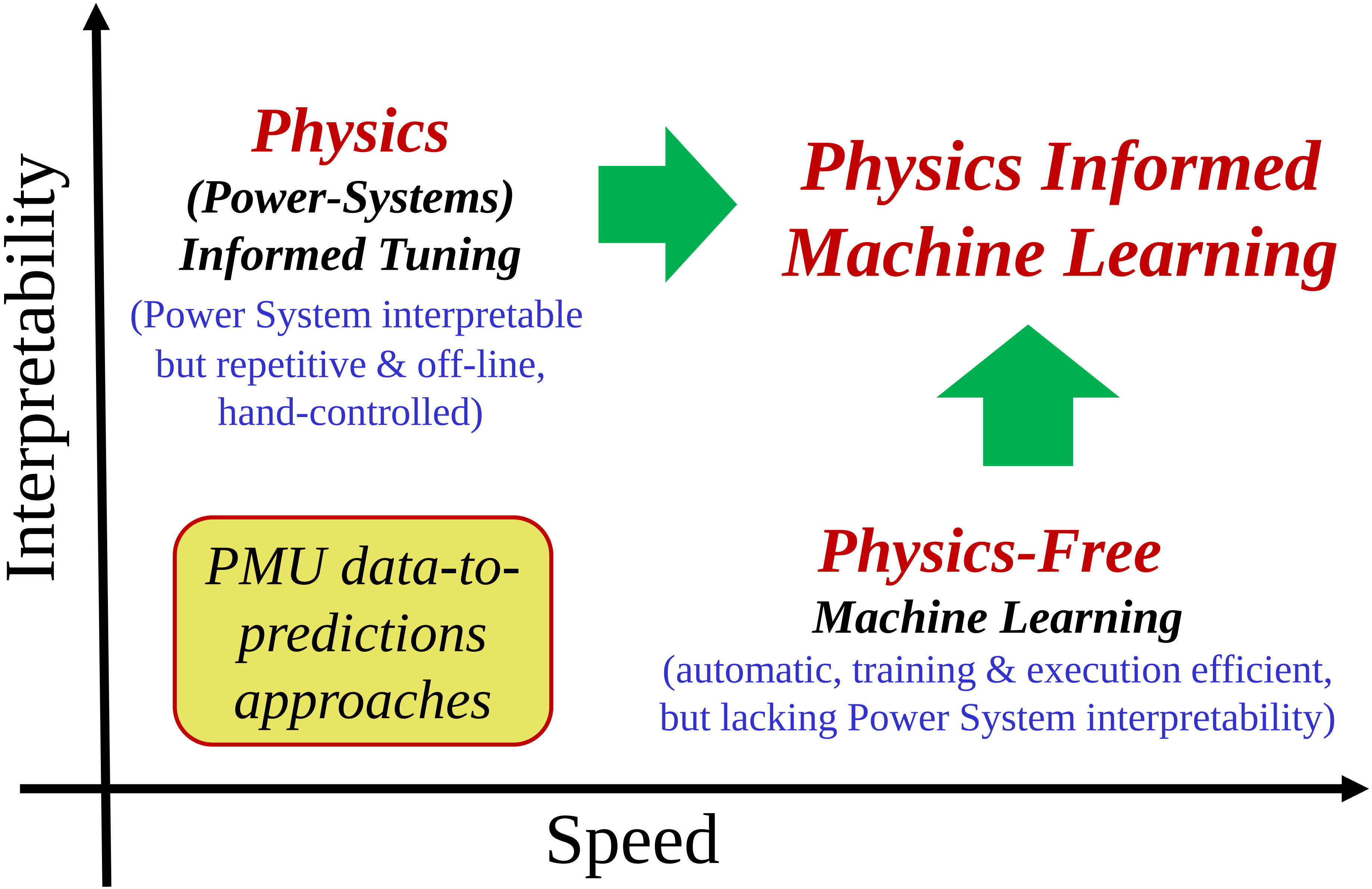
Data Analytics in Power Grids: Tractable Algorithms & Path Forward

