaye, was the first author of two of the listed peer-reviewed publications that are the formal cornerstones of this dissertation [139, 140]. The peer-reviewed publications with original layout are attached to the end of dissertation. Specifically, [139, 140] are attached as published in the corresponding journal/proceedings and "Distorting Political Communication: The Effect of Hyperactive Users in Online Social Networks" as the accepted version because of IEEE copyrights/RightLinks.

Table 1 List of original publications

Title	Conference/journal
[139] *Estimating the Political Orientation of Twitter Users in Homophilic Networks*	AAAI 2019 Spring Symposia
[140] *Measuring the Ease of Communication in Bipartite Social Endorsement Networks*	10th International Conference on Social Media & Society
[120] *Distorting Political Communication: The Effect of Hyperactive Users in Online Social Networks*	IEEE INFOCOM 2019

Apart from the original scientific contributions that have been presented in Table 1, the data pipeline developed by the author of this dissertation has been leveraged in other publications. The peer-reviewed publications presented in Table 2 have employed the functionalities of the data pipeline developed by the author of this dissertation for performing empirical analysis of the developed models.

Table 2 List of publications that leveraged the data pipeline

Title	Conference/journal
[119] *Social Media and Microtargeting: Political Data Processing and the Consequences for Germany*	Big Data & Society
[21] *Social Media Report: The 2017 German Federal Elections*	TUM.University Press
[138] *The rise of the AfD: A Social Media Analysis*	10th International Conference on Social Media & Society
[117] *Social Media und Microtargeting in Deutschland*	Informatik-Spektrum

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Acronyms

API	application programming interface.
GB	gigabyte.
JSON	JavaScript Object Notation.
KB	kilobyte.
NAS	Network-Attached Storage.
REST	Representational State Transfer.
WWW	World Wide Web.
ZB	zettabyte.

1 Introduction

"The rationale is that if a claim is not replicable, then it is not true and, hence, not science, no matter how novel or interesting it might be."

—Watts, Duncan J

The invention of the Web 2.0 concurrent with the proliferation of electronic mobile devices has resulted in the establishment of a new digitalized era of big data. Web 2.0 refers to the online platforms that facilitate the direct generation of content by end users. Any interaction with the services offered in Web 2.0 leaves some bits of information. Generally, users check their online social networking accounts multiple times per day, add comments and likes on online posts, or check their messages and friends' activities. Additionally, everything from moving to different places with our GPS-enabled phones in our pockets, ordering coffee and food using our credit cards, making calls and sending hundreds of text messages, recording and streaming videos, to participating in sports with wearables, including wristbands that constantly measure the heartbeats, leave a digital trace. All these activities generate huge amounts of private and public data that are stored by the corresponding service providers. According to Cisco, the total global generated traffic per year on the World Wide Web (WWW) will increase from 1.5 zettabyte (ZB)[1] in 2017 to more than 4.8 ZB by 2022, from which more than 71% will be generated by mobile devices. The global monthly internet traffic will reach 44 GB per capita by 2022, up from less than 1 GB in 2007 [2] (see Fig. 1.1).

This data, when accumulated over time from different users around the globe, offers novel potentials to study different social and nonsocial characteristics of humans, both in individual and group levels [83, 16]. This provides scientists from different fields with an opportunity to answer the unanswered questions and to prove unproved theories with a high precision based on thousands or millions of observations.

This renaissance of big data is characterized by the continuous production of high dimensional and unstructured data collected in an unprecedented scale and at low cost. This data is huge in volume, fast in terms of generation, diverse in variety, exhaustive in scope, and fine-grained in resolution [77]. The generation of this data constitutes an enormous potential for data-driven social science. "The availability of unprecedented amounts of data about human interactions in different social spheres or environments opens the possibility of using those data to leverage knowledge about social behaviour beyond research on the scale of tens of people. The data can be used to check and

[1] $1e + 12$ gigabyte (GB)

[2] https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white-paper-c11-741490.html

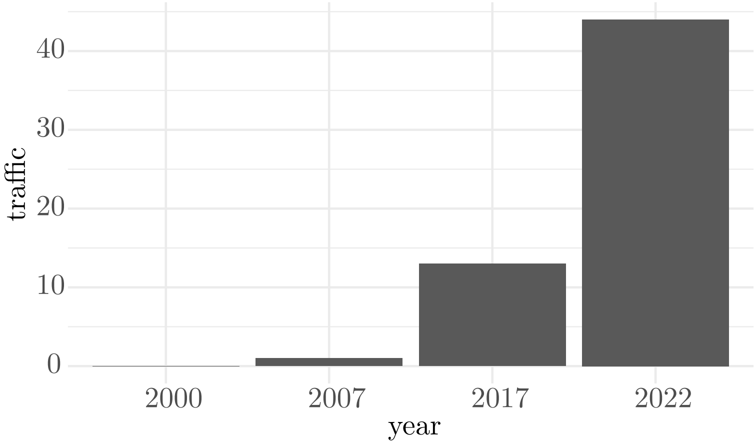

Fig. 1.1. Global monthly internet traffic per capita (GB)

validate the results of simulation models and socio-economic theories, but a further step in using them is to take them into account already at the modelling stage" [27].

This dissertation mainly focused on the big data generated through online social networking platforms such as Facebook and Twitter. We refer to this type of data as *social big data* and to the field of research as *computational social science*. Besides developing a comprehensive data pipeline in Chapter 2, this dissertation attempts to answer the following theoretical questions:

1. Research question 1 (see Chapter 3): Is it possible to estimate the political orientation of the users of online social platforms by only using their friends' structure and few labeled users?

2. Research question 2 (see Chapter 3): Is it possible to estimate the political orientation of the users of online social platforms even if they do not exhibit any political activity on the online social platforms?

3. Research question 3 (see Chapter 4): Is it possible to project the complex social networks generated on online social platforms to simple networks that are easy to analyze and to generate knowledge from?

4. Research question 4 (see Chapter 4): Is it possible to track the political polarization or the extent of political disagreement between members of different political parties based on their activities on online social platforms?

5. Research question 5 (see Chapter 5): Is it possible to evaluate if being a more-than-average active user on online social platforms implies more real contribution to political discourse?

All the aforementioned theoretical questions are answered in Chapters 3,4, and 5. A huge effort has been invested to answer these questions in a replicable, testable, and generalized manner. Additionally, the developed models are applicable to different online social platforms and are not limited to only one of them.

1.1 Social Big Data, Opportunities, and Challenges

The amount of stored business and social big data is estimated to double every two years [22]. Along with being large in size and having a high potential to uncover complex hidden patterns, social big data could also have intricate characteristics as follows:

- Extremely high-dimensional; as an example, a tweet generated on Twitter can contain more than 1000 fields.
- Extremely high-frequent; as an example, an average of more than 5,000 tweets were generated each second in 2018.
- Dramatically imbalanced; as an example, a tweet generated on Twitter can have between approximately few hundreds to more than 1000 fields.
- Extremely varying dynamics; as an example, a tweet posted by a famous politician or celebrity can get millions of retweets in less than an hour.
- Heterogeneity or high variability of the data types and formats and low quality due to missing values and high data redundancy [156].
- Uncertainty or deviation from the accurate, intended, or original values due to the complexity of data generation and data handling process.

These features result in much noise, incidental endogeneity or random unrelated correlation between real variables and noise [43], and spurious correlations or correlation between the response variable and unrelated variables [43] in social big data.

Many statistical algorithms that perform well for low-dimensional data face significant challenges while analyzing the social big data. Therefore, new statistical and computational methods should be developed by the so-called computational social scientists. These newly developed algorithms should guarantee computational scalability while dealing with the mentioned challenges. Computational scalability refers to computational algorithms that can always handle large volumes of input data when large amount of resources or computational resources is available. Computational social science brings "along challenging demands on the experimental side, in terms of design and procedures, which can only be solved by working together with the computational science community" [27]. This data is often characterized by the 5 Vs of big data: volume, velocity, variety, veracity, and value (Fig. 1.2) [162].

Social big data contains different types of unstructured data in the form of texts, images, videos, sounds, and combinations of them. An unstructured data stream is a stream of data that has no predefined and fixed structure, and the structure of the observations may vary from one to the next one. In contrast to the unstructured data streams, relational data streams have a fixed structure that remains the same regardless of the

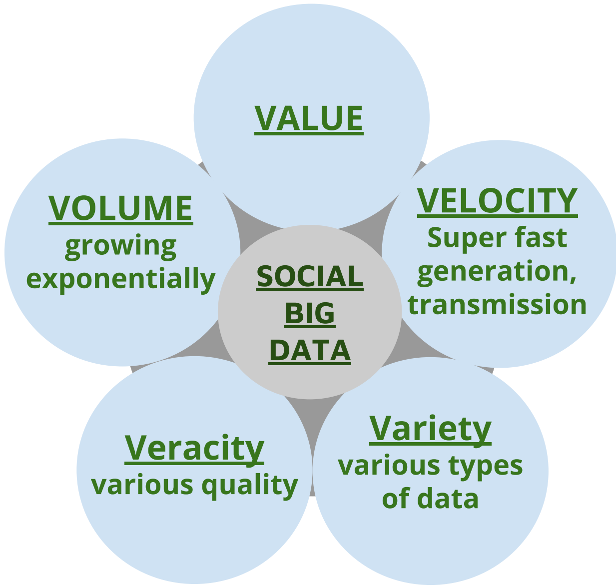

Fig. 1.2. 5Vs of big data

number of observations. The massive streams of unstructured data cannot be stored and analyzed using off-the-shelf technologies utilized for relational type of data, for example, SQL. Therefore, several technological challenges must be addressed to efficiently store and analyze the social big data [162].

1.1.1 Data Management and Data Processing Challenges

The exponentially increasing unstructured and heterogeneous data require new data management platforms to clean, store, and organize raw data [22]. The traditional data management platforms, such as SQL, are not suitable for managing social big data. Therefore, new data management platforms should be implemented that should be:

- fast in writing/reading data;
- fault tolerant, which means that the platform is expected to always work properly or maybe at a reduced/limited level, even in case of failure in parts of the platform; and
- seamlessly scalable, which means that it should be relatively effortless to store and analyze large volumes of new data by adding new hardware to the platform.

Consequently, new data management platforms, such as Hadoop, MongoDB, and Elasticsearch, are developed that are easily scalable in terms of both capacity and computational management and that can manage unstructured data of heterogeneous formats.

The clusters of each of the mentioned data management platforms can scale up to thousands or millions of machines or computational nodes. These data management platforms offer automatic load balancing, copy consistency and deduplication [144]. Automatic load balancing refers to automatic balancing of the data storage and computations among available resources without any additional effort by the users. Copy consistency and deduplication ensure that all the documents or observations are always available in any number of computation tasks even in case of failure in some computational nodes; nevertheless, the data would not be lost across the nodes.

1.1.2 Elasticsearch

Elasticsearch is an open-source distributed full-text search engine developed in Java and based on the Apache Lucene search engine library. Full-text search engines examine every single word in the document while running a search query. Elasticsearch has an HTTP web interface and APIs in several programming platforms, such as PHP, Python, Ruby and Java.

Elasticsearch exhibits several interesting features. It is seamlessly scalable, distributed, real-time and also compatible with JavaScript Object Notation (JSON) documents and includes built-in full-text analytic features; further, it is compatible with the natural language and geolocation data. In terms of architecture, Elasticsearch supports the nested documents, and complex architecture and relations between the data fields.

The data employed for performing the empirical analysis of this dissertation contain billions of JSON documents downloaded from Twitter or Facebook that are heavily text-based and unstructured. Each single JSON document can include more than 1000 data fields and arrays of tens of thousands length. Elasticsearch is considered to be a good choice to store and analyze this type of data because the JSON documents are 100% text-based. Therefore, a local Elasticsearch cluster has been implemented to store the JSON data. This Elasticsearch cluster has four nodes of Xeon E5-2620 v4 CPUs with each having a memory of 64 GB and running on Ubuntu 14.04.5 LTS.

1.2 Quantitative and Theoretical Challenges: Computational Social Sciences

1.2.1 Replicability in Social Sciences

Social science is an academic discipline that studies human and social dynamics. Social scientists seek for interpretable causal mechanisms to explain the cognitive and behavioral phenomena at different levels ranging from individuals to groups, organizations, and whole societies. Social sciences constitute different fields of political science, economics, sociology, linguistics, public health, history and anthropology among several other fields. Social scientists have generated a tremendous number of novel theories over the previous century [157].

The theories and publications in social sciences, although numerous in count, exhibit several weaknesses. First, the social scientists are usually not successful at harmonizing the incoherencies and inconsistencies among the competing theories that attempt to explain the same social phenomena. There are many speculations why this level of contradictions exists among the theories of social sciences. Watts [157] argues in his novel work the main two sources of inconsistencies in social sciences are "the institutional and cultural orientation of social-science disciplines, which have historically emphasized the advancement of particular theories over the solution of practical problems [...] and lack of appropriate data for evaluating social scientific theories".

Second, in many cases, social scientists have made scattered efforts to explain a unique phenomenon using different non-generalizable approaches. Generalization is the process based on which the researchers reflect on the details and descriptions presented in a case study to formulate general insights and concepts [99]. Social science theories, even if not necessarily contradictory, are not usually systematically summarized and generalized [90].

Finally, the scientific research in general comprises two indispensable complementary parts, namely, explanation and prediction. Further, scientific research is generally evaluated based on the degree to which it can explain a physical or human-related phenomenon and also how accurately it can predict new observations. "Social scientists, in contrast, have generally deemphasized the importance of prediction relative to explanation, which is often understood to mean the identification of interpretable causal mechanisms" [65]. This may be due to the innate heterogeneity and multifacetedness of the humans' behavior that makes predictions in social contexts more complex when compared with the deterministic physical systems.

The three weaknesses of the research method in social sciences make the theories of sciences less replicable and testable when compared with the theories of natural sciences. Watts [157] claimed that if a theory "is not replicable then it is not true, and hence not science, no matter how novel or interesting it might be".

During the previous decade, many suggestions have been made for how to redefine the research methods used in social sciences. The main suggestions are to:

- initially establish the prediction-driven explanation of social phenomena and to strive solving real-world problems. In other words, social scientists should "reject the traditional distinction between basic and applied science" [157] and

- secondly, stop emphasizing on the unbiased estimation of model parameters by neglecting the prediction power of theories and instead ask whether a theory can predict the future observations. This would increase the reliability and robustness of the theories [65].

Because of the heterogeneity and complexity of human behavior as well as the scarcity of relevant data, the conventional resources and tools that are available to social scientists are limited. Regardless, the renaissance of big data created an enormous potential for data-driven computational methods in social sciences, with the promise of generating robust, easily replicable, and consistent theories that facilitate comparison across different case studies [65].

1.2.2 Computational Social Sciences

To handle the previously mentioned complexities of social big data, two main branches of scientific fields and their several sub fields are to be synthesized. First, the natural complexity of the social big data requires the computer and computational scientists to contribute to tools and algorithms that make it easy to handle and analyze the data. However, the computational scientists lack the necessary field knowledge in social sciences and the relevant methodologies and concepts. Second, social scientists are those who have the field knowledge and can ask relevant questions that could be answered using the social big data. They are aware of the historical development of the theories of social sciences but they "are often not aware of cutting edge advances in computational methods and algorithmic biases in organic data (i.e., data that has not been designed for a specific research purpose) that can be found on the Web" [158].

Therefore, to leverage the potentials of social big data, one should deal with the computational and theoretical challenges. This implies that a mix of different disciplines, namely, statistical modelling, mathematical modelling, computer science, sociology, cognitive science, and behavioral science are to be employed for performing research using the social big data. This new field of social science, computational social science, empowers social the scientists to reverse the conventional explanatory research style to a more prediction-driven research style that aims to explain real-world problems using the hidden complex association, correlation, dependence, and causality embodied in social big data.

The recommended methodology is to begin with a relevant question that should be clarified and explained. Then, the researcher has to design a statistical or mathematical model that can leverage the social big data to answer the question in hand. The researcher must explain and justify the process of modelling and the reason because of which specific model and parameters are chosen. Subsequently, the explained model is validated if the relevant social big data complies with the expected predictions. "Mechanisms revealed in this manner are more likely to be replicable, and hence to qualify as "true", than mechanisms that are proposed solely on the basis of exploratory analysis and interpretive plausibility. Properly understood, in other words, prediction and explanation should be viewed as complements, not substitutes, in the pursuit of social scientific knowledge" [65].

2 Data Maintenance

"Big data is not about the data."

—King, Gary

The social big data generated on online social networking services, such as Facebook and Twitter, has pros and cons associated with it that should be addressed with precaution (Fig. 2.1).

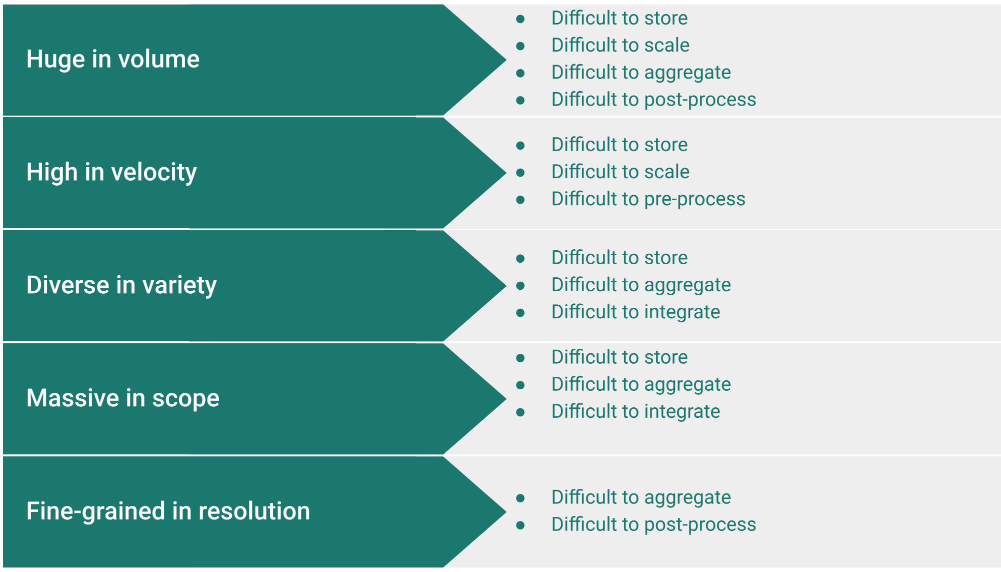

Fig. 2.1. Pros and cons of social big data

The three publications that form this dissertation study the intersection of social big data and political science. More specifically, different aspects of the political discourse led by political parties on online social media platforms, the contribution of citizens, and the effect of the algorithms are studied. The research strategy is mainly a prediction-driven explanatory strategy suggested by Hofman et al. [65]. Each of the publications begin with a relevant question that should be answered. Then, a mathematical or statistical model that explains the question is designed and tested using the relevant social data acquired from one of the online social media platforms and/or simulated data. Finally, the explained mathematical or statistical model is validated by showing that the relevant social big data are compliant with the expected predictions.

The validation process may include two different independent stages. One would be to simulate the model by considering the assumptions and to verify whether the results of the simulations are in accordance with the expected predictions. However, the more inevitable and important stage is validating the model based on real-life data. As elaborated, the type of data implemented to validate the models underlying this dissertation, is the publicly available data generated on social media platforms such as Twitter and Facebook. Both these online social media platforms offer public APIs to access the data. The public APIs enable the researchers to access the data using a program or software.

One can use a long list of programming platforms to access the public APIs offered by online social media platforms such as Facebook and Twitter. For this dissertation, the main platform employed to access the APIs is Cran R. R, which is relatively easy to use and is available on all the Linux operating systems. Linux shell and Crontab scripts have been employed to schedule the R scripts. Even though the exact scripts are not presented in this dissertation, the pseudo-algorithms are carefully and completely demonstrated.

2.1 Public APIs

2.1.1 Twitter

The Twitter data can be either accessed through Representational State Transfer (REST) or the so-called streaming application programming interface (API). To use these APIs, a Twitter consumer account and an access token should be generated. Different rate limits are applicable to different end points of the API. The REST API offers several end points including but not limited to the following:

- Accounts and users
  - Subscribe to account activity
  - Manage account settings and profile
  - Mute, block, report, follow, search, and get users
- Tweets
  - Post, retrieve and engage with Tweets
  - Get Tweet timelines
  - Get batch historical Tweets
  - Search Tweets
- Managing direct messages
- Upload media
- Get trends

While the REST API works based on the request and response process, the streaming API is based on a continuous connection. After opening a connection to the streaming API using a standard unpaid key token, the connection pushes up to 1% of the relevant public tweets that is shown not to be a realistic random sample of the whole Twitter [127, 102]. The streaming API provides possibility to track specific keywords, specific users, and tweets published within a specific geographical box.

2.1.2 Facebook

Facebook also offers multiple endpoints to let developers access the data. The API from which the data for this dissertation is acquired, is the Graph API, "[...] which is the primary way to get data into and out of the Facebook platform. It's an HTTP-based API that apps can use to programmatically query data, post new stories, manage ads, upload photos, and perform a wide variety of other tasks"[1]. The fact that this API is HTTP-based, makes it easy to access by any platform that supports the HTTP library such as cURL in C, urllib in Python and even any off-the-shelf internet browser, provided that the requested URL includes a valid access token. Pages API is the endpoint that gives access to the public pages. Using the pages API and a standard access token, one can download all the public posts published on public pages and also all the interaction of the users with the posts.

After a series of data scandals following the 2016 US election, Facebook restricted the pages API in April 2018. Subsequently, developers could not access the Facebook API anymore unless they applied for special access to the data [2]. The process of downloading Facebook data for the sake of this thesis has been halted since the mentioned date.

2.2 Data Framework

The data pipeline is completely designed and implemented using the Linux operating system. The whole pipeline includes the following Linux machines,

- 20 Raspberry Pis
- 3 desktop computers
- 4 Workstations
- 3 Network-Attached Storage (NAS) servers

All these Linux machines are on the same local network, and a passwordless SSH is enabled between all of them. The passwordless SSH enables the machines on the cluster to securely transfer data and files without additional authentication steps.

The data pipeline is designed such that different team members could add new search and track queries to the database. Furthermore, it is designed such that the fault

[1] https://developers.facebook.com/docs/graph-api/overview/
[2] https://developers.facebook.com/docs/graph-api/changelog/breaking-changes/#pages-4-4

tolerance of the whole data pipeline is maximized. For the sake of data security, the whole data pipeline and backup procedures are implemented on local machines.

2.2.1 Twitter

Two two main sources of Twitter data that are gathered and analyzed is the user and keyword specific tweets. The objective is to gather and analyze the the political discourse on Twitter within the political sphere of Germany. Two different SQL tables are created that contain the Twitter users and keywords that are to be targeted on Twitter. Different team members could add different keywords and Twitter user IDs to these tables. Each keyword or user ID is associated with an Elasticsearch index name that indicates the Elasticsearch index in which the downloaded tweets should be stored. The Elasticsearch index name is required because different concurrent projects are usually going on, and the data for each project should be indexed in the corresponding Elasticsearch database (Fig. 2.2).

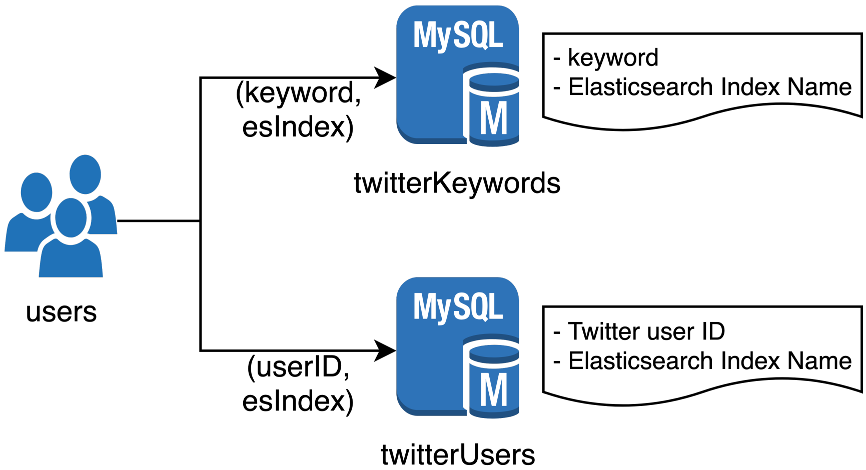

Fig. 2.2. Twitter, SQL tables

There is a text file in the home folder of each of the 20 Raspberry Pis that contains the configuration items, as presented in table 2.1

The Raspberry Pis are divided between the different tasks of tracking keywords and following Twitter users on Twitter. The Twitter streaming script, programmed in the R platform, is scheduled using Linux Crontab to run every one minute on each of the Raspberry Pis. If the Raspberry Pi is already streaming data, the process terminates. Otherwise, based on the task that the Pi is assigned to (conf.task in the configuration file), each Raspberry Pi reads the keywords or user IDs from the corresponding SQL table. Then, the entries are initially divided by project name or esIndex value acquired from the SQL tables, and subsequently by the number of entries per project. Further, the streaming process will be started and continued for the number of seconds mentioned

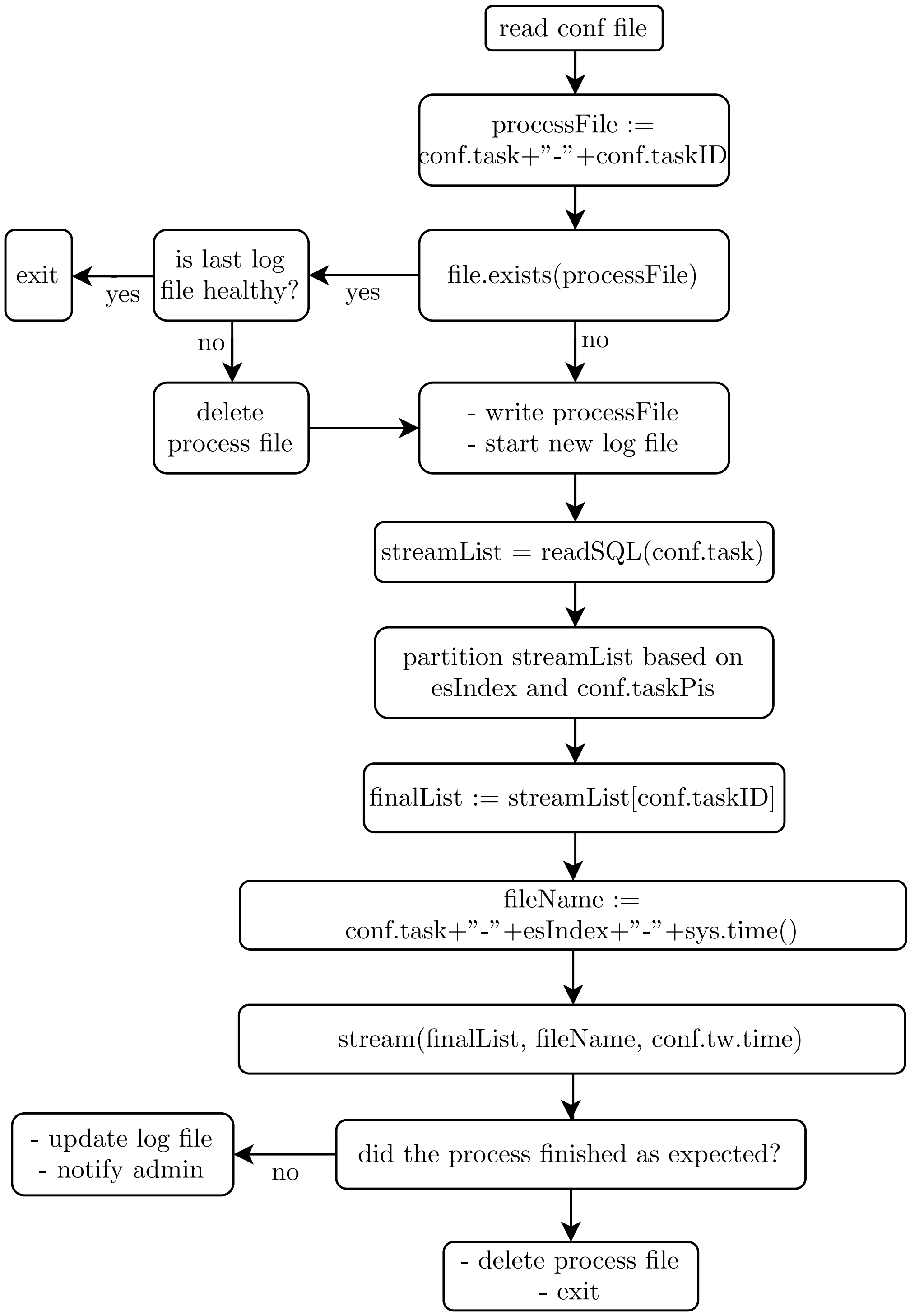

Fig. 2.3. Twitter streaming script

Table 2.1 Items in Raspberry Pis' configuration file for twitter

Configuration Item	Possible Values	Description
work_directory	String	The folder containing the project files
tw.time	Integer	How many seconds to stream on Twitter
task	{follow, track}	If this Raspberry is tracking keywords or following users
taskID	Integer	the ID of the Raspberry
taskPis	Integer	How many Raspberries are performing the following task

in the configuration file (conf.tw.time). A new JSON file, stored on a local folder on the Raspberry Pis, will be generated every 30 seconds, containing all the tweets downloaded within this time. The name of each JSON file contains all the relevant information about its content and also its Elasticsearch index (see Fig. 2.3).

To design a fault tolerant process, different tasks are independently programmed. Therefore, the JSON files are pushed to Elasticsearch using a different script.

Each step of the Twitter streaming script is logged, meaning that any error that occurs while running the script is captured in a log file. Additionally, for some more terminal errors, such as the expiration of the Twitter access key, the script will immediately inform the administrator by sending an email.

