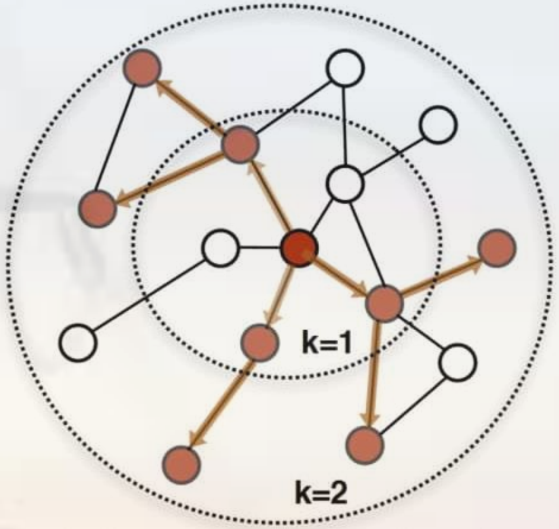

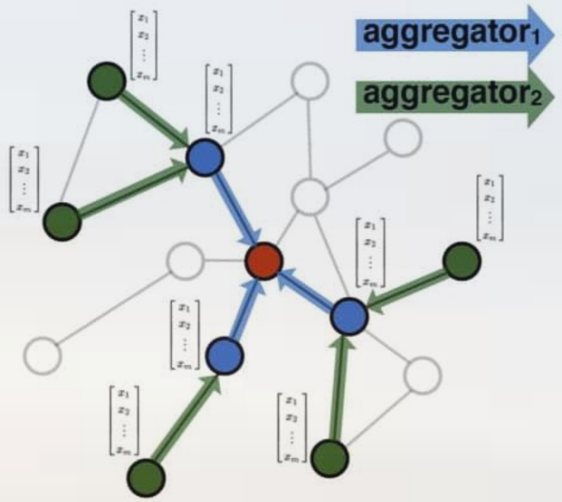

Opportunities & challenges in graph-based learning for power system application

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Jochen Cremer

Delft AI Energy Lab

Mission & objective

- combine groundbreaking ML with the reliable theory of the physical energy system
- make energy systems sustainable, reliable, effective

Education

- EE4C12 ML for Electrical Engineering
- SET 3125 Machine Learning Workflows for Digital Energy Systems
- SC42150 Statistical Signal Processing
- SC42110 Dynamic Programming and Stochastic Control
- MOOC Digitalization of Intelligent and Integrated Energy Systems
- Crash course of “Data-science”

Research

- Supervised learning for real-time grid assessment
- Distributed learning for power system congestion management
- Data-driven grid models for electricity load and weather forecasts
- Characterizing healthy/normal trajectories of complex dynamical systems using dictionary learning
- From fast Fourier transform to fast reinforcement learning

Key innovations

- AI-based algorithms for grid operation
- Real-time security assessment and anomaly detection
- Real-time learning algorithms for control and security of complex dynamical systems

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TU Delft | AI Initiative

https://www.tudelft.nl/ai/delft-ai-energy-lab

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Olayiwolo Arowolo


Jochen Stiasny


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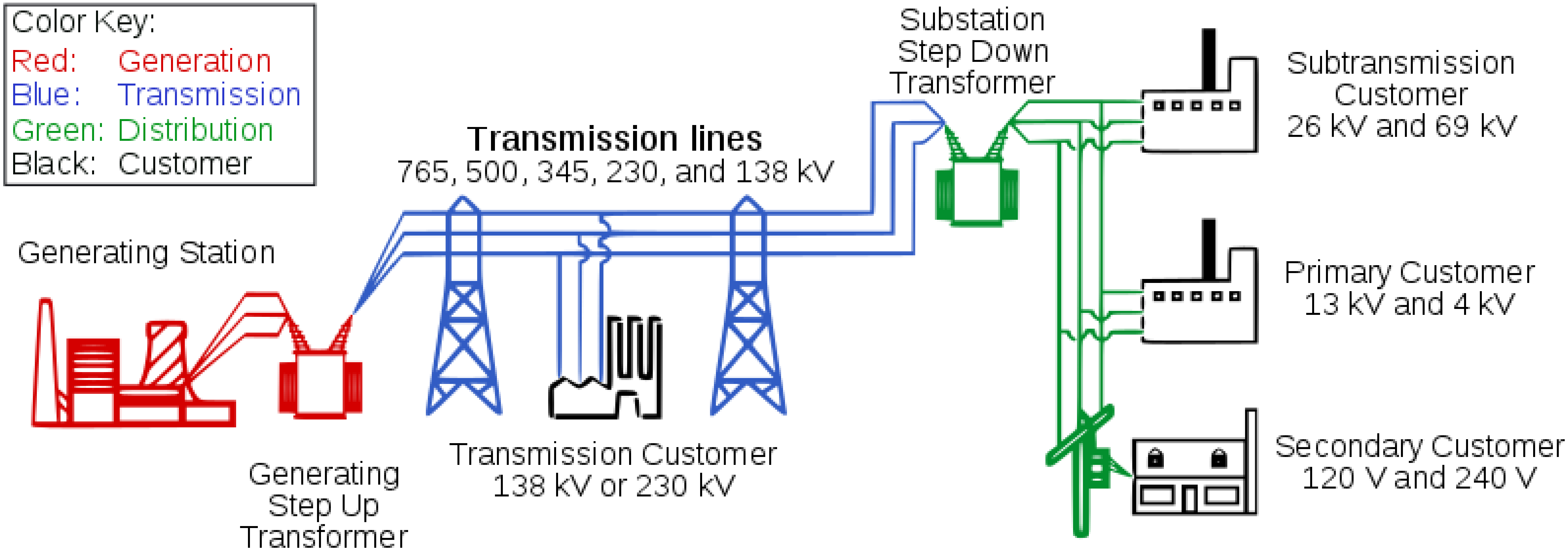
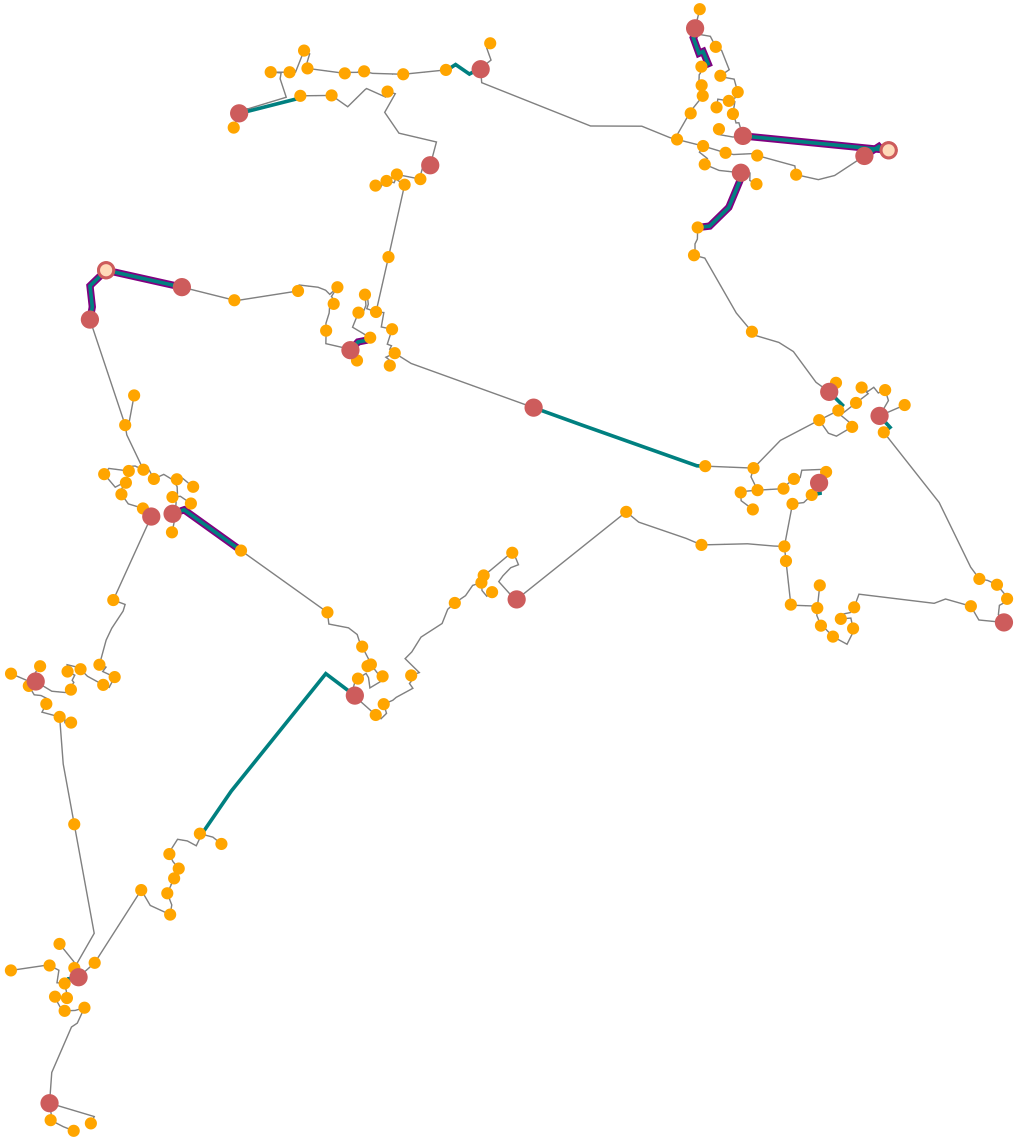
Power systems



Distribution system (MV)



- Trafo
- Lines
- MV/LV buses
- HV buses
- Power flow measurement
- Voltage measurements
- Focus bus

