Chair of Communication Networks
Department of Electrical and Computer Engineering
Technical University of Munich

Boost your Communication Network with Machine Learning

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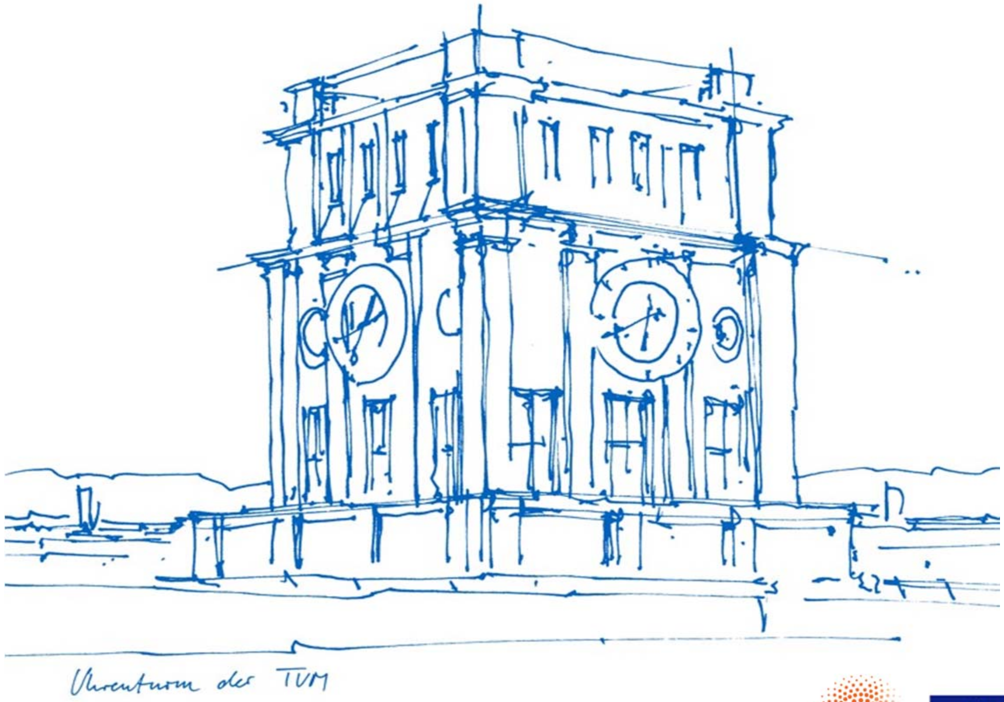
based on work done together with

Dr. Andreas Blenk

Patrick Kalmbach

Johannes Zerwas

and several others



Bundesministerium für Bildung und Forschung

SENDATE PLANETS

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European Research Council

Machine Learning (ML) in Communication Networking

receives a lot of attention recently, e.g.

- ML for flow classification and anomaly detection
- ML replacing optimization for virtual network embedding, function placement,…

in this talk, we show another application

- **ML to preprocess models leaving existing algorithms or optimizers untouched**

Boost your network algorithm with ML preprocessing

- ***Neurovine****: Hopfield neural network to preprocess (subgraph extraction) VNE algorithms*
- ***o‘zapft is****: supervised learning to learn from previous solutions of network algorithms*

This talk is mainly based on our following work

- Andreas Blenk, Patrick Kalmbach, Johannes Zerwas, Michael Jarschel, Stefan Schmid, Wolfgang Kellerer: ***NeuroViNE: A Neural Preprocessor for Your Virtual Network Embedding Algorithm*** IEEE INFOCOM 2018 (main conference), Honolulu, HI, USA, April 15-19, 2018.

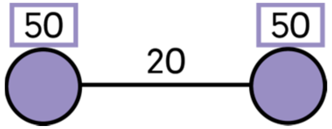
- Blenk, Andreas; Kalmbach, Patrick; Schmid, Stefan; Kellerer, Wolfgang: ***o'zapft is: Tap Your Network Algorithm's Big Data!*** ACM SIGCOMM 2017 Workshop on Big Data Analytics and Machine Learning for Data Communication Networks (Big-DAMA), 2017.

- Patrick Kalmbach, Andreas Blenk, Markus Klügel, Wolfgang Kellerer: ***Stochastic Block Models for Analysis and Synthetic Generation of Communication Networks*** 2nd IFIP/IEEE International Workshop on Analytics for Network and Service Management (AnNet), 2017.

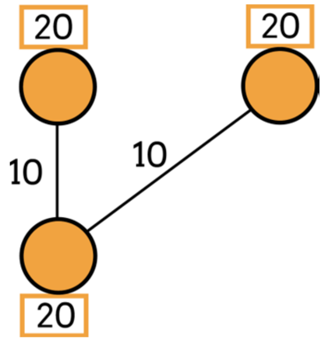
… and the Dissertation of Dr. Andreas Blenk: Towards Virtualization of Software-Defined Networks: Analysis, Modeling, and Optimization (defended March 2, 2018)

Our Use Case: Virtual Network Embedding (VNE)

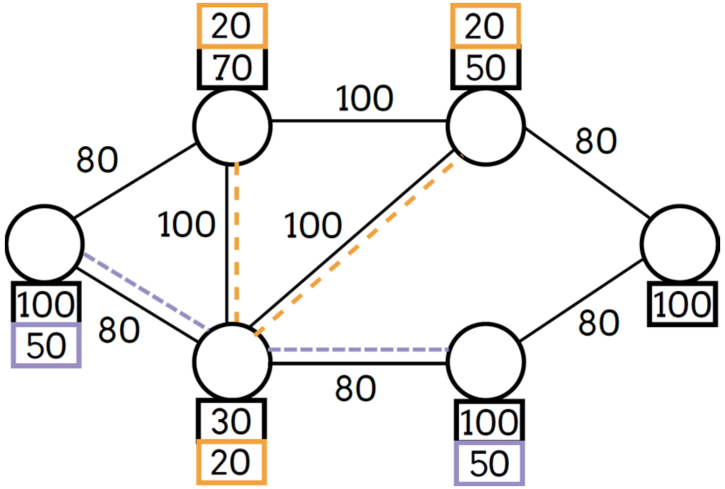
VN Request 1



VN Request 2



Substrate Network & Embedded Requests



NP-hard!

VN Request (VNR) requires node and link resources

Capacities of the substrate nodes and links are limited

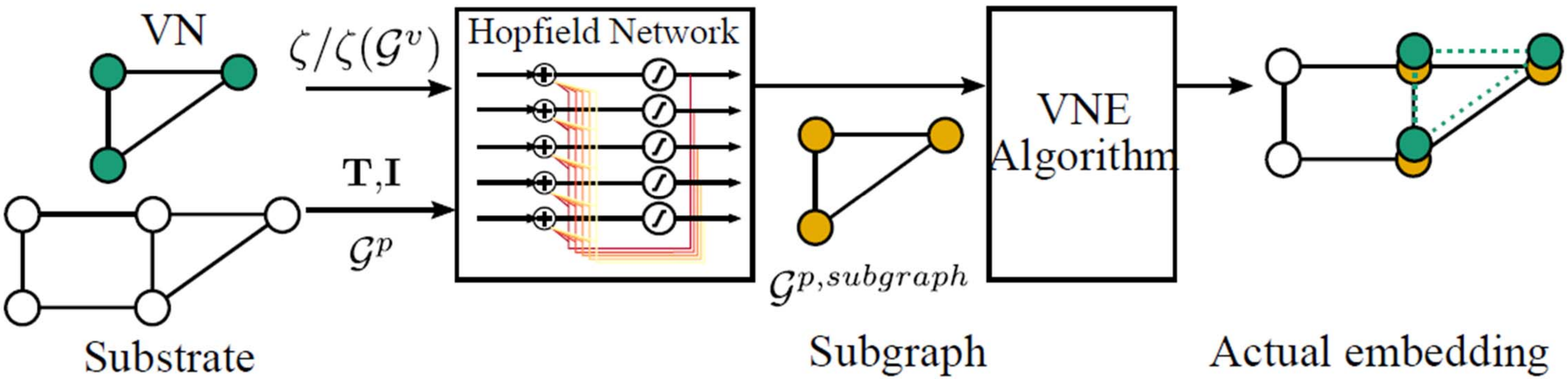
- Challenge: Regularly solving computation hard problems
- Goal: Speed-up and/or improve Virtual Network Embedding