The reason that the script is scheduled to run every minute is to add fault tolerance to the data pipeline. In case of possible network, Internet, or other failures, the log file will record the problem. In that case, the next run of the script (in maximum one minute) will be notified of the error in the last run, and a new attempt will be triggered to stream the data. Otherwise, in case the script works as scheduled, no new streaming process will be started, and the script will terminate when the old script is running in the background. Therefore, in case of failure or errors, the streaming process will be stopped for maximum one minute.

The reason because of which the streaming process is being continued for the limited time of tw.time is that the streaming process should be updated to include the new queries if the users add new queries to the SQL tables. Therefore, if new keywords or user IDs are added to the SQL tables that are to be tracked, a maximum of tw.time seconds is required to start tracking the new item without any additional effort.

The twitterKeywords SQL table as in 13.04.2019 is reported in the appendix (Table A.1). This table contains 253 entries that cover two different projects until the date of publication. Additionally, the twitterUsers SQL table has 13,829 entries. The table contains data obtained from different types of twitter users. For example, politicians, political parties, media agencies, journalists, as well as many other politically active and influential individuals.

The actual implemented data pipeline includes 20 Raspberry Pis, 12 of which are assigned to follow the Twitter users and the remaining are assigned to track the Twitter keywords. The Twitter data pipeline is developed such that it is easily scalable, meaning that it is easy to add new Raspberry Pis to the system and to update the configuration files on each Raspberry Pi in case of new projects. The system will automatically scale to distribute the data gathering jobs between different Raspberry Pis including new ones.

2.2.2 Facebook

The main type of Facebook data gathered and analyzed are obtained from the public posts published on targeted public pages. Therefore, an SQL table containing the page name and ID of the targeted pages is crated. Also, different team members are able to add additional public Facebook pages to the table (Fig. 2.4).

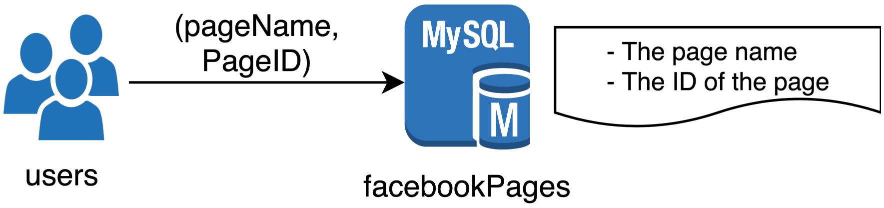

Fig. 2.4. Facebook, SQL Diagram

There is a text file in the home folder of each of the three desktop computers containing the following configuration items,

Table 2.2 Items in desktop computers' configuration file for facebook

Configuration Item	Possible Values	Description
work_directory	String	The folder containing the project files
timeWindow	Integer	The posts not older than this value would get updated
taskID	Integer	the ID of the desktop computer
taskPcs	Integer	How many desktop computers are downloading Facebook data

The process of downloading the data from the Facebook API is completely different when compared to the one in cases of Twitter. This is due to the manner in which the Facebook API functions and also the type of research questions that were planned ahead of time. Apart from the facebookPages SQL table, there is one more SQL tables relevant to Facebook data, namely, the facebookPostIDs table (Fig. 2.5).

There are two main scripts that download the Facebook data. The first script updates the facebookPostIDs table. In the first step, the id of the Facebook pages is loaded from

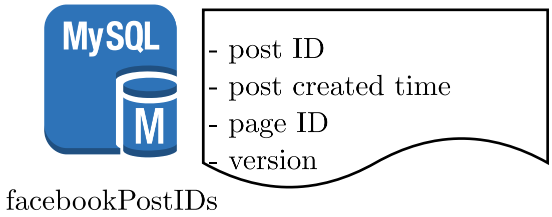

Fig. 2.5. facebookPostIDs SQL table

the facebookPages SQL table. Then, for each page, the last existing post ID from the facebookPostIDs SQL table is queried. For each Facebook page, the IDs of the posts not older than the corresponding existing oldest post ID will be requested from the Facebook API. Finally new post IDs will be sent to the facebookPostIDs SQL table with version zero.

The second Facebook script downloads the complete Facebook posts (Fig. 2.7). In the first step, all the post IDs are loaded from the facebookPostIDs SQL table. Then, those of them older than the timeWindow value, that is in the configuration file, are filtered out. For the remaining IDs the following fields are downloaded using the REST API call,

1. caption
2. created_time
3. target
4. description
5. from
6. full_picture
7. id
8. link
9. message
10. message_tags
11. name
12. place
13. shares
14. source
15. status_type
16. story
17. story_tags
18. type
19. permalink_url
20. attachments
    a) description
    b) description_tags
    c) media
    d) target
    e) title
    f) type
    g) url
21. comments
    a) comment_count
    b) created_time
    c) from
    d) id
    e) like_count
    f) message
    g) message_tags
    h) object
    i) parent
    j) likes
    k) comments
        i. created_time
        ii. from
        iii. message
        iv. message_tags
        v. likes
22. reactions
23. sharedposts
    a) created_time
    b) message
    c) id
    d) from
    e) name
    f) likes
    g) comments

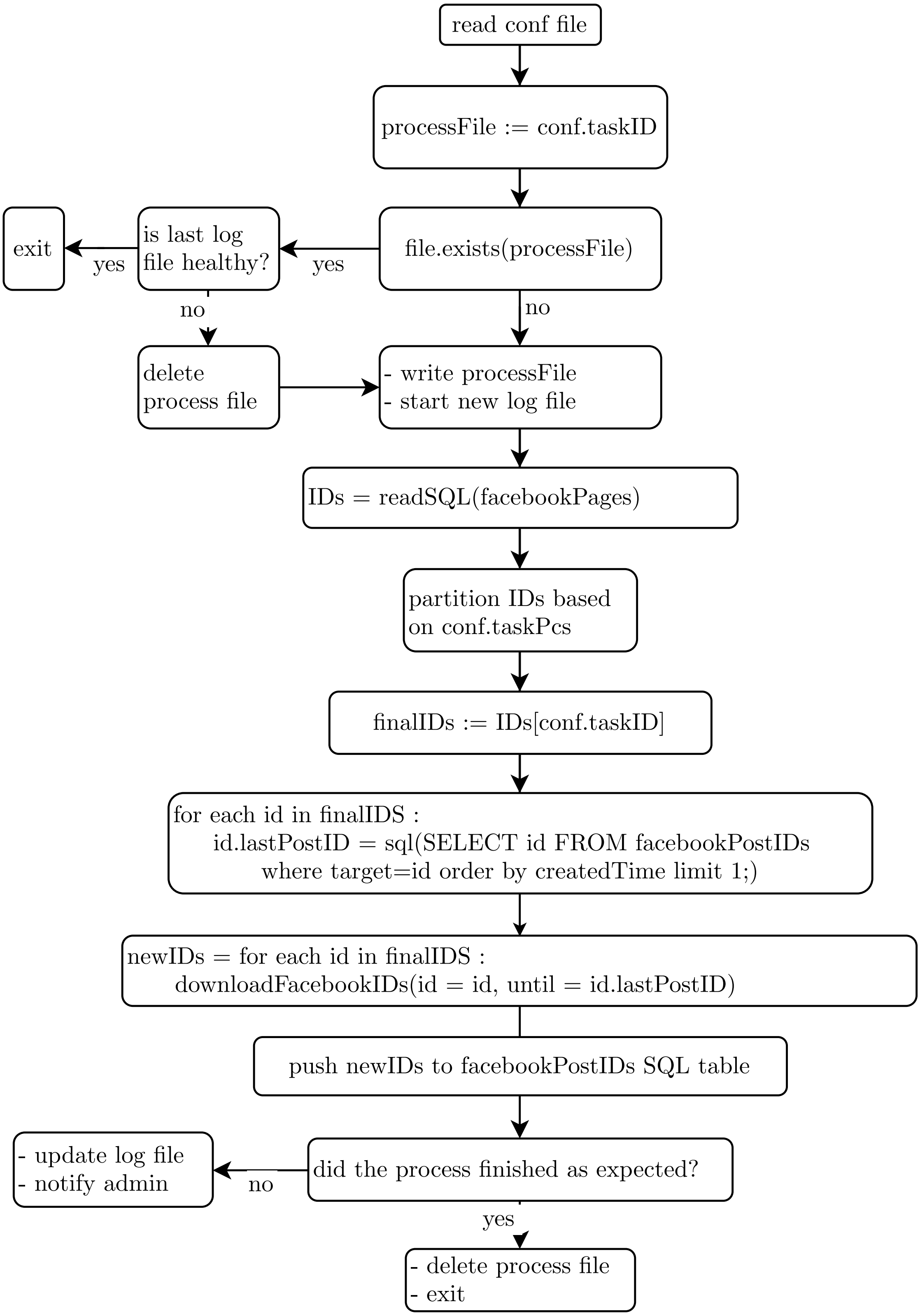

Fig. 2.6. Facebook script to download new post IDs

A sample Facebook HTTP request has the form as in listing 2.1.

```
https://graph.facebook.com/78502295414_10152667211860415?fields=
      caption,created_time,target,description,from,full_picture,id,link,message,message_tags,name,place,shares,source,stats_type,story,story_tags,type,permalink_url,
      attachments.limit(50){
            description,description_tags,media,target,title,type,url
      },
      comments.limit(50){
            comment_count,created_time,from,id,like_count,message,message_tags,object,parent,
            likes.limit(100),comments.limit(100){
                  created_time,from,message,message_tags,likes.limit(100)
            }
      },
      reactions.limit(50),
      sharedposts.limit(50){
            created_time,message,id,from,name,likes.limit(100),comments.limit(100)
      }&access_token=
```

Listing 2.1: Sample Facebook API request

Some Facebook posts can have millions of reactions or comments. However, since the response to each request cannot be larger than a certain size in terms of kilobyte (KB), such that it is no problem ....

Subsequently, the number of items returned for each field cannot be more than 100. Therefore, after the first response to a post request is received, new loops will be triggered to download the rest of the items in the following fields,

1. comments
   a) comments
   b) likes
2. reactions
3. attachments
4. shared posts

It is relatively straightforward to run the loops for downloading all the items in the mentioned fields. If there are more data to be downloaded for a field, the last response contains a link to download the rest of the items of that field.

Similar to the Twitter script, Facebook scripts are scheduled to run every minute. This adds a significant level of fault tolerance to the algorithms. Additionally, the Facebook script designed to download the posts gets different versions of each post. In other words, in each run of the script, all the posts not older than the time window value will get a

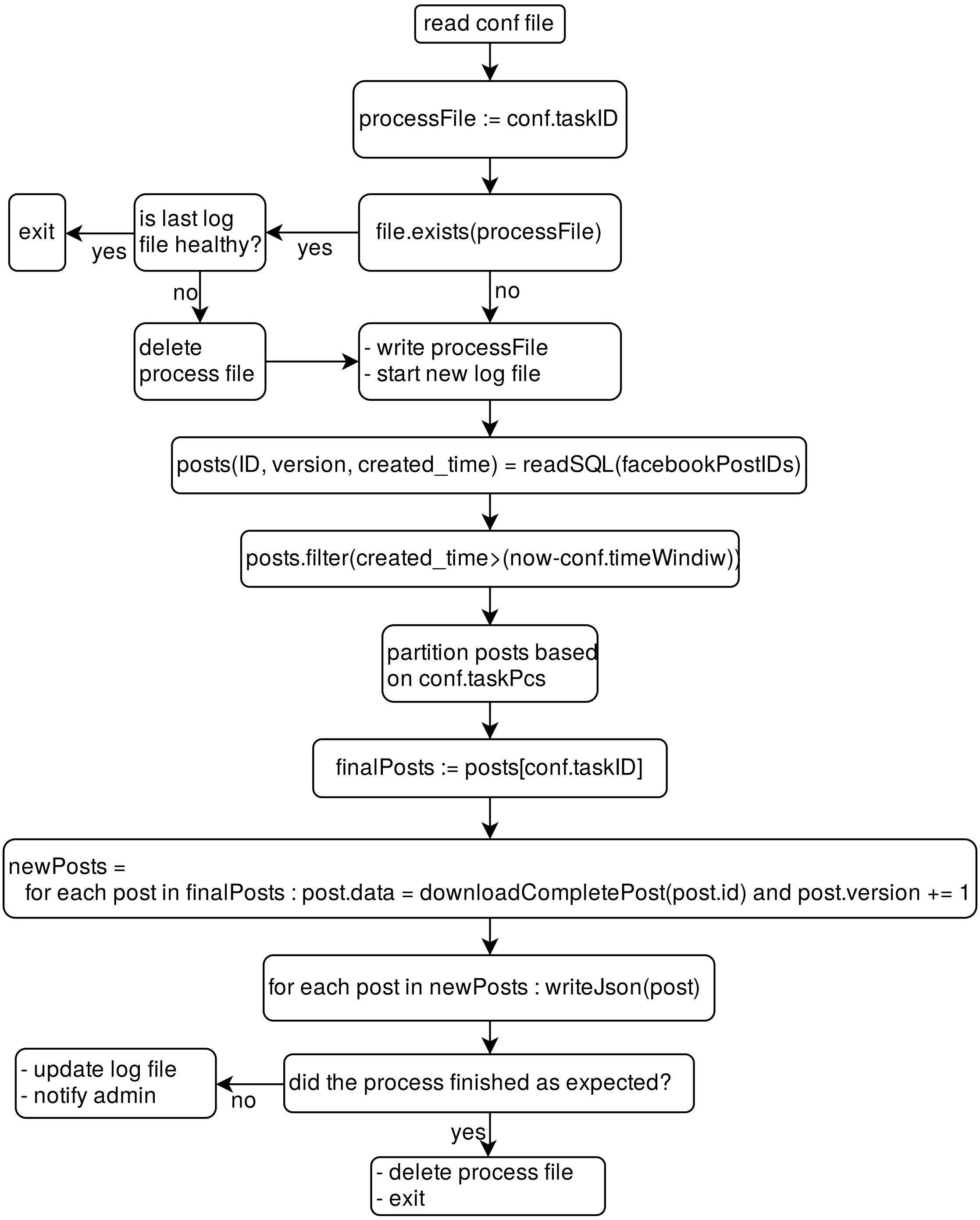

Fig. 2.7. Facebook script to download complete posts

new update. Different version of the same post that are downloaded in different times enables us to run a time series analysis on the Facebook data.

The actual facebookPages SQL table contained 121 official public Facebook pages of different German political parties and media agencies (see Table A.2 in the Appendix). The facebookPageIDs SQL table on the other side hosted 286,646 post IDs published on the 121 pages. The Facebook data pipeline included three desktop computers.

2.3 NoSQL Distributed Data Management: Elasticsearch

The Twitter and Facebook data are downloaded and saved as JSON files. The Twitter streaming script on each Raspberry Pi writes a new JSON file containing the downloaded tweets every 30 seconds. Each file can contain up to tens of thousands of new tweets. The files are initially saved on the local hard drives of the Raspberry Pi machines. Additionally, the Facebook scripts write a new JSON file for each version of the downloaded posts. The Facebook JSON files are also initially stored on the local hard drives of the desktop computers.

The final step of the data pipeline is to push or index the JSON files to the Elasticsearch database. Elasticsearch offers multiple APIs for pushing the data. The one that is implemented for this dissertation is the Bulk API. Using the Bulk API one can push JSON files that contain minimum one document. The only requirement is that each document or observation should be followed by a line that that contains the index name, where the document should be stored, along with the Elasticsearch unique ID of the document. Because the ID of each Tweet and Facebook post is unique, the same ID is also used as the Elasticsearch ID. For Facebook, due to the fact that there are different versions of each post, the Elasticsearch ID is the Facebook post ID concatenated to the version number of the post. A sample Facebook JSON output is similar to that in listing A.1 and a sample Twitter JSON with only one tweet is similar to that in listing A.2 (to make them shorter long field values are replaced with "[...]").

Using a Linux bash script all the JSON files are transferred to one of the Elasticsearch nodes, and the files are indexed to the Elasticsearch server using the Linux curl library. Subsequently, the JSON files are backed up in the NAS servers.

An important point is that the JSON files are pushed to the right index based on the file names. Thus, the JSON file names include all the necessary information about where and when the corresponding JSON file should be indexed. Fig. 2.8 visualizes the details of the complete data pipeline.

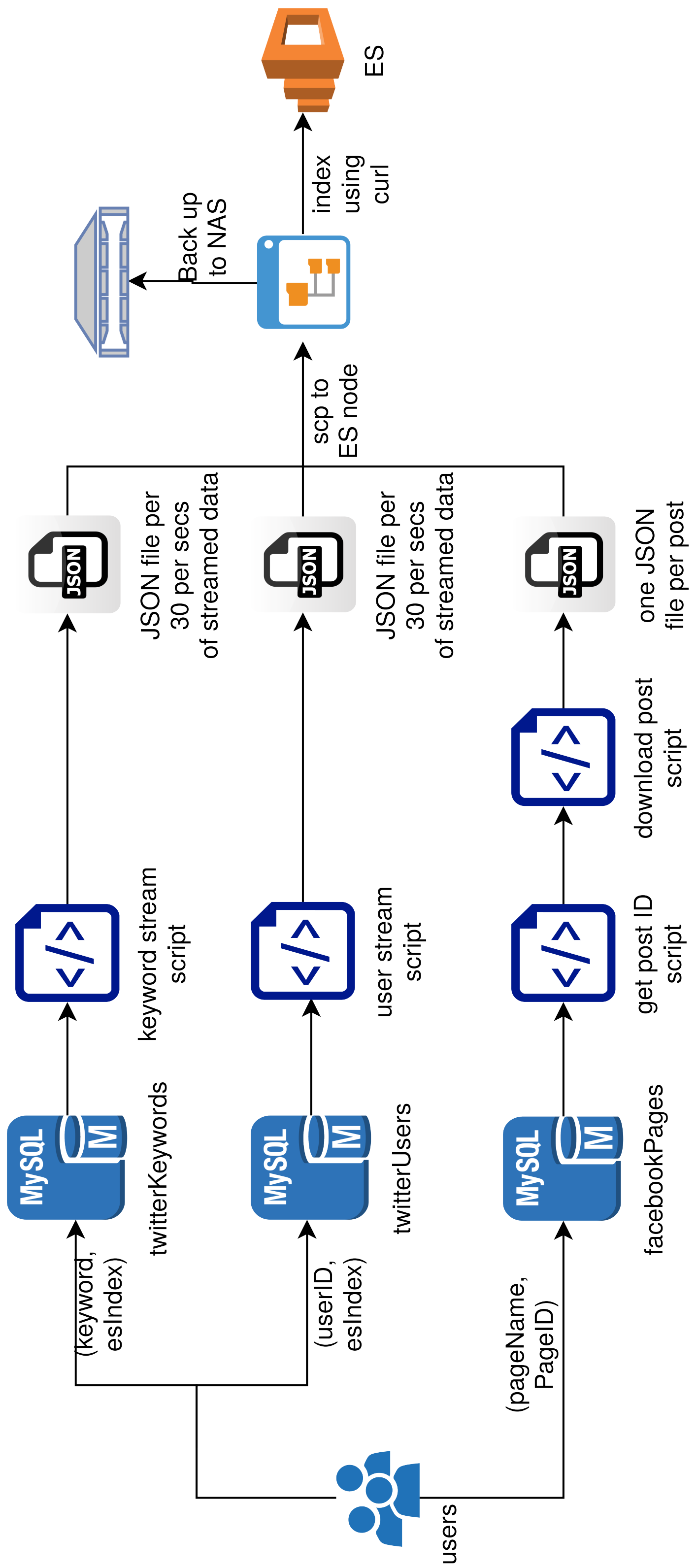

Fig. 2.8. Complete data pipeline

3 Estimating the Political Orientation of Twitter Users in Homophilic Networks

3.1 Preface

Measuring and estimating the political orientation of normal citizens and political actors have always been a relevant question to electoral campaigns, policy making, and also research purposes [49, 35, 118, 96, 51, 6, 124, 125].

The availability of online social media platforms and the volume and diversity of activities on these service, has introduced new opportunities to answer this critical question. In recent years there have been many scattered efforts to estimate the political orientation of users on online social media platforms [161, 54, 6, 25]. These methods have one or few of the following drawbacks:

- They require thousands or more of labeled observations or/and features to train a model.
- They are not generalizable to normal users who may or may not have any political activity on the online platform.
- They predict on a one dimensional latent space and are not generalizable to predict on a multidimensional latent space.

In the following paper I developed a method that requires few labeled training observations per class, requires few learning features, is based on a multidimensional latent space, and is easily expendable to new users even if they have had zero political activity on the platform. The only input to the method is the friends network of the users. Therefore, the method is applicable to almost all major online social networking platforms.

I borrowed the Metric Learning for Large Margin Nearest Neighbor Classification (LMNN) method that is initially developed for computer vision use cases. This method is based on the observation that a precise k-nearest neighbors classification will correctly classify a labeled observation if its k-nearest neighbors share the same label. The algorithm then attempts to increase the number of labeled observations with this property by learning a linear transformation of the input space that proceeds the final learning method. The linear transformation of LMNN is derived by minimizing a loss function with two terms. The first term minimizes the large distances between observations within class, and the second term maximizes the distances between the observation between the classes [160].

In the second step a k-nearest neighborhood network based on the LMNN-transformed friend's network is formed. After which, a label propagation algorithm based on the Gaussian fields and Harmonic functions is applied in order to estimate the label of the unknown nodes in the graph [170].

I applied the method to a sample of Twitter users in Germany's six-party political sphere. The method obtained a significant accuracy of 62% using only 40 observations of training data for each political party. Without the LMNN transformation the method had accuracy of 20% that is significantly lower than 62%. I argue that the LMNN transformation accentuates the already existing clustering in the network that is formed due to the homophily bias. Homophilic networks are user clusters formed due to cognitive motivational processes linked with cognitive biases.

Estimating the Political Orientation of Twitter Users in Homophilic Networks

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3.2 Abstract

There have been many efforts to estimate the political orientation of citizens and political actors. With the burst of online social media use in the last two decades, this topic has undergone major changes. Many researchers and political campaigns have attempted to measure and estimate the political orientation of online social media users. In this paper, we use a combination of metric learning algorithms and label propagation methods to estimate the political orientation of Twitter users. We argue that the metric learning algorithm dramatically increases the accuracy of our model by accentuating the effect of homophilic networks. Homophilic networks are user clusters formed due to cognitive motivational processes linked with cognitive biases. We apply our method to a sample of Twitter users in Germany's six-party political sphere. Our method obtains a significant accuracy of 62% using only 40 observations of training data for each political party.

3.3 Introduction

Measuring and estimating the political orientation of normal citizens and political actors has always been a relevant question. The answer to this question is essential for electoral campaigns [49, 35, 118], agenda setting, policy making [96], and research purposes [51, 6, 60]. The methodological efforts to answer this crucial question possess three qualities.

The first quality is related to the number and type of inputs in the algorithm: What type of features are considered while estimating the latent political orientation of the users? The second quality is if the method is designed to estimate the political orientation of a specific group of political actors [161, 54] or a more general group of citizens [6]. If a method is designed based on a specific group of political actors or citizens, it cannot be generalized to estimate the political orientation of other groups of political actors or citizens. Cohen and Ruths [25] have presented that methods that have accuracy greater than 90% in estimating if a Twitter user is a Democrat or Republican, would have accuracy level of less than 65% when applied on general Twitter users. The last quality is if the method measures the political orientation on a one dimensional or a multidimensional latent space. Most of the literature has been designed based on the two-party political system of the United States. Thus, they are inherently designed to estimate a one-dimensional latent variable.

In this work, we use a combination of metric learning algorithms and label propagation methods to estimate the political orientation of Twitter users. Our method has three distinguishing features. First, the method requires a minimal number of features as training data because it exploits the homophilic structure of social networks [50, 93]. Second, the proposed method estimates on a multidimensional latent space; therefore, the proposed method can be used to estimate the political orientation of users in a multiparty political system. The third feature is that our method is extendable to multiple groups or cluster of users. Our method can estimate the political orientation of users even if the target users have zero political activity on the platform.

3.4 Methodology

We use a combination of metric learning algorithms with label propagation methods to estimate the political orientation of Twitter users. The goal of label propagation algorithms is to estimate the labels of a large set of unlabeled observations from the small set of labeled observations.

Suppose there are l labeled observations $(x_1, y_1), \dots, (x_l, y_l)$ and u unlabeled observations such that $l < u$, and $n = l + u$. Consider a connected graph $G = (V, E)$ with nodes $L = \{1, \dots, l\}$ and $U = \{l + 1, \dots, l + u\}$ corresponding, respectively, to the labeled or training observations and unlabeled or test observations. A label propagation algorithm propagates the labels for the set U, based on the distances between its observations to the observations in L. Within the label propagation algorithm, the labels of the vertices in set L would be fixed, but the labels of the set U would be estimated based on a function of their distance to set L.

Let n be the total number of Twitter users we have including l users for whom we already know their political orientation and u users for whom we want to estimate their political orientation. We use only the structure of the friends' network to estimate the political orientations. Let F be the set of friends of all n users with size m. Therefore, we can create the binary matrix A with dimension $n \times m$, which would represent the friends of each of the n users. Before constructing graph G from matrix A, we transform matrix A by using a proper metric learning algorithm.

The reason for transforming matrix A is that we believe there are hidden information within the network structure, which we could use to increase the estimation accuracy. By contrast with the rational choice theory, the human judgment is influenced by various cognitive biases, prior judgments, environmental features, and stimulus-feedback loops [75, 36]. Cognitive biases reproduce human judgments that could be systematically different from rational reasoning [73, 58]. The cognitive biases make the human brain process the information in a distorted manner compared with an objective reality [142]. Although there is a list of cognitive biases that affect the online activity of the users, we are specifically interested in cognitive biases related to self-categorization. Self-categorization describes the motivations and circumstances under which communities with shared identities form. The self-categorization theory articulates that the spectrum of human behavior can be analyzed from a pure interpersonal or individualistic and a pure intergroup or collectivist perspective. Humans have the desire for a positive and secure self-concept; therefore, they connect with individuals that confirm their pre-existing attitudes, verify their self-views, and increase their social identity. The aforementioned behaviour is called confirmation bias [50]. In addition, "If we are to accept that people are motivated to have a positive self-concept, it flows naturally that people should be motivated to think of their groups as good groups" [67]. Striving for a positive and secure self-concept, humans' collectivist behaviors contribute to the formation of online and offline communities with shared social identities [128]. Consequently, users with similar labels, that is, similar political preferences, are expected to be relatively closer to each other. Therefore, if we were to supposedly apply a k-nearest neighbors learning method, it makes sense to use a distance function that interprets similar users closer to each other. Instead of using an off-the-shelf distance function such as Euclidean distance, we use an alternative distance function that guarantees higher accuracy for the labeled or training observations after running the learning method.

A brief description of the steps of our method is as follows. First, we acquire matrix A, which includes the labeled observations and the unlabeled observations as rows. Second, we learn the optimized distance or metric function that guarantees higher accuracy within the labeled observations by exhausting the special structure of homophilic networks. We transform matrix A by using the learned metric to construct graph G. Finally, we apply the learning method or the label propagation algorithm.

3.4.1 Metric Learning for Large Margin Nearest Neighbor Classification (LMNN)

The accuracy of each learning algorithm is a function of the distance function or the metric used to compute the distance between the observations. The metric learning algorithm we use is based on the following: a precise k-nearest neighbors classification will correctly classify a labeled observation if its k-nearest neighbors share the same label. The algorithm then attempts to increase the number of labeled observations with this property by learning a linear transformation of the input space that proceeds the final learning method. The linear transformation of *LMNN* is derived by minimizing a loss function with two terms. The first term minimizes the large distances between observations within class, and the second term maximizes the distances between the observation between the classes [160].

In general, metric learning algorithms estimate the positive semidefinite transformation matrix $\mathcal{M}$ such that the distance between two observations, x_i and x_j, is derived by the Mahalanobis distance,

$$d_{\mathcal{M}}(x_i, x_j) = \sqrt{(x_i - x_j)^T \mathcal{M} (x_i - x_j)}$$

which follows certain features. If we replace $\mathcal{M}$ with the identity matrix, the resulting metric would be Euclidean metric. *LMNN* learns a linear transformation matrix $\mathcal{M}$, such that the training or labeled observation satisfies the following items [160]:

- Each labeled observation should share the same label as its k- nearest neighbors. This is achieved by introducing a loss function that penalizes large distances between observations belonging to the same class,

$$\epsilon_{pull}(L) = \sum_{j \rightsquigarrow i} ||L(\bar{x}_i - \bar{x}_j)||^2$$

  where $j \rightsquigarrow i$ indicates that j is an observation that we desire to be close to i, and L is the function representing the transformation by matrix $\mathcal{M}$.

- The labeled observations with different labels should be significantly separated. This separation is achieved by introducing a loss function that penalizes small distances between observations belonging to different classes,

$$\epsilon_{push}(L) = \sum_{i,j \rightsquigarrow i} \sum_{l} [1 + ||L(\bar{x}_i - \bar{x}_j)||^2 - ||L(\bar{x}_i - \bar{x}_l)||^2]$$

  where the inner sum iterates over all the observations with a different class to i, and l invades the perimeter of i and j plus unit margin. In other words, the observation l satisfies

$$||L(\bar{x}_i - \bar{x}_l)||^2 \leq ||L(\bar{x}_i - \bar{x}_j)||^2 + 1$$

The final loss function is a weighted combination of the two defined components,

$$\epsilon(L) = (1 - \mu)\epsilon_{pull}(L) + \mu\epsilon_{push}(L)$$

Although the general loss function above is not convex, by limiting the solution space to positive semidefinite matrices, the loss function will be a convex function.

The solution to the minimization of the loss function, given the labeled subset of A, is the desirable matrix $\mathcal{M}$. We transform matrix A to obtain matrix $A_{\mathcal{M}}$ by

$$A_{\mathcal{M}} = A \times \mathcal{M}$$

We construct graph G using the $A_{\mathcal{M}}$ of size $n \times m$ by using the nearest neighbor graph method. In other words, using n rows of $A_{\mathcal{M}}$, we define n vertices of G and then define edges between each vertex and its k_G nearest neighbors by using the Euclidean distance function.