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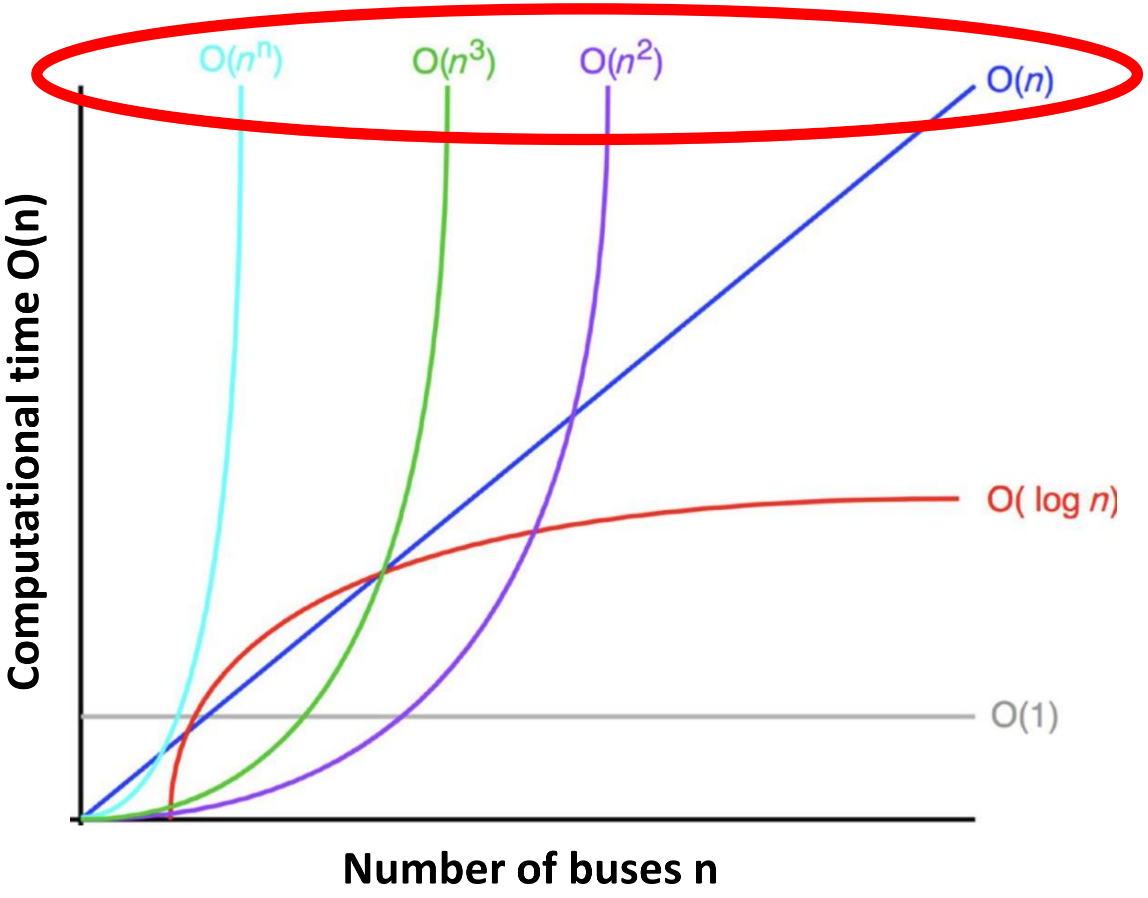
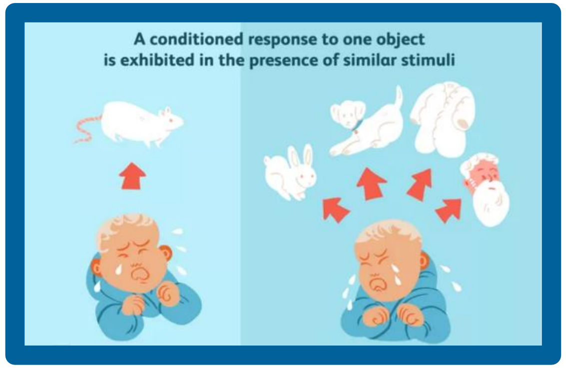
Scaling power system analysis to very large grids

Example: reliability assessment

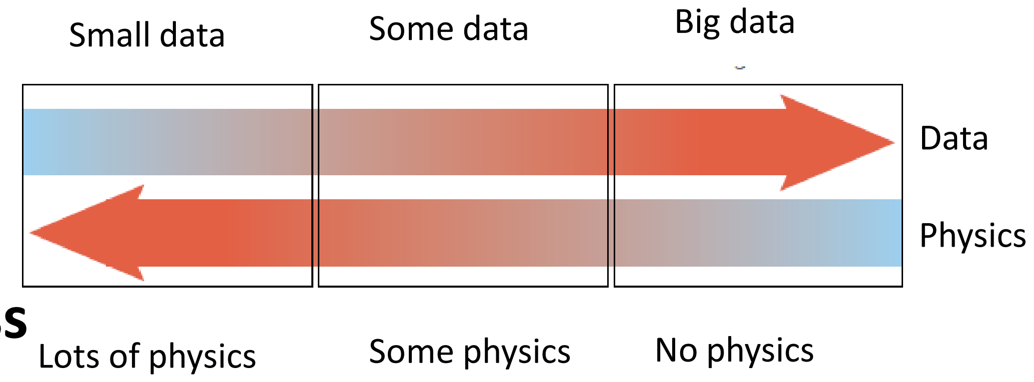


What are barriers applying AI?



1. **Generalising to out-of-distribution data**
   - Different energy scenarios in the future
   - Historical observations are not suitable
   - Energy systems will be ever-evolving

2. **Large training data is needed**
   - Power systems are extremely large systems
   - Training an AI for such large systems requires a lot of data



3. **AI does not provide explanations or robustness**
   - Energy systems are critical and sensitive infrastructures

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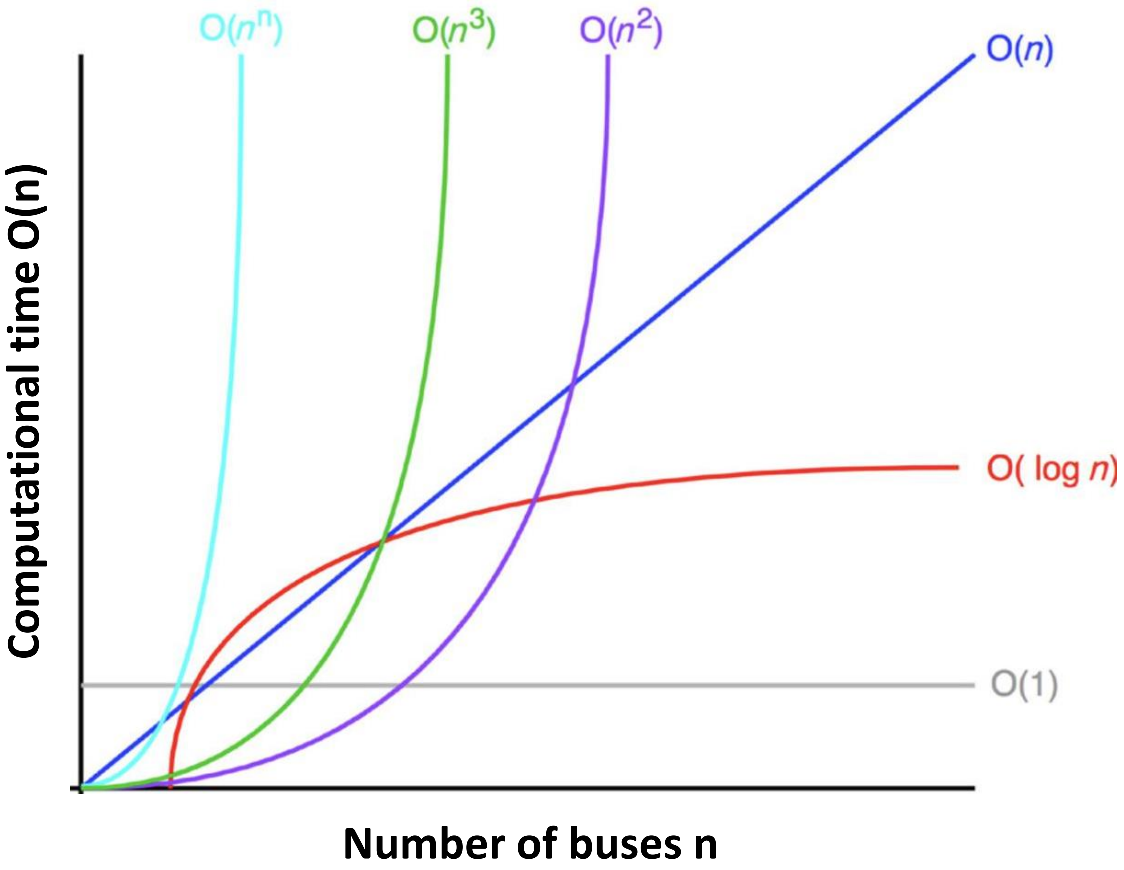
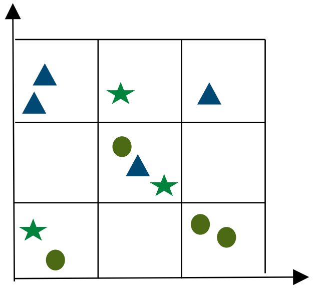
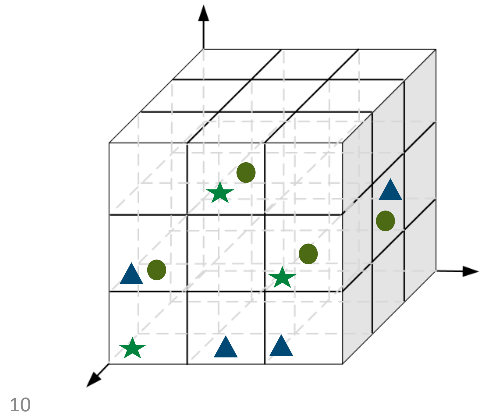
ML-driven ‘proxies’ for power system analysis

Challenge: scaling to system size



Curse of dimensionality





?

1d: 3 regions

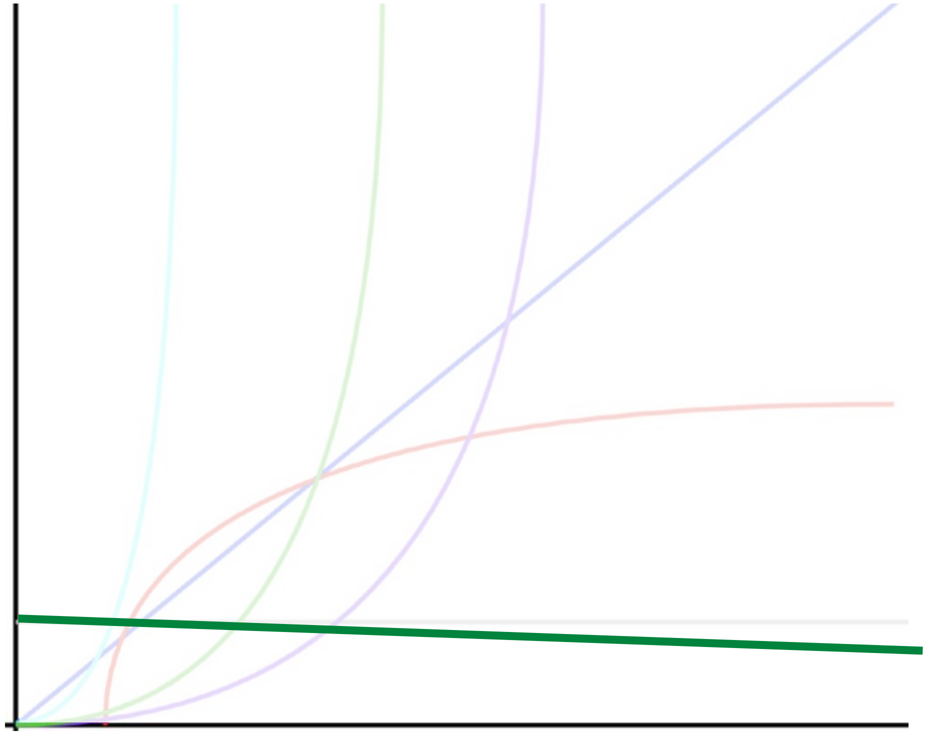
2d: 3^2 regions

3d: 3^3 regions

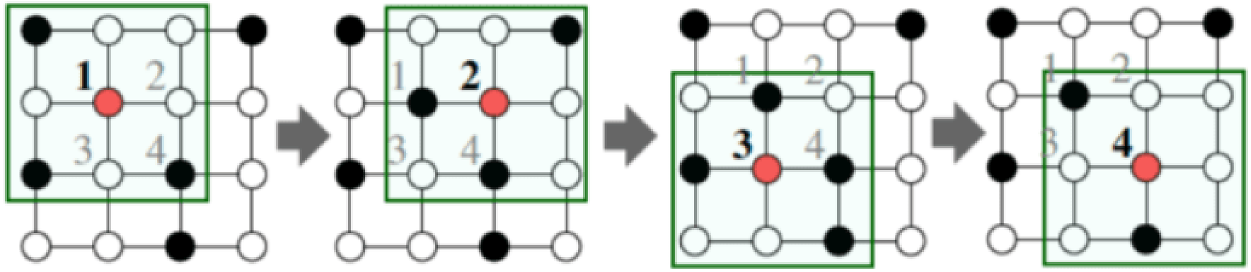
As dimensionality grows: fewer samples per region.