Neurovine:

Hopfield neural network to preprocess (subgraph extraction) VNE algorithms

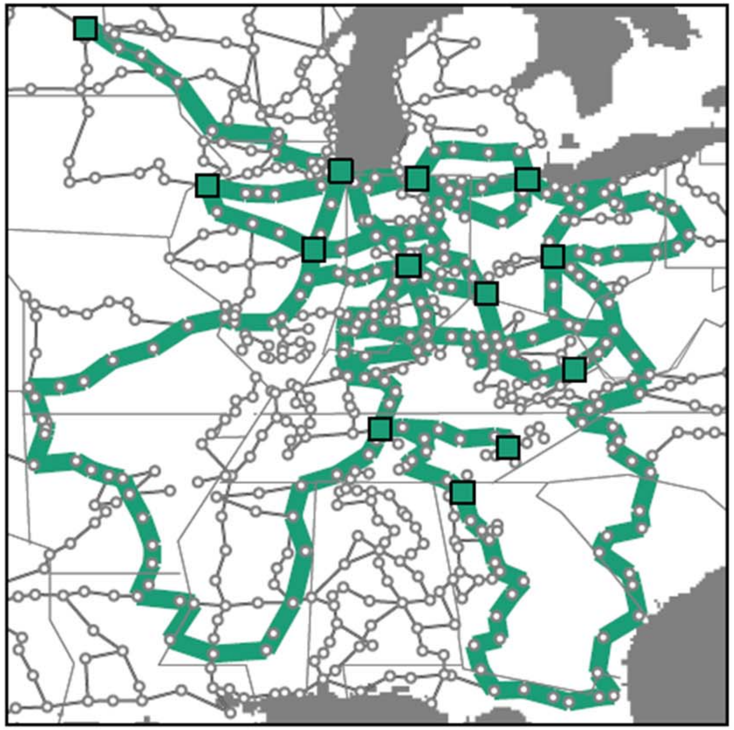
Andreas Blenk, Patrick Kalmbach, Johannes Zerwas, Michael Jarschel, Stefan Schmid, Wolfgang Kellerer:
NeuroViNE: A Neural Preprocessor for Your Virtual Network Embedding Algorithm
IEEE INFOCOM 2018 (main conference), Honolulu, HI, USA, April 15-19, 2018.

Neural Preprocessor for Virtual Network Embedding: NeuroViNE

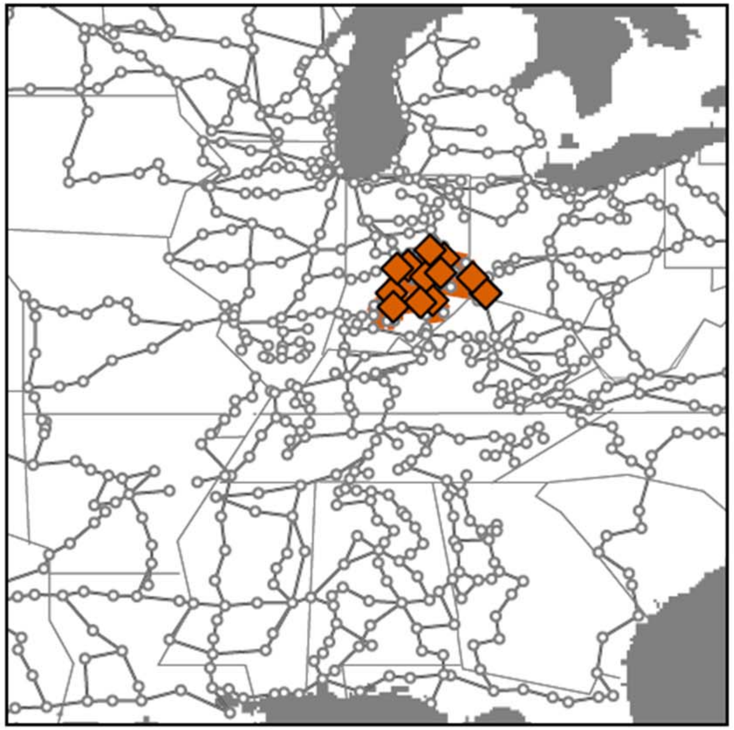


- State-of-the-art: Heuristics judge nodes independently from each other

Heuristics judge nodes independently from each other



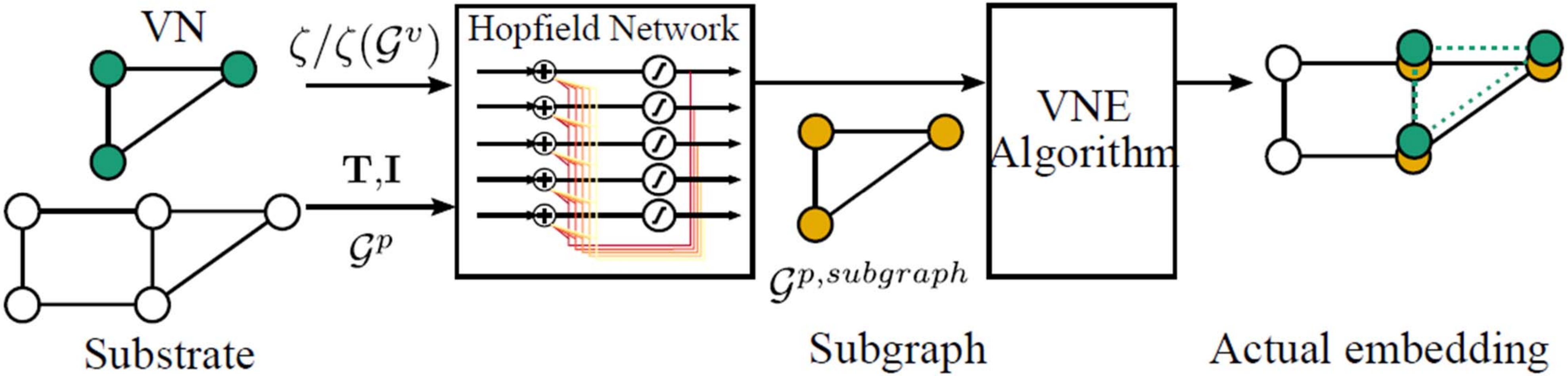
GRC



Our proposal: HF-GRC

Example: Comparison of node locations for a single VNR between GRC and HF-GRC

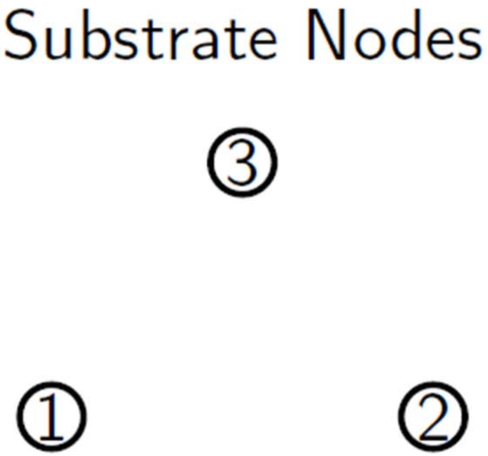
Neural Preprocessor for Virtual Network Embedding: NeuroViNE

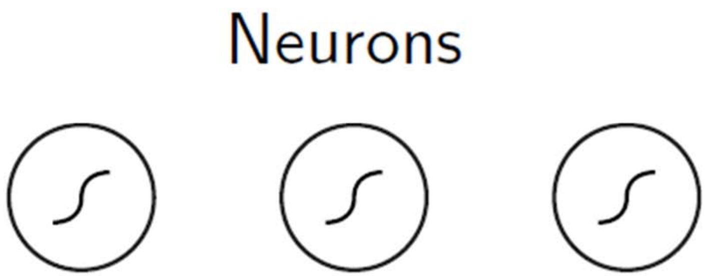


- State-of-the-art: Heuristics judge nodes independently from each other
- Idea: Extract subgraph with physical nodes close to each other and high available capacities