3.4.2 Label Propagation Using Gaussian Fields and Harmonic Functions

The goal of applying a label propagation algorithm to a graph is to estimate the labels of unlabeled vertices by using their connections to the few labeled vertices. This problem is usually formulated as an iterative process within which the labels are gradually diffused over the matrix, such that the state of the graph would converge to a stationary state. This iterative process might have an analytical solution that would be more efficient than applying the algorithm iteratively [8, 169]. The most crucial implication of a label propagation algorithm for our question regarding estimating political orientation of Twitter users is that the only requirement for estimating the political requirement of a user is that the user should be connected to graph G. Hence, the user should not necessarily have politicians or other political actors as friends.

The algorithm we use for label propagation is based on Zhu et al. [170]. Let the simple graph $G = (V, E)$ and the set of the labeled and unlabeled vertices, L and U, be as defined. The goal is to compute the real-valued function $f : V \to \mathbb{R}$ on the simple graph G. f must assign the same given labels for the set L or $f_l(i) \equiv y_i$ for $i \in l$. To estimate the function f they defined the energy function

$$E(f) = \frac{1}{2} \sum_{i,j} w_{i,j}(f(i) - f(j))^2$$

and the Gaussian field

$$p_\beta(f) = \frac{-e^{\beta E(f)}}{Z_\beta}$$

where β is an inverse temperature function and $Z_\beta = \int_f exp(-\beta E(f))$ which normalizes over all functions constrained to the constraint $f_l(i) \equiv y_i$ on the labeled vertices. Then, they demonstrate the result of the minimization

$$f = \arg\min_f E(f)$$

which is a harmonic function that satisfies the constraint $f_l(i) \equiv y_i$ on the labeled vertices. The harmonic property implies that the value of f at each unlabeled vertex is the average of f at neighboring vertices. Therefore, the estimated labels would be a function of the similarity of all neighboring vertices.

The estimated f has an interpretation within the framework of random walks. The estimated $f(i)$ for an unlabeled vertex $i \in U$ would be a vector of size equal to number of possible classes. The jth element of $f(i)$ would be the probability that a particle that started at vertex i would first hit a vertex with class j. Therefore, the resulting algorithm can be used to estimate the political orientation of a user in a multidimensional latent space.

3.5 Data and Results

3.5.1 Data Preparation

We require two sets of data for training and testing. We acquire both sets from the public Twitter API. In the first step, we obtained the list of all the members of the main and local German parliaments who are available on Twitter. This list contains 623 Twitter users from one of the six parties CDU/CSU, SPD, Grüne, Linke, FDP and AfD.

From a database of German political Tweets, we obtained a list of 400,000 random Twitter users. We downloaded the list of all their friends and their last 4,000 Tweets by using the public API. We counted how many times each user retweeted the Tweets of members of each of the political parties we acquired in the first step. If a user has retweeted a minimum of five Tweets from members of party j but no retweets from other parties, we tag this user as a user with a political orientation to party j. From the 400,000 initial users, we could label 8,146 based on the mentioned heuristic.

To reduce the complexity of the computations, we reduced the sample size to 50,000 from 400,000. Thus, we created matrix A using 50,000 random users including all of the 8,146 labeled users. Matrix A has at this step 50,000 rows as users, which we want to use for our training and test set, and 7,194,153 columns as the friends. To further reduce the complexity of the computations, we removed the friends who are friends of less than 0.01% of the users. The final matrix A has the dimension 50,000$\times$ 552,136.

We confirm that our test data has a minor bias in the sense that we already know our test data includes users who have engaged in some type of political activity. This assumption is because these users are randomly chosen from a database of German political Tweets. On the other side, this bias is mildly mitigated in two steps. First, matrix A is created by a list of friends of all 50,000 random users and not only the friends of the labeled 8,146 users. Thus, the feature sets are from a bigger set of observations. Second, we added some randomness by removing some columns of matrix A in the final step.

3.5.2 Metric Learning and Label Propagation

We resampled 40 users per political party out of the 8,146 labeled users of A. We learned matrix $\mathcal{M}$ based on the 240 users. Next, we transformed the whole matrix A using $\mathcal{M}$ by applying

$$A_{\mathcal{M}} = A \times \mathcal{M}$$

Using the transformed $A_{\mathcal{M}}$, we made a 10-nearest neighbors graph using a Euclidean distance function to make graph G. Finally, we applied the label propagation algorithm on G that has 50,000 vertices, out of which, the labels of 240 are introduced to the algorithm. The labels of the other 49,760 are estimated using the label propagation algorithm.

random forest	A (not transformed)	0.23
label propagation		0.20
random forest	$A_{\mathcal{M}}$ (transformed)	0.30
label propagation		0.62

Table 3.1 Average accuracy of the predictions over 10 resamples

3.5.3 Results

We performed the resampling and the computations 10 times to make sure the results are robust. For each trial, we applied a random forest classifier on the 240 training data as a benchmark result. We also applied the random forest classifier and the label propagation method on A directly to improve our understanding regarding how much the $LMNN$ metric learning method contributes to the accuracy of the results. Table 3.1 shows the average accuracy of the estimations on the remaining 8,146-240=7,906 labeled users with a known political orientation.

Referring to Table 3.1, we observe that the transformation increases the accuracy of the random forest classifier and the label propagation algorithm. We also observe that the combination of the metric learning algorithm and the label propagation method results to a much higher accuracy of estimation.

3.6 Discussion

In this paper, we proposed a new method to estimate the political orientation of Twitter users. Our method has many distinguishing features: The method requires few training observations, requires few learning features, is based on a multidimensional latent space, and is easily expendable to new users even if they have zero political activity on Twitter.

Based on Table 3.1, the high accuracy of the model is due to the transformation of the initial matrix using the function learned by the *LMNN* algorithm. The cost function of the *LMNN* algorithm has two parts. One part pulls the observations of the same class closer to each other, and the other part pushes the observations of different classes far apart. Additionally, since the *LMNN* algorithm is based on optimizing a k-nearest neighbor model on the training observations, the trained matrix $\mathcal{M}$ transforms the observations based on their relation to other observations in their vicinity and not the whole dataset. These characteristics have crucial implications reagarding the accuracy of our estimation.

As aforementioned, the initial matrix, A, has a special structural feature because it represents a homophilic social network, which means that users with similar political identity are assumed to demonstrate similar behavior on Twitter. Therefore, we expected that users with similar political identity would follow similar politicians, similar celebrities, similar sportsmen, and so forth.

When we apply the *LMNN* algorithm to this homophilic network, we accentuate the extant distinctive features formed due to the existing cognitive biases in self-categorization and group formation [50, 93].

The matrix $\mathcal{M}$ learns different combinations of features that help distinguish normal Twitter users based on their political orientation. The matrix $\mathcal{M}$ also allows different combination of features for each class because it is based on a k-nearest neighbor algorithm that considers a bounded proximity of the users. Our model detects the political orientation of users with high accuracy, and by far outperforms other algorithms that have been applied to this task.

Due to the use of label propagation algorithm, this model can be later applied on any new user e to estimate her or his political orientation, as long as e is connected to the graph G. More generally, to predict the political orientation of user e, we must find a new set of users including e, forming a small graph g connected to the initial graph G.

This study provides valuable insights into the study of user behavior on online social networks. This study illustrates, that using mathematical algorithms that exhaust properties of social theories, we can improve the performance of models explaining human behavior. Furthermore, this study contradicts the general claim that a huge amount of data is required to make accurate predictions on social and political behavior. Finally, our method provides a novel technique to assign political partisanship, by having as input only the network of interpersonal connections.

4 Measuring the Ease of Communication in Bi-partite Social Endorsement Networks

4.1 Preface

Bipartite networks are networks that contain two different types of nodes in contrast to simple networks that contain only one type of nodes. Even though these networks are applicable to many real-life case studies, the methods to analyze and extract knowledge from them are strictly limited comparing to the simple networks [113, 110, 30, 56, 84, 108, 131].

The bipartite social networks representing the activity of the users on online social services have two distinctive features compared to most real-life networks. While real-life networks often have disassortative mixing or negative correlations with neighboring vertices, social networks mostly show assortative mixing or positive degree correlations with the neighboring vertices. A second distinctive feature of social networks is their topology. While non-social networks generally have no significant local clustering compared to random networks with similar degrees of distribution, social networks have been found to have significant clustering [109].

In this paper I developed the tools to efficiently study assortative social networks that posses strong local clusters. Firstly, I introduced the bipartite social endorsement networks. These networks represent the endorsement of users to discussions of different classes (as sample left, right or liberal, conservative) on online social platform. Then the tools to project these networks to simple networks are developed. The projection method preserves the two special features of social networks, assortative mixing and local clustering. Finally, using the search information index, the ease of communication between all pair of discussion vertices is computed [151, 146].

The concept of political polarization as the extent of disagreement between different people is then borrowed from the political science literature [34]. After that, I argued that as political polarization increases, it is expected that the users contribute more to the discussion vertices of a single political orientation. This leads to lower availability of information between each pair of discussion vertices with contrasting political orientation. Therefore, the average search information index between all possible pairs of discussion vertices with contrasting political orientation is expected to be higher.

To validate the expected link between the search information index and political polarization, I applied the methods on simulated endorsement networks and also a real-life

Facebook endorsement network that spans one complete year. The Facebook data includes 4,438,157 likes on 2,452 public Facebook posts posted in the official AfD page[1].

The results of the both simulations and the real-life Facebook data were inline with the expected outcomes. The results on the real-life Facebook network were specifically in line with previous studies on the rise of the AfD that found that the party adopted a political agenda that was quite different from the other parties, and consequently they had attracted alienated voters who had become segregated from the rest of the electorate [70, 87]. It was also found that the rise in party support had been accompanied by increased radicalization and polarization [53, 32, 129].

[1]https://www.facebook.com/alternativefuerde/

Measuring the Ease of Communication in Bipartite Social Endorsement Networks

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4.2 Abstract

In this work, complex weighted bipartite social networks are developed to efficiently analyze, project and extract network knowledge. Specifically, to assess the overall ease of communication between the different network sub-clusters, a proper projection and measurement method is developed in which the defined measurement is a function of the network structure and preserves maximum relevant information. Using simulations, it is shown how the introduced measurement correlates with the concept of political polarization, after which the proposed method is applied to Facebook networks to demonstrate its ability to capture the polarization dynamics over time. The method successfully captured the increasing political polarization between the *Alternative für Deutschland*'s (AfD) supporters and the supporters of other political parties, which is in line with previous studies on the rise of the AfD in Germany's political sphere.

4.3 Introduction

4.3.1 Social Networks

Following of the uptake in social media services, social scientists have been presented with significant new challenges and opportunities. The generation of huge data sets, which record the interactions of millions of users, has dramatically changed the quantitative models, research style and empirical methods that social scientists use. This renaissance requires social scientists to adapt to new quantitative methods [76].

Network analysis theory can now provide the theory and tools required for social scientists to model, study and generate knowledge from the complex interactions of millions of social media users on services such as Facebook and Twitter. However, social networks can be complex as unlike most biological, technological, and other real-life networks that often have disassortative mixing or negative correlations with neighboring vertices, social networks mostly show assortative mixing or positive degree correlations with the neighboring vertices. A second distinctive feature of social networks is their topology. While non-social networks generally have no significant local clustering compared to random networks with similar degrees of distribution, social networks have been found to have significant clustering [109].

These two special social network features emerge at the time of the network formation; that is, sub-communities and assortative mixing are formed while the whole network emerges. These features emerge because of many reasons such as technological design or cognitive biases. Geschke et al. [50] used agent-based modeling to show that sub-communities formed even in the absence of technological filters. Therefore, any effort to study social networks needs to consider that these networks have special features that cannot be ignored.

This paper focused on a special type of social network. While most social and non-social networks are one-mode networks, some are two-mode or bipartite networks. While one-mode networks have only one type of vertices, bipartite networks have two different types of vertices and each edge is between a vertices pair of different types. For example, a friendship network is a one-mode network in which each edge between two vertices indicates that the corresponding users are friends. However, Facebook posts are part of a bipartite network, in which each edge indicates a user who has commented on the corresponding Facebook post. Both types of the mentioned networks might have weighted edges that measure the strength of the edge, or binary simple edges which only shows an unweighted connection. Bi-partite networks have been analyzed in a wide variety of different contexts, such as sports activity networks [113], actors networks [110], economics and finance networks [30], online file sharing networks [56, 84] and scientific authoring networks [108, 131].

Because bipartite networks are more complex to study, they require different tools than studies on simple one-mode networks [105, 164, 11, 166]. Studying bipartite networks requires either projecting the network to a one-mode network or developing the proper measurements applicable to the bipartite case [40]. The result of projecting a bipartite network to a one-mode network is a binary or weighted one-mode network, which could lead to the deletion of some important information [167, 115]; for example, the global and local clustering coefficients on bipartite networks differ significantly from the counterpart values in corresponding projected networks [114].

This paper argues that the usual projection methods lose a great deal of information because they do not account for the existing assortativity and the network clustering within social networks. Therefore, in this paper, first a new projection method is suggested for weighted bipartite social networks that is able to preserve the relevant information from the initial network. Afterwards, methods applicable to the resulting simple one-mode networks are employed to generate knowledge from the projected networks. The proposed method is used to demonstrate that these methods could be used as proxy measurements for monitoring political polarization dynamics, and a mathematical method is developed to study this important social and political process. Because of the rise in online social networks, political polarization has become a key research topic in social sciences; therefore, this study contributes to research in these areas and could be used to understand the tenor of a particular development.

4.3.2 Political Polarization

From well-known online news services to the political candidates themselves, citizens can now obtain information from a myriad of sources, and are also able to engage in political discourse with many (often unknown) social media users and website commentators [14, 100, 123, 137]. Although there has been an exponential increase in the information flow on online platforms, the human abilities to digest, analyze and process such information has been bounded due to the biological brain constraints. It is argued that due to the bounded rationality theorem, when the humans have incomplete information about the alternatives the probability of behaving irrationally is higher [145, 72, 63]. Therefore, social media users are generally unable to rationally analyze the abundant information flows on these emerging heterogeneous media.

In the other side, people have a natural tendency to bond with those who are similar; a behaviour which is also imprinted in their selection of information sources and discussion groups. This principle, known as homophily, explains people's tendency to seek situations that imbue similarity and agreement; that is people tend to bond with similar individuals [31, 98, 106, 5].

Because of the bounded rationality theorem and homophily, normal citizens interact with information sources and people who have similar beliefs during the selection process on social media services [13]. Thus, the widely accessible social media services turn potentially into breeding grounds of polarization. DiMaggio et al. [34] defined political polarization as the distance between the political orientations of different people. They argued that political polarization is a process as well as a state. While the latter refers to the distance an opinion is from some theoretical maximum or average, the former refers to development of the distance between the political orientations of different people over time.

DiMaggio et al. [34] introduced four independent and different polarization measurements, two of which referred to single distribution properties, while the others were focused on the relationships between the distributions. These measurements included variances or the dispersion of opinions, the kurtosis or bimodality of opinions, the tau-equivalent reliability or association between the opinions, and the correlation of opinions with salient individual characteristics. It was rationalized that political polarization would possibly entail a higher variance, a lower kurtosis, a higher tau-equivalent reliability and a higher correlation of opinions with salient individual characteristics.

4.3.3 Current Research

The motivation for creating reliable tools to measure and understand political polarization comes from political theory. In a democratic system, citizens should be aware of all cross-ideological points of view and also have the right to defend their own beliefs [61, 148]. Communication environments that expose citizens to a range of cross-ideological points allow citizens to be able to better develop justifications for their own viewpoints, establish a better understanding about alternative cross-ideological viewpoints, and develop a higher tolerance toward the opinions of others. DiMaggio et al.

[34] claimed that “other things being equal, attitude polarization militates against social and political stability by reducing the probability of group formation at the center of the opinion distribution and by increasing the likelihood of the formation of groups with distinctive, irreconcilable policy preference”. Therefore, as political polarization has been found to have undesirable effects, this paper seek to develop a methodology to measure, analyze, and understand political polarization. Because online social media interactions are complex, a unique political polarization measurement is needed that is able to capture the dynamics or the evolution of political polarization over time.

This paper introduces social weighted bipartite endorsement networks, develops efficient methods to project weighted bipartite social networks that preserve the maximum amount of relevant information, and then applies the projection method to a simulated weighted bipartite social networks while controlling the political polarization. It is demonstrated that the search information index introduced by Trusina et al. [151] and Sneppen et al. [146] is positively correlated with the extent of the political polarization when applied to the projected networks. The newly developed methods are then applied to a one year longitudinal Facebook endorsement politically active network in Germany. The introduced measurements allow for the monitoring of the political polarization dynamics within social networks.

4.4 Related Work

The relevant literature from two different topics is reviewed in this section; bipartite networks and political polarization.

4.4.1 Projecting Bipartite Networks

As mentioned, bipartite networks are applicable to many different fields of sciences. However, because of their inherent complexity, previous research has tended to only analyze their most basic features, such as the degree distribution of the vertices. There have been some attempts to introduce bipartite notion of local clustering coefficients [130, 114, 165], centrality [45], correlation of vertex degree [122] and community detection [57, 163] that have been developed and directly applied to bipartite networks. However, as pointed out by Latapy et al. [82], as most of these measurements have been somewhat ad hoc and specific to the case, they could not be easily extended to general bipartite networks.

The other approach to the study of bipartite networks is reducing the bipartite network to a binary or weighted one-mode network [9, 115, 167], with the most prominent projection methods being binary projection, sum projection, and the celebrated weighted sum projection of Newman [107]. Based on binary projection, two vertices of the same type are connected with a simple edge if both are at least connected to one vertex of the other type in the initial network. Under the sum projection, two vertices of the same type are connected with an edge weight p if both are connected to p vertices of the other type in the initial network. The Newman projection is similar to the sum projection except that each shared vertex of the other type is given a weight equal to $\frac{1}{N_p - 1}$ when N_p is the degree of that vertex.

Each projection method is based on a similarity function. For example, the binary projection is based on the following similarity function,

$$Sim_{binary}(u_i, u_j) = \begin{cases} 1 & \text{if } u_i \cdot u_j > 0 \\ 0 & \text{if } u_i \cdot u_j = 0 \end{cases}$$

where u_i is the binary vector indicating to which vertices the vertex i is connected and $\cdot$ is the dot product. The sum method is based on the following similarity function

$$Sim_{sum}(u_i, u_j) = u_i \cdot u_j$$

4.4.2 Political Polarization Measurements

DiMaggio et al. [34] introduced simple political polarization measurements that are not directly applicable to complex environment of social networks. Levendusky [89] attempted to measure and evaluate the polarization of individual Democrats and Republicans over time using National Election Study data. Fiorina and Abrams [46] studied the relationship between polarization and the geographical distribution of different groups. Freire [47] measured party polarization on the left-right scale. Using clustering methods, Conover et al. [26] showed that the network of political retweets had a segregated network of activity. Matakos et al. [95] used an opinion formation model to define a polarization index that measured the polarization in the opinions of the individuals in the network as well as the network structure. Akoglu [1] considered a bipartite network of users and subjects using Markovian Random Fields framework, and then defined the problem as a probabilistic classification task in which the polarity rank of the users in the political spectrum were to be predicted. The most related work to our methodology is Garimella et al. [48]. They used network theory tools to measure how controversial political topics in social media appeared to be.

4.5 Methodology

4.5.1 Problem Overview

The type of social networks which we considered are weighted bipartite social networks of users and discussion vertices. A bipartite network $\mathcal{G} = (\mathcal{U}, \mathcal{V}, \mathcal{E})$ was established in which n users $\mathcal{U} = \{u_1, ..., u_n\}$ and m discussions $\mathcal{V} = \{v_1, ..., v_m\}$ are connected with weighed edges $e(u, v, w) \in \mathcal{E}$ such that $\mathcal{E} \subseteq \mathcal{U} \times \mathcal{V} \times \mathbb{R}$. The weighted edges $e(u, v, w)$ represent positive endorsement of magnitude w from user u to discussion v. It was further assumed that each discussion v belongs to one of $p > 1$ possible non-empty classes $\mathcal{C}_{\mathcal{V}} = \{c_1, ..., c_p\}$ such that $p \ll m$; that is, each class c is a sub-cluster of the network $\mathcal{G}$.

This structure can be applied to online user activities, such as the retweet and favorite networks on Twitter, the like and share networks on Facebook, and the share networks of blog posts. For example, set $\mathcal{C}$ might be $\{Republicans, Democrats\}$ and set $\mathcal{V}$ might be a set of Facebook pages or blog pages that are politically oriented toward either Republicans or Democrats. Then, given the positive endorsement of n users on the Facebook posts or blog pages, the task is to measure the ease of communication and also to capture dynamics of political polarization between the different network sub-clusters, $\{Republicans, Democrats\}$.

In the first step, tools were developed to project the weighted bipartite network $\mathcal{G}$ to the simple network $\mathcal{H} = (\mathcal{V}, \mathcal{V})$. To project $\mathcal{G}$ to $\mathcal{H}$, similar to other projection methods, a similarity function was needed. For the similarity function a distance function is employed and If the distance between two vertices was less than a maximum threshold, an edge between the two corresponding vertices was established. Then information theory concepts were applied to $\mathcal{H}$ to measure the ease of communication between every two random $\mathcal{H}$ vertices using the search information index introduced in Trusina et al. [151] and Sneppen et al. [146].

4.5.2 Metric Function

In this section, the distance or metric function is introduced that measures the similarity between the discussion vertices. Based on e-neighborhood graph construction method, if the distance between two vertices was less than a max threshold, they were seen to be similar vertices. Consider the adjacency matrix for $\mathcal{G}$, $A_{\mathcal{G}}$, in which each row represents a discussion vertex v and each column a user vertex u. Let S_n be the set of all permutations on $\mathcal{U}$, with each row of $A_{\mathcal{G}}$ being an element of S_n. For all $\sigma \in S_n$ define $\sigma(i)$ as the rank of the element $i \in \mathcal{U}$ in σ. For two elements $\sigma, \tau \in S_n$ the Kendall's tau $K(\sigma, \tau)$ is the initial metric introduced by Kendall [74]. Kendall's tau metric is identity invariant; that is the value of the metric does not depend on the actual identity of the elements in $\mathcal{U}$. Therefore, it suffices to consider $K(\sigma) = K(\sigma, 1)$ where 1 is the identity permutation. Then

$$K(\sigma) = \sum_{(i,j):i>j} \mathbb{1}[\sigma(i) < \sigma(j)]$$

where $\mathbb{1}$ is the indicator function. $K(\sigma)$ counts the total number of pairwise inversions between the elements of σ and τ.

In this study, one of the three new generalizations to the distance function introduced by Kumar and Vassilvitskii [79] was employed. The generalization aims to adjust the effect of swapping similar items. The intuition is that a pairwise inversion of two similar items should be penalized less than a pairwise inversion of two dissimilar items. Let D be a non-empty metric on $\mathcal{U}$ and let D_{ij} be the distance between users $i, j \in \mathcal{U}$. In this study, we defined the metric D using the Jaccard index

$$D(u_i, u_j) = 1 - J(u_i, u_j) = 1 - \frac{|P_i \cap P_j|}{|P_i \cup P_j|}$$

where P_i is a set consisting of the discussion vertices in which user i has a non-zero endorsement on.

Then the similarity-adjusted distance between the rankings would be

$$K^*(\sigma) = \sum_{(i,j):i<j} D_{ij}\mathbb{1}[\sigma(i) > \sigma(j)] \tag{4.1}$$

$K^*(\sigma)$ as defined above was used to transform $\mathcal{G}$ by finding the distance between every two rows of $A_{\mathcal{G}}$. After transforming $\mathcal{G}$, $\mathcal{H}$ was defined based on the e-neighborhood graph construction method. In other words, $\mathcal{H} = (\mathcal{V}, \mathcal{V})$ was defined such that there would be an edge between two discussion vertices $v, v' \in \mathcal{V}$ if the distance between v and v' in the transformed $\mathcal{G}$ was smaller than $e \in \mathbb{R}^+$.

This similarity measurement preserves the local clustering in the initial bipartite network since it takes the similarity in users' behavior into consideration. If two users belong to the same local cluster, they would endorse similar discussion vertices. Therefore, the similarity measure $D(u_i, u_j)$ would be close to zero. This means that users of the same political orientation who lie within the same local cluster did not significantly affect the overall distance between two discussion vertices.

$\mathcal{H}$ is a simple one-mode network in which the vertices represent the discussion vertices. It inherits the classes of the discussion vertices from $\mathcal{G}$.

4.5.3 Measurement of Accessibility Between Network Vertices

The information flow between different vertices is only feasible through the local interactions between the adjacent vertices; therefore, close vertices are more accessible than distant vertices. The overall accessibility of the vertices or the reliability of the information transfer is thus a function of the network topology.

To measure the accessibility of vertices $v, v' \in \mathcal{V}$ of $\mathcal{H}$, it was assumed that a bit of information is released from v to v', which was then assumed to randomly traverse the network until it reaches v'. Then, the probability of this bit of information traversing the shortest path is

$$P\{p(v, v')\} = \frac{1}{k_v} \prod_{j \in p(v,v')} \frac{1}{k_j - 1} \tag{4.2}$$

where $p(v, v')$ is the shortest path between v and v', j is counting each vertex on the path, and k_j is the degree of the vertex j. If some information is sent from v to v' without the knowledge of the network map, then $P\{p(v, v')\}$ measures the probability that this information goes through the shortest path from v and v' [151, 146].

The *search information index* or the amount of the information needed to identify one of all the possible shortest paths between v, v' is defined as

$$S(v \to v') = -\log_2 \Big(\sum_{p(v,v')} P\{p(v, v')\} \Big) \tag{4.3}$$

where the sum runs over all the shortest paths between v and v'. A high value for $S(v \to v')$ means that many yes/no questions are needed to locate v'; therefore, a higher search information index between two vertices implies less availability of information between the vertices.

4.5.4 Link Between the Search Information Index and Political Polarization

DiMaggio et al. [34] defined political polarization as the distance between the political orientation of different people or "the extent of disagreement. [...] It is in the extremity of and distance between responses, not in their substantive content, that polarization inhere. [...] Polarization as a process refers to the increase in such opposition over time". As political polarization increases, it is expected that the users contribute more to the discussion vertices of a single political orientation. This leads to lower availability of information between each pair of discussion vertices with contrasting political orientation. Therefore, the average search information index between all possible pairs of discussion vertices with contrasting political orientation is expected to be higher.

The set $\mathcal{T}$ is defined as,

$$\mathcal{T}_{c,c'} = \{S(v \to v') : \forall v, v' \in \mathcal{V} | c_v = c, c_{v'} = c'\}$$

where c_v indicates the class of the discussion vertex v. We defined the polarization index between the two sub-clusters c and c' as the average of the elements in set $\mathcal{T}$, which is named $\mathcal{P}_{\mathcal{T}}$. $\mathcal{P}_{\mathcal{T}}$ is expected to be increasing over time as the political polarization increases.

4.6 Results

4.6.1 Simulations

Our ultimate goal of the simulations was to demonstrate that the search information index was highly correlated with the political polarization as introduced in DiMaggio et al. [34] DiMaggio et al. [34]. Based on DiMaggio et al. [34] political polarization is a process that refers to the increase in the extent of disagreement over time. To simulate the polarization, two different parameter sets were defined; one that related to the distribution of endorsements when the political orientation of the user matched the political orientation of the discussion vertex, and the other that corresponded to the distribution of endorsements when the orientation of the user and the orientation of the discussion vertex did not match. When the distance between these two distributions increases, the political polarization also increases.

To run the simulations, a two-class Facebook political sphere of Republicans and Democrats $\{r, d\}$ was assumed. Twenty Facebook political posts were simulated and in each run were randomly assigned to one of the parties. A pool of 800 users was created, and in each run, it was assumed that each user had a 50% probability of being Democratic or the Republican party supporter. $X_{partisan,page}$ was defined as the random variable for the number of likes a partisan gave to the Facebook posts of pages of a specific party. The following distribution for the number of likes a user contributes to Facebook posts with similar political orientation was also assumed; e.g., a Democrat on Democratic pages or a Republican on Republican pages:

$$X_{p,p} \sim \lfloor lnorm(0, 1) \rfloor \text{ for } p \in \{r, d\}$$

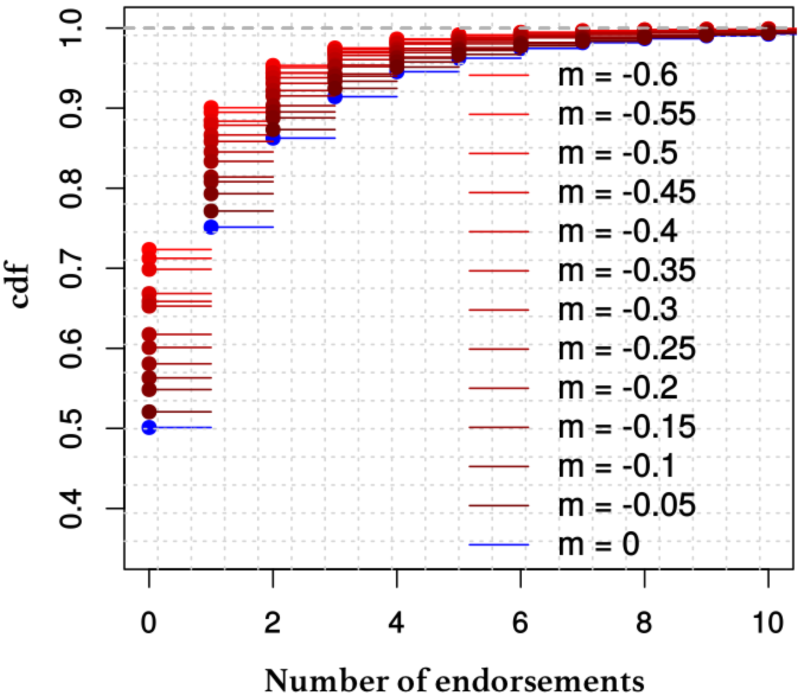

Fig. 4.1. CDF of the endorsement distribution for different values of m.

where $lnrom(\mu, \sigma)$ stands for a log-normal distribution with a mean μ and standard deviation σ. The number of likes a user contributed to a Facebook page that had a contrasting political orientation, e.g., a Republican on a Democratic pages, was assumed to have the following distribution:

$$X_{p,q}(m) \sim \lfloor lnorm(m, 1) \rfloor \text{ for } p \in \{r, d\}, p \neq q$$

where $m \in \{-0.05, -0.10, -0.15, -0.20, ..., -0.6\}$.