Deep Deka

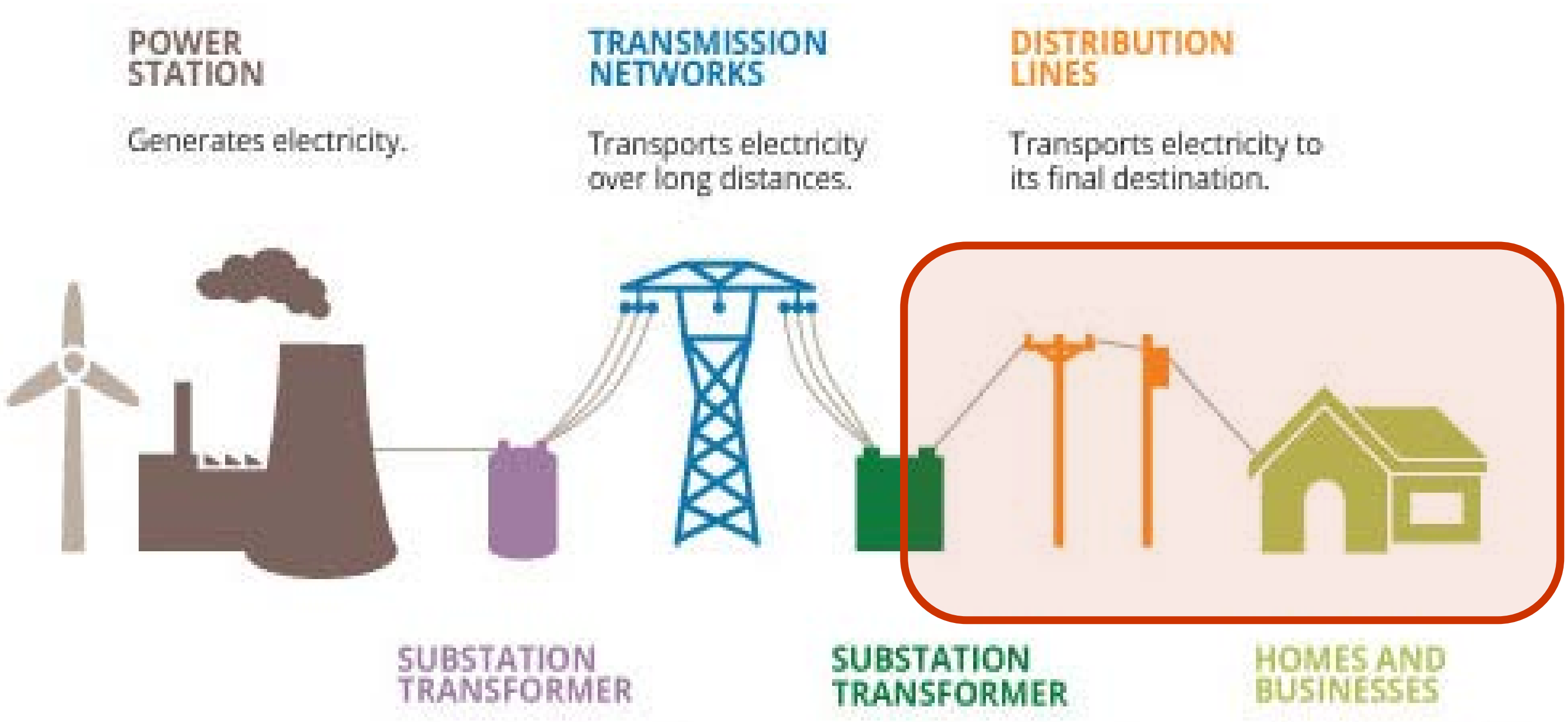
Theory Division

deepjyoti@lanl.gov



- Advantage: Provable results, Missing data extensions

Transmission and Distribution Grid

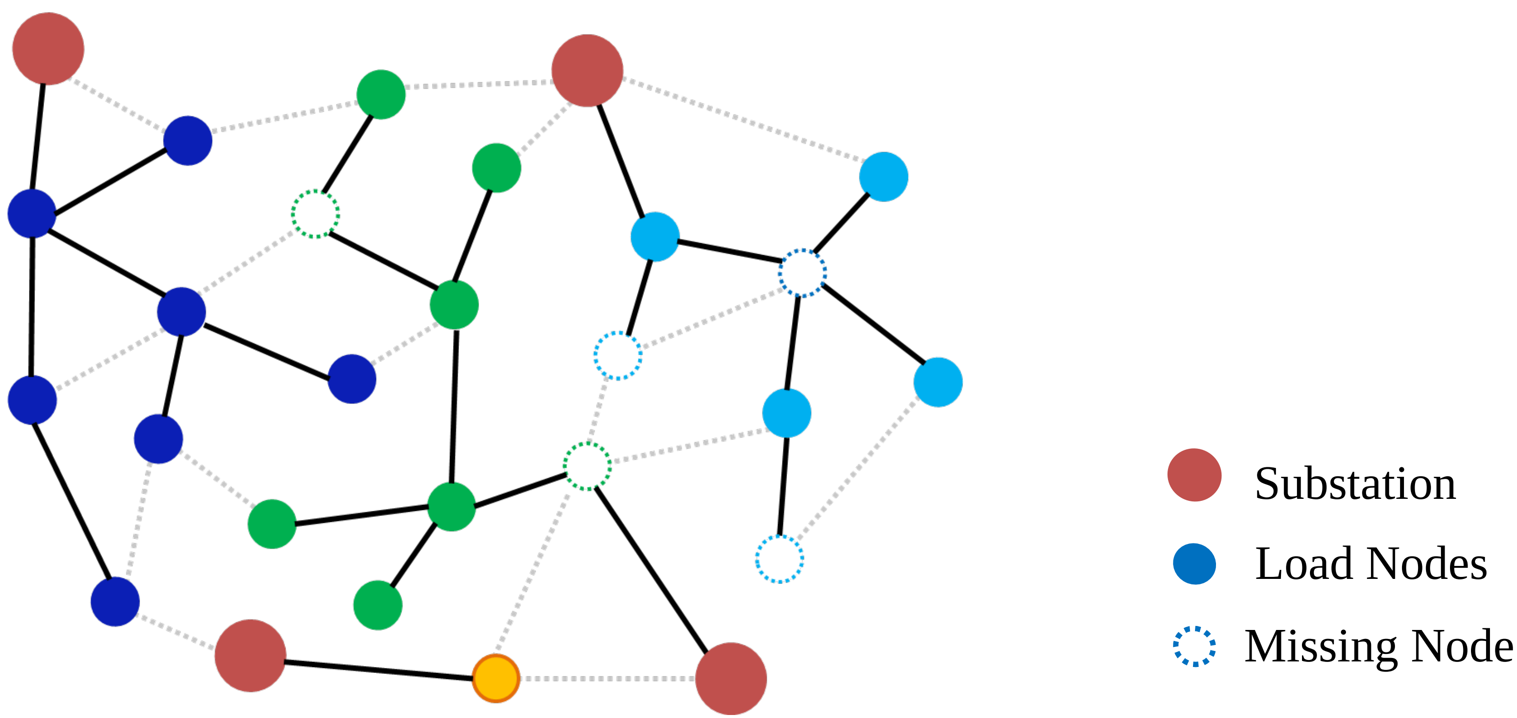


- Voltage: High → Medium → Low

Distribution Grid Learning Problems:

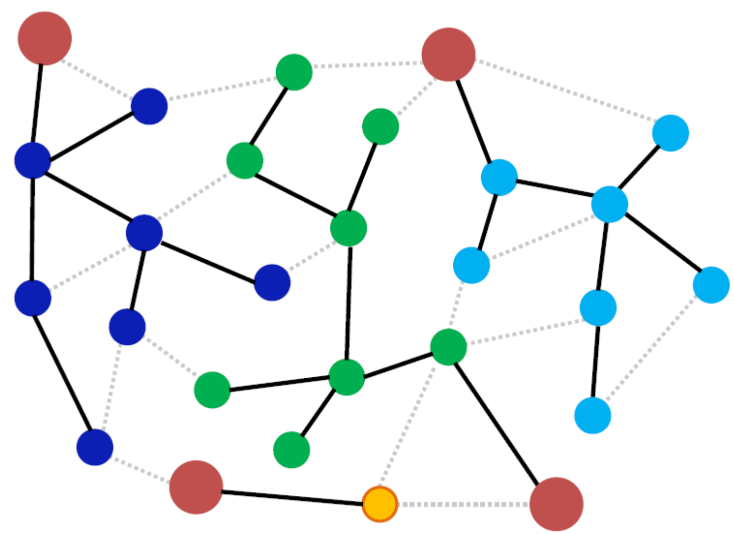
- Structure Learning
- Learning Line Impedances
- Incomplete observations

with theoretical guarantees



Applications of PMUs

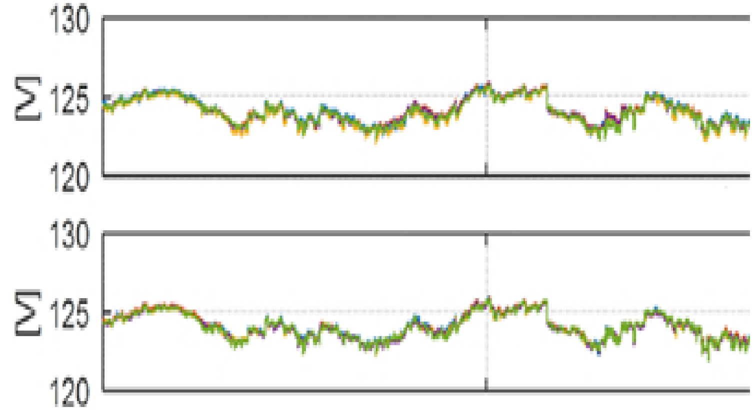
- Structure:
  - Failure/Fault Identification
  - Connection/phase verification
- Impedance Estimation:
  - Non-intrusive control
  - Use in DSO optimization
- Learning with Missing Data:
  - Privacy quantification
  - Meter Location Selection