Optimization with Hopfield Neural Networks

Graph Inputs → Neural Network → Solution

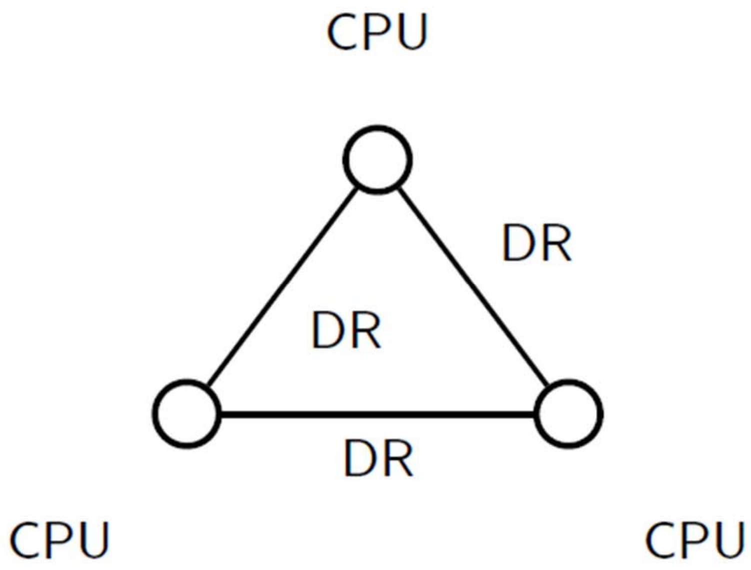


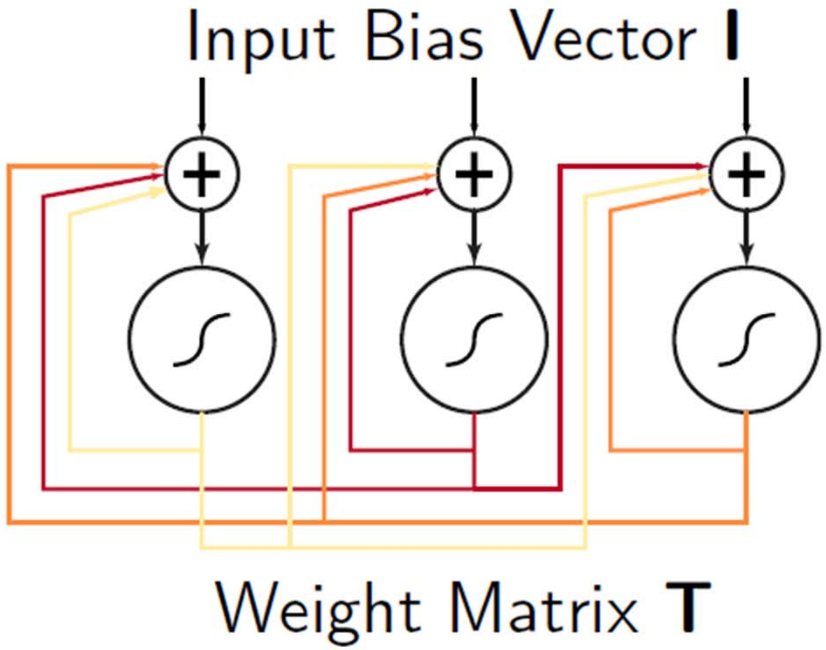


- According to optimization problem

Optimization with Hopfield Neural Networks

Graph Inputs → Neural Network → Solution

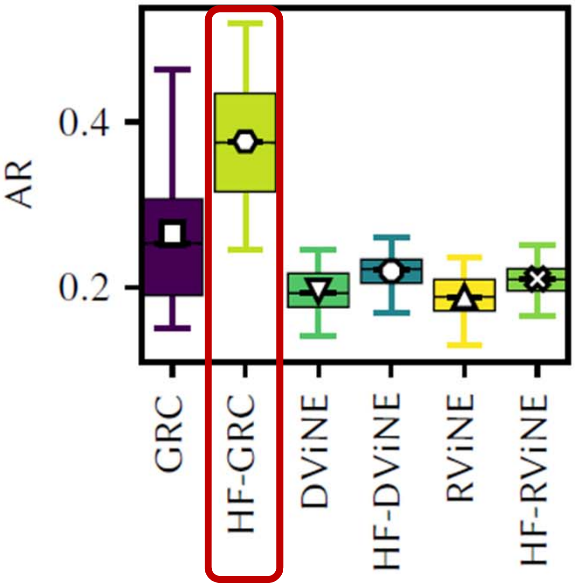




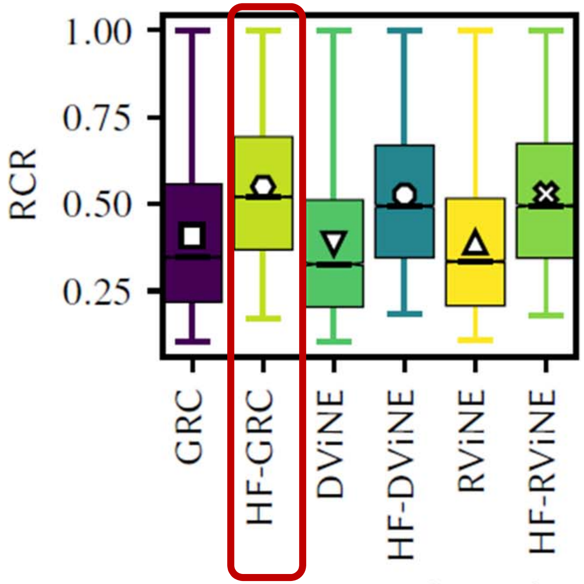
- According to optimization problem:
  - Input Bias Vector **I** integrates available node capacities (CPU)
  - Weight Matrix **T** integrates available datarate capacities (DR)
  - **I** and **T** take care of number of selected nodes (ζ) [1]
- Executing means solving: $\frac{d\mathbf{U}(t)}{dt} = -\frac{\mathbf{U}(t)}{\tau_{HF}} + \mathbf{TV}(t) + \mathbf{I}$

[1] G Tagliarini, J Christ, and E Page. "Optimization using neural networks". In: IEEE Trans. Comp. 40.12 (Dec. 1991), pp. 1347-1358.

Efficiency on Real Network Topologies



Acceptance Ratio (AR)



Revenue-cost-ratio (RCR)

- VNE algorithms (GRC, DViNE, RViNE) vs. Hopfield variants (HF-GRC, HF-DViNE, HF-RViNE)
- NeuroViNE accepts more networks with less costs

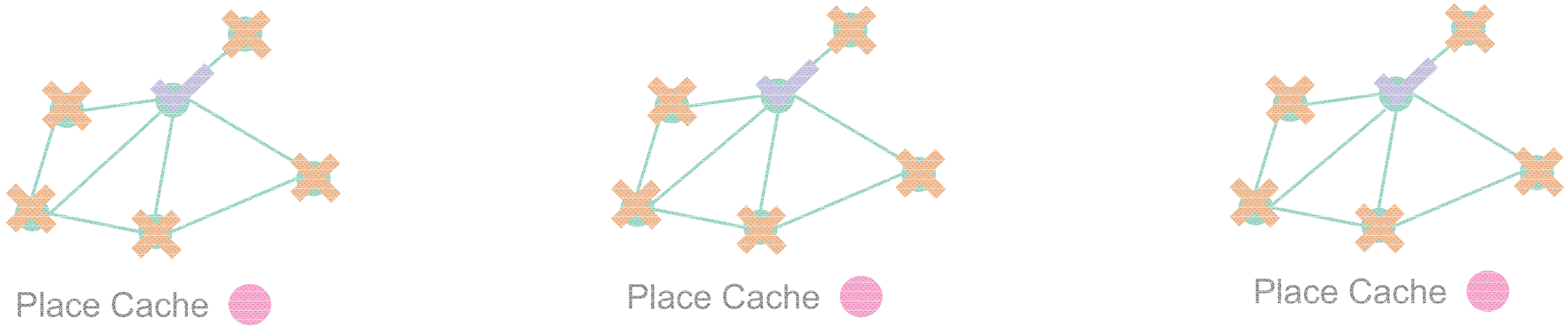
another way of filtering:
Data-driven Networking

o‘zapft is:

supervised learning
to learn from previous solutions (the data)
of (general) network algorithms