As the value of m decreases from 0 to -0.6, the distance between the $X_{p,p}$ distribution and the $X_{p,q}(m)$ increases (see Fig. 4.1), which implies that as the value of m decreases, the users contribute fewer endorsements to the vertices of the contrasting political inclination; therefore, based on the definition in DiMaggio et al. [34], political polarization increases as the value of m decreases.

For each value of m, we ran our method on the simulated data for 1000 times and averaged the results. As can be seen in Fig. 4.2, it was confirmed that as the political polarization increased (m decreases), as expected the value of the political polarization index $\mathcal{P}_{\mathcal{T}}$ also increased (with a correlation of 0.904).

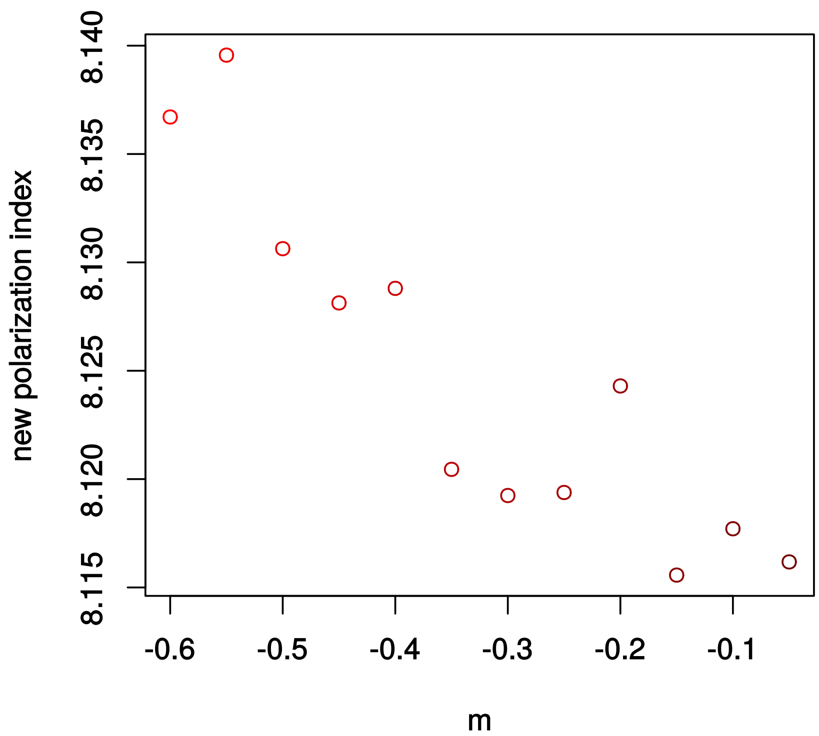

Fig. 4.2. $\mathcal{P}_{\mathcal{T}}$ values against m.

4.6.2 Facebook Data

In this section, the proposed method was applied to Facebook data to determine whether the results agreed with the previous theoretical findings. Using Facebook's public API, all the posts on the official pages of all six active political parties in Germany (AfD, CDU, SPD, Die Linke, Grünen, and CSU) published in 2017 and all users who had endorsed these posts by making Facebook likes were downloaded. In total, 4,438,157 likes on 2,452 public Facebook posts were collected from 2,021,987 unique Facebook users. The data was then split into one-week windows and the bipartite network of user endorsements were constructed on the discussion vertices. It is important to notice that in this case the constructed network is a binary bipartite network but not weighted. This is because each user can like each Facebook post only for one time. Fig. 4.3 shows the search information index between the AfD sub-cluster and all other sub-clusters, from which it can be seen that the average search information index between the AfD Facebook posts and the Facebook posts of the other parties was increasing over time. This implies that the AfD and non-AfD supporters had increased their endorsement activities on the pages connected to their own political orientation, and had decreased their activities on the pages connected to opposite political views. Therefore, these results could be seen as an increase in the levels of polarization between the AfD supporters and the other partisans. This is in line with previous studies on the rise of the AfD that found that the party adopted a political agenda that was quite different from the other parties, and consequently they had attracted alienated voters who had become segregated from the rest of the electorate [70, 87]. It was also found that the rise in party support had been accompanied by increased radicalization and polarization [53, 32, 129].

4.7 Discussion

In this paper, a new methodology for analyzing social networks was introduced that considered all the important properties of the structure of social networks such as associative mixing and local clustering. When the method was applied to political activity networks, it functioned as a proxy for the dynamics of political polarization; that is, the $\mathcal{P}_{\mathcal{T}}$ positively correlated to the level of political polarization in the network. The methodology was tested on both simulated data and user endorsement Facebook data from the German political party pages.

The development of this new method provides new insights for analyzing and understanding online political interactions. Social media service data can be used to evaluate theoretical social science questions, and this study provides a new tool to allow for this possibility. Given the multiplicity of social media data available today, researchers can use the newly proposed mathematical method to reveal the dynamics of political polarization. As this method does not discriminate endorsement types, it can be applied to different platforms. However, there are some limitations for the use of this method. While it can be used as a proxy for the dynamics of political polarization, it cannot directly provide insights as to the degree of polarization because the $\mathcal{P}_{\mathcal{T}}$ measure has no theoretical maximum value.

Similar to other online social network research, this study was dependent on the input data. Therefore, it is important to highlight the difficulties associated with extracting the proper data to ensure insightful scientific results. Unfortunately, there are often restrictions on the amount and type of data that can be acquired from social media platforms [118], and data quality is also a problem because of the level of bias [126]. Therefore, these features need to be considered in social media research and especially when studying important political processes.

The following further future directions are proposed: 1. the application of the proposed method on case studies such as the polarization in U.S. online media , which appears extremely segregated [44]; 2. the extension of the method to define a theoretical maximum value of political polarization; and 3. the extension of the method to determine the discussion vertices that act as gatekeepers: all of which would assist in identifying the specific topics connecting citizens and those that are separating them.

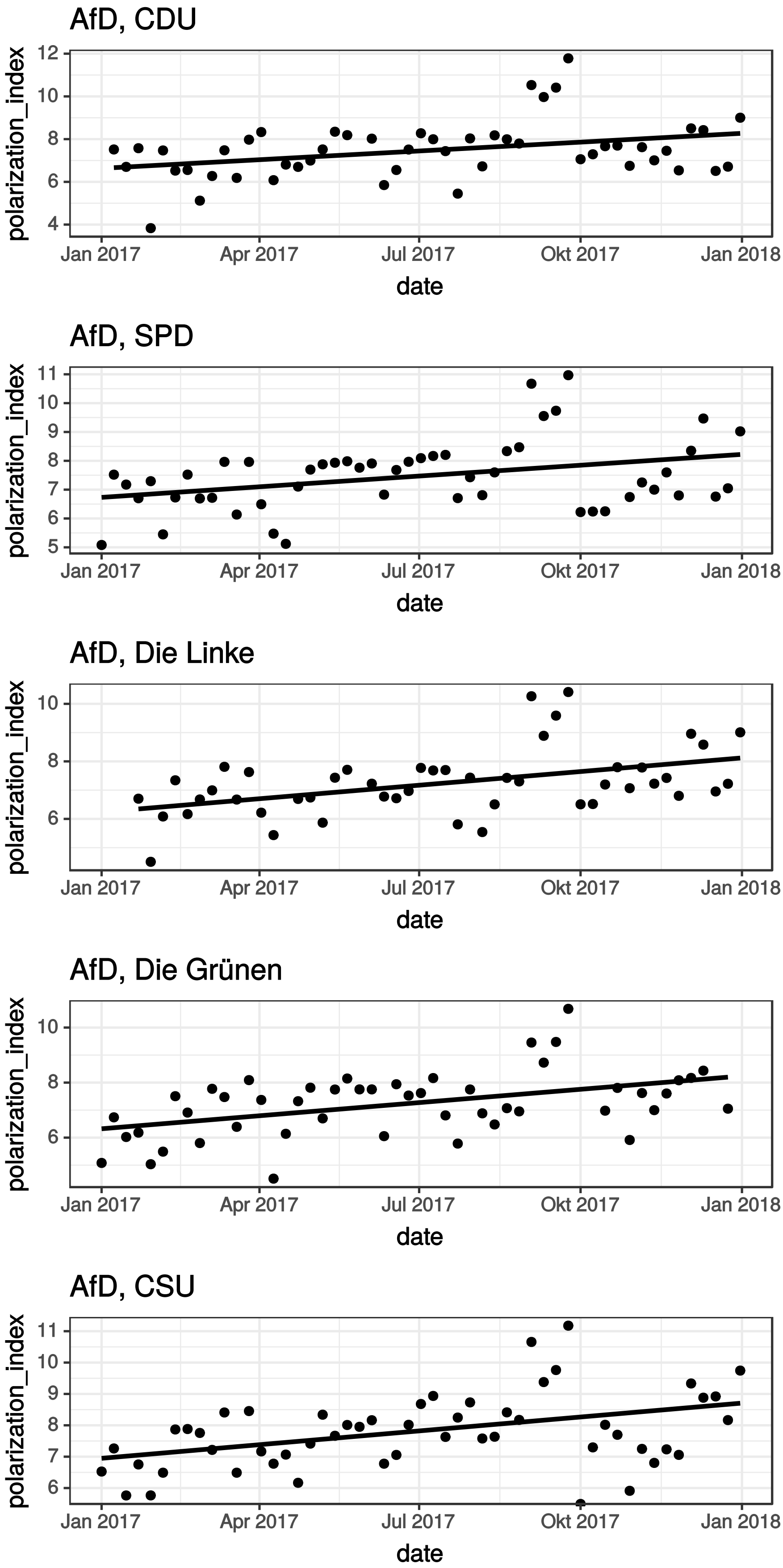

Fig. 4.3. $\mathcal{P}_\mathcal{T}$ weekly values for the party *AfD*

5 Distorting Political Communication: The Effect Of Hyperactive Users In Online Social Networks

5.1 Preface

This publication is mainly conducted by Orestis Papakyriakopoulos. In this publication hyperactive users, the users that are over-proportionally active on online social media platforms, are carefully defined. Hyperactive users are not defined as outliers from a different data generation process, but rather as outliers from the same data generation process that contain more information. Then the possible effect of these users on online political discourse and the effect of the recommendation systems are discussed.

The complete posts and user activities of online citizens to official Facebook pages of seven political parties in Germany is then acquired from the Elasticsearch index. A geometric topic modelling algorithm is the applied on the comments published by the users to find the main discussion topics. The hyperactive users are 5.3% of the users commenting on the mentioned Facebook pages. These users contributed 25.8% of the whole comment.

Then it is argued that the algorithmic recommendation systems employed by online social networking platforms may get biased due to the volume of activity of hyperactive users. In other words, these algorithms might over-estimate the importance of the hyperactive users. In this case, an algorithmic bias automatically becomes a political one. Recommendation systems come with a social influence bias, i.e. have the power to change users' opinion. Hence, online social networking platforms promoting biased political content may result in the algorithmic manipulation of political communication.

The author of this dissertation had limited contributions to this publication. Morteza Shahrezaye provided the real-life Facebook data and insights to the methods to define the hyperactive users.

Distorting Political Communication: The Effect Of Hyperactive Users In Online Social Networks

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5.2 Abstract

Online Social Networks (OSNs) are used increasingly for political purposes. Among others, politicians externalize their views on issues, and users respond to them, initiating political discussions. Part of the discussions are shaped by hyperactive users. These are users that are over-proportionally active in relation to the mean. In this paper, we define the hyperactive user on the social media platform Facebook, both theoretically and mathematically. We apply a geometric topic modelling algorithm (GTM) on German political parties' posts and user comments to identify the topics discussed. We prove that hyperactive users have a significant role in the political discourse: They become opinion leaders, as well as set the content of discussions, thus creating an alternate picture of the public opinion. Given that, we discuss the dangers of replicating the specific bias by statistical and deep learning algorithms, which are used widely for recommendation systems and the profiling of OSN users.

5.3 Introduction

Today, internet prevails as a prominent communication and information medium for citizens. Instead of watching TV or reading newspapers, increasing numbers of people get politically informed through online websites, blogs, and social media services. The latest statistics demonstrate that internet as a news source has become as important as television, with its share increasing year by year [52]. Given this shift in the means of news broadcasting, politicians have altered their tactics of communication to the society. OSNs, such as Twitter, Facebook and Instagram, have become a cornerstone of their public profiles as they use OSNs to transmit their activities and opinions on important social issues [60, 39, 2].

The growth of online communities on social media platforms have created a public amenable to political campaigning. Political parties and actors have adapted to the new digital environment [136], and besides the application of new campaigning methods as microtargeting [118], have created microblogs through which they can inform citizens of their views and activities. In addition, OSNs have enabled to users to respond to or comment on the politicians' messages, giving birth to a new type of political interaction and transforming the very nature of political communication.

On OSNs, the flow of information from politicians to citizens and back follows a different broadcasting model than the classical one [97]. Instead of journalists monitoring the political activity, political actors themselves produce messages and make them publicly available on the platforms. Each platform provides its users with access to the generated content, as well as distributes it to them through recommendation algorithms [4, 152]. The received information is then evaluated both directly or indirectly [64, 23]: The political message is interpreted immediately, or subsequently through further social interactions among citizens on the related topics. On OSNs, not only can users respond to politicians in the traditional manner -i.e. through their political activity in the society-, but also respond to or comment on the politicians' views online. This creates a new type of interactivity, as users, who actively engage in online discussions sharing their views, are able to influence the way the initial political information will be assimilated by passive users as well as directly influencing political actors.

This new form of political interactivity transforms political communication. Given the possibility of users to directly respond to the political content set by political actors, and discuss online about political issues with other citizens, OSNs emerge as a fruitful space for agonistic pluralism. They provide the necessary channels for different interests and opinions to be expressed, heard and counterposed; elements that constitute the very essence of political communication. If the discussions held are legitimized within a democratic framework, they form the basis for reaching a conflictual consensus [103], based on which societal decisions can be made. Hence, political communication on OSNs opens new possibilities for citizens to participate in the political shaping of the society, providing them with additional space to address their interests.

5.3.1 Problem Statement

Although the above type of political communication has the potential to improve the function of democracy, OSNs possess a structural property that obstructs the unbiased constructive interaction between political actors and citizens: The activities of users on OSNs follow an extreme value distribution [104, 153, 88, 12]. Practically, this means that users are not equally active when using a specific OSN. Among others, the majority of users remain passive, or participate with a very low frequency; they either simply read the content or like, comment, tweet, etc. very rarely. On the contrary, a very small part of the users is hyperactive, as they over-proportionally interact with the platform they use. Thus, in political communication on OSNs, hyperactive users are citizens who over-proportionally externalize their political attitudes compared to the mean. This could be done by liking, commenting, tweeting or using any other interaction possibility provided by a platform to declare an attitude to a political issue.

The given activity asymmetry becomes a major issue, considering that a considerable part of the society is politically informed via OSNs. As hyperactive users externalize their political attitudes more than the others, they have the potential to distort political communication; political issues that are important to them become overrepresented on OSNs, while the views of normally active users become less visible. Hence, hyperactive users may influence the political discussions towards their ends, creating a deformed picture of the actual public opinion on OSNs. This fact violates the assumption of an equitable public political discourse as part of political communication [134], because the interests and views of normally active users appear as less important.

The above distortion of political communication is intensified by the business models of the OSN platforms. OSNs were not created to be arenas of political exchange. Their aim is to maximize the number of platform users, by keeping them satisfied [143], and to transform this social engagement to profits, i.a. through advertisement. Hence, on OSNs, users are both consumers and citizens [149]. In order to maximize their profits, OSN platforms adjust their recommendation algorithms to the content popularity, with a view to promoting information that most users will like. As hyperactive users influence asymmetrically the popularity of political content, these algorithms might replicate this asymmetry. Thus, a platform might recommend content, which is actually consistent with the political interests of hyperactive users. This phenomenon per se denotes a form of algorithmic manipulation of the political communication: The platform unintentionally magnifies hyperactive users' interests, thus posing the risk of political invisibility for the ones of normal users [19].

Last but not least, the aforementioned misrepresentation of public opinion has a direct impact on political campaigning. Contemporary political actors develop their influence strategies based on the perceived voter model [62], which presupposes the gathering of demographic and political data for the development of statistical models about the electorate's attitudes. As major part of these data is derived from social media, models that fail to take the effect of hyperactive users into account would face an important bias.

Considering the above, we want to answer following questions regarding the activity of hyperactive users:

RQ1: How can we define hyperactive users mathematically?

RQ2: How can we compare and evaluate the political attitudes of hyperactive users in relation to the mean?

5.3.2 Original Contribution

We mathematically define hyperactive users on OSN Facebook, and identify them on the public pages of the major German political parties. By applying a state-of-the-art topic modelling algorithm, we investigate whether they spread or like different messages on political issues other than normal users and politicians do. We prove that hyperactive users not only are responsible for a major part of online political discussions, but they also externalize different attitudes than the average user, changing the discourse taking place. We quantify their effect on content formation by measuring their popularity and showing that they adopt an opinion leader status. Finally, given the potential influence of hyperactive users on recommendation algorithms, we initiate an important discussion on OSNs as spaces of political communication.

5.4 Data & Method

5.4.1 Data Description

To investigate the effect of hyperactive users, we chose to analyse the public Facebook pages of the main German political parties. Our sample included CDU, CSU, SPD, FDP, Bündnis 90/Die Grünen, Die Linke, and AfD. CDU is the main conservative party of Germany, while CSU is the conservative party active in Bavaria. SPD represents the main German social-democratic party, and Die Linke the radical left. AfD has a nationalist, anti-immigrant, and neo-liberal agenda, while FDP is a conservative, neo-liberal party. Finally, Bündnis 90/Die Grünen is the German green party. We focused on Facebook, because the platform's api restrictions and its monitoring system largely prevent automated activities, as e.g. performed by social bots on other platforms [41, 154]. Therefore we could evaluate the natural behaviour of hyperactive users and not an algorithmically generated one.

We took into consideration all party posts and their reactions in the year 2016. This choice was made, because we wanted to investigate a full year of user activities. We preferred 2016 over 2017, because 2017 was an election year, with most content produced by the parties being campaign related. By contrast, 2016 was marked by the Refugee Crisis in Europe, and we were interested in evaluating the discussions on the topic. In total, by accessing the Facebook Graph API, we collected 3,261 Posts, 3,084,464 likes and 382,768 comments, made by 1,435,826 users. The sample included all posts and comments on the posts generated for the period under investigation.

5.4.2 Defining Hyperactive Users

We consider hyperactive users as people, whose behaviour deviates from the standard on an OSN platform. To obtain an understanding of the overall behaviour of the users, we fitted discrete power-law and extreme value distributions to mathematically describe the users' like and comment activities. Additionally, we ran bootstrapped and comparative goodness-of-fit tests based on the Kolmogorov-Smirnov [3] and the Vuong [155] statistic to evaluate the potential fits, as proposed by Clauset et al. [24]. The KS test examines the null hypothesis that the empirical sample is drawn from the reference distribution, while the Vuong test measures the log-likelihood ratio of two distributions and, based on it, investigates whether both empirical distributions are equally far from a third unidentified theoretical one.

In order to mathematically describe the activities of hyperactive users, we selected to treat them as outliers of the standard OSN population. We adopt the definitions made by Barnett and Lewis [7], Johnson and Wichern [71] and Ben-Gal [10], and see outliers not as errors, or coming from a different generative process, but as data containing important information, which is inconsistent with and deviating from the remainder of the data-set. Therefore, given the extreme skewed distribution of the activities, we followed the method proposed by Hubert and Vam der Veeken [68] and Hubert and Vandervieren [69] for outlier detection. We calculated the quartiles of our data Q_1 and Q_3, the interquartile range $IQR = Q_3 - Q_1$ and the whiskers w_1 and w_2, which extend from the Q_1 and Q_3 respectively to the following limits:

$$[Q_1 - 1.5e^{-4MC} IQR, Q_3 + 1.5e^{3MC} IQR] \tag{1}$$

where MC is the medcouple [18], a robust statistic of the distribution skewness. Data beyond the whiskers were marked as outliers.

5.4.3 Topic Modeling

After evaluating the likes and comments distributions, as well as identifying the existing hyperactive users, we prepared our data for the application of a topic modelling algorithm. As it has been shown that a noun-only topic modelling approach yields more coherent topic-bags [94], we cleaned our posts and comments from the remaining part-of-speech types. To do so, we applied the spaCy pretrained convolutional neural network (CNN) classifier [66] based on the Tiger [17] and WikiNER [112] corpuses, classified each word in our document collection, and kept only the nouns.

We wanted to investigate the various topics that users and parties discussed about but did not want to differentiate on the way they talked about them. Parties usually use a more formal language when posting on a topic than users. Therefore, there was the risk that the topic modelling algorithm would create different topics on the same issue, one for the parties and one for the users. To avoid this, we fitted our model on the user comments, and then classified the parties' posts through the trained model.

For our analysis, we applied a non-parametric Conic Scan-and-Cover (CoSAC) algorithm for geometric topic modeling [112]. Our decision was based on the fact that most topic modelling algorithms (e.g. LDA [15], NMF [86]) need a priori as input the number of topics to split the corpus. CoSAC has the advantage of electing itself the number of topics to find the most efficient topic estimates.

The algorithm presupposes that the optimal number of topics K are embedded in a V-1 dimensional probability simplex Δ^{V-1}, where V the number of words in the corpus. Each topic β_K corresponds to a set of probabilities in the word simplex. The totality of topics build hence a convex polytope $B = conv(\beta_1, ..., \beta_K)$. Each document corresponds to a point $p_m = (p_{m1}, ..., p_{mV})$ inside Polytope B, with $p_m = \sum_k \beta_k \theta_{mk}$. θ_{mk} denotes the proportion that topic k covers in document m. Finally each document is drawn from a multinomial distribution of words: $w_m \sim Multinomial(p_m, N_m)$, where N_m the number of words in document m.

The CoSAC algorithm iteratively scans the polytope B and finds the furthest point from its center Cp. It then constructs a conical region with angle ω, starting from Cp and embedding the specific point (see Fig. 5.1). All points within the cone are considered to belong in the same topic and are removed from the polytope. The procedure is iterated

K-1 times, until almost no points remain in the polytope. A cone is considered sufficient if it covers at least a proportion of documents λ. After fitting the cones, CoSAC places a sphere with radius R to the polytope, to cover the remaining points. The K geometric objects and their respective points correspond to the K topics created by the algorithm. In our model, the hyperparameters were set to $\omega = 0.6, \lambda = 0.001$ and $R = 0.05$, as proposed by the authors.

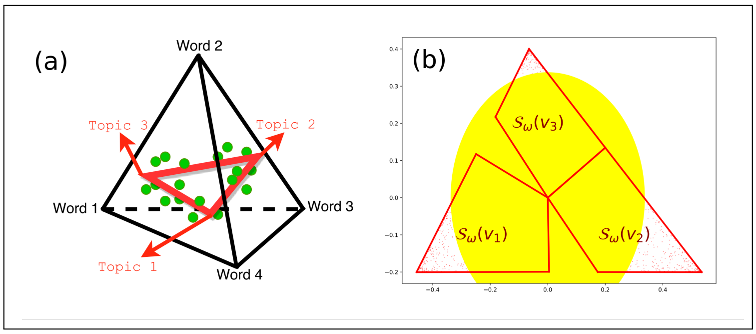

Fig. 5.1. The topic polytope embedded in the word simplex

5.4.4 Comparison of Activities

Given our topics, we wanted to evaluate the differences in the activity of normal and hyperactive users. Therefore, we calculated the empirical distributions $f(comment|topic)$ over all topics for the comments of normal and hyperactive users respectively. We pairwise compared the distributions for each topic, by applying a 2-Sample Anderson-Darling Test [135]. The test calculates the probability that the populations from which two groups of data were drawn are identical.

Besides testing the empirical comment-topic distributions, we assigned to each comment the topic with the highest probability and compared the most commented topics for normal and hyperactive users. Similarly, we assigned the classified party posts to their most probable topic and aggregated the likes of normal and hyperactive users. In this way, we were in the position to locate the concrete political interests of users.

5.5 Results

The results are split into three parts. First, we present our findings on the general user distribution on the investigated pages. Based on that, we analyze the number and distribution of hyperactive users among the different pages. Then, we compare the behaviour between hyperactive and normal users by taking into consideration the topic modelling results and further statistical tests. Given that, we evaluate the importance and role of hyperactive users in the political discourse on OSNs.

Table 5.1 Vuong test results

Log-normal vs	Likes LL-ratio (p-value)	Comments LL-ratio (p-value)
Power-law	15.1 (<0.01)	34.9 (<0.01)
Poisson	34.9 (<0.01)	12.7 (<0.01)
Exponential	12.7 (<0.01)	26.6 (<0.01)

5.5.1 Describing User Activity

As a first result, we identified the log-normal distribution as the the best measure for describing the user activities (see Fig. 5.2). The bootstrapped KS-Tests (100 samples, two tailed) for both comments and likes failed to reject the null that our data come from a log-normal distribution (gof < 0.01, p > 0.05 and gof < 0.01, p > 0.2 respectively), while the comparative Vuong tests showed a better fit of the log-normal in comparison to the power-law, poisson and exponential distributions (Table I). Our results comply with the existing literature, which states that usually complex social network properties are log-normally distributed [88, 147, 80]. Fig. 5.2 shows the empirical frequencies of user activities and their respective log-normal fits.

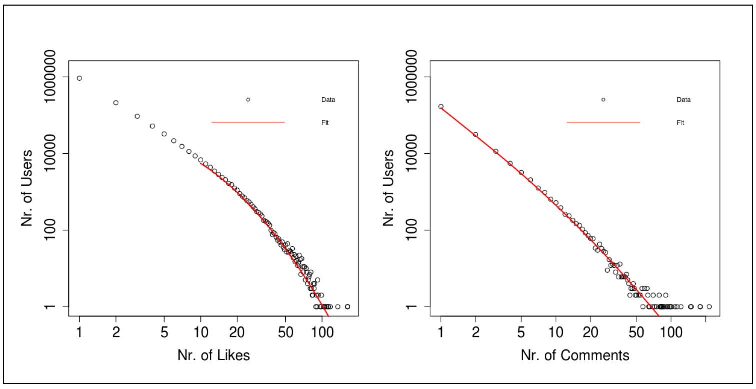

Fig. 5.2. Empirical frequencies of user activities and their respective log-normal fits

5.5.2 Detecting Hyperactive Users

Through our outlier detection methodology, we detected 12,295 hyperactive users on the comment section of pages, who correspond to 5.3% of the total users commenting on the pages. Due to the extreme skewness of the comments' distribution, a user was characterized as hyperactive if they made three or more comments. This is justified by the fact that actually 74% of the users under investigation made only one comment. Although hyperactive users represented 5.3% of the total commenting population, they accounted for 25.8% of the total comments generated on the parties' pages. Furthermore, 56% of these hyperactive users commented on two or more party pages, denoting that they generally interacted with users across the political spectrum. By evaluating the popularity of the users' comments, it was found that hyperactive users tend to get more support than the rest. Comments made by hyperactive users on average gained 3.52 likes, while normal users' comments only 3.07, a difference that was statistically significant (Mann-Whitney Test with continuity correction, one tailed: $W = 1.4^{10}$, $p < 0.01$). This complies with previous research stating that highly active users tend to have the characteristics of opinion leaders [159].

Table 5.2 Hyperactive Users per party - Comments

Party	Comments by Hyperactive Users	Ratio
AfD	43,017	0.24
CDU	20,929	0.45
CSU	18,312	0.22
FDP	1,400	0.15
Die Grünen	8,946	0.36
Die Linke	2,343	0.16
SPD	3,926	0.13

Similarly, the evaluation of the pages' likes resulted in the characterization of 61,372 users as hyperactive, or 4.3% of the total users that liked the parties' posts. As before, the methodology labelled users as hyperactive if they made three or more likes, because the majority of the active Facebook population rarely interacted with the related pages. The likes of these hyperactive users accounted for 26.4% of total likes, hence having a major effect on the overall content liked. In addition, 29% of hyperactive users liked posts of more than one party, denoting again that their activities were spread over the entire parties' network. The overview of the hyperactive users' commenting and like activities for each party can be found in tables II and III. We also compared the like and comment distributions, by calculating their gini index. The measure provides a proxy for inequality, with 0 denoting perfect equality and 1 extreme inequality. In our case, we calculated a value of 0.35 and 0.45 for the comment and like distribution respectively. This denotes that like activities are more unequally distributed than the comment activities, i.e. hyperactive users play a bigger role in the formation of likes. In addition, the values denote a degree of inequality between normal and hyperactive users, but not an extreme one. Nevertheless this is misleading, because the measure does not take into consideration the inactive users. Given that information, the gini index would have been much higher in both cases.