Learning without labels and inducing bias

- Self-supervised learning
- Physics-informed ML
- Weakly-supervised learning



Utopia?



Graph neural networks
learn from the neighbours

Distribution system state estimation

- Measurements $z \in \mathbb{R}^m$ with noise $\varepsilon \in \mathbb{R}^m$
- System state $x \in \mathbb{R}^{2n}$
- State estimation $f(z) \rightarrow x$
- Challenge: partial observable, scarce measurements $m \ll n$

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A. Primadianto and C. -N. Lu, "A Review on Distribution System State Estimation," in *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3875-3883, Sept. 2017, doi: 10.1109/TPWRS.2016.2632156.

Distribution system (MV)

- Trafo
- Lines
- MV/LV buses
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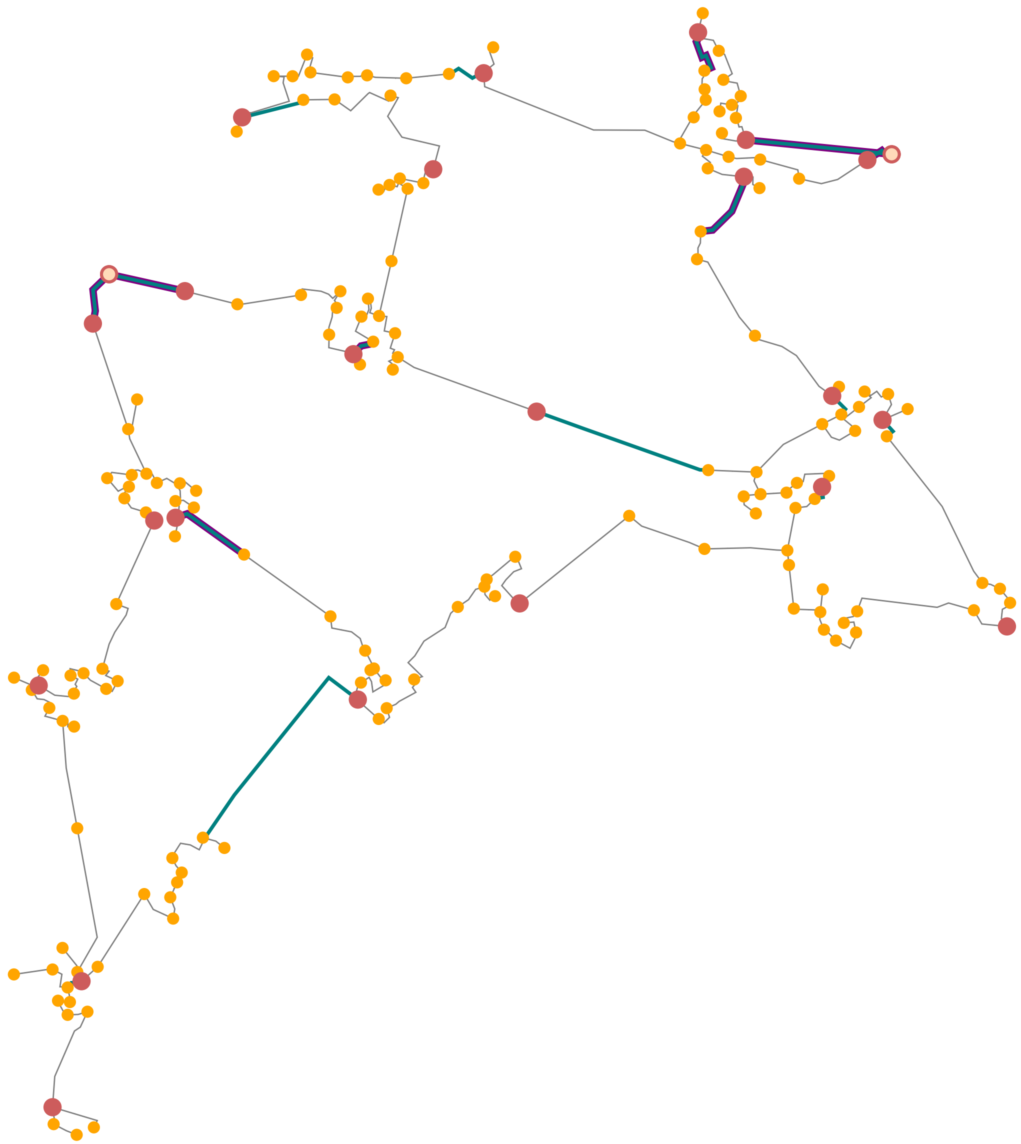
- Power flow measurement
- Voltage measurements

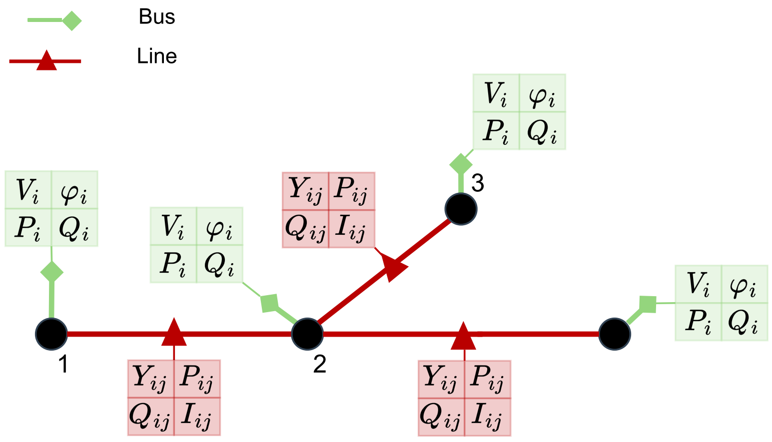


Model of the power flow

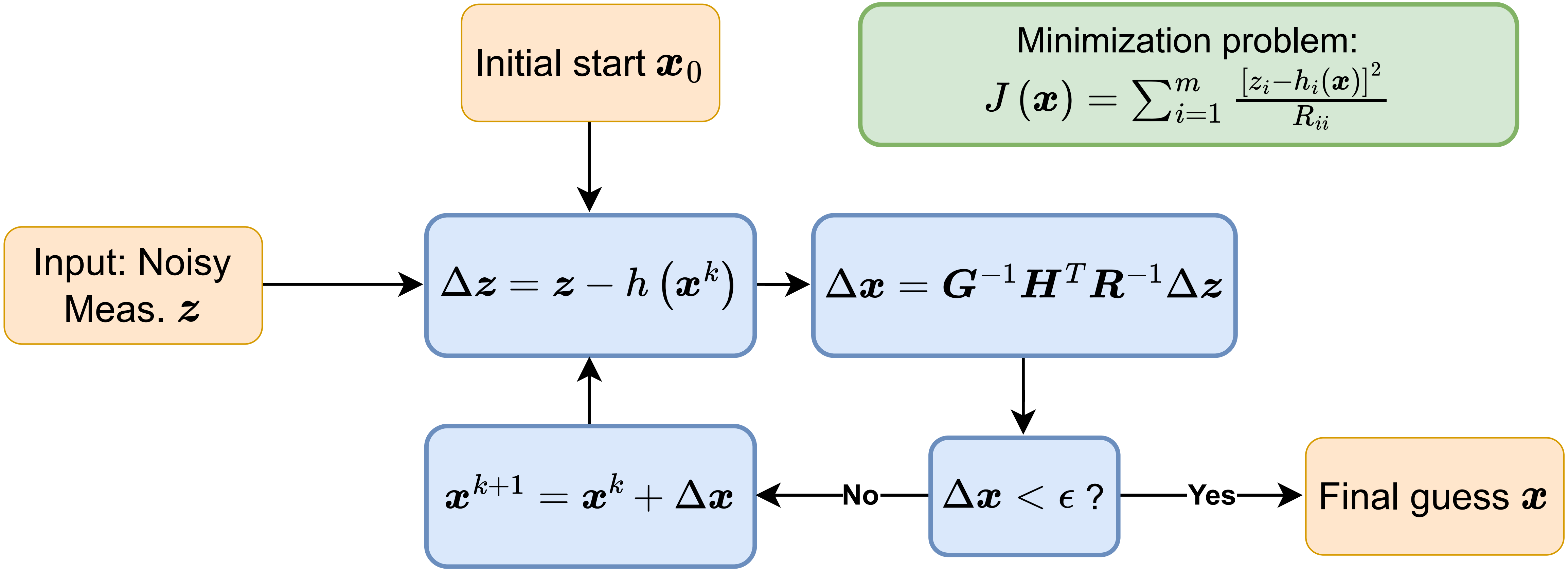
$$x = [V, \varphi]$$

$$z = h(x) + \varepsilon$$

$$h(x) = \begin{cases} V_i = V_i \\ \varphi_i = \varphi_i \\ P_{ij\rightarrow} = -V_iV_j[\mathbb{R}(Y_{ij})\, cos\, \Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\, sin\, \Delta\varphi_{ij}]] + V_i^2\left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ P_{ij\leftarrow} = V_iV_j[-\mathbb{R}(Y_{ij})\, cos\, \Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\, sin\, \Delta\varphi_{ij}]] + V_j^2\left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ Q_{ij\rightarrow} = V_iV_j[-\mathbb{R}(Y_{ij})\, \sin \Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\, \cos \Delta\varphi_{ij}]] - V_i^2\left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ Q_{ij\leftarrow} = V_iV_j[\mathbb{R}(Y_{ij})\, sin\, \Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\, cos\, \Delta\varphi_{ij}]] - V_j^2\left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ I_{ij\rightarrow} = -\left|\frac{P_{ij\rightarrow} - jQ_{ij\rightarrow}}{\sqrt{3}V_i e^{-j\varphi_i}}\right| \\ I_{ij\leftarrow} = -\left|\frac{P_{ij\leftarrow} - jQ_{ij\leftarrow}}{\sqrt{3}V_j e^{-j\varphi_j}}\right| \\ P_i = -\sum_{j\in N_x(i)} P_{ij\leftarrow} + P_{ij\rightarrow} \\ Q_i = -\sum_{j\in N_x(i)} Q_{ij\leftarrow} + Q_{ij\rightarrow} \end{cases}$$



Weighted least squares method



How accurate is x?
Convergence?