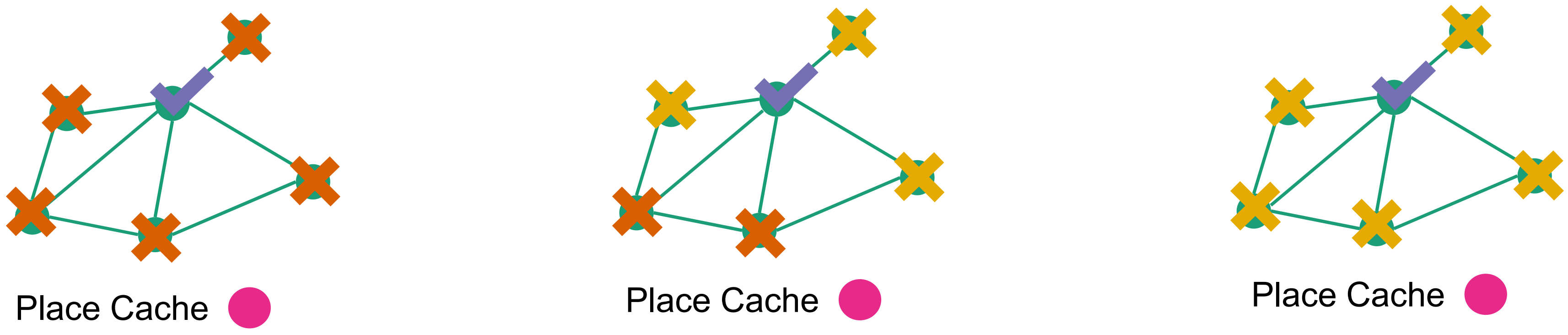
Blenk, Andreas; Kalmbach, Patrick; Schmid, Stefan; Kellerer, Wolfgang:
o'zapft is: Tap Your Network Algorithm's Big Data!
ACM SIGCOMM 2017 Workshop on Big Data Analytics and Machine Learning for Data Communication Networks (Big-DAMA), 2017.

The Limitation of today's network algorithms: *Fire and Forget*

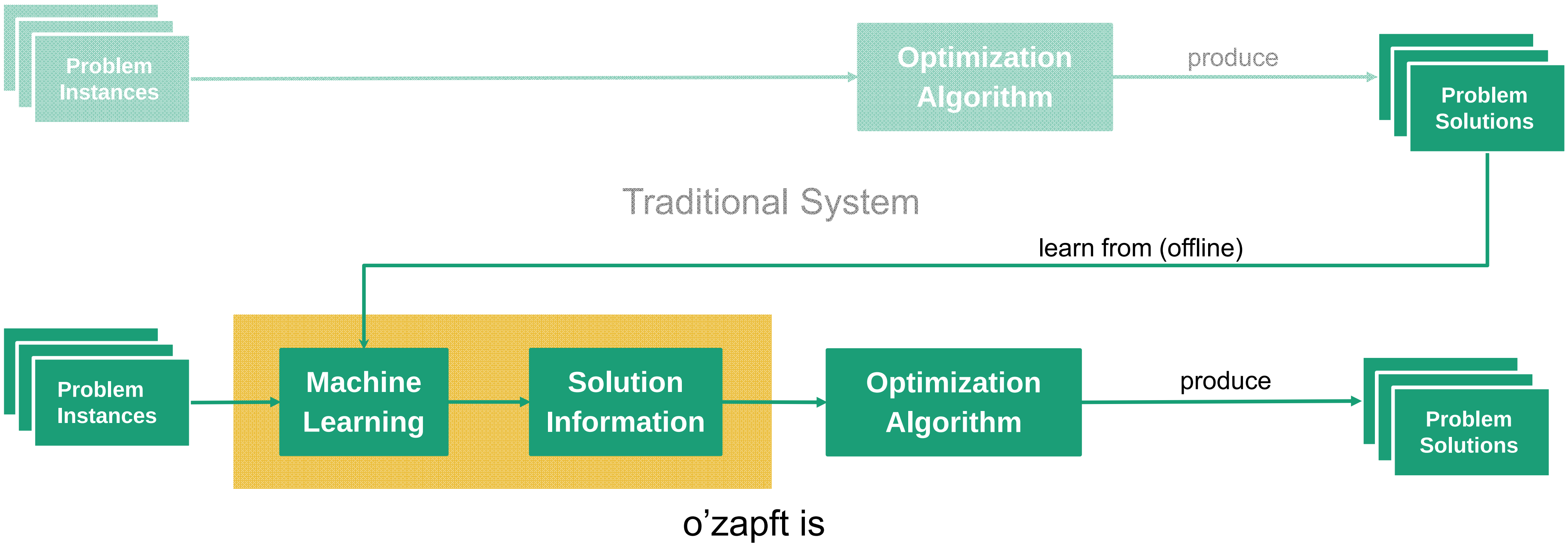


Algorithms repeatedly solve similar problems **from scratch.** This is not only boring for the algorithm but also a waste of information and resources

The Opportunity – Tap into your Algorithm's Big Data



Traditional vs. Proposed System

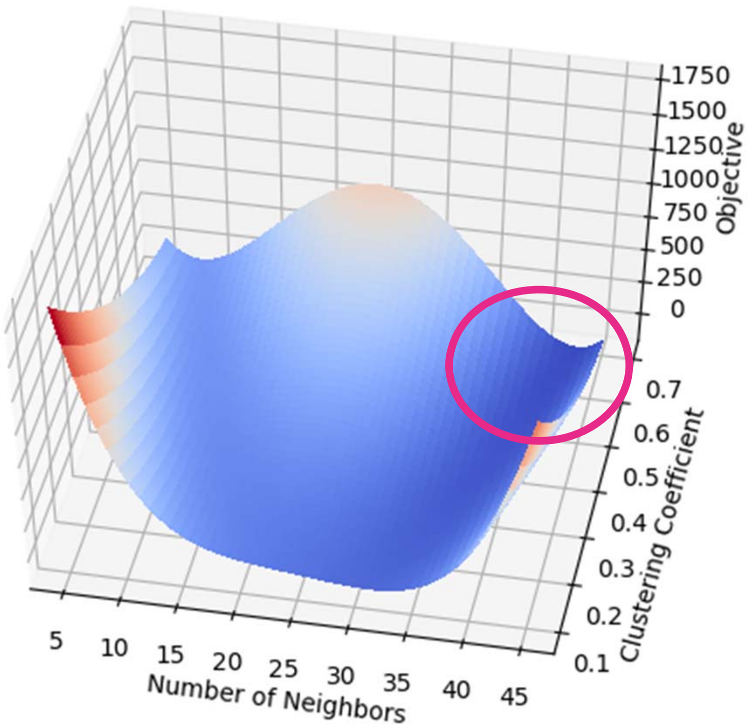


- State-of-the-art: Neglects produced data!
- Idea: Use problem/solution data generated by algorithms regularly solving problems

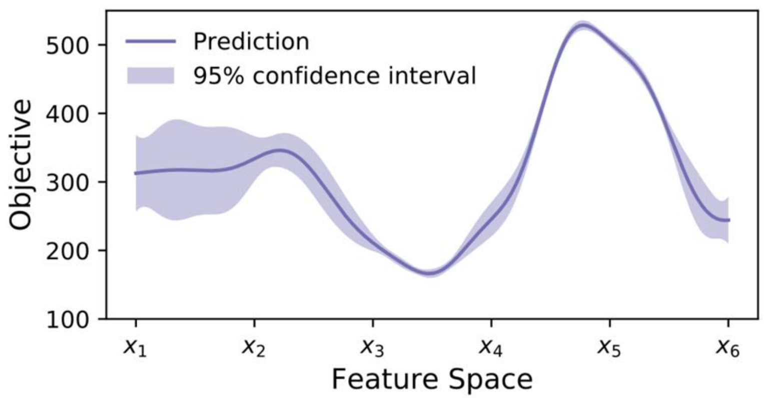
Data Available at: Patrick Kalmbach, Johannes Zerwas, Michael Manhart, Andreas Blenk, Stefan Schmid, and Wolfgang Kellerer. 2017. Data on "o’zapft is: Tap Your Network Algorithm’s Big Data!". (2017). https://doi.org/10.14459/2017md1361589