5.5.3 Evaluating the Political Attitudes of Hyperactive Users

Based on the categorization of users as hyperactive or normal, we could then evaluate the results of the topic modelling algorithm. The model clustered the users' comments in 69 main topics. A major part of the topics concerned the refugee crisis of 2016 and the related discussions about Islam. A set of topics aggregated comments on German Chancellor Merkel, on the leaders of other parties, on female and male politicians and

Table 5.3 Hyperactive Users per party - Likes

Party	Likes by Hyperactive Users	Ratio
AfD	555,564	0.35
CDU	16,997	0.2
CSU	139,493	0.2
FDP	20,188	0.16
Die Grünen	28,777	0.19
Die Linke	24,546	0.14
SPD	29,057	0.12

the German parties in general. There was one topic summing up comments in English language, as well as a topic containing hyperlinks. Furthermore, the algorithm created policy related topics regarding foreign affairs, as well as the economy and labour market and the state in general. Other topics were related to the German national identity, society and solidarity, and the nature of democracy. Users also discussed about family and gender policy, homeland security, transportation and environmental policy. There were topics that included wishes, fear, ironic and aggressive speech, as well as topics aggregating user thoughts. Finally, a set of topics was about political events and communications and a number of topics included comments against mainstream media and the political system. An overview can be found in table IV. The geometric topic modelling algorithm was able to provide a broad picture of the discussion topics on the parties' pages, revealing numerous insights about the way Facebook users commented on the parties' posts. By splitting the comments into two categories, one for the ones generated by hyperactive users and one for the comments of normal users, and by assigning them to the topics to which they were mostly related, we created a stacked chart illustrating the share of hyperactive users' comments for every topic (see Fig. 5.3). It is evident that hyperactive users covered a major part of the comments, and although more active, they commented more or less similarly to the normal users among the various topics. Despite that, the Anderson-Darling tests rejected the null hypothesis that hyperactive and normal users' comments come from the same distribution for 54 out of the 69 topics. Practically, this means that the topic density distributions varied between the comments of normal and hyperactive users. This is caused when the comments contain different words in different proportions. Hence, hyperactive and normal users used different vocabularies when referring to a topic and, consequently, externalized overall different views and sentiment, or focused on different issues in each case.

Besides the fact that hyperactive users had a different behaviour on the posts' comments, our analysis showed that they also had different liking preferences. After classifying each party post to the most relevant topic, we counted the likes of the posts that belong to each topic. We took into consideration only topics that were based on either political vocabulary or politicians, and ignored topics that contained aggressive speech or sentiment, because the related vocabulary was rarely used by the parties. Fig. 5.4

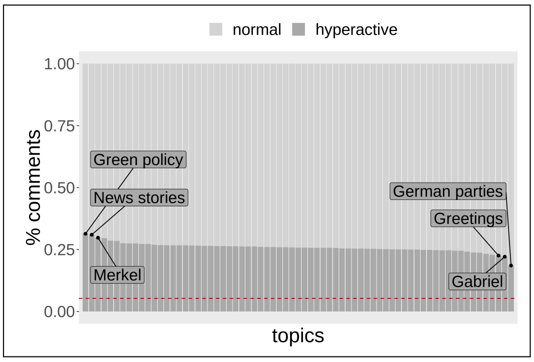

Fig. 5.3. Proportion of comments generated by normal and hyperactive users

illustrates a stacked chart depicting the share of hyperactive users' likes. In contrast to the comments' chart, it is obvious that hyperactive users liked specific topics with different intensity than normal users. Even though hyperactive users performed on average 26.4% of the likes, they liked much more content related to EU politics and labour policy, while had less interest on the conservative party AfD, citizens' rights and the region of Bavaria. Therefore, it is clear that hyperactive users influence the like distribution of the public to party posts.

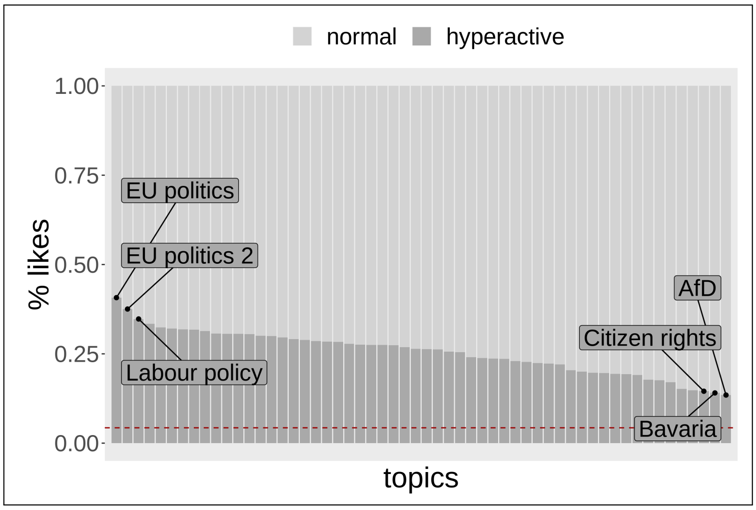

Fig. 5.4. Proportion of likes generated by normal and hyperactive user

It must be noted that our analysis gives an overview of the content of posts. It cannot identify sentiment, or specific predispositions of users. For a firm understanding of the issues that were over- or under-represented by hyperactive users an additional extensive analysis is needed, which is beyond the scope of this paper. Our analysis demonstrated that, both on commenting and liking, hyperactive users have a different behaviour than the other users.

Taking the above into consideration, it was possible to show that political communication on Facebook is strongly constituted by the behaviour of hyperactive users. By describing the user like and comment activities on the platform, we managed to characterize users as hyperactive or normal through outlier detection. We proved that hyperactive users account for a significant part of the total users' activities, they participate in discussions differently from the rest, and they like different content. Moreover, they become opinion leaders, as their comments become more popular than these of the normal users. Taking Facebook as an example, we showed that user activities on OSNs are neither equally nor evenly distributed.

5.6 Discussion

Given that activity asymmetries are a feature of online social networks, it is important to evaluate the consequences for science and the society. Although our analysis was concentrated on Facebook, previous research has proven that hyperactive accounts, either human or automated, have the potential to equally influence political communication on other platforms [150, 141]. The specific formation and distribution of political interactions on OSNs gives rise to various questions regarding the role and impact of OSNs on the political and algorithmic level, as well as on the intersection of both.

In the political dimension, the OSN activity asymmetries are transformed into an asymmetry of disseminated political content, as the attitudes and interests of hyperactive users appear over-proportionally in the discussions taking place. Until now, research [28, 37] has stated that OSNs suffer from a population bias: The people using OSNs are not representative of the actual society. On top of that, a content bias is now added: The content disseminated on OSNs is not even representative of the mean users' attitudes on the platform. This poses a scientific problem, since it might lead to false research results. Equally important, it poses a political problem, because political discussions and opinion exchange is distorted by the effect of hyperactive accounts. This happens not only because the diffused information in the network is transformed or changed, but also because hyperactive users strongly contribute to the type of information diffused. Their attitudes fill the communication space, leading to a bias on the political feedback to politicians, and to a shift on the issues that shape the political agenda. Although OSNs provide a more open environment to express opinions than traditional media, it ends up being partly a gathering of political echoes [92] that struggle to be imposed on each other.

In the algorithmic dimension, the extreme skewness of the activity distributions raises specific issues regarding the recommendation algorithms used by OSN platforms. The first problem is related to algorithmic accuracy: skewed data are, imbalanced data, and their raw use, either as input features or as output labels, can yield weak classification results. The imbalanced learning problem applies to both standard statistical algorithms, collaborative filtering and neural networks [59, 168, 116], with algorithms over-estimating the importance of outliers and under-estimating the importance of the rest. This also happens in the case of a poor selection of a cost function [85]. Furthermore, it is proven that statistical models as Markov-chains might fail to capture the signal immanent in highly skewed data, while deep learning methods might face the same issue given power-law distributions of data [91].

The second potential problem is that an algorithm might fail, not in the sense that it might be unable to learn from the data, but rather learn the wrong signal. Hyperactive users can be seen as physical adversaries [81] of the mean user attitudes. Algorithms trained in the full data will include the bias, tracking and predicting behavioural associations that correspond to hyperactive users rather than to the population majority. It is not coincidental that the detection of adversaries in machine learning can be done by sample distribution comparison [55], in the same way as we tracked the different preferences of hyperactive users.

Solutions to the aforementioned issues exist and are usually taken into consideration by data scientists, who develop recommendation algorithms. Nevertheless, in the case of political communication, an algorithmic issue automatically becomes a political one. Recommendation systems come with a social influence bias [78, 29], i.e. have the power to change users' opinion. Hence, OSNs promoting biased political content might result in the algorithmic manipulation of political communication.

In addition, social media platforms are not designed to foster political discourses [38], but rather aim at increasing active users, in order to sell advertisement and attract funding from venture capitalists [42]. Hence, the structure and impact of recommendation algorithms distorts human behaviour [132], having transformative effects that were not foreseen a priori [101].

It is evident from the above, that each algorithm mediates and redefines the importance of political interests [111], raising further questions about the opacity of the recommendation systems [20]. In a political context, it becomes important to know as citizens, how, why and with what impact algorithms change political communication. This presupposes awareness of the data processed and, the mathematical method applied, as well as knowledge of what exactly a machine learning cost function optimizes and to what extent recommendation systems alter human behaviour. Proposals for algorithmic transparency have already been made [133, 33, 121], and wait to be applied in practice.

The above issues need to be extensively analyzed, in order to evaluate and shape the structure of political communication in the digital era. In this paper we laid the foundations for this discussion, by defining, demonstrating and quantifying the effect of hyperactive users on OSNs, through the example of Facebook. We also illustrated and defined the risks of algorithmic manipulation by the OSN recommendation systems. Future research needs to focus on the aforementioned consequences, evaluate the structure of OSNs ethically, politically and normatively as political intermediators, as well as propose and apply solutions to the newly posed problems.

Table 5.4 Topic Modeling, AD-Test results and proportion of hyperactive users

Nr.	Topic	AD-test gof, (p-value)	Comments	Likes
1	Immigration	3.8, (0.0)	0.27	0.30
2	Merkel	104.2, (1.0)	0.28	0.24
3	AfD	15.9, (0.0)	0.25	0.30
4	News stories	17.4, (0.0)	0.31	0.29
5	English	8.8, (0.0)	0.26	-
6	Green policy	15.1, (0.0)	0.31	0.18
7	Islam	4.8, (0.0)	0.26	0.31
8	Integration – immigrants	6.7, (0.0)	0.27	0.28
9	Female politicians	9.5, (0.0)	0.26	0.22
10	Deportion – immigrants	9.2, (0.0)	0.26	0.20
11	EU politics	2.5, (0.0)	0.26	0.41
12	Economic policy	6.1, (0.0)	0.28	0.31
13	Greetings	17.7, (0.0)	0.23	-
14	Polls	16.3, (0.0)	0.25	0.26
15	Union	71.2, (1.0)	0.29	0.26
16	CSU	69.2, (1.0)	0.24	0.24
17	National identity	11.5, (0.1)	0.26	0.29
18	Human rights	1.5, (0.1)	0.26	0.24
19	Security	2.6, (0.0)	0.27	0.24
20	Democracy	32.3, (0.0)	0.25	0.27
21	Citizen rights	33.9, (0.0)	0.25	0.15
22	Congratulations	26.5, (0.0)	0.24	0.26
23	Gabriel	43.2, (1.0)	0.22	0.23
24	Foreign affairs	5.0, (0.0)	0.26	0.26
25	Homeland security	17.3, (0.0)	0.25	0.25
26	Interviews	23.9, (0.0)	0.25	0.18
27	Turkey affairs	11.0, (0.0)	0.26	0.19
28	Terrorism	7.1, (0.0)	0.26	0.19
29	Fear	1.6, (0.1)	0.26	-
30	Party system	4.3, (0.0)	0.27	0.29
31	The people	3.2, (0.0)	0.27	0.27
32	News media	1.3, (0.1)	0.27	0.31
33	Erdogan	7.1, (0.0)	0.27	0.23
34	German parties	25.4, (0.0)	0.19	0.19
35	Social policy	10.9, (0.0)	0.26	0.27
36	Reflection	14.5, (0.0)	0.26	-
37	TTIP/CETA	15.7, (0.0)	0.25	0.28
38	Syria	2.4, (0.0)	0.25	0.17
39	Labour policy	20.9, (0.0)	0.24	0.30
40	Party policies	0.2, (0.3)	0.26	0.27
41	Media	32.1, (0.0)	0.25	-
42	DDR	12.9, (0.0)	0.26	0.33
43	Male politicians	2.5, (0.0)	0.25	0.28
44	East Germany	5.0, (0.0)	0.26	0.32
45	Speeches	53.6, (1.0)	0.25	-
46	Bavaria	67.1, (1.0)	0.25	0.14
47	State media	21.4, (0.0)	0.25	-
48	Female politicians 2	12.0, (0.0)	0.30	0.20
49	Bundestag	10.4, (0.0)	0.25	0.32
50	Interviews 2	16.9, (0.0)	0.25	0.28
51	Irony	42.4, (1.0)	0.26	-
52	Trump	16.2, (0.0)	0.26	0.22
53	Welfare policy	12.3, (0.0)	0.26	0.32
54	Videos	13.0, (1.0)	0.25	-
55	Government	26.1, (0.0)	0.26	0.31
56	Transportation policy	37.0, (0.0)	0.23	0.15
57	Green policy 2	3.7, (0.0)	0.27	0.20
58	Politicians	12.1, (0.0)	0.23	-
59	Public services	18.4, (0.0)	0.25	0.20
60	Gender Equality	19.7, (0.0)	0.26	0.31
61	Insults	30.5, (0.0)	0.25	-
62	Boarder security	3.4, (0.0)	0.27	0.32
63	Media 2	13.5, (0.0)	0.27	-
64	EU politics 2	2.3, (0.0)	0.25	0.38
65	Merkel 2	39.9, (0.1)	0.30	0.15
66	AfD 2	2.6, (0.0)	0.26	0.13
67	Funny	23.9, (0.0)	0.25	-
68	Germans	0.5, (0.2)	0.27	0.22
69	Labour policy 2	8.5, (0.0)	0.27	0.35

6 Discussion

This dissertation began by arguing that the emergence of the online social participatory culture in the twenty-first century has created an unprecedented volume of social big data. Social big data is characterized by the continuous production of high dimensional and unstructured data collected on an unprecedented scale and low cost. The social big data records huge volumes of both social and nonsocial activities of the users on the online social platforms. Different features and characteristics of humans' behavior are embodied in social big data. Therefore, the exponentially accumulating volumes of social big data have enabled social scientists of different fields to address questions that could have not been addressed without social big data [27].

Social big data is huge in volume, high in velocity, diverse in variety, exhaustive in scope, fine-grained in resolution, and rational in nature[77]. These features coupled with other sources of complexity, such as heterogeneity, uncertainty, varying structure, and multiplicity of sources, make the extraction of knowledge from social big data complex. Several computational algorithms and methods that are developed to deal with experimental or laboratory data fail to perform and scale on social big data [43]. To tame the potentials of social big data, a blend of mathematical and statistical tools, computer science algorithms and methods, and theories of social sciences are required. The new field of computational social sciences is developed to address the challenges associated with these complexities.

In Chapter 1 of this dissertation, the research method of computational social science and its advantages are explained. In more detail, the drawbacks of classical social sciences in comparison to computational social sciences are elaborated. The following drawbacks are addressed:

- Incoherencies and inconsistencies among the competing theories that try to explain the same social phenomena [157].
- Lack of generalization among the theories of social sciences [90].
- Over-emphasizing the explanatory research methods while deemphasizing the prediction power of the theories [65].

These drawbacks make the classical social science less reproducible and testable when compared with the natural sciences [157]. Watts [157] and Hofman et al. [65] suggested that the social scientists should redirect their focus to a prediction-driven explanation of social phenomena given the new possibilities of computational social sciences. This approach would increase the robustness of the social science theories.

This dissertation mainly focused on extracting relevant knowledge and answering questions regarding the political discourse on mainstream online social platforms, such as Facebook and Twitter. The context of empirical analysis is always bound to the political sphere of Germany.

In Chapter 2 of this dissertation, the data pipeline has been introduced to continuously download and analyze large-scale Twitter and Facebook data. The data pipeline includes more than 30 Linux machines that cover the following four main tasks:

1. Downloading the real-time political tweets published on Twitter using 20 Linux machines
   a) Tracking 253 different political keywords spanning the political discourse in Germany
   b) Following 13,829 unique politically relevant Twitter users
2. Downloading all the posts published on 121 official public Facebook pages of different Germany's political parties and media agencies, including all the contributions of the citizens such as likes, comments and shares.
3. Storing all the downloaded data in Elasticsearch servers. On the day of submission of this dissertation the Elasticsearch servers cover approximately 15 TB of data.
4. Providing tools to query the stored data and to run aggregation tools the tools to post-process the data in third-party platforms such as Python.

The data pipeline is on a hybrid synthesis of different platforms, including Elasticsearch and SQL, implemented. The design of the pipeline is such that the team members could easily add new track keywords or user IDs to the SQL tables. The data downloading process automatically includes the new queries, and no additional interventions are required. It is also possible to seamlessly add new machines for downloading data when new projects are introduced by the team. The total workload is automatically divided between the machines based on the number of the queries, number of the projects, and the number of the machines.

Further, the data pipeline is designed such that the fault tolerance of the system is maximized. Therefore, an advanced logging module is implemented that logs the whole process of downloading, preprocessing, and post-processing the data. In case of any failure of any of the machines, a recovery try will be ran in a time window of less than one minute. If the failure happens to be not recoverable, the admin of the system will be automatically notified by an email.

The developed data pipeline has been completely or partly employed in seven different publications [139, 140, 120, 119, 21, 138, 117].

Shahrezaye et al. [139] focuses on estimation of the political orientation of normal social media users. There are many challenges while addressing this question. An efficient algorithm must:

1. require a reasonable number of labeled users for training.

2. require a reasonable number of training features.

3. be generalizable to different sets of users.

4. predict on a multidimensional space .

The developed algorithm possesses all of the above features to some degree.

1. It requires tens of labeled users per political party.

2. It requires only the friends network of the users.

3. It is generalizable to any online social platform with a friends network.

4. It is generalizable to any group of online users even if they have zero-political activity on their network.

5. It predicts on any number of classes.

Among all the above contributions, item four is the most remarkable contribution of the publication. The use of label propagation enables the algorithm to predict the political orientation of the users even if they have zero political activity on the platform. The only requirement is that the friends network of the labeled users should form a connected network. In this case, the algorithm would predict the political orientation of any new user connected to this friends network, regardless of the distance of that user from the labeled users.

This publication is a novel application of mathematical modelling and computational sciences in the computation social science field. First, the goal of the publication is to answer an important question within the field of political science. Second, the algorithm falls within the predictive explanatory research method, which makes the algorithm both reproducible and testable.

Despite of the high accuracy of the developed algorithm, the algorithm can be improved in many different ways.

- In usual cases the dimension of the friends network increases exponentially. In the real-life Twitter data used in the publication, the real dimension of the friends network of the 50,000 users in question is reported to be $50,000 \times 7,194,153$, which is impossible to be stored in the memory of any normal computer or even a supercomputer. The fact that this matrix has huge sparsity makes it easy to load it but still impossible to do mathematical transformations on it. In the publication, the friends who are friends of less than 0.01% of the users are removed to reduce the complexity of the computations. This reduced the dimension of the friends network to $50,000 \times 552,136$. It would be interesting to revise the model such that the computations would exhaust the sparsity of the network to ensure that no down-sampling would be required.

- In this study, it is reported that the data used to evaluate the algorithm is biased in a manner that it is already known that the test data includes users who have engaged in some type of political activity. It would be interesting to revise the test data and evaluate the model based on unbiased data.
- In this study, only one specific metric learning (Large Margin Nearest Neighbor Classification) and one specific label propagation algorithm (based on the Gaussian fields and Harmonic functions) are applied. It would be interesting to implement different metric learning and label propagation algorithms to evaluate the performance of different algorithms.

Shahrezaye et al. [140] defined bipartite social endorsement networks. These networks exist on different online social platforms. Because the tools to study these networks are limited, a new projection method is suggested that preserves the two special features of these networks, assortative mixing and local clustering. The projection method is based on a generalized version of Kendall Tau and Jaccard distance function.

Further, the search information index that measure the accessibility of nodes in a network is introduced. The search information index is extended further to define the polarization index, $\mathcal{P}_{\mathcal{T}}$. $\mathcal{P}_{\mathcal{T}}$ between two clusters of discussion nodes, cluster c and c', is defined as the average search information index among every two nodes, each belonging to one of the two clusters. $\mathcal{P}_{\mathcal{T}}$ is expected to increase as the political polarization increases.

Then, using simulated networks and controlling the political polarization as defined by DiMaggio et al. [34], it is validated that the political polarization index is indeed highly correlated with political polarization. The correlation coefficient between the two variables is reported to be 0.904.

In the final step the algorithm is applied on the 1-year activity of the official Facebook pages of the six political parties in Germany. The posts published in each week are taken in to consideration and the weekly endorsement networks are created. Then, the weekly polarization index between the far-right party, AfD, and the other parties is measured. The results show that over 2017, the political polarization between the AfD supporters and other parties is increasing. This is in accordance with the previous studies on the rise of the AfD [70, 87, 53, 32, 129].

Even thought both the simulations and real-life Facebook data confirm the developed model, it can be improved in several different ways.

- the proposed polarization measurements is defined such that it has no theoretical maximum. Therefore, the current version only offers an insight when it is measured over a period of time on the same environment. In other words, one cannot use the current model to compare the polarization between different environments. It would be interesting to revise the model such that the model would have a theoretical maximum.
- the proposed model can be used to find the gatekeeper topics that can alleviate the level of polarization. In other words, it is feasible to extend the model such

that the discussion points that mostly lead to polarization are identified. This can shed light on the topics that lead to polarization in the societies.

- the initial projection is implemented such that the final simple network contains only discussion nodes. This leads to the measurement of the ease of communication between the discussion nodes. It would be interesting to apply reverse projection and implement the projection method such that the final simple network contains only active users. Thus, one can measure the ease of communication between users and also define the gatekeepers in terms of users who facilitate discussions among users.

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A Appendix

Table A.1 twitterKeywords SQL table

#	keyword	esIndex	#	keyword	esIndex
1	FutureofEurope	europawahl	128	datenschutz	twitter19
2	EP2019	europawahl	129	lohnpolitik	twitter19
3	EUelections2019	europawahl	130	politik	twitter19
4	Europawahl	europawahl	131	hochschulpolitik	twitter19
5	MEP	europawahl	132	hartzIV	twitter19
6	Europaparlament	europawahl	133	hartz4	twitter19
7	europaistdieantwort	europawahl	134	sozialpolitik	twitter19
8	EUWahl	europawahl	135	mindestlohn	twitter19
9	EUWahl2019	europawahl	136	klimaschutz	twitter19
10	betterEurope	europawahl	137	energiepolitik	twitter19
11	deinEuropa	europawahl	138	energiewende	twitter19
12	europaSPD	europawahl	139	klimawandel	twitter19
13	zukunkfteuropas	europawahl	140	wirtschaftspolitik	twitter19
14	abmerkeln	twitter19	141	integrationspolitik	twitter19
15	achgut	twitter19	142	rentenpolitik	twitter19
16	afd	twitter19	143	frauenquote	twitter19
17	afdwahrheiten	twitter19	144	gesundheitspolitik	twitter19
18	afdwatch	twitter19	145	bildungspolitik	twitter19
19	aliceweidel	twitter19	146	kinderarmut	twitter19
20	alternativefuer	twitter19	147	arbeitsmarktpolitik	twitter19
21	asylchaos	twitter19	148	altersarmut	twitter19
22	bereicherung	twitter19	149	elterngeld	twitter19
23	btw17	twitter19	150	freihandel	twitter19
24	bundeskanzlerin	twitter19	151	bündnis90	twitter19
25	Bundeswehr	twitter19	152	buendnis90	twitter19
26	buntevielfalt	twitter19	153	bundestag	twitter19
27	cdu	twitter19	154	länderfinanzausgleich	twitter19
28	csu	twitter19	155	direktedemokratie	twitter19
29	dasND.de	twitter19	156	überhangsmandat	twitter19
30	debatometer	twitter19	157	bundesministerin	twitter19
31	Deutschland	twitter19	158	bundesminister	twitter19
32	DGB	twitter19	159	bürgerentscheid	twitter19
33	dielinke	twitter19	160	wahlsystem	twitter19

Table A.1 twitterKeywords SQL table

#	keyword	esIndex	#	keyword	esIndex
34	epochtimes.de	twitter19	161	bundesrat	twitter19
35	faktenfinder	twitter19	162	bundespräsident	twitter19
36	faschismus	twitter19	163	wähler	twitter19
37	fckeu	twitter19	164	direktmandat	twitter19
38	fdp	twitter19	165	wahlrecht	twitter19
39	fluechtlinge	twitter19	166	verfassungsgericht	twitter19
40	g20	twitter19	167	bverfg	twitter19
41	genugfueralle	twitter19	168	bundesregierung	twitter19
42	grüne	twitter19	169	verfassungsrichter	twitter19
43	grenzedicht	twitter19	170	finanzpolitik	twitter19
44	gutmensch	twitter19	171	steuerpolitik	twitter19
45	ichwähleafd	twitter19	172	staatshaushalt	twitter19
46	islamisierung	twitter19	173	wirtschaftslage	twitter19
47	journalistenwatch	twitter19	174	arbeitslosigkeit	twitter19
48	jungefreiheit	twitter19	175	steuerreform	twitter19
49	kanzlerkandidat	twitter19	176	linkspartei	twitter19
50	kriminalitaet	twitter19	177	npd	twitter19
51	Landtag	twitter19	178	piratenpartei	twitter19
52	landtagswahl	twitter19	179	koalition	twitter19
53	landtagswahlen	twitter19	180	groko	twitter19
54	lügenpresse	twitter19	181	schwampel	twitter19
55	lindner	twitter19	182	ampelkoalition	twitter19
56	linke	twitter19	183	jamaikakoalition	twitter19
57	ltw2017	twitter19	184	schwarzgrün	twitter19
58	martinschulz	twitter19	185	schwarzgelb	twitter19
59	merkel	twitter19	186	rotgrün	twitter19
60	merkeldeutschland	twitter19	187	fckafd	twitter19
61	merkelismus	twitter19	188	einwanderungsgesetz	twitter19
62	merkelmussweg	twitter19	189	willkommenskultur	twitter19
63	migranten	twitter19	190	remigration	twitter19
64	morgenpost.de	twitter19	191	familiennachzug	twitter19
65	mutzurwahrheit	twitter19	192	uploadfilter	twitter19
66	nahles	twitter19	193	goeringeckardt	twitter19
67	nazi	twitter19	194	göringeckardt	twitter19
68	naziholocaust	twitter19	195	kretschmann	twitter19
69	nazipack	twitter19	196	oezdemir	twitter19
70	nazis	twitter19	197	özdemir	twitter19
71	NetzDG	twitter19	198	hofreiter	twitter19
72	noafd	twitter19	199	dobrindt	twitter19
73	nog20	twitter19	200	fraukepetry	twitter19
74	Nog20hamburg	twitter19	201	gauland	twitter19

Table A.1 twitterKeywords SQL table

#	keyword	esIndex	#	keyword	esIndex
75	nonazis	twitter19	202	weidel	twitter19
76	offenegrenzen	twitter19	203	petry	twitter19
77	pegida	twitter19	204	schäuble	twitter19
78	philosophia-perennis	twitter19	205	schaeuble	twitter19
79	politikversagen	twitter19	206	johannawanka	twitter19
80	Polizei	twitter19	207	karrenbauer	twitter19
81	pretzell	twitter19	208	altmeier	twitter19
82	rassismus	twitter19	209	vonderleyen	twitter19
83	refugeecrimemap	twitter19	210	michaelmüller	twitter19
84	refugeecrisis	twitter19	211	heikomaas	twitter19
85	rp-online	twitter19	212	carstensieling	twitter19
86	russlanddeutsche	twitter19	213	schwesig	twitter19
87	schulz	twitter19	214	barbarahendricks	twitter19
88	schulzexpress	twitter19	215	sellering	twitter19
89	schulzmussweg	twitter19	216	olafscholz	twitter19
90	smartgerecht	twitter19	217	maludreyer	twitter19
91	sozialschmarotzer	twitter19	218	steinmeier	twitter19
92	spd	twitter19	219	scheuer	twitter19
93	spon.de	twitter19	220	spahn	twitter19
94	sputniknews	twitter19	221	claudiaroth	twitter19
95	stopimmigration	twitter19	222	jungewelt	twitter19
96	stopptcdu	twitter19	223	jungleworld	twitter19
97	tagesspiegel	twitter19	224	nachdenkseiten	twitter19
98	tichyseinblick	twitter19	225	indymedia	twitter19
99	TVDuell	twitter19	226	derFreitag	twitter19
100	uebermedien	twitter19	227	ndaktuell	twitter19
101	unzensuriert	twitter19	228	zeitonline	twitter19
102	Wahl2017	twitter19	229	handelsblatt	twitter19
103	wahlen2017	twitter19	230	dlf	twitter19
104	wahlrecht.de	twitter19	231	ard	twitter19
105	aufstehen	twitter19	232	zdf	twitter19
106	wirsindmehr	twitter19	233	ntvde	twitter19
107	cicero	twitter19	234	compactmagazin	twitter19
108	correctiv	twitter19	235	sz	twitter19
109	spiegel	twitter19	236	taz	twitter19
110	rtdeutsch	twitter19	237	wdr	twitter19
111	vorratsdatenspeicherung	twitter19	238	stern	twitter19
112	ezb	twitter19	239	bild	twitter19
113	bankenaufsicht	twitter19	240	welt	twitter19
114	finanzmarktsteuer	twitter19	241	focus	twitter19
115	forschungspolitik	twitter19	242	wiwo	twitter19

Table A.1 twitterKeywords SQL table

#	keyword	esIndex	#	keyword	esIndex
116	verkehrspolitik	twitter19	243	mdr	twitter19
117	familienpolitik	twitter19	244	dwnews	twitter19
118	umweltpolitik	twitter19	245	germannews	twitter19
119	rentenreform	twitter19	246	merkur	twitter19
120	netzpolitik	twitter19	247	dpa	twitter19
121	netzwerkdurchsetzungsgesetz	twitter19	248	grünen	twitter19
122	zensur	twitter19	249	diegrünen	twitter19
123	atomkraft	twitter19	250	epochtimes	twitter19
124	atomenergie	twitter19	251	akk	twitter19
125	antiatom	twitter19	252	krampkarrenbauer	twitter19
126	atomausteig	twitter19	253	europawahl2019	europawahl
127	überwachung	twitter19			