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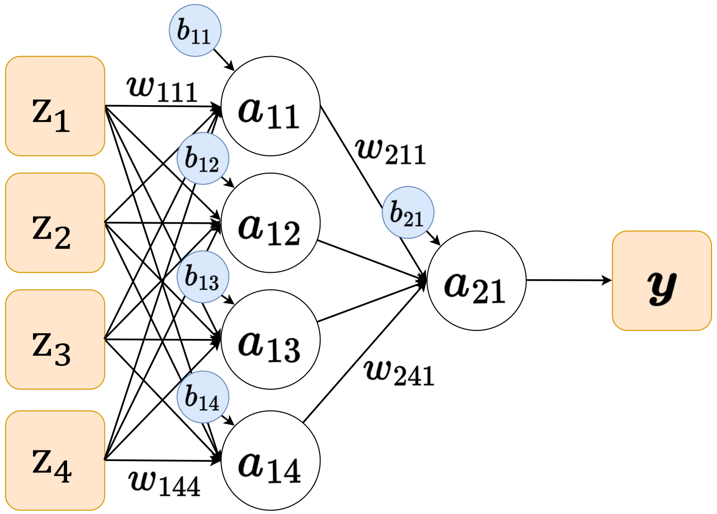
Statistical learning

- Training set $S = \{(z_1, y_1), (z_2, y_2) \dots (z_t, y_t)\}$ with t samples

- Inference problem is to find a function $f: Z \rightarrow Y$ such that $f(z) \sim y$

- Common loss function $\mathrm{L}(f(z), y)$ for regression is the square loss

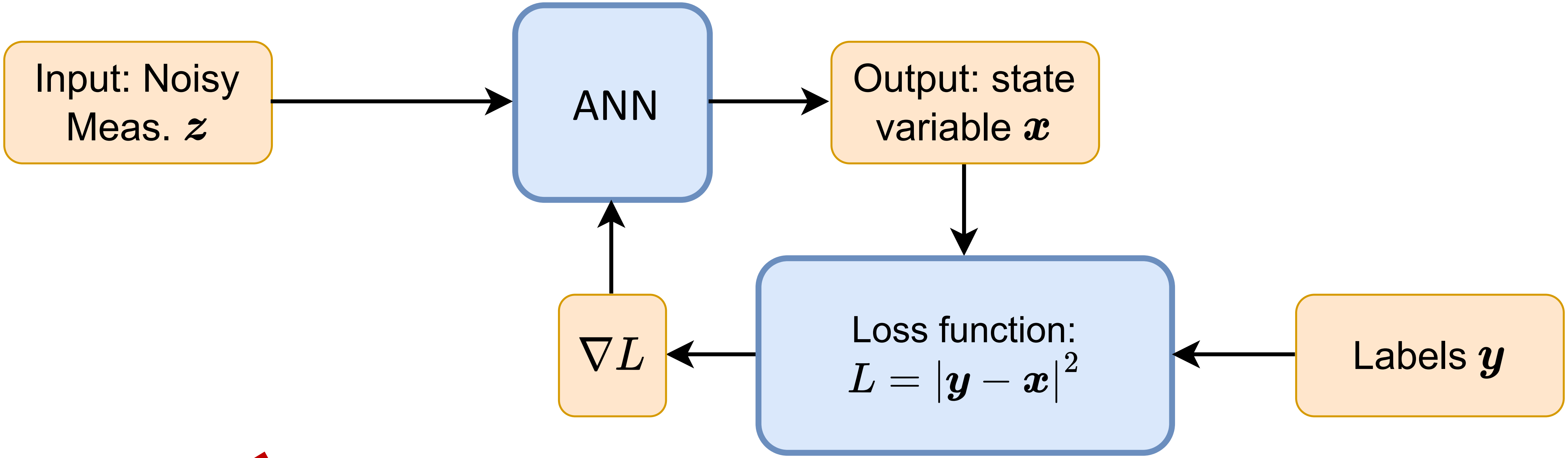
Artificial Neural Network (ANN)



$$f_\theta: Z \rightarrow Y$$

Note: this notation differs to conventional statistical learning where x is feature

Supervised learning for state estimation



Labels are not known

Newton's method generates label with "errors" $\hat{y} = y + \gamma^N$

Weakly-supervised learning

- Inaccurate input and output
- Learn with inaccurate labels $S = \{(z_1, \hat{y}_1), (z_2, \hat{y}_2) \ldots (z_t, \hat{y}_t)\}$
- Design a loss function $\mathrm{L}(f(z), \hat{y})$
- Objective: learning $f: Z \rightarrow Y$ such that $f(z) \sim y$

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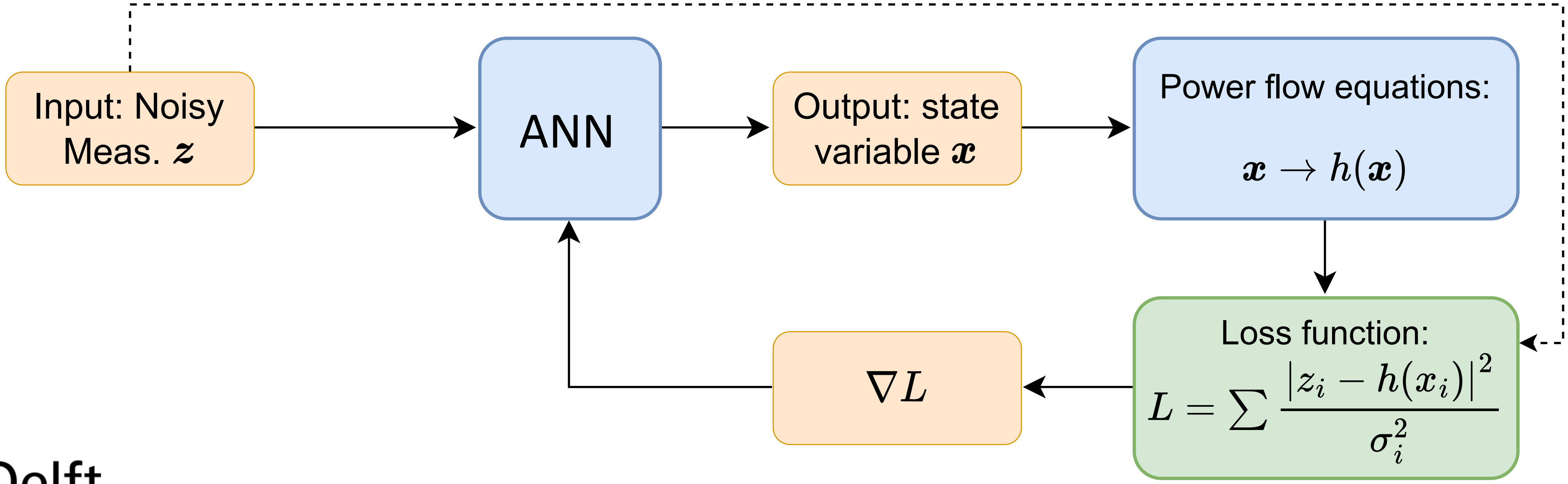
Y. -F. Li, L. -Z. Guo and Z. -H. Zhou, "Towards Safe Weakly Supervised Learning," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 1, pp. 334-346, 1 Jan. 2021, doi: 10.1109/TPAMI.2019.2922396.

Weakly-supervised learning for state estimation

- ANN $f(z) \rightarrow x$
- Measurement function using power flow equations $\mathrm{h}(\mathrm{x}) \rightarrow \hat{z}$



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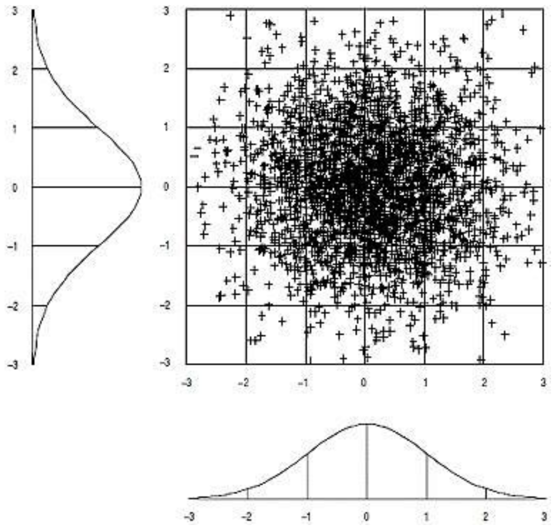
Respect the structure of the domain

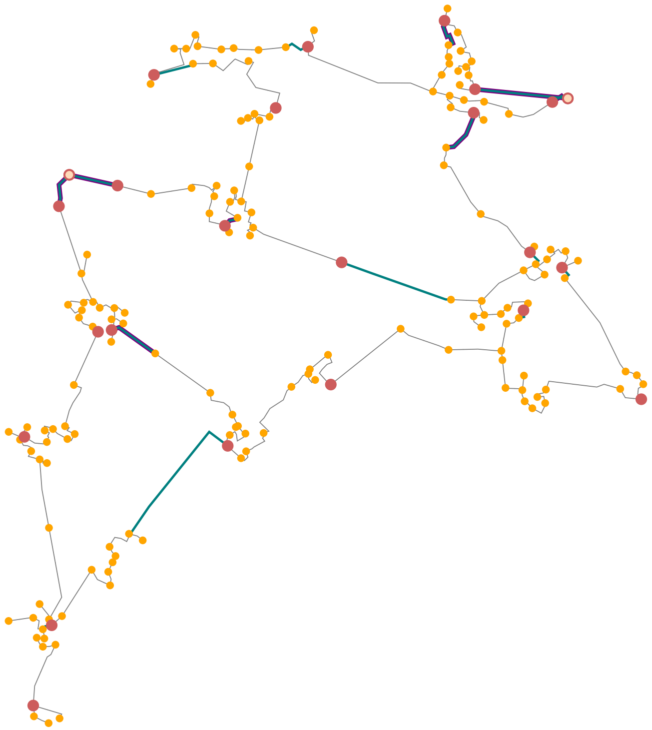
Noisy measurements



Power flow equations

$$h(x) = \begin{cases} V_i = V_i \\ \varphi_i = \varphi_i \\ P_{ij\rightarrow} = -V_i V_j\left[\mathbb{R}(Y_{ij})\cos\Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\sin\Delta\varphi_{ij}\right] + V_i^2\left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ P_{ij\leftarrow} = V_i V_j\left[-\mathbb{R}(Y_{ij})\cos\Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\sin\Delta\varphi_{ij}\right] + V_j^2\left[\mathbb{R}(Y_{ij}) + \frac{\mathbb{R}(Y_{sij})}{2}\right] \\ Q_{ij\rightarrow} = V_i V_j\left[-\mathbb{R}(Y_{ij})\sin\Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\cos\Delta\varphi_{ij}\right] - V_i^2\left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ Q_{ij\leftarrow} = V_i V_j\left[\mathbb{R}(Y_{ij})\sin\Delta\varphi_{ij} + \mathbb{I}(Y_{ij})\cos\Delta\varphi_{ij}\right] - V_j^2\left[\mathbb{I}(Y_{ij}) + \frac{\mathbb{I}(Y_{sij})}{2}\right] \\ I_{ij\rightarrow} = -\left|\frac{P_{ij\rightarrow} - jQ_{ij\rightarrow}}{\sqrt{3}V_i e^{-j\varphi_i}}\right| \\ I_{ij\leftarrow} = -\left|\frac{P_{ij\leftarrow} - jQ_{ij\leftarrow}}{\sqrt{3}V_j e^{-j\varphi_j}}\right| \\ P_i = -\sum_{j\in N_x(i)} P_{ij\leftarrow} + P_{ij\rightarrow} \\ Q_i = -\sum_{j\in N_x(i)} Q_{ij\leftarrow} + Q_{ij\rightarrow} \end{cases}$$