Potentials

- Potentials: (a) Reduce search space and (b) Predict problem outcome



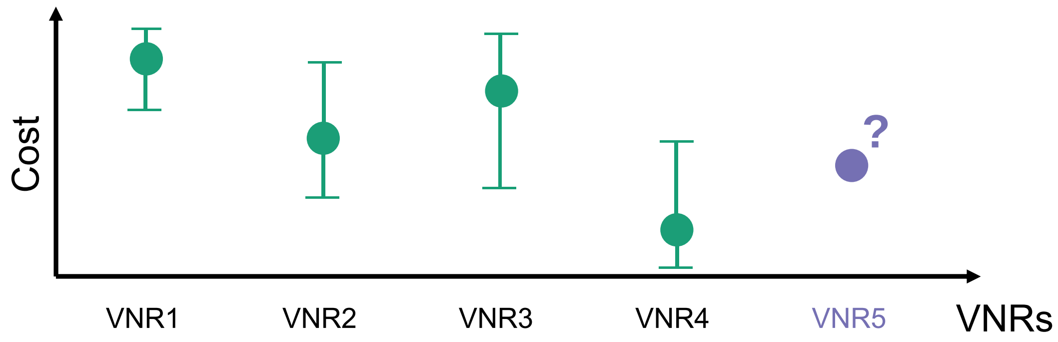
(a) Search Space Reduction/Initial Solutions



(b) Predict Value of Objective Function
→ admission control

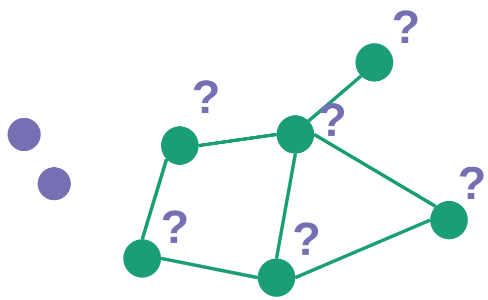
Use Cases

Virtual Network Embedding (VNE) – Predict Embedding Costs



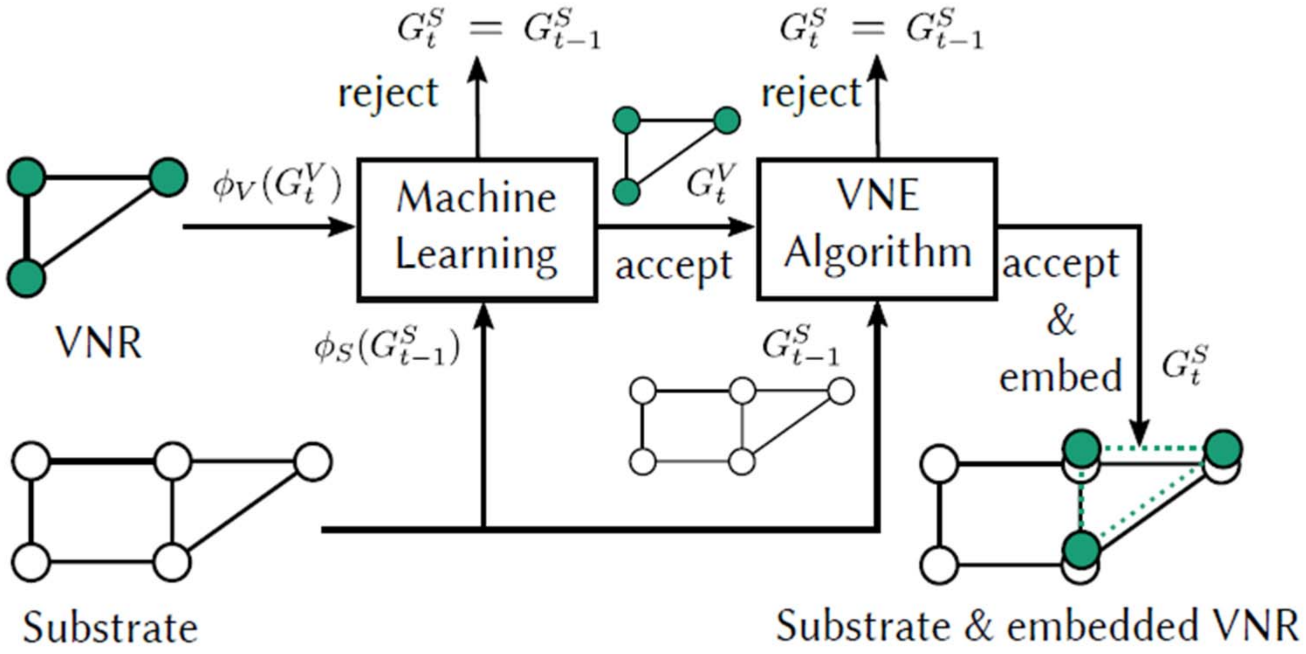
Problem: Given a VNR and Substrate, what will the cost be?

Facility Location (Controller Placement) – Guess Initial solutions



Problem: Given a network and a number of controllers, where to place the controllers?

Case Study I: Virtual Network Embedding Cost

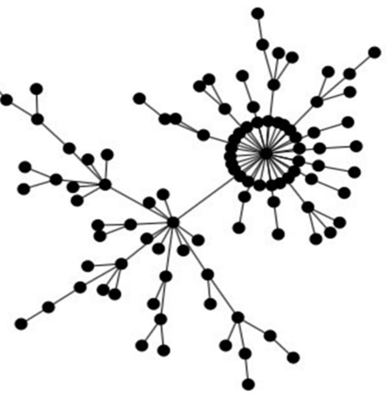


- Learn and predict the embedding cost of a VNR
- Embedding cost = total length of the virtual links interconnecting the requested virtual nodes
- Supervised learning: regressors predict the cost of to-be-embedded virtual networks
- Offline training!

Methodology

Optimization Algorithms

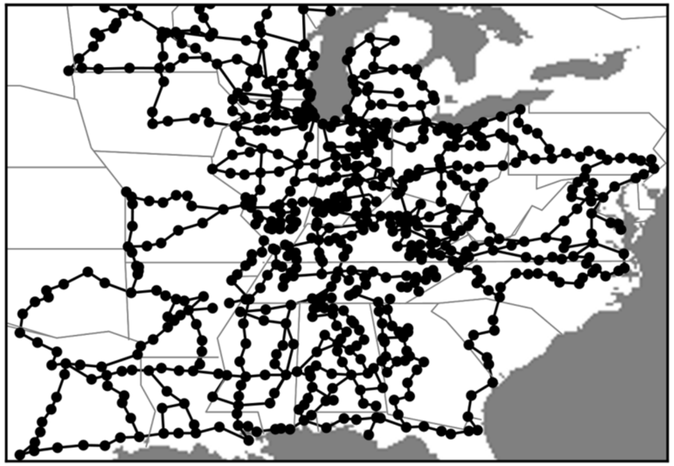
- Greedy [20]
- GRC (Global Resource Capacity) [8]
- SDP (optimal, Mixed Integer Program (MIP))
- Strawman (SM) (“VNR#nodes&links → cost”)



Barabasi-Albert Graph [3]

Substrates

- Erdős-Rényi (ER) 40 nodes
- Barabasi-Albert (BA) [2] 40 nodes
- Topology Zoo [1]: Kentucky Data Link (KDL) 734 nodes
- 6-ary Fat Tree (DC-FT)
- BCube2 (DC-BC)



Kentucky Data Link

Objective:

Minimize embedding cost

5 runs with 2500 VRs of each combination

[1] Knight et al., The Internet Topology Zoo. *IEEE J. on Sel. Areas in Communications 29*, 9 (2011)
[2] Saino et al., A Toolchain for Simplifying Network Simulation Setup, in *Procs. SIMUTOOLS '13*, Cannes, France, March 2013
[3] Picture taken from http://graphstream-project.org/media/img/generator_overview_barabasi_albert.png
[8] Long Gong, Yonggang Wen, Zuqing Zhu, and Tony Lee. 2014. Toward profitseeking virtual network embedding algorithm via global resource capacity. IEEE INFOCOM 2014
[20] Minlan Yu, Yung Yi, Jennifer Rexford, and Mung Chiang. 2008. Rethinking Virtual Network Embedding: Substrate Support for Path Splitting and Migration. SIGCOMM CCR 38, 2 (3/2008)

Learning embedding cost

Library:

- Sci-Kit Learn [1]

Graph features:

- Node degree
- Closeness

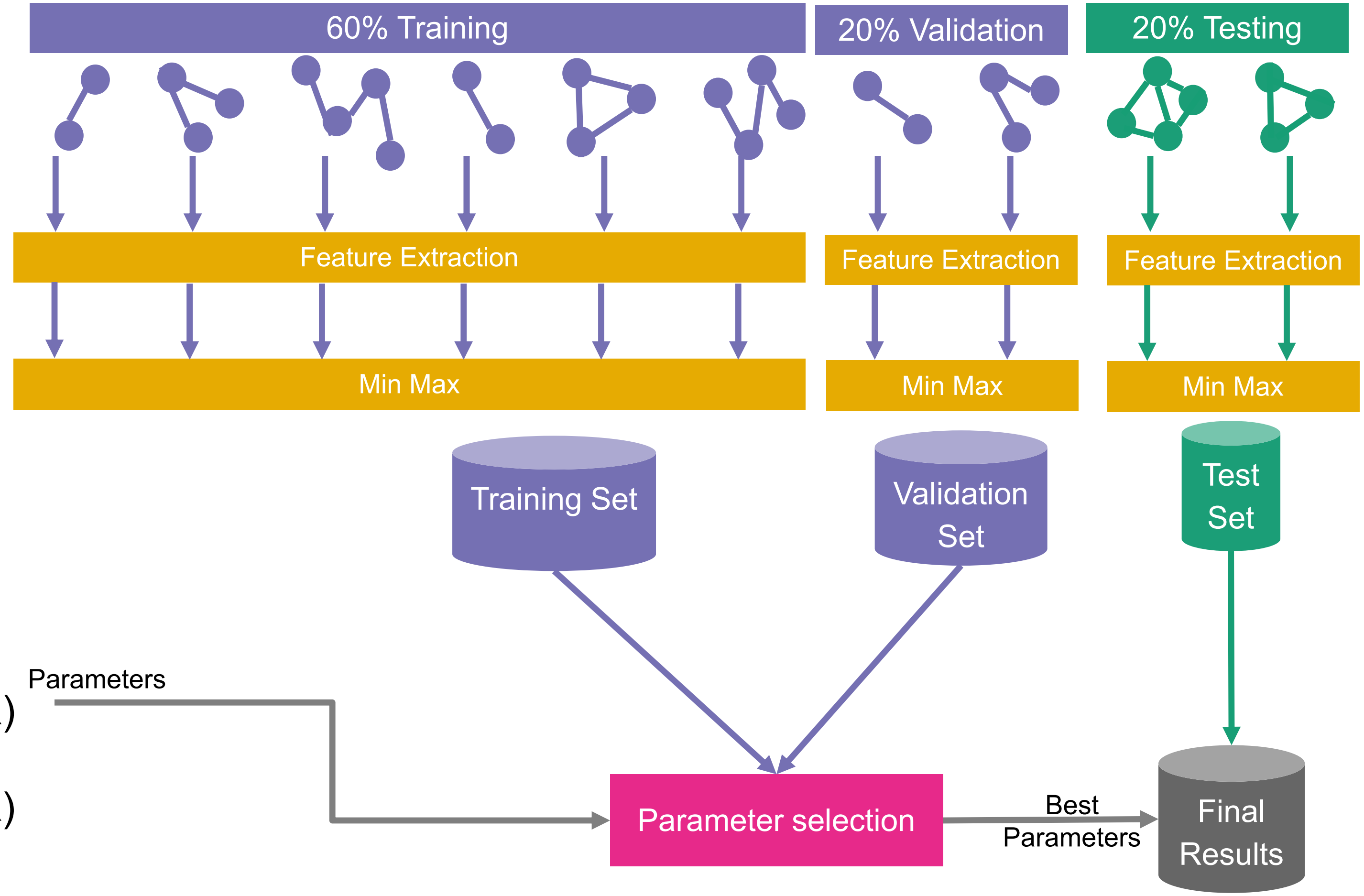
Measures:

- R^2 (goodness of fit for ML models)

Classifier:

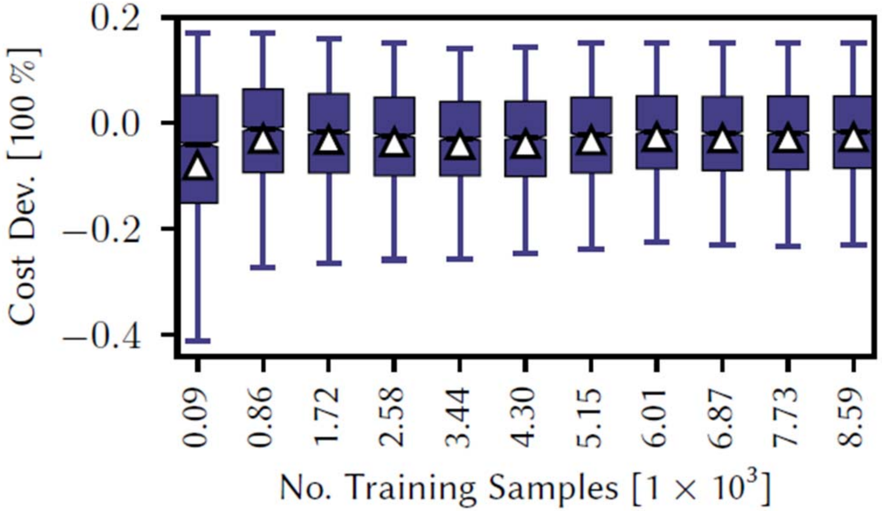
- Linear Regression (LR)
- Bayesian Ridge Regressor (BRR)
- Random Forest Regressor (RF)
- Support Vector Regression (SVR)

Model Training and Selection:

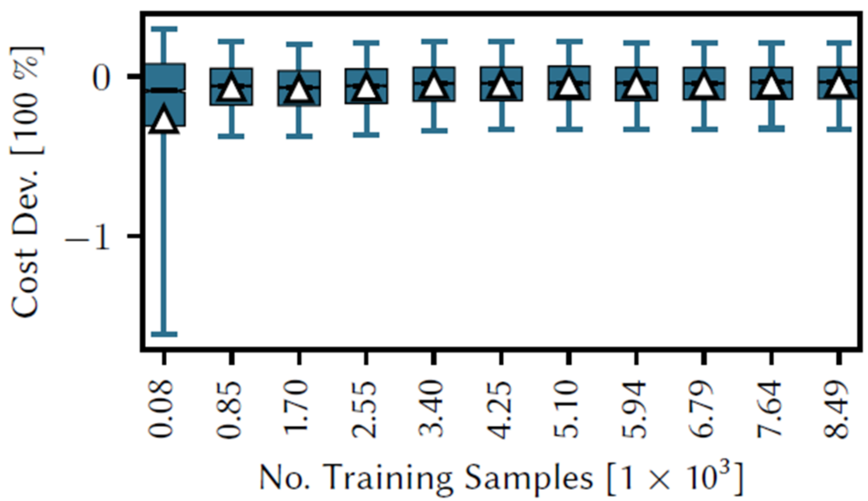


[1] Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.