Learning with nodal voltages

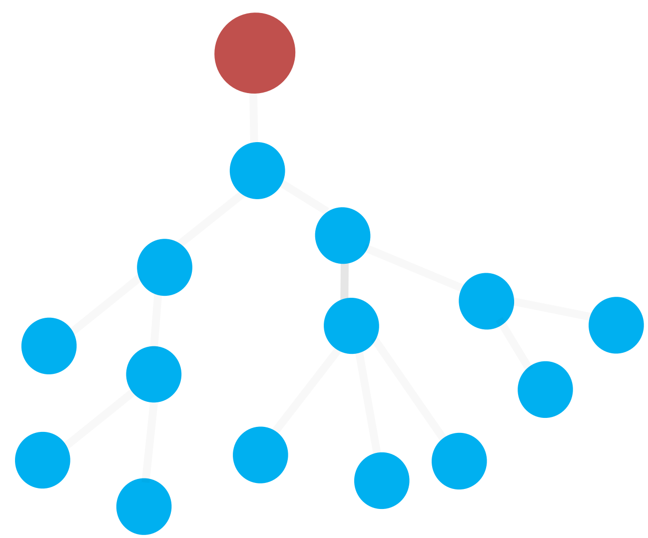
- Data: Time-series Nodal voltages at all nodes

$$\mu_V = \mathbb{E}[V]$$
$$\Omega_V = \mathbb{E}[V - \mu_V][V - \mu_V]^T$$



- Unobserved: all lines
- Estimate: Operational Topology

- IEEE Trans. Control of Networks 2017



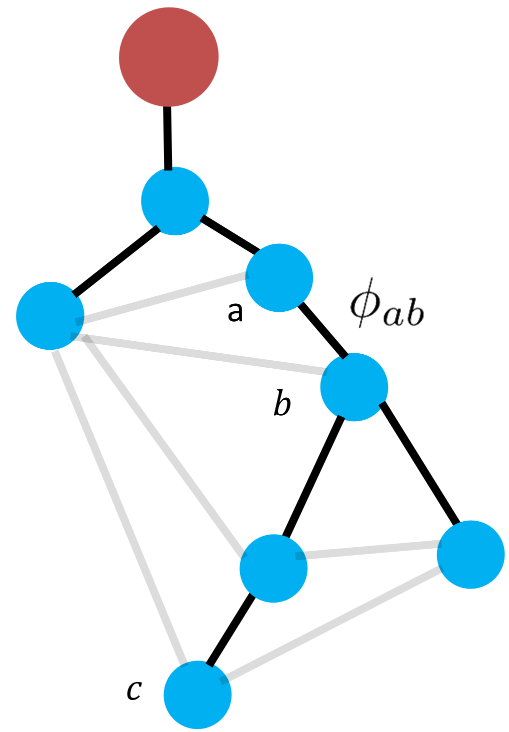
Topology Reconstruction

Greedy Topology Learning:

- Spanning Tree with edge weights given by

$$\boxed{\phi_{ab} = \mathbb{E}[(V_a - \mu_{V_a}) - (V_b - \mu_{V_b})]^2}$$

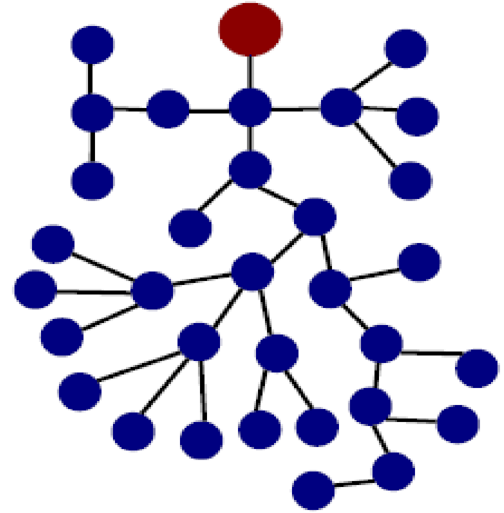
- NO additional information needed
- Works for monotonic flows (gas,water, heating)



Sample Complexity :

For a grid with constant depth and sub-Gaussian complex power injections, $O(|V|^2 \log(|V|/\eta))$ samples recovers the true topology with probability $1-\eta$.

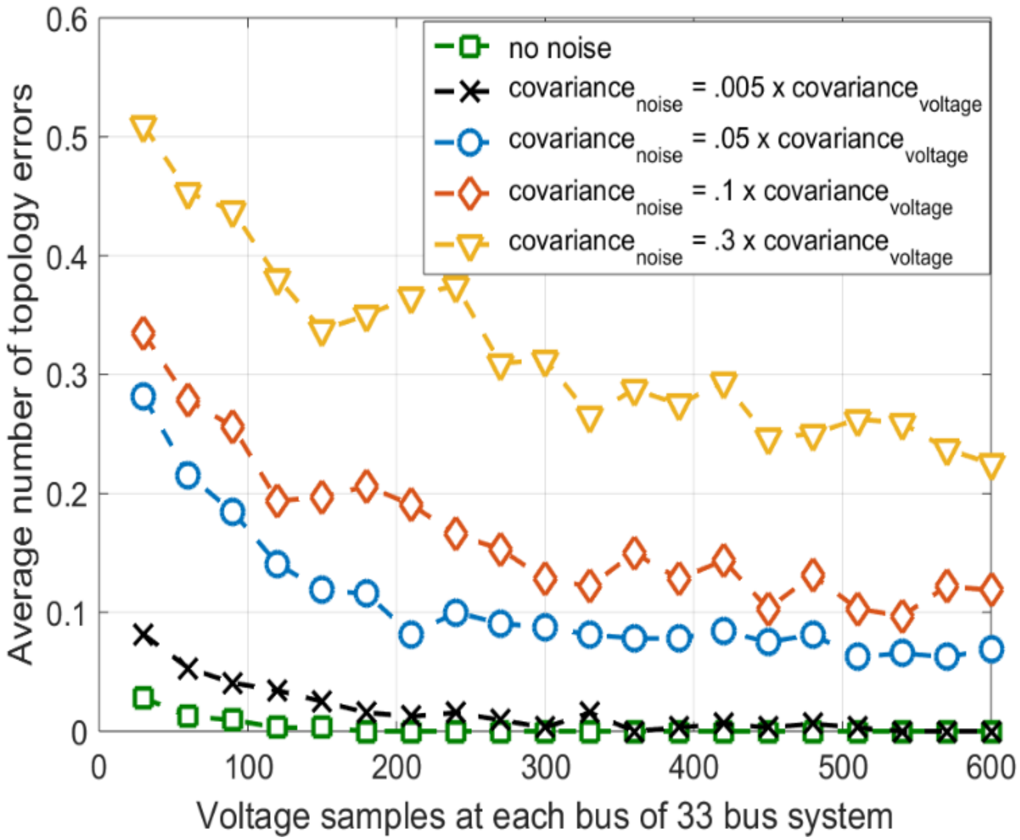
Topology Learning (No missing nodes)



33-bus test system, Matpower

Reference: 12 KV substation voltage

Effect of Noise



Extension:

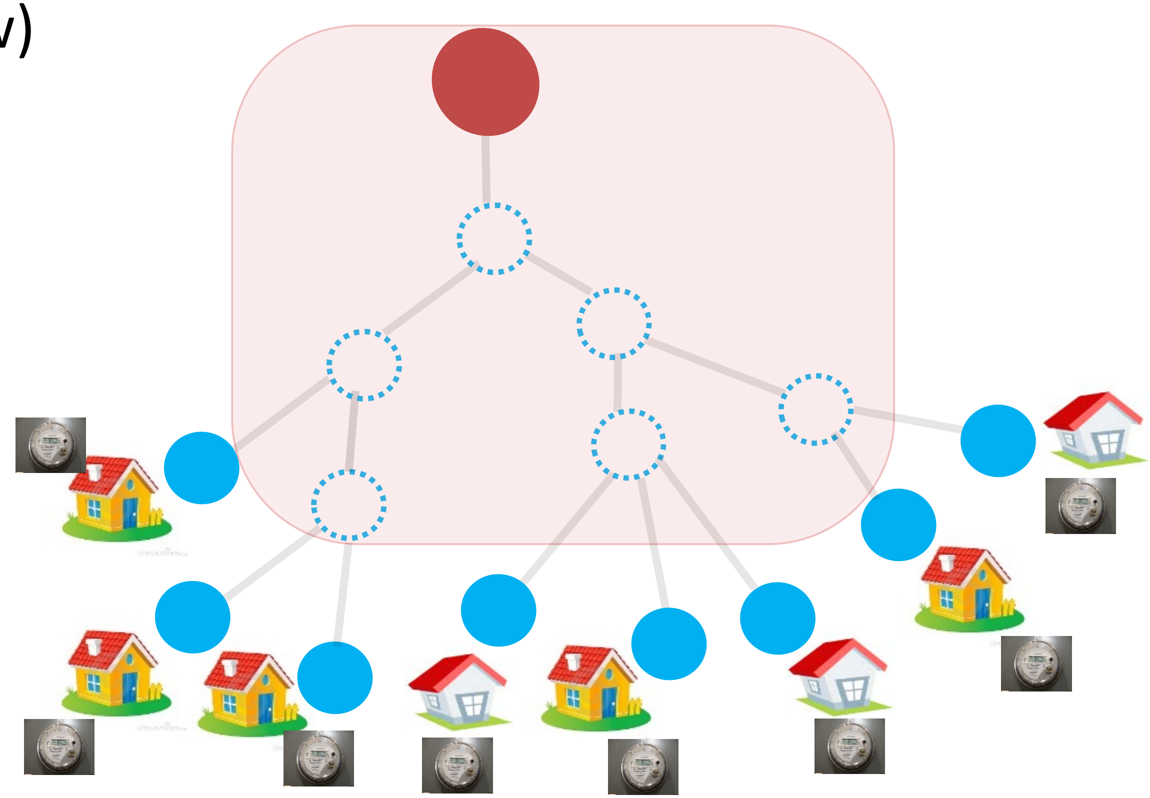
a. Missing nodal voltages (under review, TCNS)

b. Three phase systems (Trans. Power Systems, 2019.)

Learning with *end-users*

- Data: Nodal voltages and **injection samples** at leaves
- Estimate: Operational Topology **+ Line Impedance**

- PSCC 2018,
- IEEE TCNS (under review)



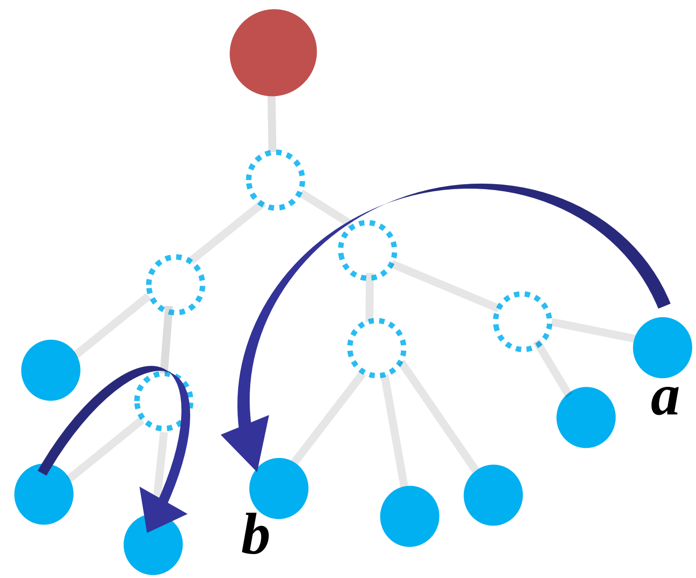
Learning with *end-users*

- Data: Time-series Nodal voltages and injection samples at leaves
- Algorithm:

➢ Find *effective impedances* between leaves (using voltage, injections)

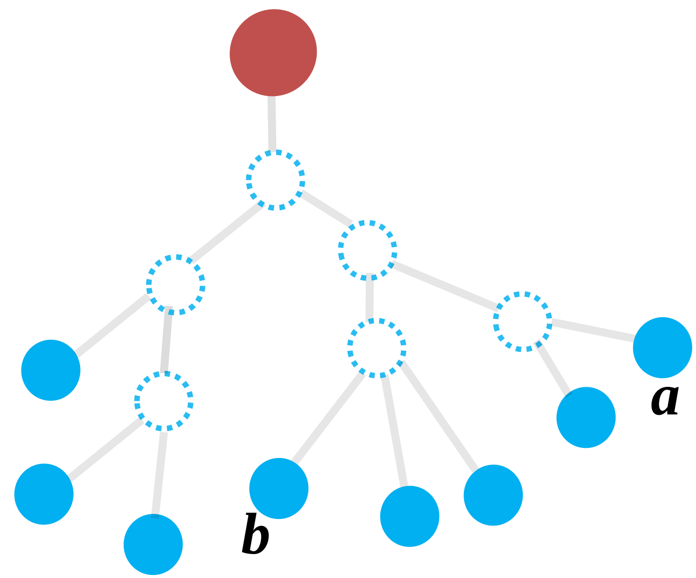
$$R_{eff}(a,b) = \sum_{edge \in Path_{ab}} R_{edge}$$

❖ Key: Effective resistances are additive on trees

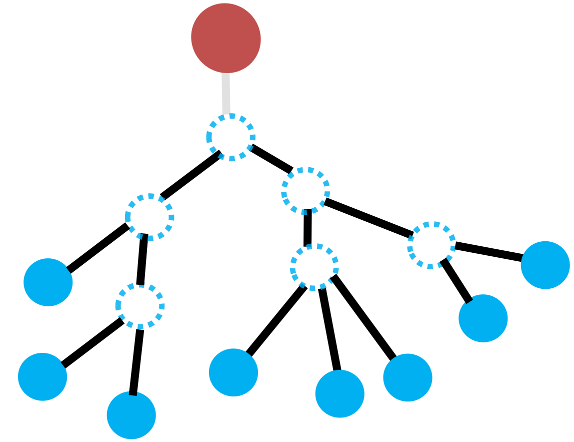


Learning with *end-users*

- Data: Time-series Nodal voltages and injection samples at leaves
- Algorithm:
  - Find *effective impedances* between leaves
  - ***Recursive Grouping Algo*** to learn topology & distances from known effective impedances