Table A.2 facebookPages SQL table

#	pageName	pageID
1	CDU	78502295414
2	CSU	81386795687
3	FDP	21289227249
4	Bündnis 90/ Die Grünen	47217143218
5	SPD	47930567748
6	Die LINKE	47694585682
7	AfD	540404695989874
8	Junge Alternative	109330799257463
9	JUSOS	40415227476
10	JU	46098347293
11	Linksjugend	97006679395
12	Junge Liberale	110976485656573
13	Grüne Jugend	159474940754336
14	CDU Baden- Württemberg	77094470902
15	CDU Hessen	217523541326
16	CDU Rheinland-Pfalz	178032906642
17	CDU Schleswig Holstein	275335619167195
18	CDU Bremen	112326918787579
19	CDU Berlin	126952903983246
20	CDU Brandenburg	168325299887228
21	CDU Hamburg	173796242642081
22	CDU Niedersachsen	109460782417586
23	CDU Nordrheinwestpfahlen	108185017409
24	CDU Sachsen	242877865923318
25	CDU Sachsen-Anhalt	171337982904329
26	CDU Thürigen	129459503748982
27	CDU Mecklenburg- Vorpommern	142004422534101
28	SPD Baden- Württemberg	179057176050
29	SPD Hessen	111080175616050
30	SPD Rheinland-Pfalz	330165526782
31	SPD Schleswig Holstein	165381593630826
32	SPD Bremen	524965010906886
33	SPD Berlin	134137749971478
34	SPD Brandenburg	139470429458087
35	SPD Hamburg	130273271119
36	SPD Niedersachsen	76866574484
37	SPD Nordrheinwestpfahlen	30774145303
38	SPD Sachsen	50169278122
39	SPD Sachsen-Anhalt	107652469330889
40	SPD Mecklenburg- Vorpommern	140300602673724
41	SPD Bayern	305250279569563

Table A.2 facebookPages SQL table

#	pageName	pageID
42	FDP Baden- Württemberg	241400009229424
43	FDP Hessen	188188564583
44	FDP Rheinland-Pfalz	189449641081486
45	FDP Schleswig Holstein	164131966966839
46	FDP Bremen	152934608113175
47	FDP Berlin	196999950359158
48	FDP Brandenburg	210778952288250
49	FDP Hamburg	189184071108491
50	FDP Niedersachsen	51468018860
51	FDP Sachsen	66426617453
52	FDP Sachsen-Anhalt	194789640569324
53	FDP Thürigen	217013861665887
54	FDP Mecklenburg- Vorpommern	202215676478081
55	FDP Bayern	350558562311
56	Bündnis 90/ Die Grünen Baden- Württemberg	108655285842827
57	Bündnis 90/ Die Grünen Hessen	22865297210
58	Bündnis 90/ Die Grünen Rheinland-Pfalz	88331883353
59	Bündnis 90/ Die Grünen Saarland	20672124724
60	Bündnis 90/ Die Grünen Schleswig Holstein	1608463192727450
61	Bündnis 90/ Die Grünen Berlin	103558289679671
62	Bündnis 90/ Die Grünen Brandenburg	118849647749
63	Bündnis 90/ Die Grünen Niedersachsen	351947321504088
64	Bündnis 90/ Die Grünen Nordrheinwestpfahlen	20672124724
65	Bündnis 90/ Die Grünen Sachsen	86337829141
66	Bündnis 90/ Die Grünen Sachsen-Anhalt	106637900016
67	Bündnis 90/ Die Grünen Thürigen	445962318752667
68	Bündnis 90/ Die Grünen Mecklenburg- Vorpommern	187394117987834
69	Bündnis 90/ Die Grünen Bayern	258191139993
70	Die LINKE Baden- Württemberg	167785411957
71	Die LINKE Hessen	558754197477014
72	Die LINKE Rheinland-Pfalz	154654377881669
73	Die LINKE Saarland	115707626621
74	Die LINKE Schleswig Holstein	166174613410024
75	Die LINKE Bremen	196114277078358
76	Die LINKE Berlin	156304484388194
77	Die LINKE Brandenburg	293150187371037
78	Die LINKE Hamburg	130391693652056
79	Die LINKE Niedersachsen	194593423966954
80	Die LINKE Nordrheinwestpfahlen	150480805043795
81	Die LINKE Sachsen	142603625775614
82	Die LINKE Sachsen-Anhalt	331788763571422

Table A.2 facebookPages SQL table

#	pageName	pageID
83	Die LINKE Thürigen	134080283313500
84	Die LINKE Mecklenburg- Vorpommern	205311826175998
85	Die LINKE Bayern	395274800547275
86	AfD Baden- Württemberg	570893299597210
87	AfD Hessen	222005461272345
88	AfD Rheinland-Pfalz	162707793881819
89	AfD Saarland	1389842358009240
90	AfD Schleswig Holstein	910790398984963
91	AfD Bremen	159841780842315
92	AfD Berlin	151543935027747
93	AfD Brandenburg	115602575294020
94	AfD Hamburg	585678844775646
95	AfD Niedersachsen	338480852961658
96	AfD Nordrheinwestpfahlen	459077044164282
97	AfD Sachsen	312639988865192
98	AfD Sachsen-Anhalt	363842953730453
99	AfD Thürigen	166760213476486
100	AfD Mecklenburg- Vorpommern	513381125365479
101	AfD Bayern	345598788891061
102	tagesschau	193081554406
103	ihre.sz	215982125159841
104	FOCUS-Online-Politik	492723560754814
105	focus.it	67963432194
106	zeitonline	37816894428
107	spiegelonline	38246844868
108	bild	25604775729
109	rtdeutsch	472061332924101
110	sputnik.deutschland	251154464896122
111	CDU Saarland	334120300419
112	SPD Saarland	214065808453
113	SPD Thürigen	879215109816
114	FDP Saarland	189006054445407
115	FDP Nordrheinwestpfahlen	282800387209
116	Bündnis 90/ Die Grünen Schleswig Holstein	1608463192727453
117	Bündnis 90/ Die Grünen Bremen	207429192606075
118	Bündnis 90/ Die Grünen Hamburg	25406037041
119	AfD Saarland	1389842358009237
120	SPD Thürigen	167231359972727
121	Freie Wähler	276040002549416

Listing A.1: Sample Facebook JSON file


```
{
  "index": {
    "_id": 78502295414101556449162804150
  }
}
{
  "downloadTime": "2018-10-01 09:14:33",
  "VERSION": "0",
  "comments": {
    "paging": {
      "cursors": {
        "after": "[...]",
        "before": "[...]"
      }
    },
    "data": [
      {
        "comments": {
          "paging": {
            "cursors": {
              "after": "[...]",
              "before": "[...]"
            }
          },
          "data": [
            {
              "id": "10155644916280415_10155646557225415",
              "message": "[...]",
              "created_time": "2018-06-07T06:00:32+0000"
            },
            {
              "id": "10155644916280415_10155648600655415",
              "message": "Www.tichyseinblick.de",
              "created_time": "2018-06-08T06:00:29+0000"
            }
          ]
        },
        "message": "[...]",
        "like_count": 11,
        "id": "10155644916280415_10155645025215415",
        "created_time": "2018-06-06T16:26:56+0000",
        "comment_count": 2
      }
    ]
  },
  "message_tags": [
    {
      "length": 13,
      "offset": 137,
      "type": "page",
      "name": "Angela Merkel",
      "id": "59788447049"
```

```
      }
    ],
    "message": "[...]",
    "link": "[...]",
    "id": "78502295414_10155644916280415",
    "full_picture": "[...]",
    "from": {
      "id": "78502295414",
      "name": "CDU"
    },
    "description": "[...]",
    "created_time": "2018-06-06T15:38:06+0000",
    "name": "EVP-Fraktion CDU/CSU",
    "shares": {
      "count": 18
    },
    "status_type": "mobile_status_update",
    "story": "CDU shared EVP-Fraktion CDU/CSU's live video.",
    "story_tags": [
      {
        "length": 3,
        "offset": 0,
        "type": "page",
        "name": "CDU",
        "id": "78502295414"
      }
    ],
    "type": "video",
    "permalink_url": "[...]",
    "attachments": {
      "data": [
        {
          "url": "[...]",
          "type": "video",
          "target": {
            "url": "[...]",
            "id": "1846523715406687"
          },
          "media": {
            "image": {
              "width": 720,
              "src": "[...]",
              "height": 404
            }
          }
        }
      ]
    }
  }
```

Listing A.2: Sample Twitter JSON file


```
{
  "index": {
    "_id": "906608141495709696"
  }
}
{
  "timestamp_ms": "1504987199554",
  "lang": "de",
  "filter_level": "low",
  "possibly_sensitive": false,
  "retweeted": false,
  "favorited": false,
  "entities": {
    "symbols": [],
    "user_mentions": [],
    "urls": [
      {
        "indices": [
          112,
          135
        ],
        "display_url": "[...]",
        "expanded_url": "[...]",
        "url": "https://t.co/p8qpEIM5hj"
      }
    ],
    "hashtags": [
      {
        "indices": [
          2,
          9
        ],
        "text": "TSGFCB"
      },
      {
        "indices": [
          12,
          17
        ],
        "text": "DudW"
      },
      {
        "indices": [
          20,
          40
        ],
        "text": "Ninjawarriorgermany"
      }
    ]
  },
  "favorite_count": 0,
  "retweet_count": 0,
```

```
  "reply_count": 0,
  "quote_count": 0,
  "is_quote_status": false,
  "in_reply_to_status_id_str": null,
  "in_reply_to_status_id": null,
  "truncated": false,
  "source": "[...]",
  "text": "[...]",
  "id_str": "906608141495709696",
  "id": 906608141495709700,
  "created_at": "Sat Sep 09 19:59:59 +0000 2017",
  "in_reply_to_user_id": null,
  "in_reply_to_user_id_str": null,
  "in_reply_to_screen_name": null,
  "user": {
    "notifications": null,
    "follow_request_sent": null,
    "following": null,
    "default_profile_image": false,
    "default_profile": true,
    "profile_banner_url": "https://pbs.twimg.com/profile_banners/1336218432/1455019567",
    "profile_image_url_https": "[...]",
    "created_at": "Mon Apr 08 10:01:25 +0000 2013",
    "statuses_count": 425198,
    "favourites_count": 15,
    "listed_count": 463,
    "friends_count": 49,
    "followers_count": 10059,
    "verified": false,
    "protected": false,
    "id": 1336218432,
    "id_str": "1336218432",
    "name": "Trendinalia DE",
    "screen_name": "trendinaliaDE",
    "location": "Deutschland",
    "url": "http://trendinalia.com/twitter-trending-topics/germany/",
    "description": "[...]",
    "translator_type": "regular",
    "utc_offset": 7200,
    "time_zone": "Berlin",
    "geo_enabled": true,
    "lang": "es",
    "contributors_enabled": false,
    "is_translator": false,
    "profile_background_color": "C0DEED",
    "profile_background_image_url": "[...]",
    "profile_background_image_url_https": "[...]",
    "profile_background_tile": false,
    "profile_link_color": "1DA1F2",
    "profile_sidebar_border_color": "C0DEED",
    "profile_sidebar_fill_color": "DDEEF6",
    "profile_text_color": "333333",
    "profile_use_background_image": true,
```

```
      "profile_image_url": "[...]"
    },
    "geo": {
      "coordinates": [
        52.5161,
        13.377
      ],
      "type": "Point"
    },
    "coordinates": {
      "coordinates": [
        13.377,
        52.5161
      ],
      "type": "Point"
    },
    "place": {
      "attributes": {},
      "id": "3078869807f9dd36",
      "url": "https://api.twitter.com/1.1/geo/id/3078869807f9dd36.json",
      "place_type": "city",
      "name": "Berlin",
      "full_name": "Berlin, Alemania",
      "country_code": "DE",
      "country": "Alemania",
      "bounding_box": {
        "coordinates": [
          [
            [
              13.088304,
              52.338079
            ],
            [
              13.088304,
              52.675323
            ],
            [
              13.760909,
              52.675323
            ],
            [
              13.760909,
              52.338079
            ]
          ]
        ],
        "type": "Polygon"
      }
    },
    "contributors": null
}
```

Estimating the Political Orientation of Twitter Users in Homophilic Networks

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Abstract

There have been many efforts to estimate the political orientation of citizens and political actors. With the burst of online social media use in the last two decades, this topic has undergone major changes. Many researchers and political campaigns have attempted to measure and estimate the political orientation of online social media users. In this paper, we use a combination of metric learning algorithms and label propagation methods to estimate the political orientation of Twitter users. We argue that the metric learning algorithm dramatically increases the accuracy of our model by accentuating the effect of homophilic networks. Homophilic networks are user clusters formed due to cognitive motivational processes linked with cognitive biases. We apply our method to a sample of Twitter users in Germany's six-party political sphere. Our method obtains a significant accuracy of 62% using only 40 observations of training data for each political party.

Introduction

Measuring and estimating the political orientation of normal citizens and political actors has always been a relevant question. The answer to this question is essential for electoral campaigns (Gayo Avello, Metaxas, and Mustafaraj 2011; Dokoohaki et al. 2015; Papakyriakopoulos et al. 2018), agenda setting, policy making (McCombs 2014), and research purposes (Golbeck and Hansen 2011; Barberá 2014; Hegelich and Shahrezaye 2015). The methodological efforts to answer this crucial question possess three qualities.

The first quality is related to the number and type of inputs in the algorithm: What type of features are considered while estimating the latent political orientation of the users? The second quality is if the method is designed to estimate the political orientation of a specific group of political actors (Wong et al. 2013; Groseclose and Milyo 2005) or a more general group of citizens (Barberá 2014). If a method is designed based on a specific group of political actors or citizens, it cannot be generalized to estimate the political orientation of other groups of political actors or citizens. Cohen and Ruths have presented that methods that have accuracy greater than 90% in estimating if a Twitter user is a Democrat or Republican, would have accuracy level of less than 65% when applied on general Twitter users. The last quality is if the method measures the political orientation on a one dimensional or a multidimensional latent space. Most of the literature has been designed based on the two-party political system of the United States. Thus, they are inherently designed to estimate a one-dimensional latent variable.

In this work, we use a combination of metric learning algorithms and label propagation methods to estimate the political orientation of Twitter users. Our method has three distinguishing features. First, the method requires a minimal number of features as training data because it exploits the homophilic structure of social networks (Geschke, Lorenz, and Holtz 2018; Madsen, Bailey, and Pilditch 2018). Second, the proposed method estimates on a multidimensional latent space; therefore, the proposed method can be used to estimate the political orientation of users in a multiparty political system. The third feature is that our method is extendable to multiple groups or cluster of users. Our method can estimate the political orientation of users even if the target users have zero political activity on the platform.

Methodology

We use a combination of metric learning algorithms with label propagation methods to estimate the political orientation of Twitter users. The goal of label propagation algorithms is to estimate the labels of a large set of unlabeled observations from the small set of labeled observations.

Suppose there are l labeled observations $(x_1, y_1), \dots, (x_l, y_l)$ and u unlabeled observations such that $l < u$, and $n = l + u$. Consider a connected graph $G = (V, E)$ with nodes $L = \{1, \dots, l\}$ and $U = \{l + 1, \dots, l + u\}$ corresponding, respectively, to the labeled or training observations and unlabeled or test observations. A label propagation algorithm propagates the labels for the set U, based on the distances between its observations to the observations in L. Within the label propagation algorithm, the labels of the vertices in set L would be fixed, but the labels of the set U would be estimated based on a function of their distance to set L.

Let n be the total number of Twitter users we have including l users for whom we already know their political orientation and u users for whom we want to estimate their political orientation. We use only the structure of the friends' network to estimate the political orientations. Let F be the set of friends of all n users with size m. Therefore, we can create the binary matrix A with dimension $n \times m$, which would represent the friends of each of the n users. Before constructing graph G from matrix A, we transform matrix A by using a proper metric learning algorithm.

The reason for transforming matrix A is that we believe there are hidden information within the network structure, which we could use to increase the estimation accuracy. By contrast with the rational choice theory, the human judgment is influenced by various cognitive biases, prior judgments, environmental features, and stimulus-feedback loops (Kenrick et al. 2010; Donkin, Heathcote, and Brown 2015). Cognitive biases reproduce human judgments that could be systematically different from rational reasoning (Kahneman and Tversky 1973; Haselton, Nettle, and Murray 2015). The cognitive biases make the human brain process the information in a distorted manner compared with an objective reality (Sharot, Korn, and Dolan 2011). Although there is a list of cognitive biases that affect the online activity of the users, we are specifically interested in cognitive biases related to self-categorization. Self-categorization describes the motivations and circumstances under which communities with shared identities form. The self-categorization theory articulates that the spectrum of human behavior can be analyzed from a pure interpersonal or individualistic and a pure intergroup or collectivist perspective. Humans have the desire for a positive and secure self-concept; therefore, they connect with individuals that confirm their pre-existing attitudes, verify their self-views, and increase their social identity. The aforementioned behaviour is called confirmation bias (Geschke, Lorenz, and Holtz 2018). In addition, “If we are to accept that people are motivated to have a positive self-concept, it flows naturally that people should be motivated to think of their groups as good groups” (Hornsey 2008). Striving for a positive and secure self-concept, humans’ collectivist behaviors contribute to the formation of online and offline communities with shared social identities (Ridings and Gefen 2004). Consequently, users with similar labels, that is, similar political preferences, are expected to be relatively closer to each other. Therefore, if we were to supposedly apply a k-nearest neighbors learning method, it makes sense to use a distance function that interprets similar users closer to each other. Instead of using an off-the-shelf distance function such as Euclidean distance, we use an alternative distance function that guarantees higher accuracy for the labeled or training observations after running the learning method.

A brief description of the steps of our method is as follows. First, we acquire matrix A, which includes the labeled observations and the unlabeled observations as rows. Second, we learn the optimized distance or metric function that guarantees higher accuracy within the labeled observations by exhausting the special structure of homophilic networks. We transform matrix A by using the learned metric to construct graph G. Finally, we apply the learning method or the label propagation algorithm.

Metric Learning for Large Margin Nearest Neighbor Classification (LMNN)

The accuracy of each learning algorithm is a function of the distance function or the metric used to compute the distance between the observations. The metric learning algorithm we use is based on the following: a precise k-nearest neighbors classification will correctly classify a labeled observation if its k-nearest neighbors share the same label. The algorithm then attempts to increase the number of labeled observations with this property by learning a linear transformation of the input space that proceeds the final learning method. The linear transformation of *LMNN* is derived by maximizing a loss function with two terms. The first term minimizes the large distances between observations within class, and the second term maximizes the distances between the observation between the classes (Weinberger and Saul 2009).

In general, metric learning algorithms estimate the positive semidefinite transformation matrix $\mathcal{M}$ such that the distance between two observations, x_i and x_j, is derived by the Mahalanobis distance,

$$d_{\mathcal{M}}(x_i, x_j) = \sqrt{(x_i - x_j)^T \mathcal{M}(x_i - x_j)}$$

which follows certain features. If we replace $\mathcal{M}$ with the identity matrix, the resulting metric would be Euclidean metric. *LMNN* learns a linear transformation matrix $\mathcal{M}$, such that the training or labeled observation satisfies the following items (Weinberger and Saul 2009):

- Each labeled observation should share the same label as its k- nearest neighbors. This is achieved by introducing a loss function that penalizes large distances between observations belonging to the same class,

  $$\epsilon_{pull}(L) = \sum_{j \rightsquigarrow i} ||L(\bar{x}_i - \bar{x}_j)||^2$$

  where $j \rightsquigarrow i$ indicates that j is an observation that we desire to be close to i, and L is the function representing the transformation by matrix $\mathcal{M}$.
- The labeled observations with different labels should be significantly separated. This separation is achieved by introducing a loss function that penalizes small distances between observations belonging to different classes,

  $$\epsilon_{push}(L) = \sum_{i,j \rightsquigarrow i} \sum_{l} [1 + ||L(\bar{x}_i - \bar{x}_j)||^2 - ||L(\bar{x}_i - \bar{x}_l)||^2]$$

  where the inner sum iterates over all the observations with a different class to i, and l invades the perimeter of i and j plus unit margin. In other words, the observation l satisfies

  $$||L(\bar{x}_i - \bar{x}_l)||^2 \leq ||L(\bar{x}_i - \bar{x}_j)||^2 + 1$$

The final loss function is a weighted combination of the two defined components,

$$\epsilon(L) = (1 - \mu)\epsilon_{pull}(L) + \mu\epsilon_{push}(L)$$

Although the general loss function above is not convex, by limiting the solution space to positive semidefinite matrices, the loss function will be a convex function.

The solution to the minimization of the loss function, given the labeled subset of A, is the desirable matrix $\mathcal{M}$. We transform matrix A to obtain matrix $A_{\mathcal{M}}$ by

$$A_{\mathcal{M}} = A \times \mathcal{M}$$

We construct graph G using the $A_{\mathcal{M}}$ of size $n \times m$ by using the nearest neighbor graph method. In other words, using n rows of $A_{\mathcal{M}}$, we define n vertices of G and then define edges between each vertex and its k_G nearest neighbors by using the Euclidean distance function.

Label Propagation Using Gaussian Fields and Harmonic Functions

The goal of applying a label propagation algorithm to a graph is to estimate the labels of unlabeled vertices by using their connections to the few labeled vertices. This problem is usually formulated as an iterative process within which the labels are gradually diffused over the matrix, such that the state of the graph would converge to a stationary state. This iterative process might have an analytical solution that would be more efficient than applying the algorithm iteratively (Barrett et al. 1994; Zhu and Ghahramani 2002). The most crucial implication of a label propagation algorithm for our question regarding estimating political orientation of Twitter users is that the only requirement for estimating the political requirement of a user is that the user should be connected to graph G. Hence, the user should not necessarily have politicians or other political actors as friends.

The algorithm we use for label propagation is based on Zhu, Ghahramani, and Lafferty. Let the simple graph $G = (V, E)$ and the set of the labeled and unlabeled vertices, L and U, be as defined. The goal is to compute the real-valued function $f : V \to \mathbb{R}$ on the simple graph G. f must assign the same given labels for the set L or $f_l(i) \equiv y_i$ for $i \in l$. To estimate the function f they defined the energy function

$$E(f) = \frac{1}{2} \sum_{i,j} w_{i,j} (f(i) - f(j))^2$$

and the Gaussian field

$$p_\beta(f) = \frac{-e^{\beta E(f)}}{Z_\beta}$$

where β is an inverse temperature function and $Z_\beta = \int_f exp(-\beta E(f))$ which normalizes over all functions constrained to the constraint $f_l(i) \equiv y_i$ on the labeled vertices. Then, they demonstrate the result of the minimization

$$f = \arg\min_f E(f)$$

which is a harmonic function that satisfies the constraint $f_l(i) \equiv y_i$ on the labeled vertices. The harmonic property implies that the value of f at each unlabeled vertex is the average of f at neighboring vertices. Therefore, the estimated labels would be a function of the similarity of all neighboring vertices.

The estimated f has an interpretation within the framework of random walks. The estimated $f(i)$ for an unlabeled vertex $i \in U$ would be a vector of size equal to number of possible classes. The jth element of $f(i)$ would be the probability that a particle that started at vertex i would first hit a vertex with class j. Therefore, the resulting algorithm can be used to estimate the political orientation of a user in a multidimensional latent space.

Data and Results

Data Preparation

We require two sets of data for training and testing. We acquire both sets from the public Twitter API. In the first step, we obtained the list of all the members of the main and local German parliaments who are available on Twitter. This list contains 623 Twitter users from one of the six parties CDU/CSU, SPD, Grüne, Linke, FDP and AfD.

From a database of German political Tweets, we obtained a list of 400,000 random Twitter users. We downloaded the list of all their friends and their last 4,000 Tweets by using the public API. We counted how many times each user retweeted the Tweets of members of each of the political parties we acquired in the first step. If a user has retweeted a minimum of five Tweets from members of party j but no retweets from other parties, we tag this user as a user with a political orientation to party j. From the 400,000 initial users, we could label 8,146 based on the mentioned heuristic.

To reduce the complexity of the computations, we reduced the sample size to 50,000 from 400,000. Thus, we created matrix A using 50,000 random users including all of the 8,146 labeled users. Matrix A has at this step 50,000 rows as users, which we want to use for our training and test set, and 7,194,153 columns as the friends. To further reduce the complexity of the computations, we removed the friends who are friends of less than 0.01% of the users. The final matrix A has the dimension 50,000$\times$ 552,136.

We confirm that our test data has a minor bias in the sense that we already know our test data includes users who have engaged in some type of political activity. This assumption is because these users are randomly chosen from a database of German political Tweets. On the other side, this bias is mildly mitigated in two steps. First, matrix A is created by a list of friends of all 50,000 random users and not only the friends of the labeled 8,146 users. Thus, the feature sets are from a bigger set of observations. Second, we added some randomness by removing some columns of matrix A in the final step.

Metric Learning and Label Propagation

We resampled 60 users per political party out of the 8,146 labeled users of A. We learned matrix $\mathcal{M}$ based on the 240 users. Next, we transformed the whole matrix A using $\mathcal{M}$ by applying

$$A_{\mathcal{M}} = A \times \mathcal{M}$$

Using the transformed $A_{\mathcal{M}}$, we made a 10-nearest neighbors graph using a Euclidean distance function to make graph G. Finally, we applied the label propagation algorithm on G that has 50,000 vertices, out of which, the labels of 240 are introduced to the algorithm. The labels of the other 49,760 are estimated using the label propagation algorithm.

Results

We performed the resampling and the computations 10 times to make sure the results are robust. For each trial, we applied a random forest classifier on the 240 training data as a

random forest	A (not transformed)	0.23
label propagation		0.20
random forest	$A_{\mathcal{M}}$ (transformed)	0.30
label propagation		0.62

Table 1: Average accuracy of the predictions over 10 resamples

benchmark result. We also applied the random forest classifier and the label propagation method on A directly to improve our understanding regarding how much the $LMNN$ metric learning method contributes to the accuracy of the results. Table 1 shows the average accuracy of the estimations on the remaining 8,146-240=7,906 labeled users with a known political orientation.

Referring to Table 1, we observe that the transformation increases the accuracy of the random forest classifier and the label propagation algorithm. We also observe that the combination of the metric learning algorithm and the label propagation method results to a much higher accuracy of estimation.

Discussion

In this paper, we proposed a new method to estimate the political orientation of Twitter users. Our method has many distinguishing features: The method requires few training observations, requires few learning features, is based on a multidimensional latent space, and is easily expendable to new users even if they have zero political activity on Twitter.

Based on Table 1, the high accuracy of the model is due to the transformation of the initial matrix using the function learned by the *LMNN* algorithm. The cost function of the *LMNN* algorithm has two parts. One part pulls the observations of the same class closer to each other, and the other part pushes the observations of different classes far apart. Additionally, since the *LMNN* algorithm is based on optimizing a k-nearest neighbor model on the training observations, the trained matrix $\mathcal{M}$ transforms the observations based on their relation to other observations in their vicinity and not the whole dataset. These characteristics have crucial implications reagarding the accuracy of our estimation.

As aforementioned, the initial matrix, A, has a special structural feature because it represents a homophilic social network, which means that users with similar political identity are assumed to demonstrate similar behavior on Twitter. Therefore, we expected that users with similar political identity would follow similar politicians, similar celebrities, similar sportsmen, and so forth.

When we apply the *LMNN* algorithm to this homophilic network, we accentuate the extant distinctive features formed due to the existing cognitive biases in self-categorization and group formation (Geschke, Lorenz, and Holtz 2018; Madsen, Bailey, and Pilditch 2018).

The matrix $\mathcal{M}$ learns different combinations of features that help distinguish normal Twitter users based on their political orientation. The matrix $\mathcal{M}$ also allows different combination of features for each class because it is based on a k-nearest neighbor algorithm that considers a bounded proximity of the users. Our model detects the political orientation of users with high accuracy, and by far outperforms other algorithms that have been applied to this task.

Due to the use of label propagation algorithm, this model can be later applied on any new user e to estimate her or his political orientation, as long as e is connected to the graph G. More generally, to predict the political orientation of user e, we must find a new set of users including e, forming a small graph g connected to the initial graph G.

This study provides valuable insights into the study of user behavior on online social networks. This study illustrates, that using mathematical algorithms that exhaust properties of social theories, we can improve the performance of models explaining human behavior. Furthermore, this study contradicts the general claim that a huge amount of data is required to make accurate predictions on social and political behavior. Finally, our method provides a novel technique to assign political partisanship, by having as input only the network of interpersonal connections.

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Measuring the Ease of Communication in Bipartite Social Endorsement Networks

A Proxy to Study the Dynamics of Political Polarization

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ABSTRACT

In this work, complex weighted bipartite social networks are developed to efficiently analyze, project and extract network knowledge. Specifically, to assess the overall ease of communication between the different network sub-clusters, a proper projection and measurement method is developed in which the defined measurement is a function of the network structure and preserves maximum relevant information. Using simulations, it is shown how the introduced measurement correlates with the concept of political polarization, after which the proposed method is applied to Facebook networks to demonstrate its ability to capture the polarization dynamics over time. The method successfully captured the increasing political polarization between the *Alternative für Deutschland*'s (AfD) supporters and the supporters of other political parties, which is in line with previous studies on the rise of the AfD in Germany's political sphere.

CCS CONCEPTS

• **Networks → Social media networks**; *Network simulations*; • **Human-centered computing → Social network analysis**; **Social networking sites**; • **General and reference** → *Metrics*; *Estimation*;

KEYWORDS

Social media networks, Bipartite network projection, Network simulations, Political polarization, Political discourse

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1 INTRODUCTION

1.1 Social Networks

Following of the uptake in social media services, social scientists have been presented with significant new challenges and opportunities. The generation of huge data sets, which record the interactions of millions of users, has dramatically changed the quantitative models, research style and empirical methods that social scientists use. This renaissance requires social scientists to adapt to new quantitative methods [27].

Network analysis theory can now provide the theory and tools required for social scientists to model, study and generate knowledge from the complex interactions of millions of social media users on services such as Facebook and Twitter. However, social networks can be complex unlike most biological, technological, and other real-life networks that often have disassortative mixing or negative correlations with neighboring vertices, social networks mostly show assortative mixing or positive degree correlations with the neighboring vertices. A second distinctive feature of social networks is their topology. While non-social networks generally have no significant local clustering compared to random networks with similar degrees of distribution, social networks have been found to have significant clustering [40].