Topology



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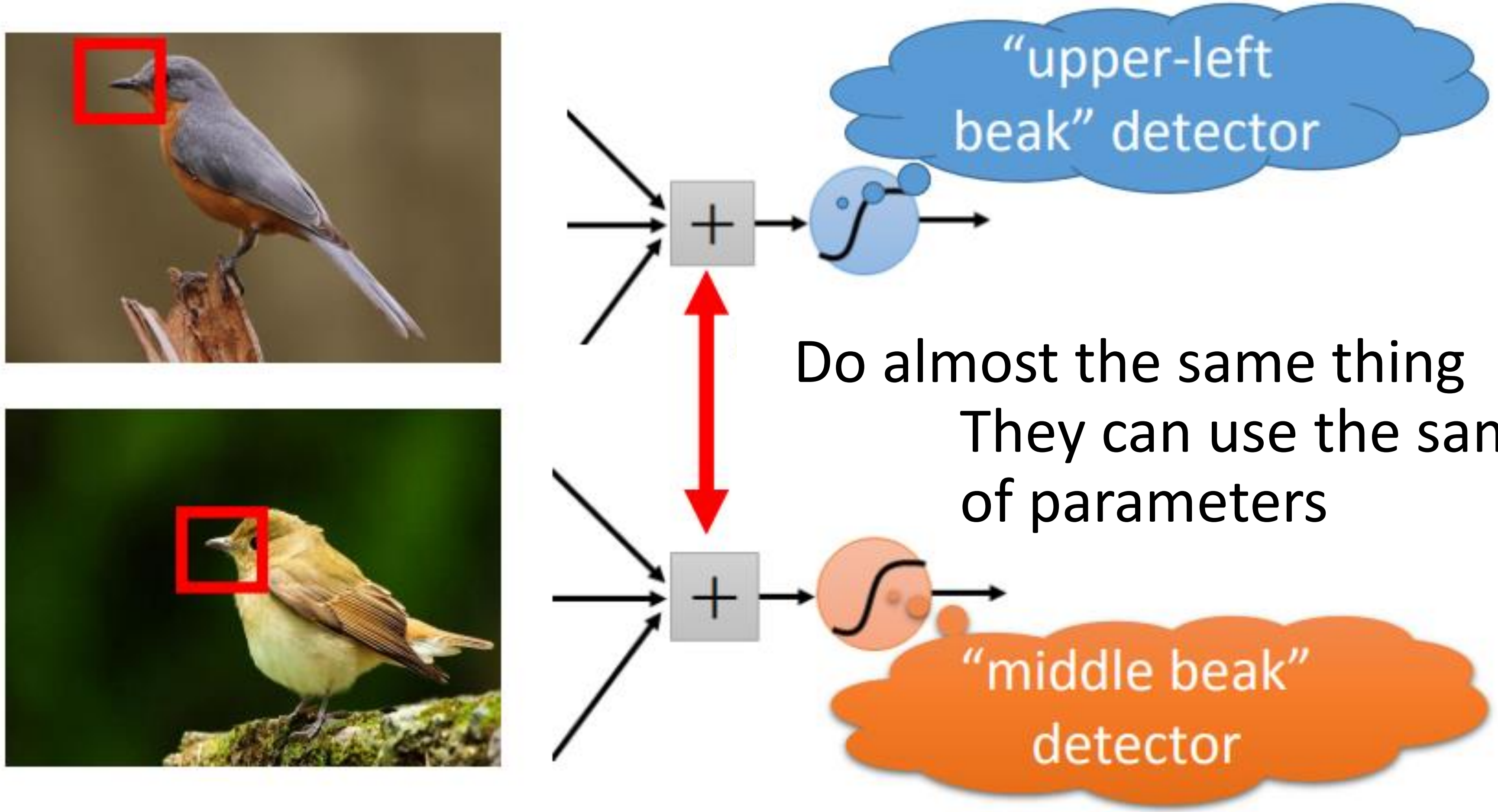
AI successes in the domain ‘images’

Property 1: Some patterns are much smaller than the whole image. A neuron does not have to see the whole image to discover the pattern.

James, Gareth, et al. *An introduction to statistical learning*. Vol. 112. New York: springer, 2013.

Property 2: The same patterns appear in different regions. (translated invariance)



Do almost the same thing

They can use the same set of parameters

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James, Gareth, et al. *An introduction to statistical learning*. Vol. 112. New York: springer, 2013.

CNN— Convolution layer

Stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	0	0	1	0
1	1	1	0	1	0
0	0	0	0	1	0

6×6 image

Those are the network parameters to be learned

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1 Matrix

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2 Matrix

3	-1	-3	-1
-2	1	-1	-3
-2	-4	0	1
-1	0	-2	-1

Property 1

Each filter detects a small pattern (3 x 3)

James, Gareth, et al. *An introduction to statistical learning*. Vol. 112. New York: springer, 2013.

CNN— Convolution layer

Stride=1

0	1	0	0	0	1
0	1	0	0	1	0
0	0	0	1	0	0
0	0	0	1	0	0
1	1	1	0	1	0
0	0	0	0	0	1

6×6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1
Matrix

0	1	-2	-1
-1	1	-1	-3
-1	-4	0	-1
-1	-1	-3	3

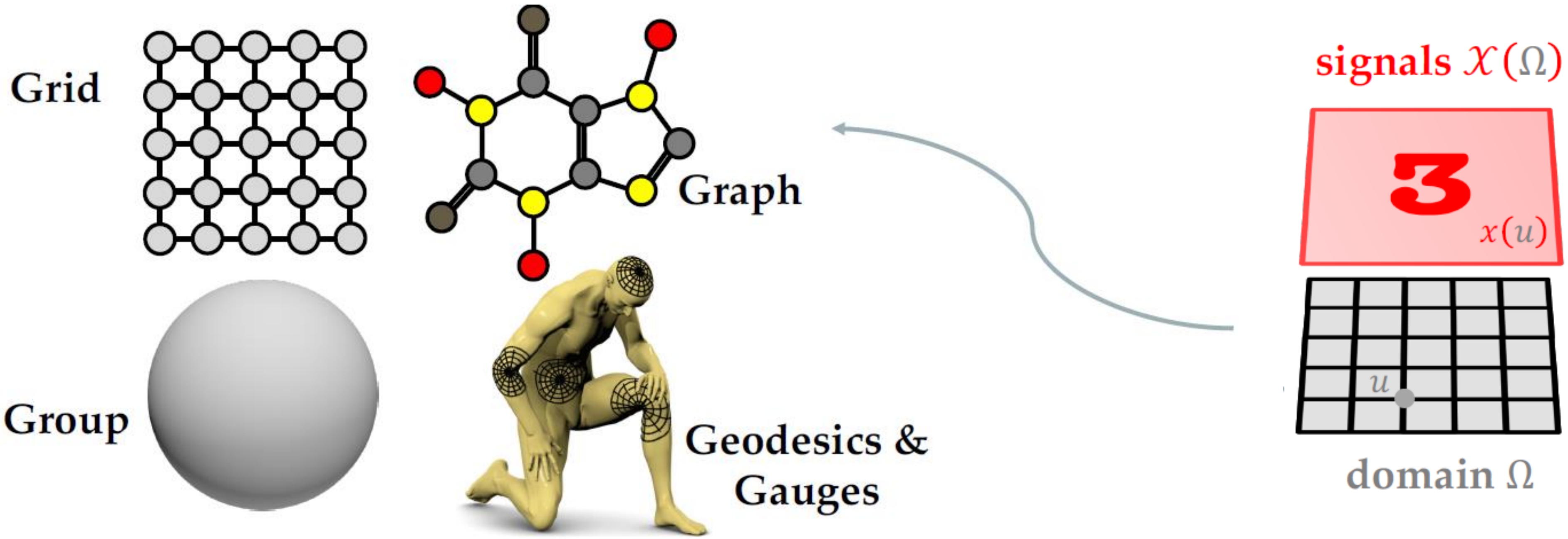
Property 2

The same patterns that appear in different regions can be detected.

Not much image-like data in power system operation and planning…

Geometric deep learning

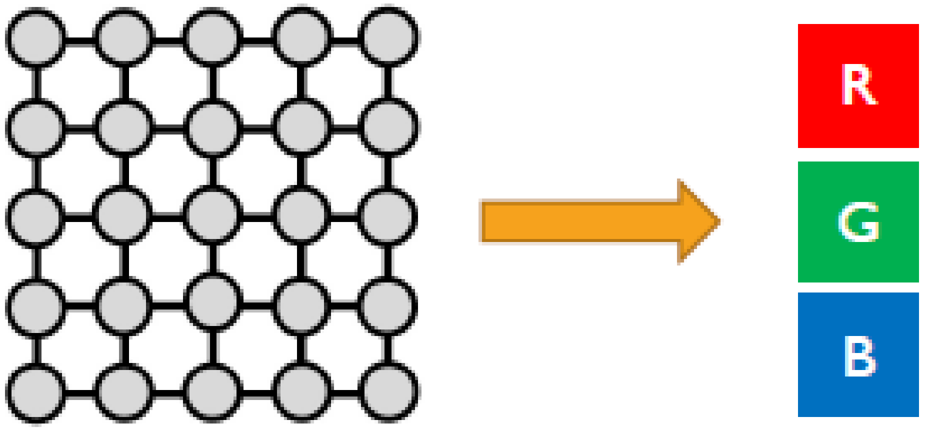
- Data are signals x on geometric domains Ω
- A signal x on Ω is a function $\chi(\Omega, C) = \{x: \Omega \to C\}$



Bronstein, M. M., Bruna, J., Cohen, T., & Veličković, P. (2021). Geometric deep learning: Grids, groups, graphs, geodesics, and gauges. *arXiv preprint arXiv:2104.13478*.

Graph Neural Networks (GNNs)

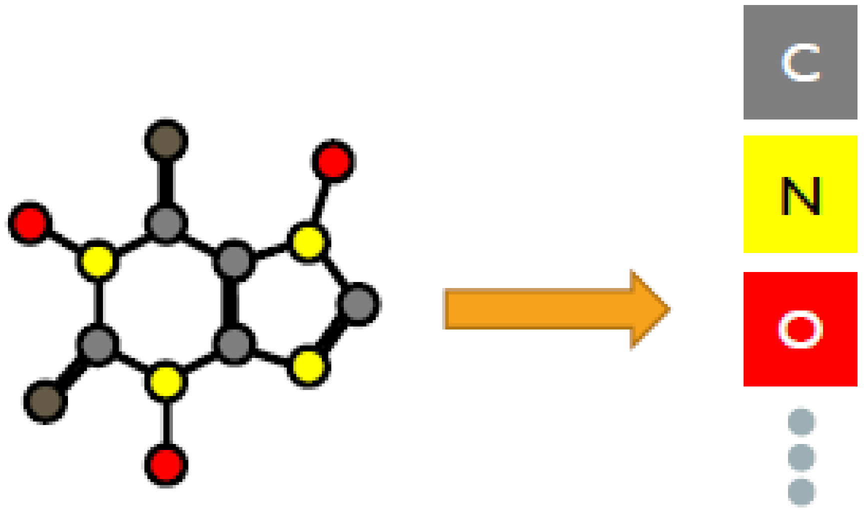
Example: $p \times p$ RGB image



$\Omega = \mathbb{Z}_p \times \mathbb{Z}_p$

$\mathcal{C} = \mathbb{R}^3$

Example: molecular graph



$\Omega = \{1, \ldots n\}$

$\mathcal{C} = \mathbb{R}^c$

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Bronstein, M. M., Bruna, J., Cohen, T., & Veličković, P. (2021). Geometric deep learning: Grids, groups, graphs, geodesics, and gauges. *arXiv preprint arXiv:2104.13478*.