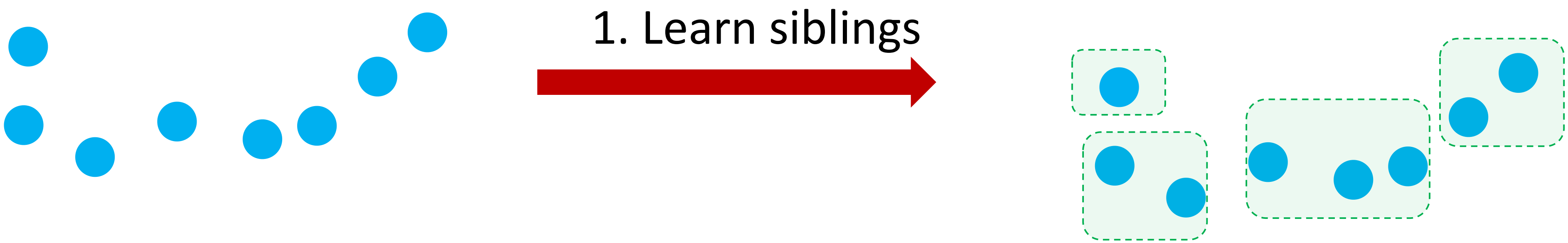
Recursive Grouping Algo



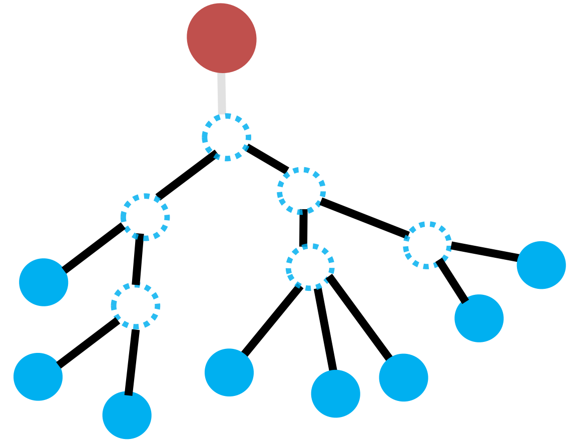
1. a, b are leaf nodes with common parent iff
$d(a,c) - d(b,c) = d(a,c') - d(b,c')$ for all $c, c' \neq a, b$

2. a is a leaf node and b is its parent iff

$d(a,c) - d(b,c) = d(a,b)$ for all $c \neq a, b$



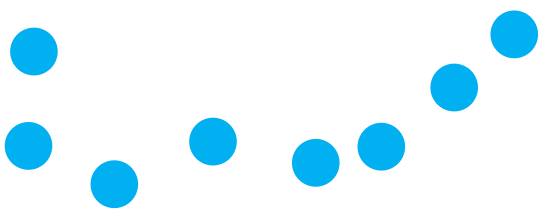
Recursive Grouping Algo



1. a, b are leaf nodes with common parent iff
$d(a,c) - d(b,c) = d(a,c') - d(b,c')$ for all $c, c' \neq a, b$

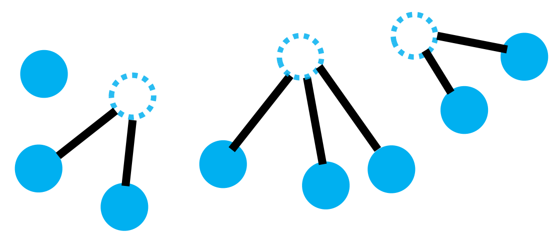
2. a is a leaf node and b is its parent iff