These two special social network features emerge at the time of the network formation; that is, sub-communities and assortative mixing are formed while the whole network emerges. These features emerge because of many reasons such as technological design or cognitive biases. Geschke et al. [18] used agent-based modeling to show that sub-communities formed even in the absence of technological filters. Therefore, any effort to study social networks needs to consider that these networks have special features that cannot be ignored.

This paper focused on a special type of social network. While most social and non-social networks are one-mode networks, some are two-mode or bipartite networks. While one-mode networks have only one type of vertices, bipartite networks have two different types of vertices and each edge is between a vertices pair of different types. For example, a friendship network is a one-mode network in which each edge between two vertices indicates that the corresponding users are friends. However, Facebook posts are part of a bipartite network, in which each edge indicates a user who has commented on the corresponding Facebook post. Both types of the mentioned networks might have weighted edges that measure the strength of the edge, or binary simple edges which only shows an unweighted connection. Bi-partite networks have been analyzed in a wide variety of different contexts, such as sports activity networks [42], actors networks [41], economics and finance networks [8], online file sharing networks [20, 30] and scientific authoring networks [38, 51].

Because bipartite networks are more complex to study, they require different tools than studies on simple one-mode networks [4, 36, 58, 60]. Studying bipartite networks requires either projecting the network to a one-mode network or developing the proper measurements applicable to the bipartite case [12]. The result of projecting a bipartite network to a one-mode network is a binary or weighted one-mode network, which could lead to the deletion of some important information [44, 61]; for example, the global and local clustering coefficients on bipartite networks differ significantly from the counterpart values in corresponding projected networks [43].

This paper argues that the usual projection methods lose a great deal of information because they do not account for the existing assortativity and the network clustering within social networks. Therefore, in this paper, first a new projection method is suggested for weighted bipartite social networks that is able to preserve the relevant information from the initial network. Afterwards, methods applicable to the resulting simple one-mode networks are employed to generate knowledge from the projected networks. The proposed method is used to demonstrate that these methods could be used as proxy measurements for monitoring political polarization dynamics, and a mathematical method is developed to study this important social and political process. Because of the rise in online social networks, political polarization has become a key research topic in social sciences; therefore, this study contributes to research in these areas and could be used to understand the tenor of a particular development.

1.2 Political Polarization

From well-known online news services to the political candidates themselves, citizens with an interest in politics can now obtain information from a myriad of sources, and are also able to engage in political discourse with many (often unknown) social media users and website commentators [6, 35, 47, 52]. Although there has been an exponential increase in the information flow on online platforms, the human abilities to digest, analyze and process such information has been bounded due to biological brain constraints. It is argued that due to the bounded rationality theorem, when the humans have incomplete information about the alternatives, the probability of behaving irrationally is higher [23, 25, 53]. Therefore, social media users are generally unable to rationally analyze the abundant information flows on these emerging heterogeneous media.

People have a natural tendency to bond with those who are similar; a behaviour which is also imprinted in their selection of information sources and discussion groups. This principle, known as homophily, explains people's tendency to seek situations that imbue similarity and agreement; that is, people tend to bond with similar individuals [2, 9, 34, 37].

Because of the bounded rationality theorem and homophily, normal citizens interact with information sources and people who have similar beliefs during the selection process on social media services [5]. Thus, the widely accessible social media services turn potentially into breeding grounds of polarization. DiMaggio et al. [11] defined political polarization as the distance between the political orientations of different people. They argued that political polarization is a process as well as a state. While the latter refers to the distance an opinion is from some theoretical maximum or average, the former refers to development of the distance between the political orientations of different people over time.

DiMaggio et al. [11] introduced four independent and different polarization measurements, two of which referred to single distribution properties, while the others were focused on the relationships between the distributions. These measurements included variances or the dispersion of opinions, the kurtosis or bimodality of opinions, the tau-equivalent reliability or association between the opinions, and the correlation of opinions with salient individual characteristics. It was rationalized that political polarization would possibly entail a higher variance, a lower kurtosis, a higher tau-equivalent reliability and a higher correlation of opinions with salient individual characteristics.

1.3 Current Research

The motivation for creating reliable tools to measure and understand political polarization comes from political theory. In a democratic system, citizens should be aware of all cross-ideological points of view and also have the right to defend their own beliefs [22, 55]. Communication environments that expose citizens to a range of cross-ideological points allow citizens to be able to better develop justifications for their own viewpoints, establish a better understanding about alternative cross-ideological viewpoints, and develop a higher tolerance toward the opinions of others. DiMaggio et al. [11] claimed that "other things being equal, attitude polarization militates against social and political stability by reducing the probability of group formation at the center of the opinion distribution and by increasing the likelihood of the formation of groups with distinctive, irreconcilable policy preference". Therefore, as political polarization has been found to have undesirable effects, this paper seeks to develop a methodology to measure, analyze, and understand political polarization. Because online social media interactions are complex, a unique political polarization measurement is needed that is able to capture the dynamics or the evolution of political polarization over time.

This paper introduces social weighted bipartite endorsement networks, develops efficient methods to project weighted bipartite social networks that preserve the maximum amount of relevant information, and then applies the projection method to a simulated weighted bipartite social networks while controlling the political polarization. It is demonstrated that the search information index introduced by Trusina et al. [56] and Sneppen et al. [54] is positively correlated with the extent of the political polarization when applied to the projected networks. The newly developed methods are then applied to politically active Facebook network in Germany. The introduced measurements allow for the monitoring of the political polarization dynamics within social networks.

2 RELATED WORK

The relevant literature from two different topics is reviewed in this section; bipartite networks and political polarization.

2.1 Projecting Bipartite Networks

As mentioned, bipartite networks are applicable to many different fields of sciences. However, because of their inherent complexity, previous research has tended to only analyze their most basic features, such as the degree distribution of the vertices. There have been some attempts to introduce bipartite notion of local clustering coefficients [43, 50, 59], centrality [14], correlation of vertex degree [46] and community detection [21, 57] that have been developed and directly applied to bipartite networks. However, as pointed out by Latapy et al. [29], as most of these measurements have been somewhat ad hoc and specific to the case, could not be easily extended to general bipartite networks.

The other approach to the study of bipartite networks is reducing the bipartite network to a binary or weighted one-mode network [3, 44, 61], with the most prominent projection methods being binary projection, sum projection, and the celebrated weighted sum projection of Newman [39]. Based on binary projection, two vertices of the same type are connected with a simple edge if both are at least connected to one vertex of the other type in the initial network. Under the sum projection, two vertices of the same type are connected with an edge weight p if both are connected to p vertices of the other type in the initial network. The Newman projection is similar to the sum projection except that each shared vertex of the other type is given a weight equal to $\frac{1}{N_p-1}$ when N_p is the degree of that vertex.

Each projection method is based on a similarity function. For example, the binary projection is based on the following similarity function,

$$Sim_{binary}(u_i, u_j) = \begin{cases} 1 & \text{if } u_i \cdot u_j > 0 \\ 0 & \text{if } u_i \cdot u_j = 0 \end{cases}$$

where u_i is the binary vector indicating to which vertices the vertex i is connected and $\cdot$ is the dot product. The sum method is based on the following similarity function

$$Sim_{sum}(u_i, u_j) = u_i \cdot u_j$$

2.2 Political Polarization Measurements

DiMaggio et al. [11] introduced simple political polarization measurements that are not directly applicable to complex environment of social networks. Levendusky [32] attempted to measure and evaluate the polarization of individual Democrats and Republicans over time using National Election Study data. Fiorina and Abrams [15] studied the relationship between polarization and the geographical distribution of different groups. Freire [16] measured party polarization on the left-right scale. Using clustering methods, Conover et al. [7] showed that the network of political retweets had a segregated network of activity. Matakos et al. [33] used an opinion formation model to define a polarization index that measured the polarization in the opinions of the individuals in the network as well as the network structure. Akoglu [1] considered a bipartite network of users and subjects using Markovian Random Fields framework, and then defined the problem as a probabilistic classification task in which the polarity rank of the users in the political spectrum were to be predicted. The most related work to our methodology is Garimella et al. [17]. They used network theory tools to measure how controversial political topics in social media appeared to be.

3 METHODOLOGY

3.1 Problem Overview

The type of social networks which we considered are weighted bipartite social networks of users and discussion vertices. A bipartite network $\mathcal{G} = (\mathcal{U}, \mathcal{V}, \mathcal{E})$ was established in which n users $\mathcal{U} = \{u_1, ..., u_n\}$ and m discussions $\mathcal{V} = \{v_1, ..., v_m\}$ are connected with weighed edges $e(u, v, w) \in \mathcal{E}$ such that $\mathcal{E} \subseteq \mathcal{U} \times \mathcal{V} \times \mathbb{R}$. The weighted edges $e(u, v, w)$ represent positive endorsement of magnitude w from user u to discussion v. It was further assumed that each discussion v belongs to one of $p > 1$ possible non-empty classes $C_{\mathcal{V}} = \{c_1, ..., c_p\}$ such that $p \ll m$; that is, each class c is a sub-cluster of the network $\mathcal{G}$.

This structure can be applied to online user activities, such as the retweet and favorite networks on Twitter, the like and share networks on Facebook, and the share networks of blog posts. For example, set C might be $\{Republicans, Democrats\}$ and set $\mathcal{V}$ might be a set of Facebook pages or blog pages that are politically oriented toward either Republicans or Democrats. Then, given the positive endorsement of n users on the Facebook posts or blog pages, the task is to measure the ease of communication and also to capture dynamics of political polarization between the different network sub-clusters, $\{Republicans, Democrats\}$.

In the first step, tools were developed to project the weighted bipartite network $\mathcal{G}$ to the simple network $\mathcal{H} = (\mathcal{V}, \mathcal{V})$. To project $\mathcal{G}$ to $\mathcal{H}$, similar to other projection methods, a similarity function was needed. For the similarity function a distance function is employed and If the distance between two vertices was less than a maximum threshold, an edge between the two corresponding vertices was established. Then information theory concepts were applied to $\mathcal{H}$ to measure the ease of communication between every two random $\mathcal{H}$ vertices using the search information index introduced in Trusina et al. [56] and Sneppen et al. [54].

3.2 Metric Function

In this section, the distance or metric function is introduced that measures the similarity between the discussion vertices. Based on e-neighborhood graph construction method, if the distance between two vertices was less than a max threshold, they were seen to be similar vertices. Consider the adjacency matrix for $\mathcal{G}$, $A_{\mathcal{G}}$, in which each row represents a discussion vertex v and each column a user vertex u. Let S_n be the set of all permutations on $\mathcal{U}$, with each row of $A_{\mathcal{G}}$ being an element of S_n. For all $\sigma \in S_n$ define $\sigma(i)$ as the rank of the element $i \in \mathcal{U}$ in σ. For two elements $\sigma, \tau \in S_n$ the Kendall's tau $K(\sigma, \tau)$ is the initial metric introduced by Kendall [26]. Kendall's tau metric is identity invariant; that is the value of the metric does not depend on the actual identity of the elements in $\mathcal{U}$. Therefore, it suffices to consider $K(\sigma) = K(\sigma, 1)$ where 1 is the identity permutation. Then

$$K(\sigma) = \sum_{(i,j):i>j} \mathbb{1}[\sigma(i) < \sigma(j)]$$

where $\mathbb{1}$ is the indicator function. $K(\sigma)$ counts the total number of pairwise inversions between the elements of σ and τ.

In this study, one of the three new generalizations to the distance function introduced by Kumar and Vassilvitskii [28] was employed. The generalization aims to adjust the effect of swapping similar items. The intuition is that a pairwise inversion of two similar items should be penalized less than a pairwise inversion of two dissimilar items. Let D be a non-empty metric on $\mathcal{U}$ and let D_{ij} be the distance between users $i, j \in \mathcal{U}$. In this study, we defined the metric D using the Jaccard index

$$D(u_i, u_j) = 1 - J(u_i, u_j) = 1 - \frac{|P_i \cap P_j|}{|P_i \cup P_j|}$$

where P_i is a set consisting of the discussion vertices in which user i has a non-zero endorsement on.

Then the similarity-adjusted distance between the rankings would be

$$K^*(\sigma) = \sum_{(i,j):i<j} D_{ij} \mathbb{1}[\sigma(i) > \sigma(j)] \tag{1}$$

$K^*(\sigma)$ as defined above was used to transform $\mathcal{G}$ by finding the distance between every two rows of $A_{\mathcal{G}}$. After transforming $\mathcal{G}$, $\mathcal{H}$ was defined based on the e-neighborhood graph construction method. In other words, $\mathcal{H} = (\mathcal{V}, \mathcal{V})$ was defined such that there would be an edge between two discussion vertices $v, v' \in \mathcal{V}$ if the distance between v and v' in the transformed $\mathcal{G}$ was smaller than $e \in \mathbb{R}^+$.

This similarity measurement preserves the local clustering in the initial bipartite network since it takes the similarity in users' behavior into consideration. If two users belong to the same local cluster, they would endorse similar discussion vertices. Therefore, the similarity measure $D(u_i, u_j)$ would be close to zero. This means that users of the same political orientation who lie within the same local cluster did not significantly affect the overall distance between two discussion vertices.

$\mathcal{H}$ is a simple one-mode network in which the vertices represent the discussion vertices. It inherits the classes of the discussion vertices from $\mathcal{G}$.

3.3 Measurement of Accessibility Between Network Vertices

The information flow between different vertices is only feasible through the local interactions between the adjacent vertices; therefore, close vertices are more accessible than distant vertices. The overall accessibility of the vertices or the reliability of the information transfer is thus a function of the network topology.

To measure the accessibility of vertices $v, v' \in \mathcal{V}$ of $\mathcal{H}$, it was assumed that a bit of information is released from v to v', which was then assumed to randomly traverse the network until it reaches v'. Then, the probability of this bit of information traversing the shortest path is

$$P\{p(v, v')\} = \frac{1}{k_v} \prod_{j \in p(v,v')} \frac{1}{k_j - 1} \tag{2}$$

where $p(v, v')$ is the shortest path between v and v', j is counting each vertex on the path, and k_j is the degree of the vertex j. If some information is sent from v to v' without the knowledge of the network map, then $P\{p(v, v')\}$ measures the probability that this information goes through the shortest path from v and v' [54, 56].

The *search information index* or the amount of the information needed to identify one of all the possible shortest paths between v, v' is defined as

$$S(v \to v') = -\log_2 \Big(\sum_{p(v,v')} P\{p(v, v')\} \Big) \tag{3}$$

where the sum runs over all the shortest paths between v and v'. A high value for $S(v \to v')$ means that many yes/no questions are needed to locate v'; therefore, a higher search information index between two vertices implies less availability of information between the vertices.

3.4 Link Between the Search Information Index and Political Polarization

DiMaggio et al. [11] defined political polarization as the distance between the political orientation of different people or "the extent of disagreement. [...] It is in the extremity of and distance between responses, not in their substantive content, that polarization inhere. [...] Polarization as a process refers to the increase in such opposition over time". As political polarization increases, it is expected that the users contribute more to the discussion vertices of a single political orientation. This leads to lower availability of information between each pair of discussion vertices with contrasting political orientation. Therefore, the average search information index between all possible pairs of discussion vertices with contrasting political orientation is expected to be higher.

The set $\mathcal{T}$ is defined as,

$$\mathcal{T}_{c,c'} = \{S(v \to v') : \forall v, v' \in \mathcal{V} | c_v = c, c_{v'} = c'\}$$

where c_v indicates the class of the discussion vertex v. We defined the polarization index between the two sub-clusters c and c' as the average of the elements in set $\mathcal{T}$, which is named $\mathcal{P}_{\mathcal{T}}$. $\mathcal{P}_{\mathcal{T}}$ is expected to be increasing over time as the political polarization increases.

4 RESULTS

4.1 Simulations

Our ultimate goal of the simulations was to demonstrate that the search information index was highly correlated with the political polarization as introduced in DiMaggio et al. [11]. Based on DiMaggio et al., political polarization is a process that refers to the increase in the extent of disagreement over time. To simulate the polarization, two different parameter sets were defined: one that related to the distribution of endorsements when the political orientation of the user matched the political orientation of the discussion vertex, and the other that corresponded to the distribution of endorsements

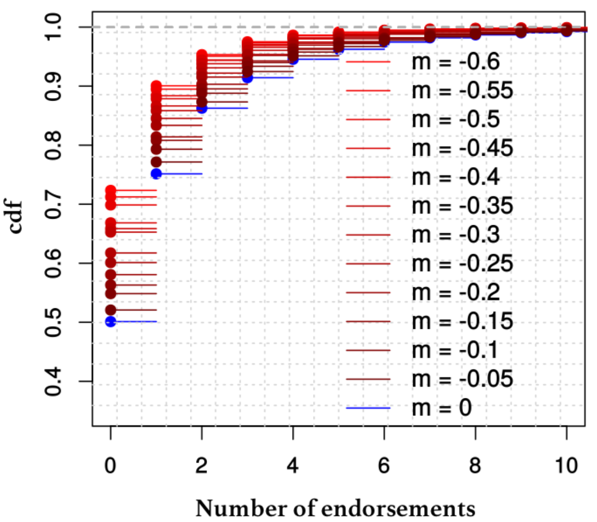

Figure 1: CDF of the endorsement distribution for different values of *m*.

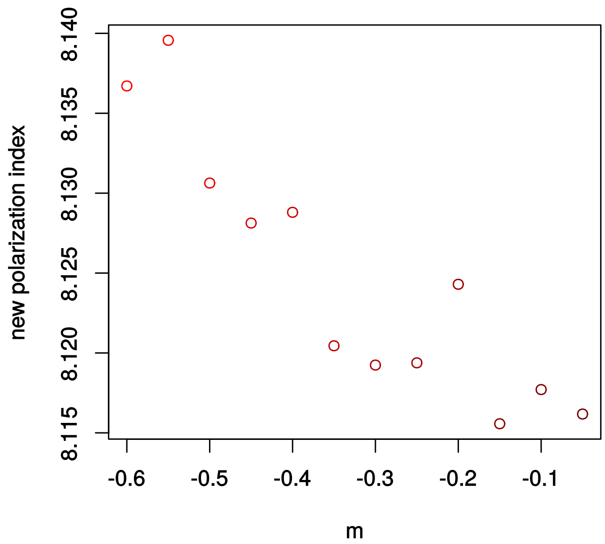

Figure 2: $\mathcal{P}_{\mathcal{T}}$ values against *m*.

when the orientation of the user and the orientation of the discussion vertex did not match. When the distance between these two distributions increases, the political polarization also increases.

To run the simulations, a two-class Facebook political sphere of Republicans and Democrats $\{r, d\}$ was assumed. Twenty Facebook political posts were simulated and in each run were randomly assigned to one of the parties. A pool of 800 users was created, and in each run, it was assumed that each user had a 50% probability of being Democratic or the Republican party supporter. $X_{partisan,page}$ was defined as the random variable for the number of likes a partisan gave to the Facebook posts of pages of a specific party. The following distribution for the number of likes a user contributes to Facebook posts with similar political orientation was also assumed; e.g., a Democrat on Democratic pages or a Republican on Republican pages:

$$X_{p,p} \sim \lfloor lnorm(0, 1) \rfloor \text{ for } p \in \{r, d\}$$

where $lnrom(\mu, \sigma)$ stands for a log-normal distribution with a mean μ and standard deviation σ. The number of likes a user contributed to a Facebook page that had a contrasting political orientation, e.g., a Republican on a Democratic pages, was assumed to have the following distribution:

$$X_{p,q}(m) \sim \lfloor lnorm(m, 1) \rfloor \text{ for } p \in \{r, d\}, p \neq q$$

where $m \in \{-0.05, -0.10, -0.15, -0.20, ..., -0.6\}$.

As the value of m decreases from 0 to -0.6, the distance between the $X_{p,p}$ distribution and the $X_{p,q}(m)$ increases (Figure 1), which implies that as the value of m decreases, the users contribute fewer endorsements to the vertices of the contrasting political inclination; therefore, based on the definition in DiMaggio et al. [11], political polarization increases as the value of m decreases.

For each value of m, we ran our method on the simulated data for 1000 times and averaged the results. As can be seen in Figure 2, it was confirmed that as the political polarization increased (m decreases), as expected the value of the political polarization index $\mathcal{P}_{\mathcal{T}}$ also increased (with a correlation of 0.904).

4.2 Facebook Data

In this section, the proposed method was applied to Facebook data to determine whether the results agreed with the previous theoretical findings. Using Facebook's public API, all the posts on the official pages of all six active political parties in Germany (AfD, CDU, SPD, Die Linke, Grünen, and CSU) published in 2017 and all users who had endorsed these posts by making Facebook likes were downloaded. In total, 4,438,157 likes on 2,452 public Facebook posts were collected from 2,021,987 unique Facebook users. The data was then split into one-week windows and the bipartite network of user endorsements were constructed on the discussion vertices. It is important to notice that in this case the constructed network is a binary bipartite network but not weighted. This is because each user can like each Facebook post only for one time. Figure 3 shows the search information index between the AfD sub-cluster and all other sub-clusters, from which it can be seen that the average search information index between the AfD Facebook posts and the Facebook posts of the other parties was increasing over time. This implies that the AfD and non-AfD supporters had increased their endorsement activities on the pages connected to their own political orientation, and had decreased their activities on the pages connected to opposite political views. Therefore, these results could be seen as an increase in the levels of polarization between the AfD supporters and the other partisans. This is in line with previous studies on the rise of the AfD that found that the party adopted a political agenda that was quite different from the other parties, and consequently they had attracted alienated voters who had become segregated from the rest of the electorate [24, 31]. It was also found that the rise in party support had been accompanied by increased radicalization and polarization [10, 19, 49].

5 DISCUSSION

In this paper, a new methodology for analyzing social networks was introduced that considered all the important properties of the structure of social networks such as associative mixing and local clustering. When the method was applied to political activity networks, it functioned as a proxy for the dynamics of political polarization; that is, the $\mathcal{P}_\mathcal{T}$ positively correlated to the level of political polarization in the network. The methodology was tested on both simulated data and user endorsement Facebook data from the German political party pages.

The development of this new method provides new insights for analyzing and understanding online political interactions. Social media service data can be used to evaluate theoretical social science questions, and this study provides a new tool to allow for this possibility. Given the multiplicity of social media data available today, researchers can use the newly proposed mathematical method to reveal the dynamics of political polarization. As this method does not discriminate endorsement types, it can be applied to different platforms. However, there are some limitations for the use of this method. While it can be used as a proxy for the dynamics of political polarization, it cannot directly provide insights as to the degree of polarization because the $\mathcal{P}_\mathcal{T}$ measure has no theoretical maximum value.

Similar to other online social network research, this study was dependent on the input data. Therefore, it is important to highlight the difficulties associated with extracting the proper data to ensure insightful scientific results. Unfortunately, there are often restrictions on the amount and type of data that can be acquired from social media platforms [45], and data quality is also a problem because of the level of bias [48]. Therefore, these features need to be considered in social media research and especially when studying important political processes.

The following further future directions are proposed:

- the application of the proposed method on case studies such as the polarization in U.S. online media , which appears extremely segregated [13].
- the extension of the method to define a theoretical maximum value of political polarization.
- the extension of the method to determine the discussion vertices that act as gatekeepers.

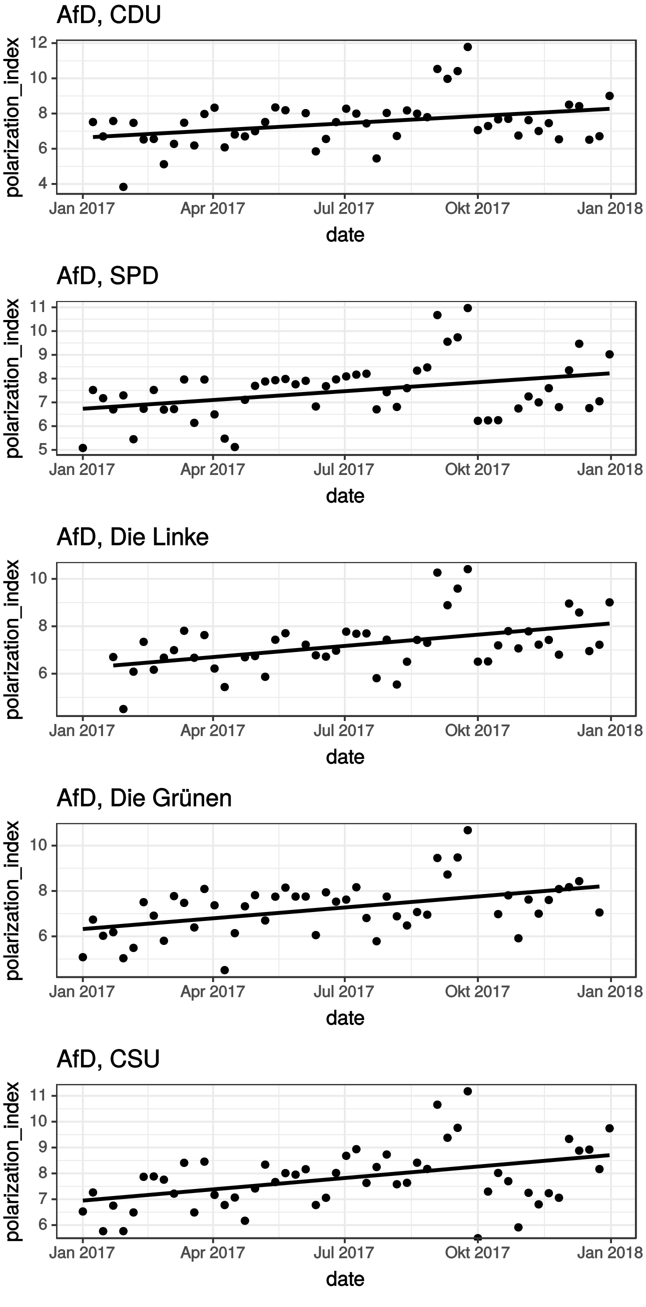

Figure 3: $\mathcal{P}_\mathcal{T}$ weekly values for the party *AfD*

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Distorting Political Communication: The Effect Of Hyperactive Users In Online Social Networks

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Abstract— **Online Social Networks (OSNs) are used increasingly for political purposes. Among others, politicians externalize their views on issues, and users respond to them, initiating political discussions. Part of the discussions are shaped by hyperactive users. These are users that are over-proportionally active in relation to the mean. In this paper, we define the hyperactive user on the social media platform Facebook, both theoretically and mathematically. We apply a geometric topic modelling algorithm (GTM) on German political parties' posts and user comments to identify the topics discussed. We prove that hyperactive users have a significant role in the political discourse: They become opinion leaders, as well as set the content of discussions, thus creating an alternate picture of the public opinion. Given that, we discuss the dangers of replicating the specific bias by statistical and deep learning algorithms, which are used widely for recommendation systems and the profiling of OSN users.**

I. INTRODUCTION

Today, internet prevails as a prominent communication and information medium for citizens. Instead of watching TV or reading newspapers, increasing numbers of people get politically informed through online websites, blogs, and social media services. The latest statistics demonstrate that internet as a news source has become as important as television, with its share increasing year by year [1]. Given this shift in the means of news broadcasting, politicians have altered their tactics of communication to the society. OSNs, such as Twitter, Facebook and Instagram, have become a cornerstone of their public profiles as they use OSNs to transmit their activities and opinions on important social issues [2], [3], [4].

The growth of online communities on social media platforms have created a public amenable to political campaigning. Political parties and actors have adapted to the new digital environment [5], and besides the application of new campaigning methods as microtargeting [6], have created microblogs through which they can inform citizens of their views and activities. In addition, OSNs have enabled to users to respond to or comment on the politicians' messages, giving birth to a new type of political interaction and transforming the very nature of political communication.

On OSNs, the flow of information from politicians to citizens and back follows a different broadcasting model than the classical one [7]. Instead of journalists monitoring the political activity, political actors themselves produce messages and make them publicly available on the platforms. Each platform provides its users with access to the generated content, as well as distributes it to them through recommendation algorithms [8], [9]. The received information is then evaluated both directly or indirectly [10], [11]: The political message is interpreted immediately, or subsequently through further social interactions among citizens on the related topics. On OSNs, not only can users respond to politicians in the traditional manner -i.e. through their political activity in the society-, but also respond to or comment on the politicians' views online. This creates a new type of interactivity, as users, who actively engage in online discussions sharing their views, are able to influence the way the initial political information will be assimilated by passive users as well as directly influencing political actors.

This new form of political interactivity transforms political communication. Given the possibility of users to directly respond to the political content set by political actors, and discuss online about political issues with other citizens, OSNs emerge as a fruitful space for agonistic pluralism. They provide the necessary channels for different interests and opinions to be expressed, heard and counterposed; elements that constitute the very essence of political communication. If the discussions held are legitimized within a democratic framework, they form the basis for reaching a conflictual consensus [12], based on which societal decisions can be made. Hence, political communication on OSNs opens new possibilities for citizens to participate in the political shaping of the society, providing them with additional space to address their interests.

Problem statement

Although the above type of political communication has the potential to improve the function of democracy, OSNs possess a structural property that obstructs the unbiased constructive interaction between political actors and citizens: The activities of users on OSNs follow an extreme value distribution [13], [14], [15], [16]. Practically, this means that users are not equally active when using a specific OSN. Among others, the majority of users remain passive, or participate with a very low frequency; they either simply read

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the content or like, comment, tweet, etc. very rarely. On the contrary, a very small part of the users is hyperactive, as they over-proportionally interact with the platform they use. Thus, in political communication on OSNs, hyperactive users are citizens who over-proportionally externalize their political attitudes compared to the mean. This could be done by liking, commenting, tweeting or using any other interaction possibility provided by a platform to declare an attitude to a political issue.

The given activity asymmetry becomes a major issue, considering that a considerable part of the society is politically informed via OSNs. As hyperactive users externalize their political attitudes more than the others, they have the potential to distort political communication; political issues that are important to them become overrepresented on OSNs, while the views of normally active users become less visible. Hence, hyperactive users may influence the political discussions towards their ends, creating a deformed picture of the actual public opinion on OSNs. This fact violates the assumption of an equitable public political discourse as part of political communication [17], because the interests and views of normally active users appear as less important.