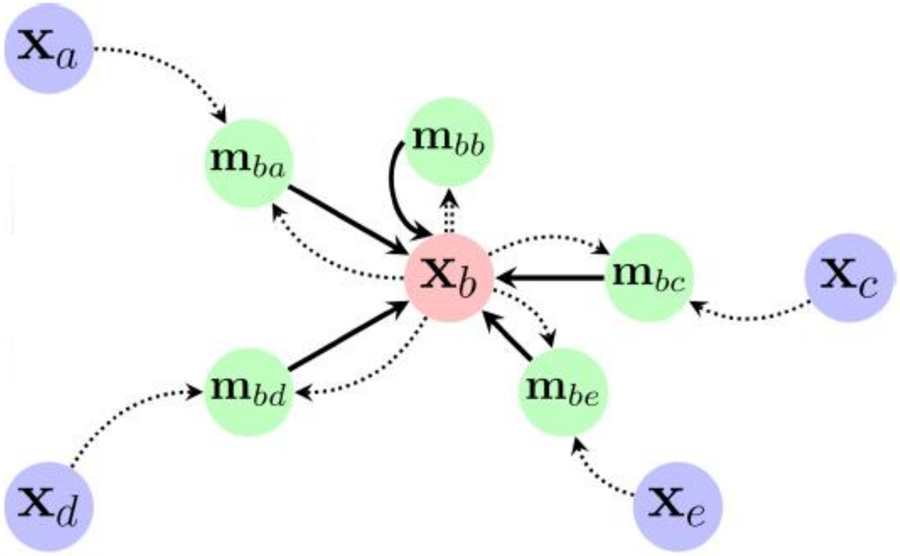
Locality on graphs: Neighbourhoods

- Consider graph $G = (V, E)$ where $E \subseteq V \times V$
- Adjacency matrix A with

$$a_{ij} = \begin{cases} 1, & (i,j) \in E \\ 0, & (i,j) \notin E \end{cases}$$

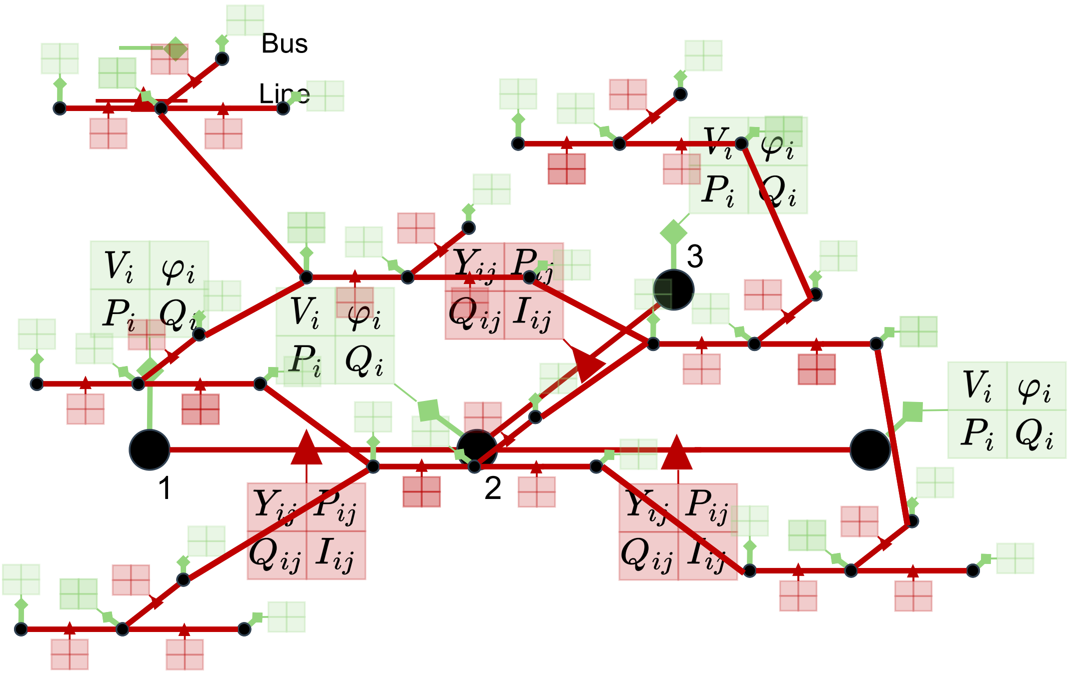
- (1-hop) neighbourhood $N_i = \{j: (i,j) \in E \cup (j,i) \in E\}$ for a node i
- Neighbourhood features $\boldsymbol{X}_{N_i} = \{\{x_j: j \in N_i\}\}$
- Local function, $\phi(x_i, \boldsymbol{X}_{N_i})$, operating over them.

Convolutional layers & message passing



$$\eta_i = \phi\left(x_i, \bigoplus_{j \in N_i} \psi(x_i, x_j)\right)$$

State estimation



Battaglia, P. W., Hamrick, J. B., Bapst, V., Sanchez-Gonzalez, A., Zambaldi, V., Malinowski, M., ... & Pascanu, R. (2018). Relational inductive biases, deep learning, and graph networks. *arXiv e-prints*, arXiv-1806.

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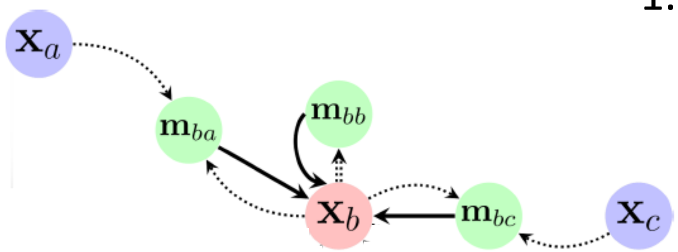
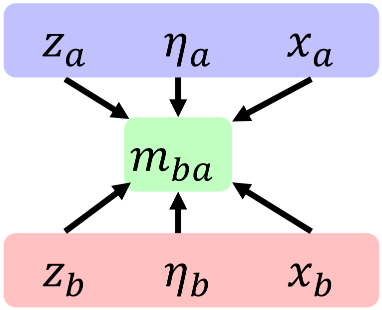
Deep statistical solver



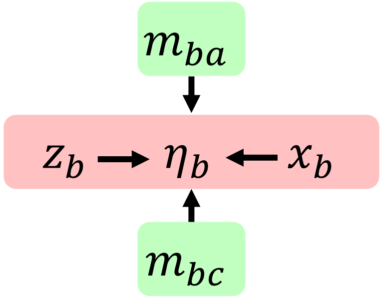
0. Initialize $x = x^0, \eta = \eta^0$

1. update edges



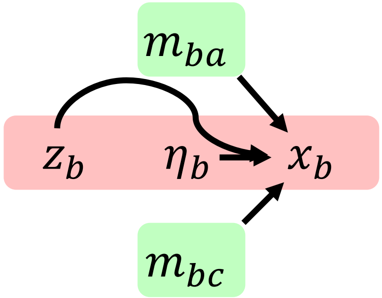
$$m_{ba} \leftarrow m_{ba} + \Delta t \times \left[\phi_\theta^{ba}(t, z_a, \eta_a, x_a) + \phi_\theta^{ba}(t, z_b, \eta_b, x_b)\right]$$

2. update vertices



$$\eta_b \leftarrow \eta_b + \Delta t \times \phi_\theta^{b}(t, z_b, \eta_b, x_b, m_{ba}, m_{bc}, m_{bb})$$

3. update label



$$x_b \leftarrow x_b + \Delta t \times \phi_\theta^{bx}(t, z_b, \eta_b, x_b, m_{ba}, m_{bc}, m_{bb})$$

Perform $t = 1, \dots T$

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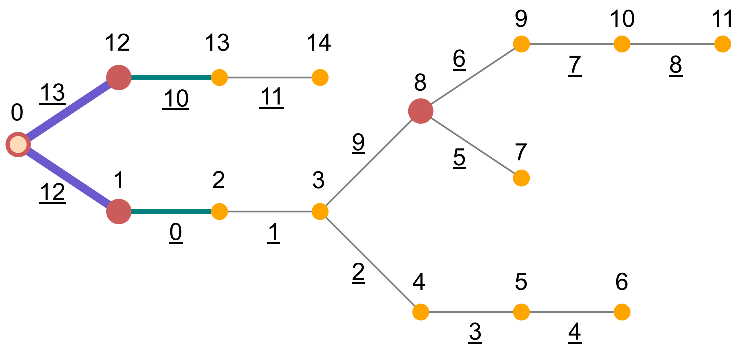
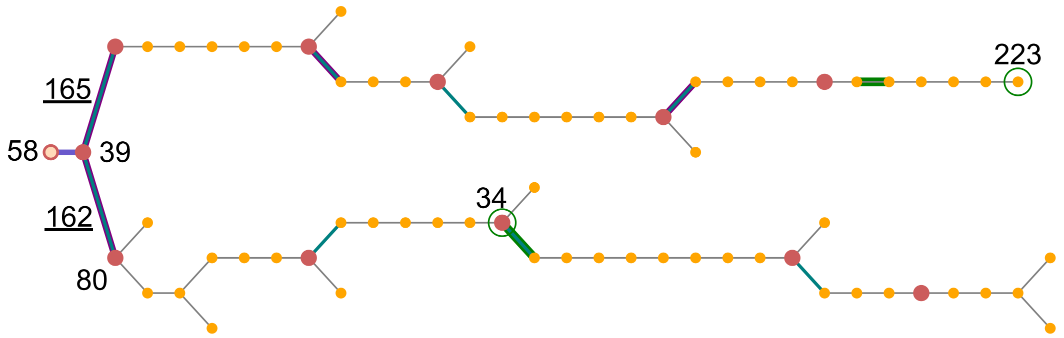
Balthazar Donon, Liu, Z., Liu, W., Guyon, I., Marot, A., & Schoenauer, M. (2020). Deep statistical solvers. *Advances in Neural Information Processing Systems*, *33*, 7910-7921.

Case study: power systems

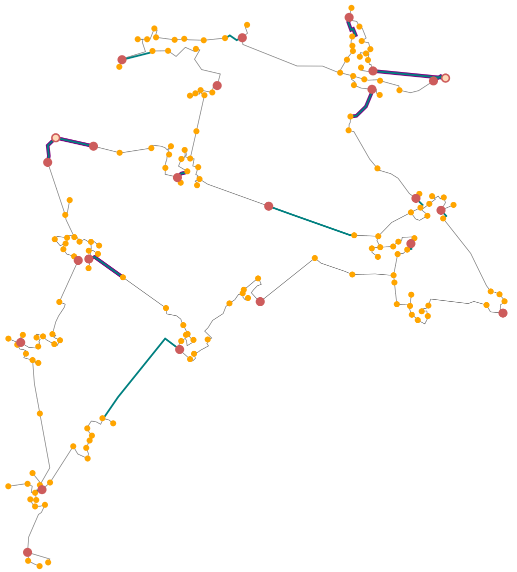
14-bus CIGRE MV grid from



70-bus Oberrhein MV sub-grid from



179-bus Oberrhein MV grid from



- Trafo
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- Focus bus

B. Habib, E. Isufi, W. v. Breda, A. Jongepier and J. L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," in IEEE Transactions on Power Systems, doi: 10.1109/TPWRS.2023.3290358.