$d(a,c) - d(b,c) = d(a,b)$ for all $c \neq a, b$

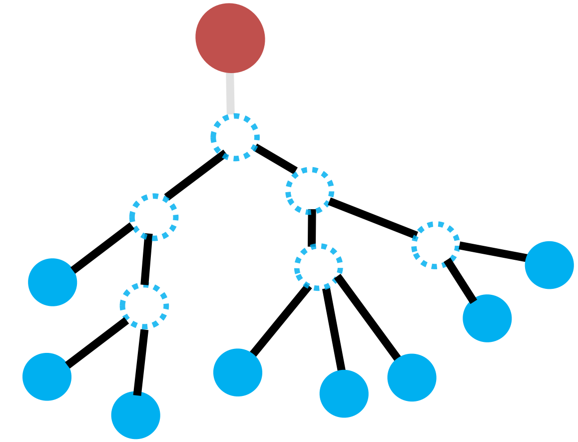


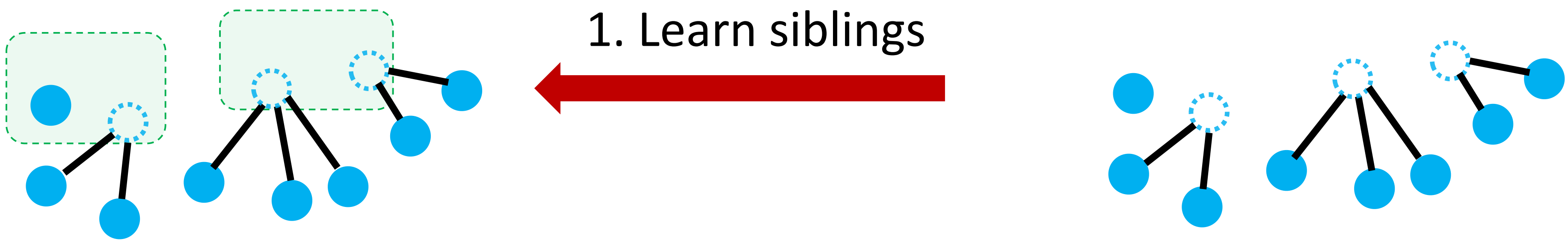
2. Introduce parents

3. Update distance

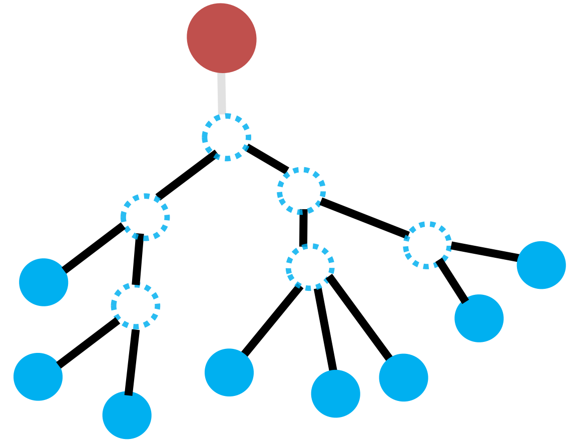


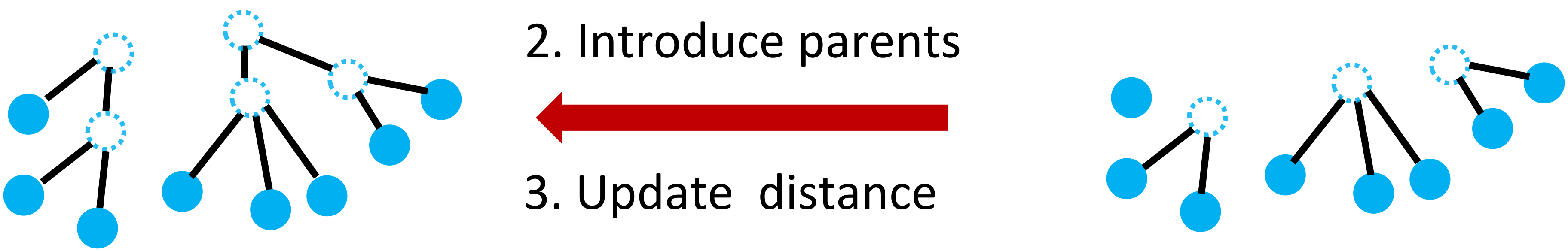
Recursive Grouping Algo



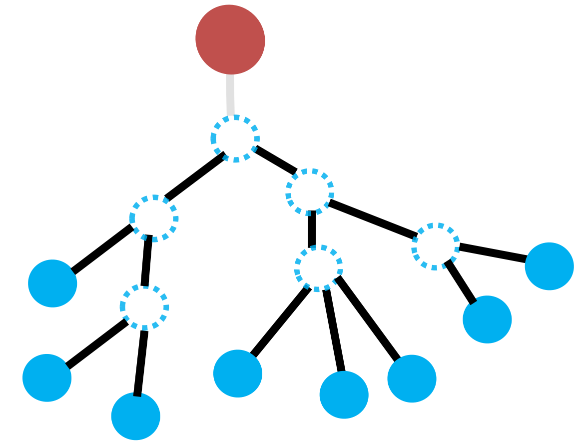


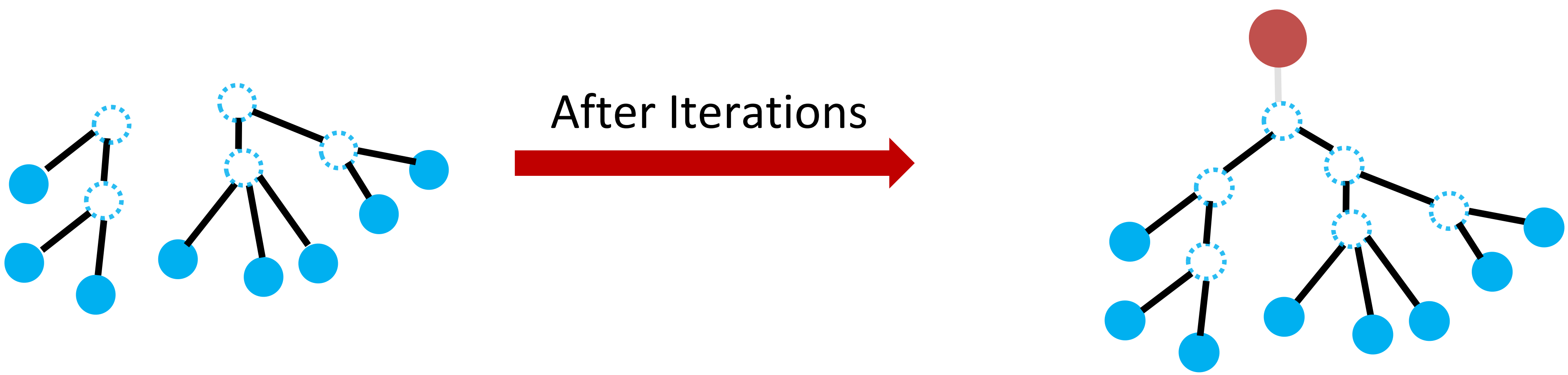
Recursive Grouping Algo





Recursive Grouping Algo



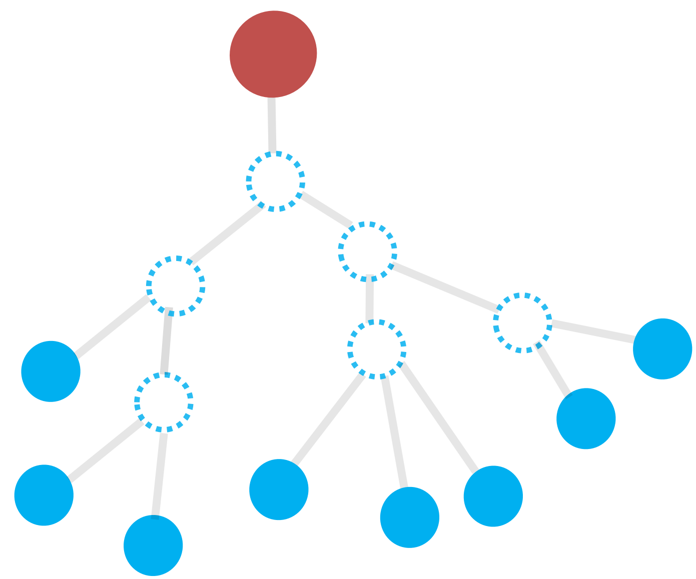


Learning with *end-users*

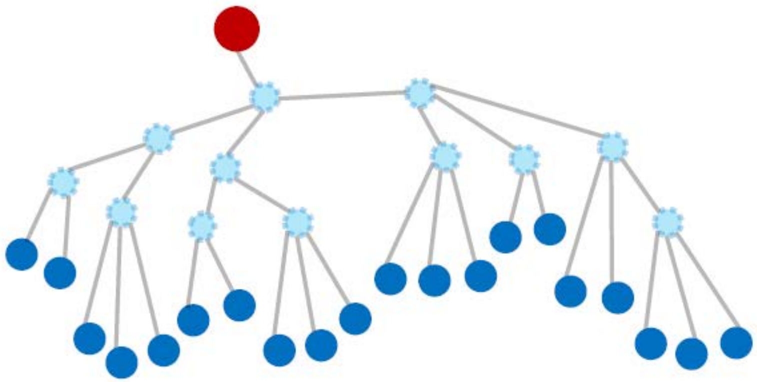
- Algorithm:
  - Compute *effective impedances* between leaves
  - Learn topology & distances iteratively
  - **Threshold** for finite samples effects: dynamically selected

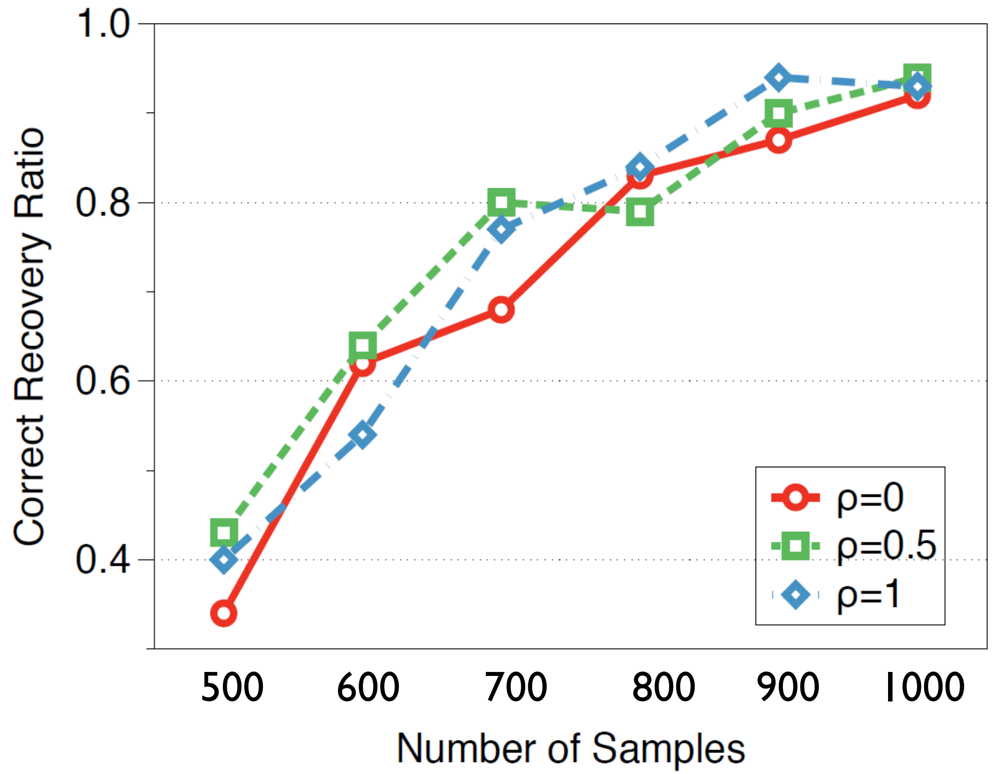
Sample Complexity :