How much learning is required?



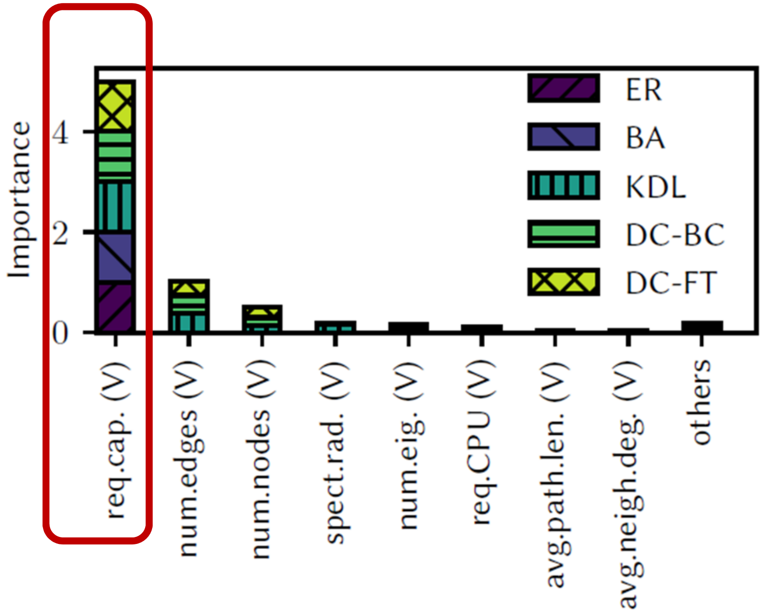
Greedy



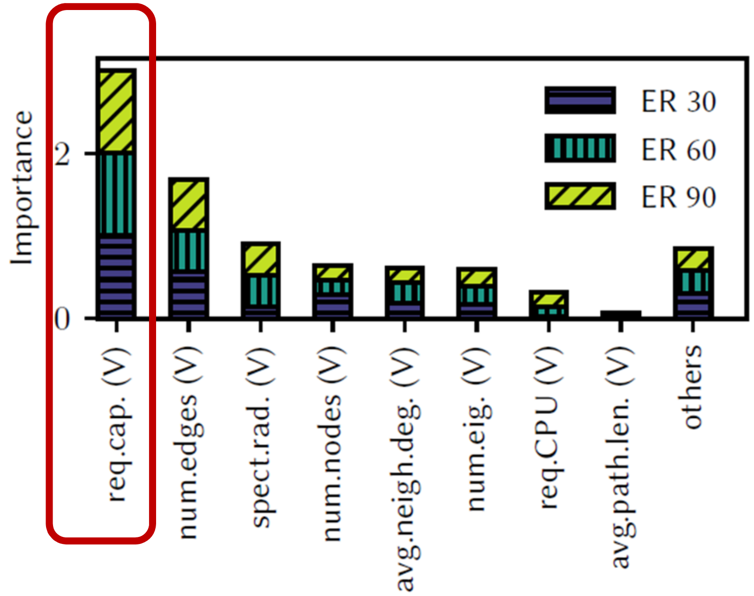
SDP

- VNR embedding costs can be estimated well after a short training period

Which graph features are important for solution learning?



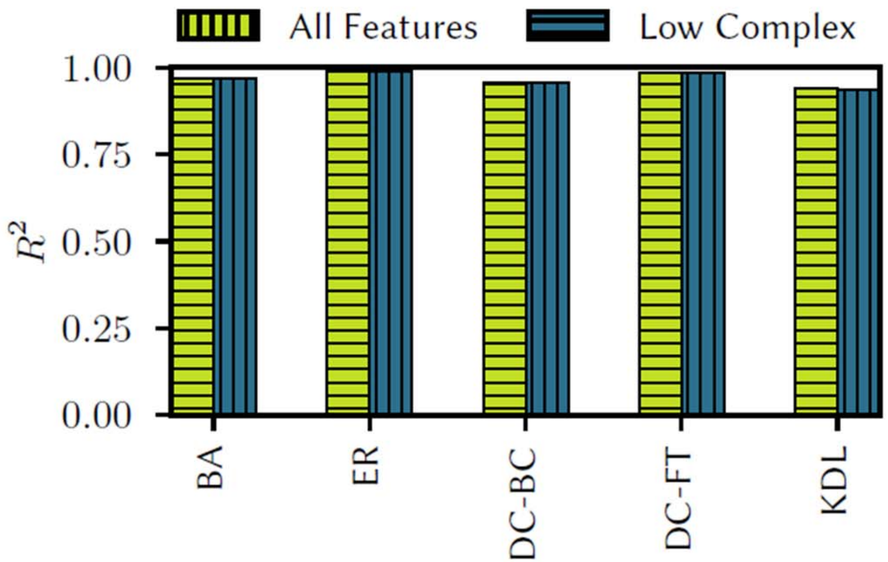
Greedy



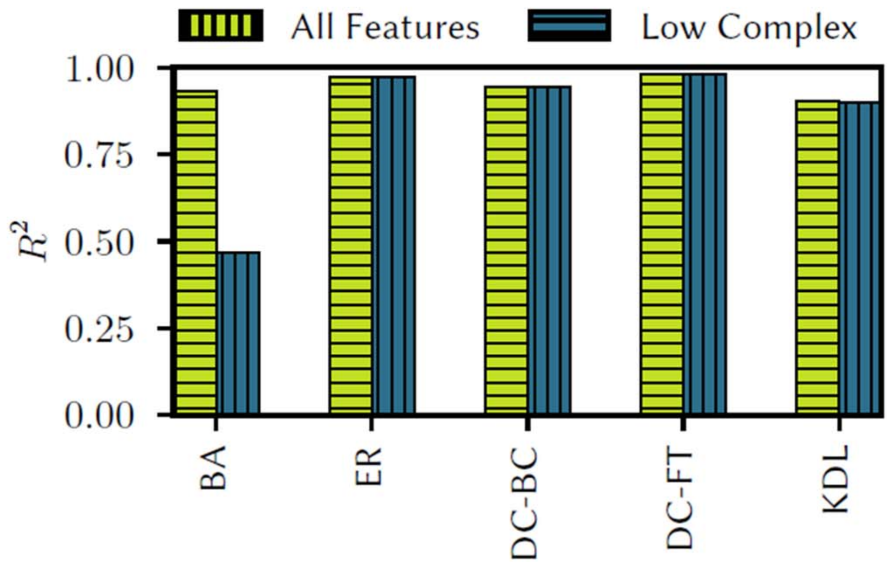
SDP

- Requested Link Capacity is most important
- For SDP the importance is more distributed (larger search space and variation of solutions)

Is one feature enough?