Case study settings

Data generation

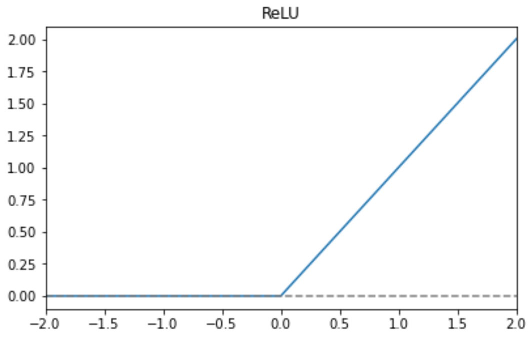
- 8640 days, with each 24 hours, +/- 15% around Gaussian on loads
- Balanced system, pandapower, AC power flow
- Measurement noise
  - $0.5\% - 2\%$ for the voltage and current measurement
  - $1\% - 5\%$ for the active and reactive power measurement
  - Pseudomeasurement were generic load profiles
- Baselines
  - Weighted least square (WLS)
  - Feedforward Neural Network (FFNN)
  - supervised DSS^2

Model & hyperparameters

- Hyper-Heterogeneous Multi GNN
- Training 80%, validation 10%, testing 10%
- Grid search on learning rate λ, layer dimensions d, and layer numbers

Assume stable system

$$L(\boldsymbol{z}, \boldsymbol{x}) = \sum_{i \in m} \frac{|z_i - h_i(\boldsymbol{x})|^2}{R_{ii}} + \lambda[\text{ReLU}(V - 1.05) + \text{ReLU}(0.95 - V) + \text{ReLU}(\text{ loading } - 100) + \text{ReLU}(\varphi - 0.25) + \text{ReLU}(-0.25 - \varphi)]$$



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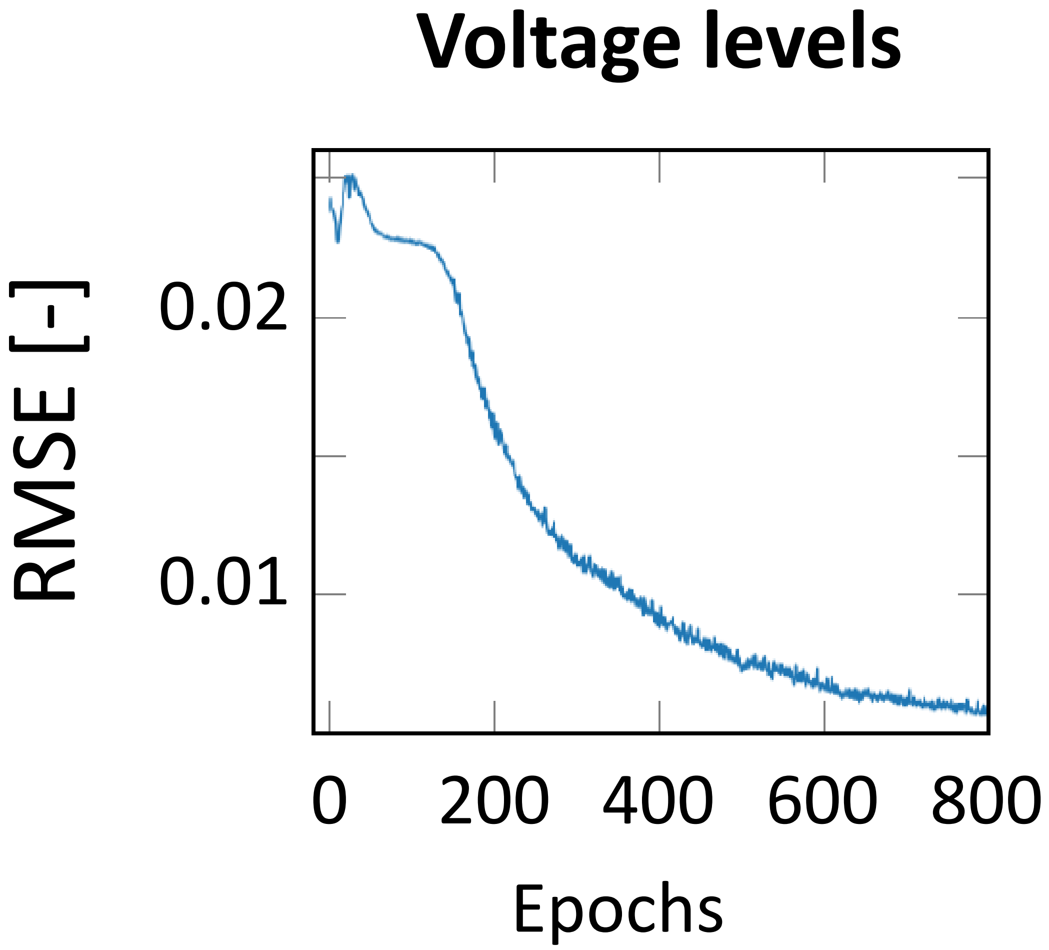
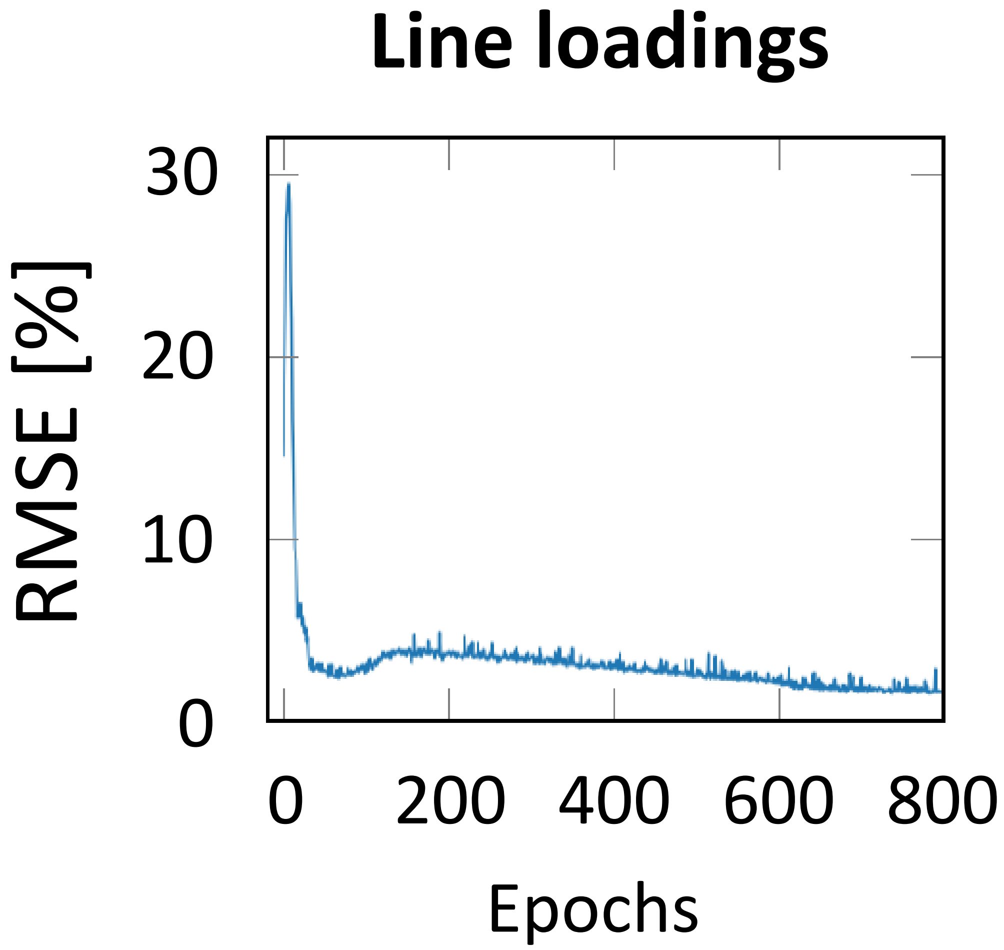
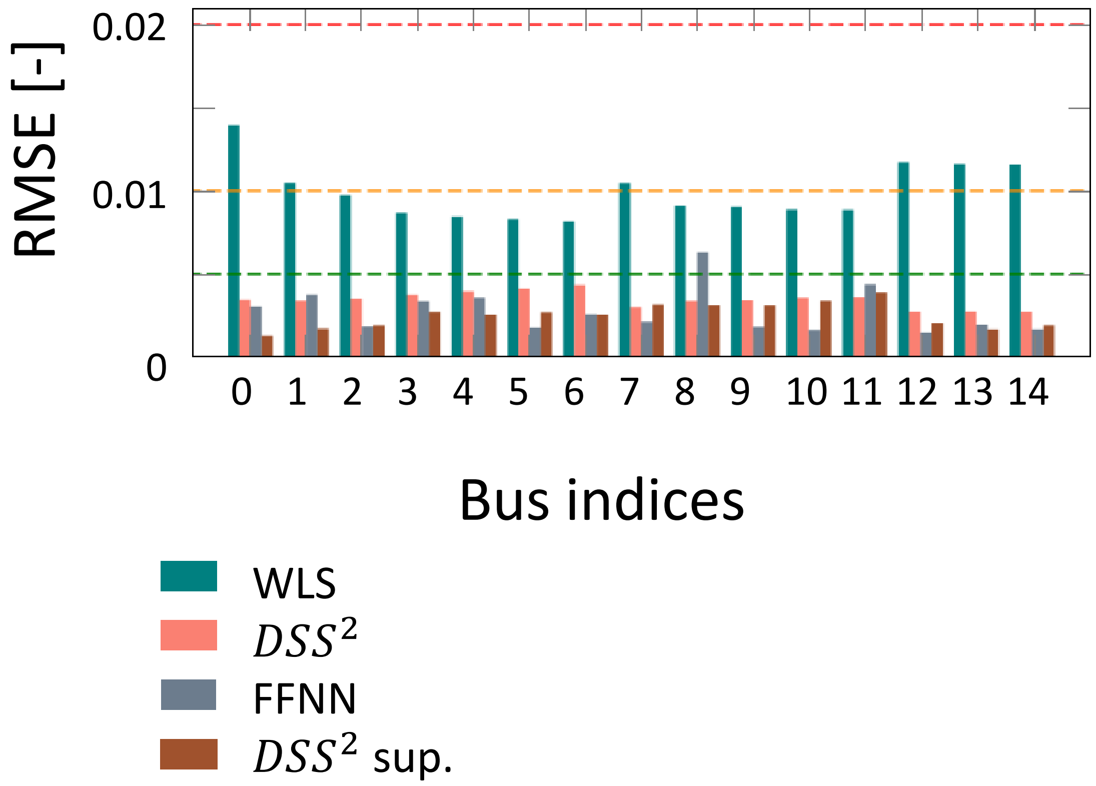
Training performance 14-bus system



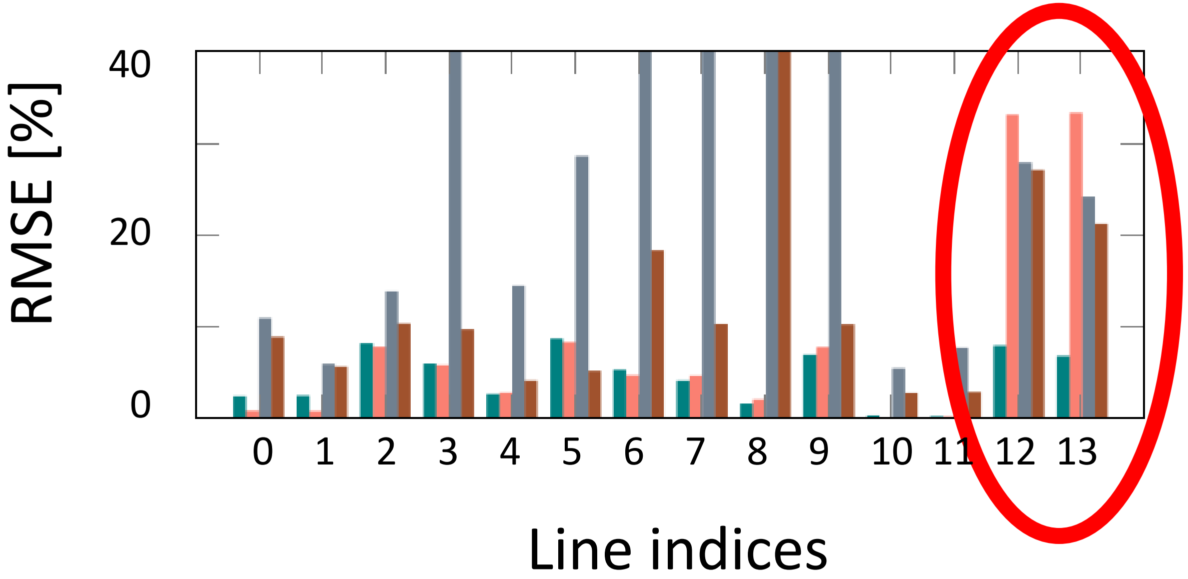


State estimation 14-bus system

Voltage levels



Line loadings



Model inaccuracies: assumed transformer = lines!