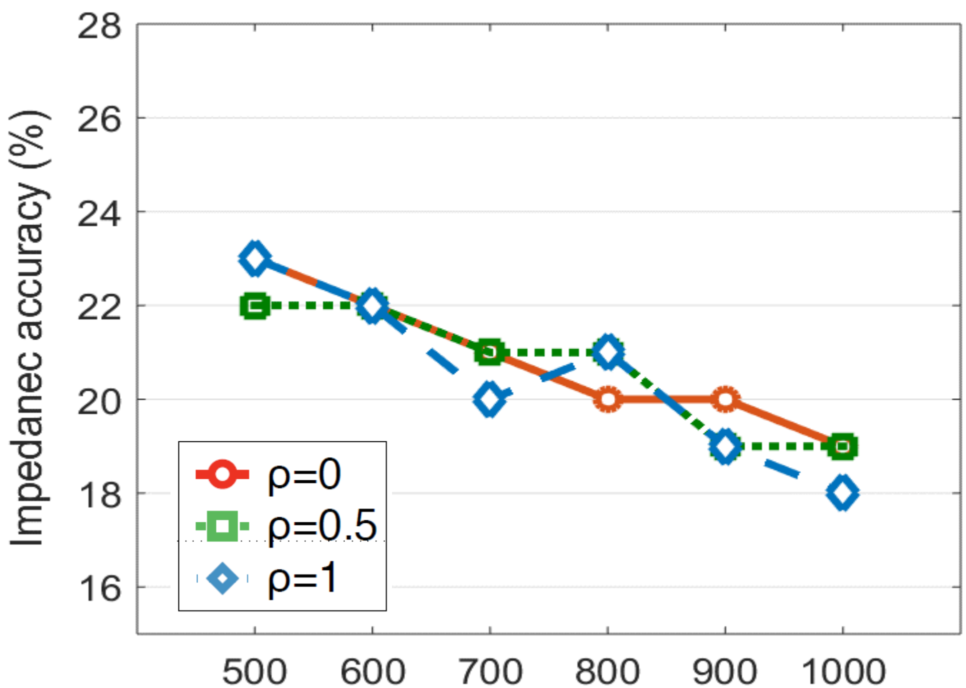
For a grid with constant depth and sub-Gaussian complex power injections, $O(|V|\log(|V|/\eta))$ samples recovers the true topology with probability $1-\eta$.



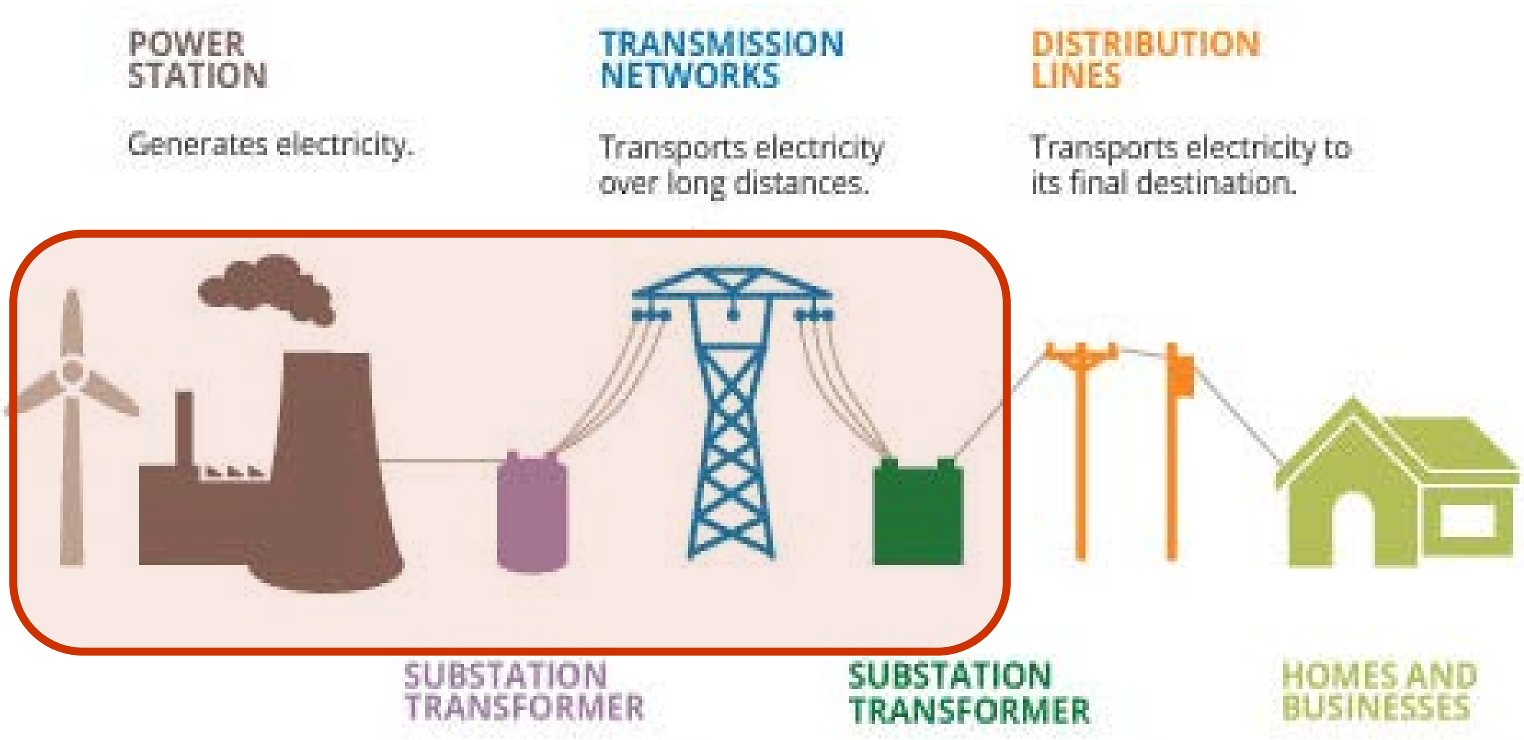
Simulations: IEEE 33 bus graphs (Matpower samples)







Machine Learning in Transmission Grid



- Voltage: High ⟶ Medium ⟶ Low

Outage Localization in Transmission Grid

- Data: Nodal voltages from few buses
- Goal: Learn locations from historical data
- IEEE Trans. Power System (under review)