The above distortion of political communication is intensified by the business models of the OSN platforms. OSNs were not created to be arenas of political exchange. Their aim is to maximize the number of platform users, by keeping them satisfied [18], and to transform this social engagement to profits, i.a. through advertisement. Hence, on OSNs, users are both consumers and citizens [19]. In order to maximize their profits, OSN platforms adjust their recommendation algorithms to the content popularity, with a view to promoting information that most users will like. As hyperactive users influence asymmetrically the popularity of political content, these algorithms might replicate this asymmetry. Thus, a platform might recommend content, which is actually consistent with the political interests of hyperactive users. This phenomenon per se denotes a form of algorithmic manipulation of the political communication: The platform unintentionally magnifies hyperactive users' interests, thus posing the risk of political invisibility for the ones of normal users [20].

Last but not least, the aforementioned misrepresentation of public opinion has a direct impact on political campaigning. Contemporary political actors develop their influence strategies based on the perceived voter model [21], which presupposes the gathering of demographic and political data for the development of statistical models about the electorate's attitudes. As major part of these data is derived from social media, models that fail to take the effect of hyperactive users into account would face an important bias.

Considering the above, we want to answer following questions regarding the activity of hyperactive users:

RQ1: **How can we define hyperactive users mathematically?**

RQ2: **How can we compare and evaluate the political attitudes of hyperactive users in relation to the mean?**

Original Contribution

We mathematically define hyperactive users on OSN Facebook, and identify them on the public pages of the major German political parties. By applying a state-of-the-art topic modelling algorithm, we investigate whether they spread or like different messages on political issues other than normal users and politicians do. We prove that hyperactive users not only are responsible for a major part of online political discussions, but they also externalize different attitudes than the average user, changing the discourse taking place. We quantify their effect on content formation by measuring their popularity and showing that they adopt an opinion leader status. Finally, given the potential influence of hyperactive users on recommendation algorithms, we initiate an important discussion on OSNs as spaces of political communication.

II. Data & Method

A. Data Description

To investigate the effect of hyperactive users, we chose to analyse the public Facebook pages of the main German political parties. Our sample included CDU, CSU, SPD, FDP, Bündnis 90/Die Grünen, Die Linke, and AfD. CDU is the main conservative party of Germany, while CSU is the conservative party active in Bavaria. SPD represents the main German social-democratic party, and Die Linke the radical left. AfD has a nationalist, anti-immigrant, and neo-liberal agenda, while FDP is a conservative, neo-liberal party. Finally, Bündnis 90/Die Grünen is the German green party. We focused on Facebook, because the platform's api restrictions and its monitoring system largely prevent automated activities, as e.g. performed by social bots on other platforms [22], [23]. Therefore we could evaluate the natural behaviour of hyperactive users and not an algorithmically generated one.

We took into consideration all party posts and their reactions in the year 2016. This choice was made, because we wanted to investigate a full year of user activities. We preferred 2016 over 2017, because 2017 was an election year, with most content produced by the parties being campaign related. By contrast, 2016 was marked by the Refugee Crisis in Europe, and we were interested in evaluating the discussions on the topic. In total, by accessing the Facebook Graph API, we collected 3,261 Posts, 3,084,464 likes and 382,768 comments, made by 1,435,826 users. The sample included all posts and comments on the posts generated for the period under investigation.

B. Defining hyperactive users

We consider hyperactive users as people, whose behaviour deviates from the standard on an OSN platform. To obtain an understanding of the overall behaviour of the users, we fitted discrete power-law and extreme value distributions to mathematically describe the users' like and comment activities. Additionally, we ran bootstrapped and comparative goodness-of-fit tests based on the Kolmogorov-Smirnov [24] and the Vuong [25] statistic to evaluate the potential fits, as proposed by Clauset et al. [26]. The KS test examines the null hypothesis that the empirical sample is drawn from the reference distribution, while the Vuong test measures the log-likelihood ratio of two distributions and, based on it, investigates whether both empirical distributions are equally far from a third unidentified theoretical one.

In order to mathematically describe the activities of hyperactive users, we selected to treat them as outliers of the standard OSN population. We adopt the definitions made by Barnett and Lewis [27], Johnson and Wichern [28] and Ben-Gal [29], and see outliers not as errors, or coming from a different generative process, but as data containing important information, which is inconsistent with and deviating from the remainder of the data-set. Therefore, given the extreme skewed distribution of the activities, we followed the method proposed by Hubert and Vam der Veeken [30] and Hubert and Vandervieren [31] for outlier detection. We calculated the quartiles of our data Q_1 and Q_3, the interquartile range $IQR = Q_3 - Q_1$ and the whiskers w_1 and w_2, which extend from the Q_1 and Q_3 respectively to the following limits:

$$[Q_1 - 1.5e^{-4MC} IQR, Q_3 + 1.5e^{3MC} IQR] \qquad (1)$$

where MC is the medcouple [32], a robust statistic of the distribution skewness. Data beyond the whiskers were marked as outliers.

C. Topic Modeling

After evaluating the likes and comments distributions, as well as identifying the existing hyperactive users, we prepared our data for the application of a topic modelling algorithm. As it has been shown that a noun-only topic modelling approach yields more coherent topic-bags [33], we cleaned our posts and comments from the remaining part-of-speech types. To do so, we applied the spaCy pretrained convolutional neural network (CNN) classifier [34] based on the Tiger [35] and WikiNER [36] corpuses, classified each word in our document collection, and kept only the nouns.

We wanted to investigate the various topics that users and parties discussed about but did not want to differentiate on the way they talked about them. Parties usually use a more formal language when posting on a topic than users. Therefore, there was the risk that the topic modelling algorithm would create different topics on the same issue, one for the parties and one for the users. To avoid this, we fitted our model on the user comments, and then classified the parties' posts through the trained model.

For our analysis, we applied a non-parametric Conic Scan-and-Cover (CoSAC) algorithm for geometric topic modeling [37]. Our decision was based on the fact that most topic modelling algorithms (e.g. LDA [38], NMF [39]) need a priori as input the number of topics to split the corpus. CoSAC has the advantage of electing itself the number of topics to find the most efficient topic estimates.

The algorithm presupposes that the optimal number of topics K are embedded in a V-1 dimensional probability simplex Δ^{V-1}, where V the number of words in the corpus. Each topic β_K corresponds to a set of probabilities in the word simplex. The totality of topics build hence a convex polytope $B = conv(\beta_1, ..., \beta_K)$. Each document corresponds to a point $p_m = (p_{m1}, ..., p_{mV})$ inside Polytope B, with $p_m = \sum_k \beta_k \theta_{mk}$. θ_{mk} denotes the proportion that topic k covers in document m. Finally each document is drawn from a multinomial distribution of words: $w_m \sim Multinomial(p_m, N_m)$, where N_m the number of words in document m.

The CoSAC algorithm iteratively scans the polytope B and finds the furthest point from its center Cp. It then constructs a conical region with angle ω, starting from Cp and embedding the specific point (Figure 1). All points within the cone are considered to belong in the same topic and are removed from the polytope. The procedure is iterated K-1 times, until almost no points remain in the polytope. A cone is considered sufficient if it covers at least a proportion of documents λ. After fitting the cones, CoSAC places a sphere with radius R to the polytope, to cover the remaining points. The K geometric objects and their respective points correspond to the K topics created by the algorithm. In our model, the hyperparameters were set to $\omega = 0.6, \lambda = 0.001$ and $R = 0.05$, as proposed by the authors.

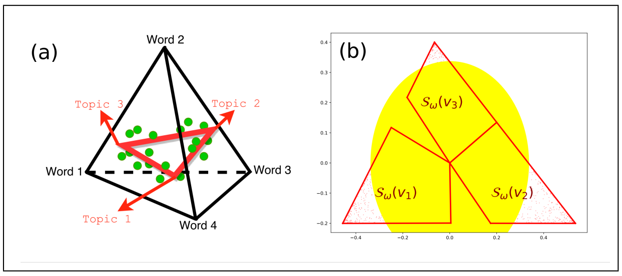

Fig. 1. (a) The topic polytope embedded in the word simplex. (b) Cones and sphere coverage of the polytope.

D. Comparison of activities

Given our topics, we wanted to evaluate the differences in the activity of normal and hyperactive users. Therefore, we calculated the empirical distributions $f(comment|topic)$ over all topics for the comments of normal and hyperactive users respectively. We pairwise compared the distributions for each topic, by applying a 2-Sample Anderson-Darling Test [40]. The test calculates the probability that the populations from which two groups of data were drawn are identical.

Besides testing the empirical comment-topic distributions, we assigned to each comment the topic with the highest probability and compared the most commented topics for normal and hyperactive users. Similarly, we assigned the classified party posts to their most probable topic and aggregated the likes of normal and hyperactive users. In this way, we were in the position to locate the concrete political interests of users.

III. Results

The results are split into three parts. First, we present our findings on the general user distribution on the investigated

TABLE I
VUONG TEST RESULTS

Log-normal vs	Likes LL-ratio (p-value)	Comments LL-ratio (p-value)
Power-law	15.1 (<0.01)	34.9 (<0.01)
Poisson	34.9 (<0.01)	12.7 (<0.01)
Exponential	12.7 (<0.01)	26.6 (<0.01)

pages. Based on that, we analyze the number and distribution of hyperactive users among the different pages. Then, we compare the behaviour between hyperactive and normal users by taking into consideration the topic modelling results and further statistical tests. Given that, we evaluate the importance and role of hyperactive users in the political discourse on OSNs.

A. Describing user activity

As a first result, we identified the log-normal distribution as the the best measure for describing the user activities (Figure 2). The bootstrapped KS-Tests (100 samples, two tailed) for both comments and likes failed to reject the null that our data come from a log-normal distribution (gof < 0.01, p > 0.05 and gof < 0.01, p > 0.2 respectively), while the comparative Vuong tests showed a better fit of the log-normal in comparison to the power-law, poisson and exponential distributions (Table I). Our results comply with the existing literature, which states that usually complex social network properties are log-normally distributed [15], [41], [42]. Figure 2 shows the empirical frequencies of user activities and their respective log-normal fits.

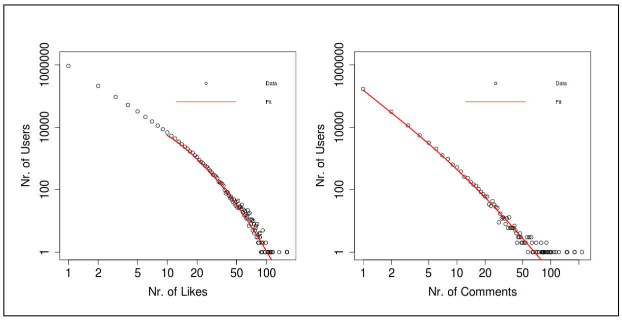

Fig. 2. (a) The topic polytope embedded in the word simplex. (b) Cones and sphere coverage of the polytope.

B. Detecting hyperactive users

Through our outlier detection methodology, we detected 12,295 hyperactive users on the comment section of pages, who correspond to 5.3% of the total users commenting on the pages. Due to the extreme skewness of the comments' distribution, a user was characterized as hyperactive if they made three or more comments. This is justified by the fact that actually 74% of the users under investigation made only one comment. Although hyperactive users represented 5.3% of the total commenting population, they accounted for 25.8% of the total comments generated on the parties' pages. Furthermore, 56% of these hyperactive users commented on two or more party pages, denoting that they generally interacted with users across the political spectrum. By evaluating the popularity of the users' comments, it was found that hyperactive users tend to get more support than the rest. Comments made by hyperactive users on average gained 3.52 likes, while normal users' comments only 3.07, a difference that was statistically significant (Mann-Whitney Test with continuity correction, one tailed: W = 1.4^{10}, p< 0.01). This complies with previous research stating that highly active users tend to have the characteristics of opinion leaders [43].

TABLE II
HYPERACTIVE USERS PER PARTY - COMMENTS

Party	Comments by Hyperactive Users	Ratio
AfD	43,017	0.24
CDU	20,929	0.45
CSU	18,312	0.22
FDP	1,400	0.15
Die Grünen	8,946	0.36
Die Linke	2,343	0.16
SPD	3,926	0.13

Similarly, the evaluation of the pages' likes resulted in the characterization of 61,372 users as hyperactive, or 4.3% of the total users that liked the parties' posts. As before, the methodology labelled users as hyperactive if they made three or more likes, because the majority of the active Facebook population rarely interacted with the related pages. The likes of these hyperactive users accounted for 26.4% of total likes, hence having a major effect on the overall content liked. In addition, 29% of hyperactive users liked posts of more than one party, denoting again that their activities were spread over the entire parties' network. The overview of the hyperactive users' commenting and like activities for each party can be found in tables II and III. We also compared the like and comment distributions, by calculating their gini index. The measure provides a proxy for inequality, with 0 denoting perfect equality and 1 extreme inequality. In our case, we calculated a value of 0.35 and 0.45 for the comment and like distribution respectively. This denotes that like activities are more unequally distributed than the comment activities, i.e. hyperactive users play a bigger role in the formation of likes. In addition, the values denote a degree of inequality between normal and hyperactive users, but not an extreme one. Nevertheless this is misleading, because the measure does not take into consideration the inactive users. Given that information, the gini index would have been much higher in both cases.

C. Evaluating the political attitudes of hyperactive users

Based on the categorization of users as hyperactive or normal, we could then evaluate the results of the topic modelling algorithm. The model clustered the users' comments in 69 main topics. A major part of the topics concerned the refugee crisis of 2016 and the related discussions about Islam. A set of topics aggregated comments on German Chancellor Merkel, on the leaders of other parties, on female and male politicians and the German parties in general. There was one

TABLE III
HYPERACTIVE USERS PER PARTY - LIKES

Party	Likes by Hyperactive Users	Ratio
AfD	555,564	0.35
CDU	16,997	0.2
CSU	139,493	0.2
FDP	20,188	0.16
Die Grünen	28,777	0.19
Die Linke	24,546	0.14
SPD	29,057	0.12

topic summing up comments in English language, as well as a topic containing hyperlinks. Furthermore, the algorithm created policy related topics regarding foreign affairs, as well as the economy and labour market and the state in general. Other topics were related to the German national identity, society and solidarity, and the nature of democracy. Users also discussed about family and gender policy, homeland security, transportation and environmental policy. There were topics that included wishes, fear, ironic and aggressive speech, as well as topics aggregating user thoughts. Finally, a set of topics was about political events and communications and a number of topics included comments against mainstream media and the political system. An overview can be found in table IV. The geometric topic modelling algorithm was able to provide a broad picture of the discussion topics on the parties' pages, revealing numerous insights about the way Facebook users commented on the parties' posts. By splitting the comments into two categories, one for the ones generated by hyperactive users and one for the comments of normal users, and by assigning them to the topics to which they were mostly related, we created a stacked chart illustrating the share of hyperactive users' comments for every topic (Figure 3). It is evident that hyperactive users covered a major part of the comments, and although more active, they commented more or less similarly to the normal users among the various topics. Despite that, the Anderson-Darling tests rejected the null hypothesis that hyperactive and normal users' comments come from the same distribution for 54 out of the 69 topics. Practically, this means that the topic density distributions varied between the comments of normal and hyperactive users. This is caused when the comments contain different words in different proportions. Hence, hyperactive and normal users used different vocabularies when referring to a topic and, consequently, externalized overall different views and sentiment, or focused on different issues in each case.

Besides the fact that hyperactive users had a different behaviour on the posts' comments, our analysis showed that they also had different liking preferences. After classifying each party post to the most relevant topic, we counted the likes of the posts that belong to each topic. We took into consideration only topics that were based on either political vocabulary or politicians, and ignored topics that contained aggressive speech or sentiment, because the related vocabulary was rarely used by the parties. Figure 4 illustrates

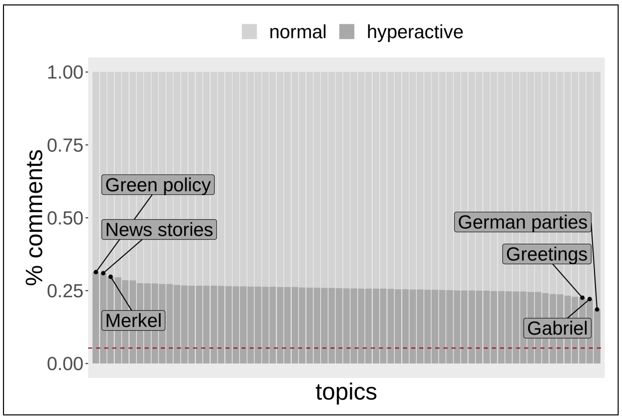

Fig. 3. Proportion of comments generated by normal and hyperactive users. The dotted red line gives the actual proportion of hyperactive users. The plot also illustrates the three most and least interesting topics for hyperactive users.

a stacked chart depicting the share of hyperactive users' likes. In contrast to the comments' chart, it is obvious that hyperactive users liked specific topics with different intensity than normal users. Even though hyperactive users performed on average 26.4% of the likes, they liked much more content related to EU politics and labour policy, while had less interest on the conservative party AfD, citizens' rights and the region of Bavaria. Therefore, it is clear that hyperactive users influence the like distribution of the public to party posts.

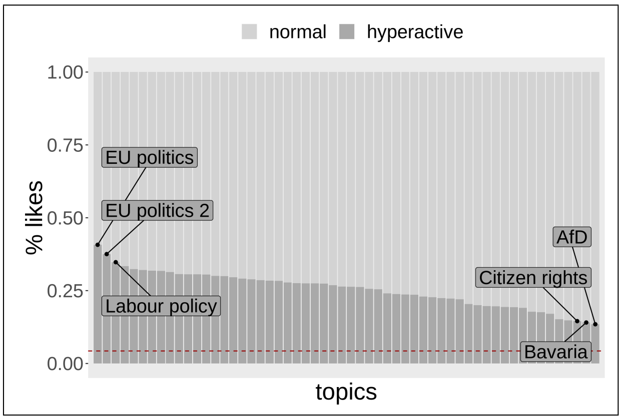

Fig. 4. Proportion of likes generated by normal and hyperactive users. The dotted red line gives the actual proportion of hyperactive users. The plot also illustrates the three most and least interesting topics for hyperactive users.

It must be noted that our analysis gives an overview of the content of posts. It cannot identify sentiment, or specific predispositions of users. For a firm understanding of the issues that were over- or under-represented by hyperactive users an additional extensive analysis is needed, which is beyond the scope of this paper. Our analysis demonstrated that, both on commenting and liking, hyperactive users have a different behaviour than the other users.

Taking the above into consideration, it was possible to show that political communication on Facebook is strongly constituted by the behaviour of hyperactive users. By describing the user like and comment activities on the platform, we managed to characterize users as hyperactive or normal through outlier detection. We proved that hyperactive users account for a significant part of the total users' activities, they participate in discussions differently from the rest, and they like different content. Moreover, they become opinion leaders, as their comments become more popular than these of the normal users. Taking Facebook as an example, we showed that user activities on OSNs are neither equally nor evenly distributed.

IV. Discussion

Given that activity asymmetries are a feature of online social networks, it is important to evaluate the consequences for science and the society. Although our analysis was concentrated on Facebook, previous research has proven that hyperactive accounts, either human or automated, have the potential to equally influence political communication in other platforms [44], [45]. The specific formation and distribution of political interactions on OSNs rises various questions regarding the role and impact of OSNs on a political level, on an algorithmic level, as well as on the intersection of both.

In the political dimension, the OSN activity asymmetries are transformed into an asymmetry of disseminated political content, as the attitudes and interests of hyperactive users appear over-proportionally in the discussions taking place. Until now, research [46], [47] has stated that OSNs suffer from a population bias: The people using OSNs are not representative of the actual society. On top of that, a content bias is now added: The content disseminated on OSNs is not even representative of the mean users' attitudes on the platform. This poses a scientific problem, as it might lead to false research results. Equally importantly, it poses a political problem, because political discussions and opinion exchange is distorted by the effect of hyperactive accounts. This happens not because the diffused information in the network is transformed or changed, but because hyperactive users strongly contribute to the type of information diffused. Their attitudes fill the communication space, leading to a bias on the political feedback to politicians, and to a shift on the issues that shape the political agenda. Although OSNs provide a more open environment to express opinions than traditional media, it ends up being partly a gathering of political echoes [48] that struggle to be imposed on each other.

In the algorithmic dimension, the extreme skewness of the activity distributions raises specific issues regarding the recommendation algorithms used by OSN platforms. The first problem is related to algorithmic accuracy: skewed data are, imbalanced data, and their raw use, either as input features or as output labels, can yield weak classification results. The imbalanced learning problem applies to both standard statistical algorithms, collaborative filtering and neural networks [49], [50], [51], with algorithms overestimating the importance of outliers and under-estimating the importance of the rest. This also happens in the case of a poor selection of a cost function [52]. Furthermore, it is proven that statistical models as Markov-chains might fail to capture the signal immanent in highly skewed data, while deep learning methods might face the same issue given power-law distributions of data [53].

The second potential problem is that an algorithm might fail, not in the sense that it might be unable to learn from the data, but rather learn the wrong signal. Hyperactive users can be seen as physical adversaries [54] of the mean user attitudes. Algorithms trained in the full data will include the bias, tracking and predicting behavioural associations that correspond to hyperactive users rather than to the population majority. It is not coincidental that the detection of adversaries in machine learning can be done by sample distribution comparison [55], in the same way as we tracked the different preferences of hyperactive users.

Solutions to the aforementioned issues exist and are usually taken into consideration by data scientists, who develop recommendation algorithms. Nevertheless, in the case of political communication, an algorithmic issue automatically becomes a political one. Recommendation systems come with a social influence bias [56], [57], i.e. have the power to change users' opinion. Hence, OSNs promoting biased political content might result in the algorithmic manipulation of political communication.

In addition, social media platforms are not designed to foster political discourses [58], but rather aim at increasing active users, in order to sell advertisement and attract funding from venture capitalists [59]. Hence, the structure and impact of recommendation algorithms distorts human behaviour [60], having transformative effects that were not foreseen a priori [61].

It is evident from the above, that each algorithm mediates and redefines the importance of political interests [62], raising further questions about the opacity of the recommendation systems [63]. In a political context, it becomes important to know as citizens, how, why and with what impact algorithms change political communication. This presupposes awareness of the data processed and, the mathematical method applied, as well as knowledge of what exactly a machine learning cost function optimizes and to what extent recommendation systems alter human behaviour. Proposals for algorithmic transparency have already been made [64], [65], [66], and wait to be applied in practice.

The above issues need to be extensively analyzed, in order to evaluate and shape the structure of political communication in the digital era. In this paper we laid the foundations for this discussion, by defining, demonstrating and quantifying the effect of hyperactive users on OSNs, through the example of Facebook. We also illustrated and defined the risks of algorithmic manipulation by the OSN recommendation systems. Future research needs to focus on the aforementioned consequences, evaluate the structure of OSNs ethically, politically and normatively as political intermediators, as well as propose and apply solutions to the newly posed problems.

TABLE IV
TOPIC MODELING, AD-TEST RESULTS AND PROPORTION OF HYPERACTIVE USERS

Nr.	Topic	AD-test gof, (p-value)	Comments	Likes
1	Immigration	3.8, (0.0)	0.27	0.30
2	Merkel	104.2, (1.0)	0.28	0.24
3	AfD	15.9, (0.0)	0.25	0.30
4	News stories	17.4, (0.0)	0.31	0.29
5	English	8.8, (0.0)	0.26	-
6	Green policy	15.1, (0.0)	0.31	0.18
7	Islam	4.8, (0.0)	0.26	0.31
8	Integration immigrants	6.7, (0.0)	0.27	0.28
9	Female politicians	9.5, (0.0)	0.26	0.22
10	Deportion immigrants	9.2, (0.0)	0.26	0.20
11	EU politics	2.5, (0.0)	0.26	0.41
12	Economic policy	6.1, (0.0)	0.28	0.31
13	Greetings	17.7, (0.0)	0.23	-
14	Polls	16.3, (0.0)	0.25	0.26
15	Union	71.2, (1.0)	0.29	0.26
16	CSU	69.2, (1.0)	0.24	0.24
17	National identity	11.5, (0.1)	0.26	0.29
18	Human rights	1.5, (0.1)	0.26	0.24
19	Security	2.6, (0.0)	0.27	0.24
20	Democracy	32.3, (0.0)	0.25	0.27
21	Citizen rights	33.9, (0.0)	0.25	0.15
22	Congratulations	26.5, (0.0)	0.24	0.26
23	Gabriel	43.2, (1.0)	0.22	0.23
24	Foreign affairs	5.0, (0.0)	0.26	0.26
25	Homeland security	17.3, (0.0)	0.25	0.25
26	Interviews	23.9, (0.0)	0.25	0.18
27	Turkey affairs	11.0, (0.0)	0.26	0.19
28	Terrorism	7.1, (0.0)	0.26	0.19
29	Fear	1.6, (0.1)	0.26	-
30	Party system	4.3, (0.0)	0.27	0.29
31	The people	3.2, (0.0)	0.27	0.27
32	News media	1.3, (0.1)	0.27	0.31
33	Erdogan	7.1, (0.0)	0.27	0.23
34	German parties	25.4, (0.0)	0.19	0.19
35	Social policy	10.9, (0.0)	0.26	0.27
36	Reflection	14.5, (0.0)	0.26	-
37	TTIP/CETA	15.7, (0.0)	0.25	0.28
38	Syria	2.4, (0.0)	0.25	0.17
39	Labour policy	20.9, (0.0)	0.24	0.30
40	Party policies	0.2, (0.3)	0.26	0.27
41	Media	32.1, (0.0)	0.25	-
42	DDR	12.9, (0.0)	0.26	0.33
43	Male politicians	2.5, (0.0)	0.25	0.28
44	East Germany	5.0, (0.0)	0.26	0.32
45	Speeches	53.6, (1.0)	0.25	-
46	Bavaria	67.1, (1.0)	0.25	0.14
47	State media	21.4, (0.0)	0.25	-
48	Female politicians 2	12.0, (0.0)	0.30	0.20
49	Bundestag	10.4, (0.0)	0.25	0.32
50	Interviews 2	16.9, (0.0)	0.25	0.28
51	Irony	42.4, (1.0)	0.26	-
52	Trump	16.2, (0.0)	0.26	0.22
53	Welfare policy	12.3, (0.0)	0.26	0.32
54	Videos	13.0, (1.0)	0.25	-
55	Government	26.1, (0.0)	0.26	0.31
56	Transportation policy	37.0, (0.0)	0.23	0.15
57	Green policy 2	3.7, (0.0)	0.27	0.20
58	Politicians	12.1, (0.0)	0.23	-
59	Public services	18.4, (0.0)	0.25	0.20
60	Gender Equality	19.7, (0.0)	0.26	0.31
61	Insults	30.5, (0.0)	0.25	-
62	Boarder security	3.4, (0.0)	0.27	0.32
63	Media 2	13.5, (0.0)	0.27	-
64	EU politics 2	2.3, (0.0)	0.25	0.38
65	Merkel 2	39.9, (0.1)	0.30	0.15
66	AfD 2	2.6, (0.0)	0.26	0.13
67	Funny	23.9, (0.0)	0.25	-
68	Germans	0.5, (0.2)	0.27	0.22
69	Labour policy 2	8.5, (0.0)	0.27	0.35

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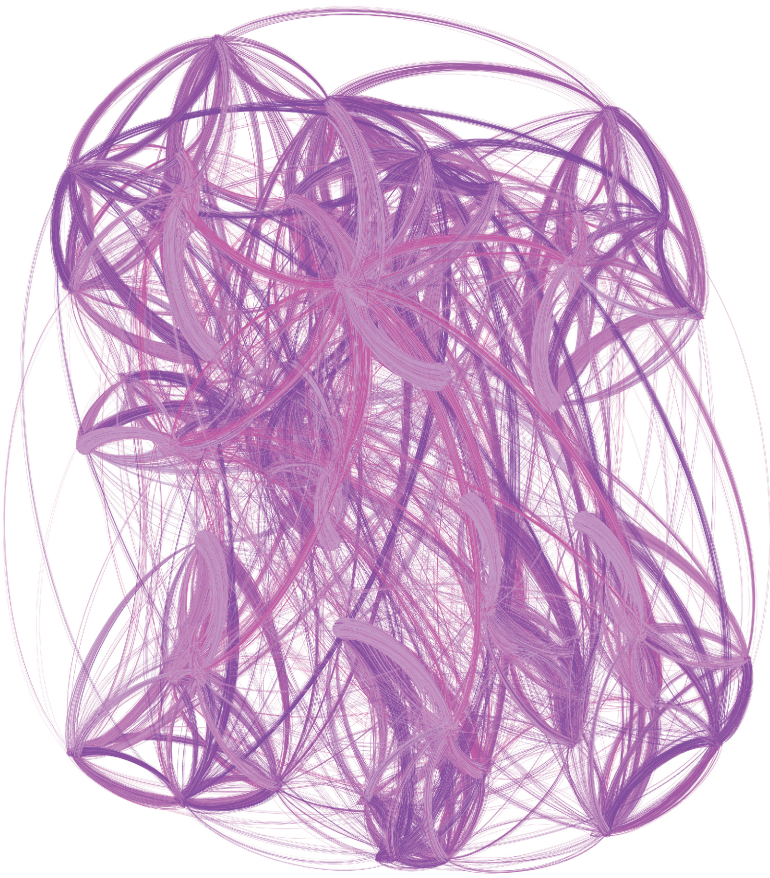

This visualization comprises a directed network containing about 3.6 million nodes and more than 10 million edges. Each directed edge shows a Facebook user liking a post published by one of the main German political parties on their official Facebook page. The data is acquired from Facebook over the period of 2015 to 2017 and the visualization is done with Gephi.

The visualization shows the extreme local clustering effect existing in a Facebook network. The local clustering effect has implications for the political discourse on online social media and for the democratic systems. This effect is studied thoroughly in this doctoral dissertation.