Accuracy

	14-bus system			
Metric \ approach	WLS	ANN	sup DSS^2	DSS^2
Voltage RMSE $[10^{-3}]$	10	3	**3**	3
Line loading RMSE [%]	**3**	42	13	4
Trafos loading RMSE [%]	**5**	39	14	8

* with increased convergence rate
** with higher tolerance and more iterations

Convergence

	14-bus system				70-bus Oberrhein			179-bus Oberrhein	
Metric \ approach	WLS	ANN	sup DSS^2	DSS^2	WLS	WLS*	DSS^2	WLS**	DSS^2
Voltage RMSE $[10^{-3}]$	10	3	3	3	31	6	2	10	2
Line loading RMSE [%]	3	42	13	4	17	15	2	6	3
Trafos loading RMSE [%]	5	39	14	8	39	24	3	4	4
Convergence [%]	100	100	100	100	25	100	100	53	100

- WLS did not converge in some instances (25%-50%)
- DSS^2 always ‘converges’ (produces a label)

* with increased convergence rate
** with higher tolerance and more iterations

Computational 'prediction' time [ms]

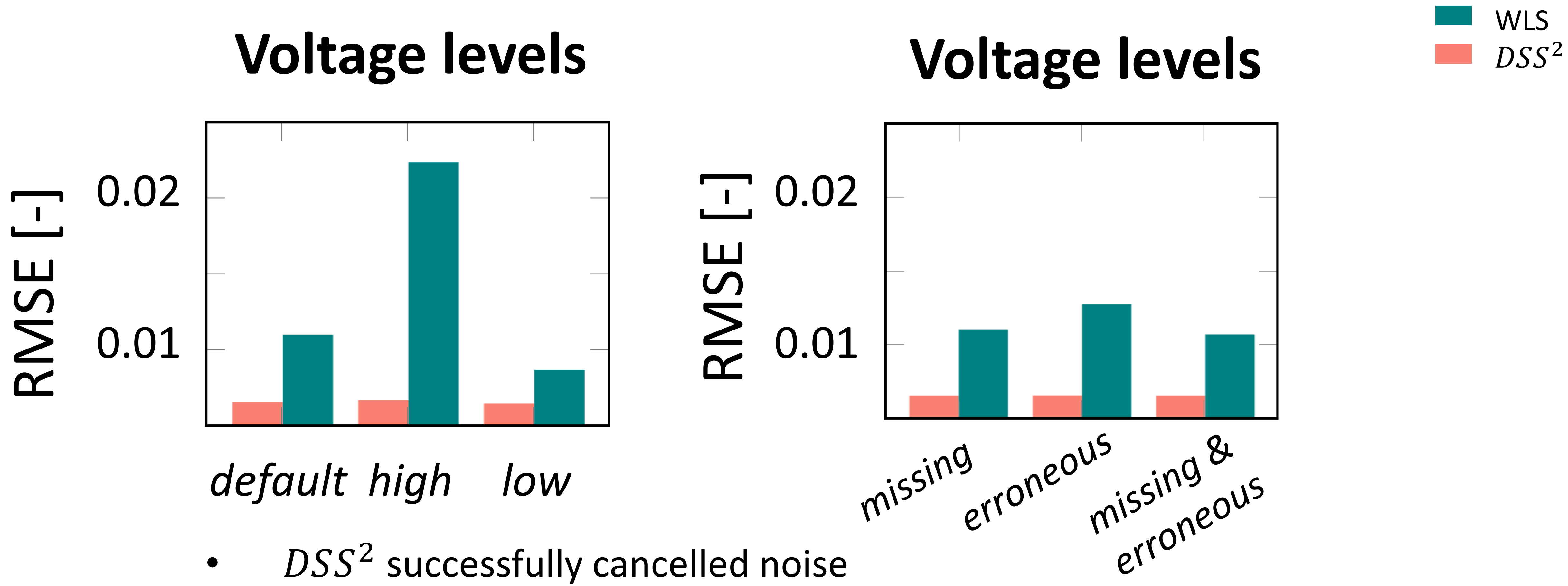
	14-bus system				70-bus Oberrhein			179-bus Oberrhein	
Metric \ approach	WLS	ANN	sup DSS^2	DSS^2	WLS	WLS*	DSS^2	WLS**	DSS^2
Voltage RMSE $[10^{-3}]$	10	3	3	3	31	6	2	10	2
Line loading RMSE [%]	3	42	13	4	17	15	2	6	3
Trafos loading RMSE [%]	5	39	14	8	39	24	3	4	4
Convergence [%]	100	100	100	100	25	100	100	53	100
Computational time $[ms]$	86	**4**	5	6	123	161	**26**	1212	**58**

~10 **~2**

- WLS increases significantly with system size
- DSS^2 increases moderately with system size

* with increased convergence rate
** with higher tolerance and more iterations

Noise and missing, erroneous data



- DSS^2 successfully cancelled noise
- DSS^2 was not trained to handle such events
- GNN architecture increased the interpolation capabilities by incorporating the data symmetries w.r.t. the underlying graph

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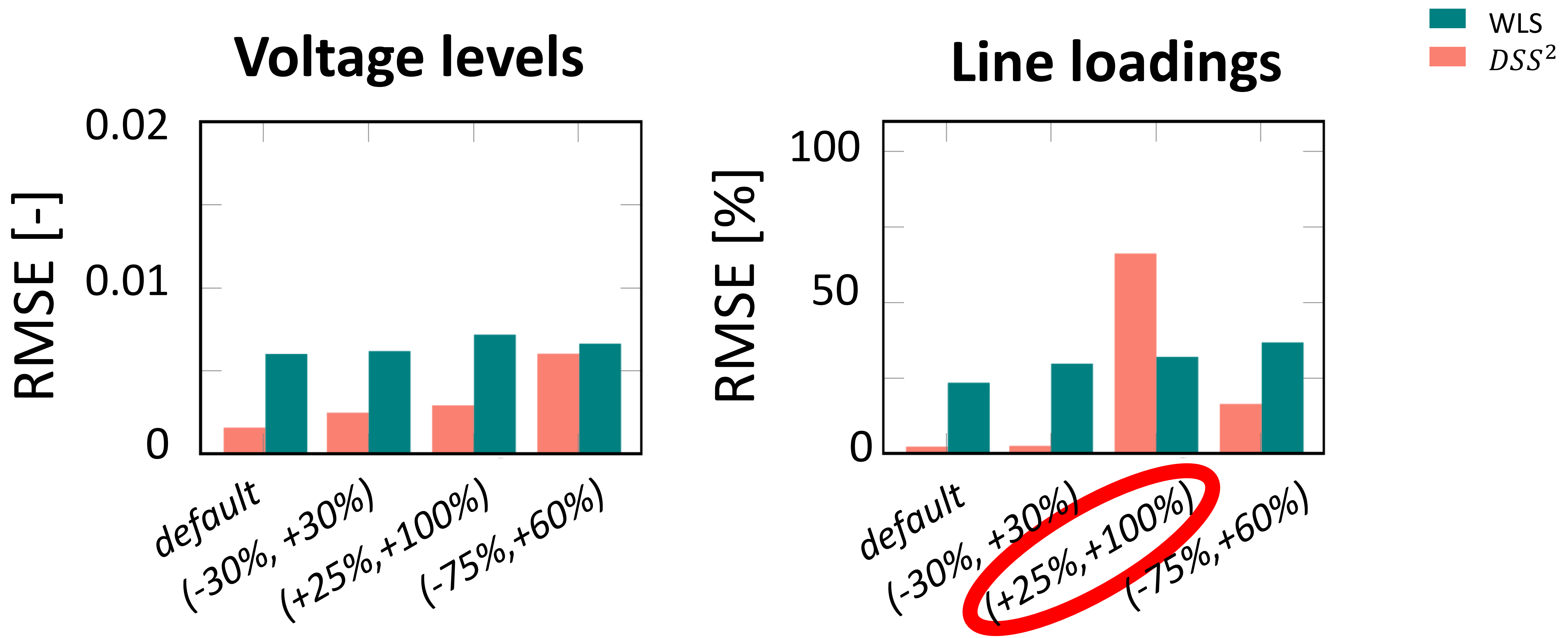
Increase in (generation, load)



Limitation: high load levels

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Drivers

- Combining interdisiplinary approaches from statistics, machine learning and mathematical optimization to a power system problem
- Learning without labels and with structural information (inducing bias, regularising with physics, etc)

Generic barriers

- Curse of dimensionality
- Performance on out-of-distribution
- Guarantees

Challenges applying GNNs to power systems

- Power systems are not always well-meshed graphs
- Enforcing power flow equations
- Addressing nonlinearity -> multiple solutions
- Graph topology changes (dynamic graphs)
- …

Contact and references

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Reference

- B. Habib, E. Isufi, W. van Breda, A. Jongepier and J. L. Cremer, "Deep Statistical Solver for Distribution System State Estimation," in *IEEE Transactions on Power Systems*, vol. 39, no. 2, pp. 4039-4050, March 2024, doi: 10.1109/TPWRS.2023.3290358. **[open access]**
- Code: https://github.com/TU-Delft-AI-Energy-Lab

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Related references & code

Workshop on AI for Energy Systems: https://github.com/TU-Delft-AI-Energy-Lab/Workshop_AI_for_Intelligent_Energy_Systems

Weakly supervised learning for power systems (**Example code:** https://github.com/TU-Delft-AI-Energy-Lab/Deep-Statistical-Solver-for-Distribution-System-State-Estimation)

- Bastien Giraud, Ali Rajaei, Jochen L. Cremer "Constraint-Driven Deep Learning for N-k Security Constrained Optimal Power Flow", *Electric Power System Research and 2024 IEEE Power System Computation Conference*
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- A. Bugaje, J. L. Cremer, M. Sun, G. Strbac, "Selecting DT Models for Security Assessment using ROC- and Cost-Curves", *Energy and AI*, 2021: 100110.
- J. L. Cremer, G. Strbac, "A Machine-learning based Probabilistic Perspective on Dynamic Security Assessment" *International Journal of Electrical Power & Energy System, 2020*

Interpretable models (**Example code:** https://github.com/JochenC/From-optimization-based-machine-learning-to-interpretable-security-rules-for-operation)

- J. L. Cremer, I. Konstantelos, G. Strbac, "From Optimization-based Machine Learning to Interpretable Security Rules for Operation", *IEEE Transactions on Power Systems, 2019*
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Sampling with optimisation-based constraints (**Example code:** https://github.com/TU-Delft-AI-Energy-Lab/Split-based-sampling)

- Al-Amin Bugaje, Jochen L. Cremer, Goran Strbac "Generating Quality Datasets for Real-Time Security Assessment: Balancing Historically Relevant and Rare Feasible Operating Condition" *International Journal of Electrical Power & Energy Systems, 2023*

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Thank you