Greedy

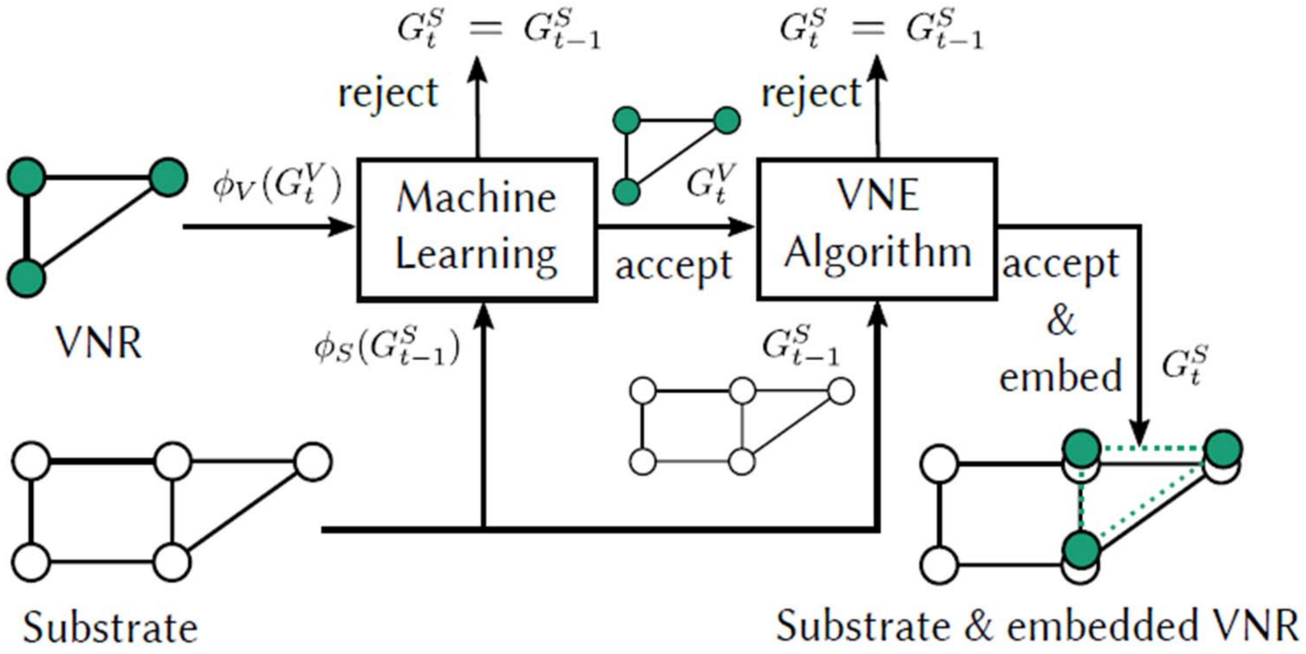


GRC

- Trained regressors with features of different complexity: O(n), O(n+m), O(n * log n) [14]
- Already low complexity features provide a high R^2 (goodness of fit for ML models)

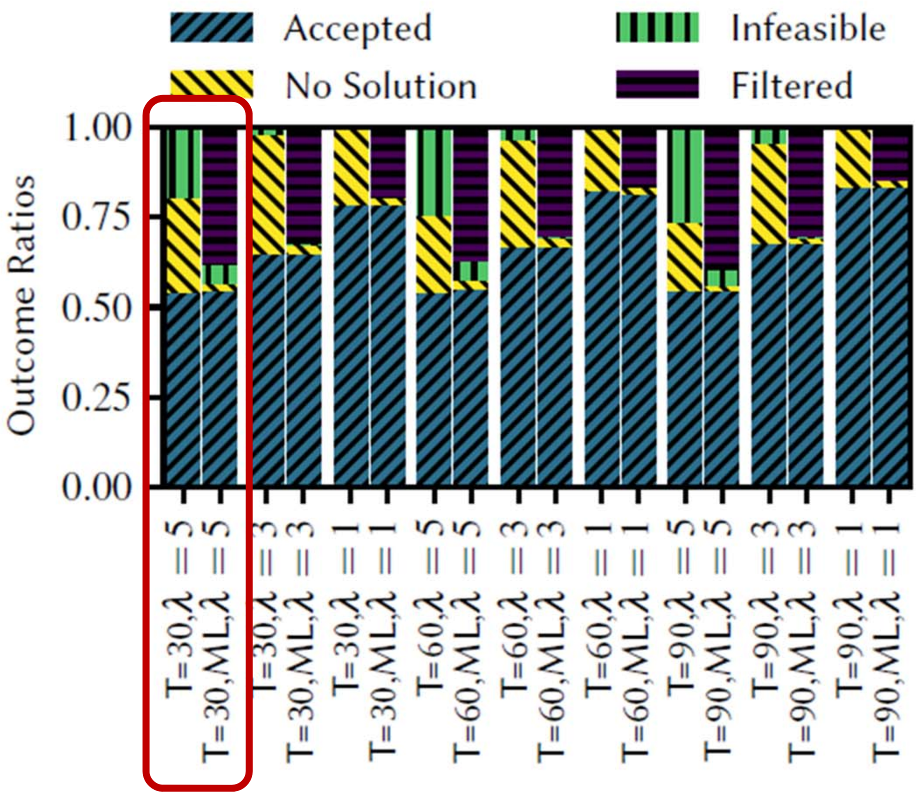
[14] Geng Li, Murat Semerci, Bülent Yener, and Mohammed J Zaki. 2012. Effective graph classification based on topological and label attributes. Statistical Analysis and Data Mining 5, 4 (Aug. 2012), 265–283.

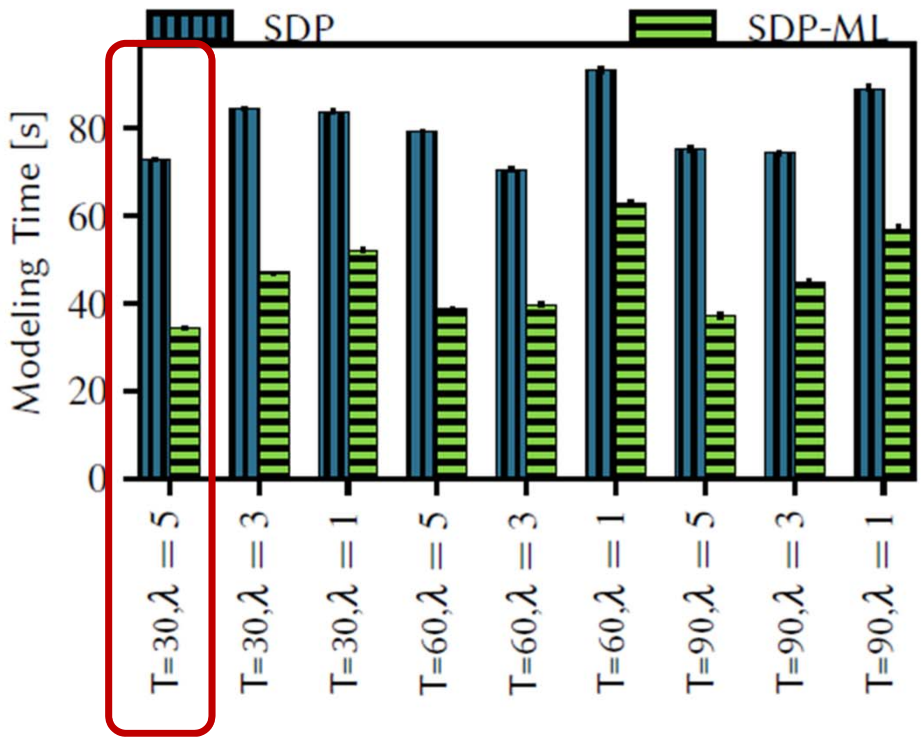
Case Study II: Predicting Acceptance Probabilities of VNE Requests



- Supervised learning: use data with accepted and rejected requests ! Offline training!
- Recurrent neural network (RNN) for classification
- Filter Infeasible and requests with unacceptable algorithm runtime (No Solution)

Can we speed-up optimal algorithms using admission control?





- Efficient Filtering of infeasible and unacceptable requests
- Efficient saving of model creation time
- Saving up to 50% computational resources

Conclusion

Machine Learning can be successfully used to **preprocess** models leaving existing algorithms or optimizers **untouched**

Boost your network algorithm with ML preprocessing – Tap your data!

- ***Neurovine**: Hopfield neural network to preprocess (subgraph extraction) VNE algorithms*
  - *tailored filtering*

- ***o'zapft is**: supervised learning to learn from previous solutions of network algorithms*
  - ***data-driven networking algorithms***

Important References

- Andreas Blenk, Patrick Kalmbach, Johannes Zerwas, Michael Jarschel, Stefan Schmid, Wolfgang Kellerer: ***NeuroViNE: A Neural Preprocessor for Your Virtual Network Embedding Algorithm*** IEEE INFOCOM 2018 (main conference), Honolulu, HI, USA, April 15-19, 2018.
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- Andreas Blenk: ***Towards Virtualization of Software-Defined Networks: Analysis, Modeling, and Optimization***. PhD Thesis, Technische Universität München, März 2018.
- Blenk, Andreas; Kalmbach, Patrick; van der Smagt, Patrick; Kellerer, Wolfgang: ***Boost Online Virtual Network Embedding: Using Neural Networks for Admission Control.*** 12th International Conference on Network and Service Management (CNSM), 2016