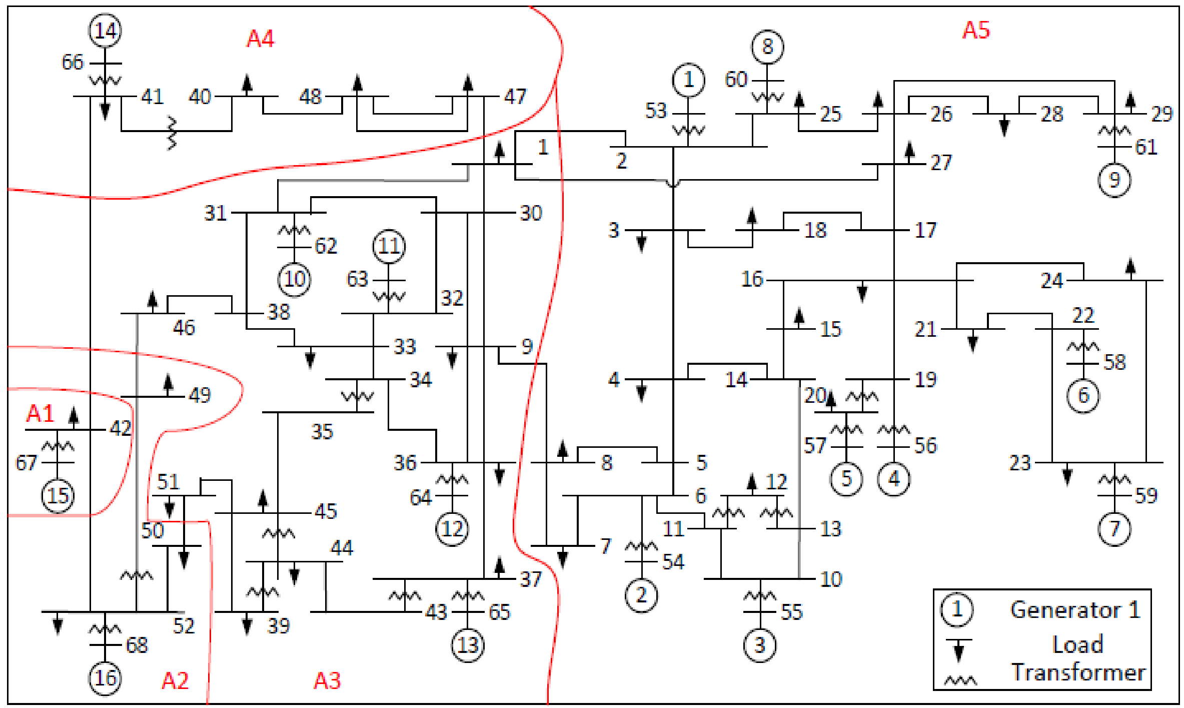
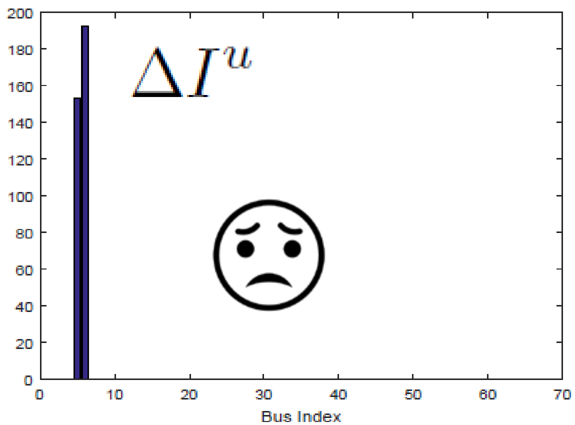
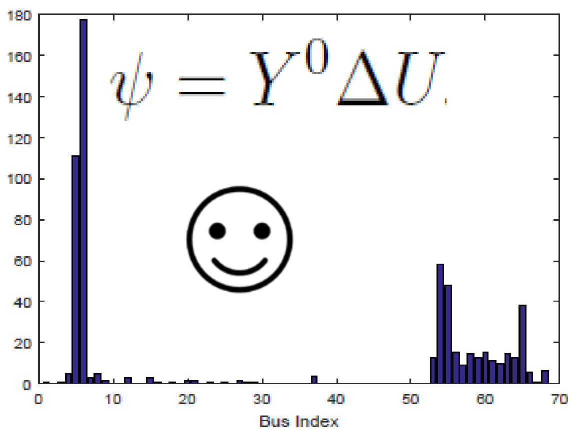


Fig. 1: IEEE 68-bus system with five coherence groups [19].

Outage Localization in Transmission Grid

- Data: Nodal voltages from few buses
- Goal: Learn locations from historical data
- Method: Use **right features** → Convolutional Neural Network (CNN)





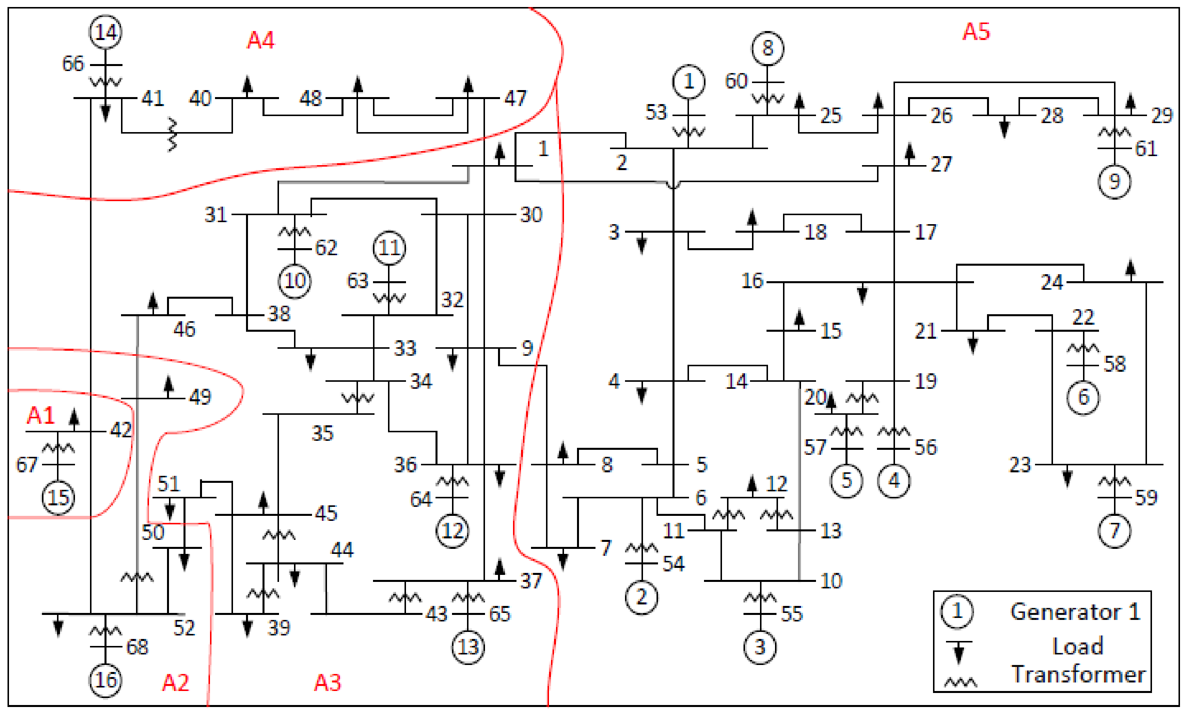
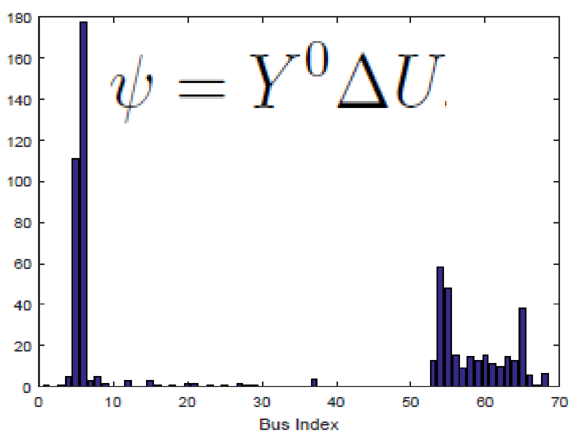
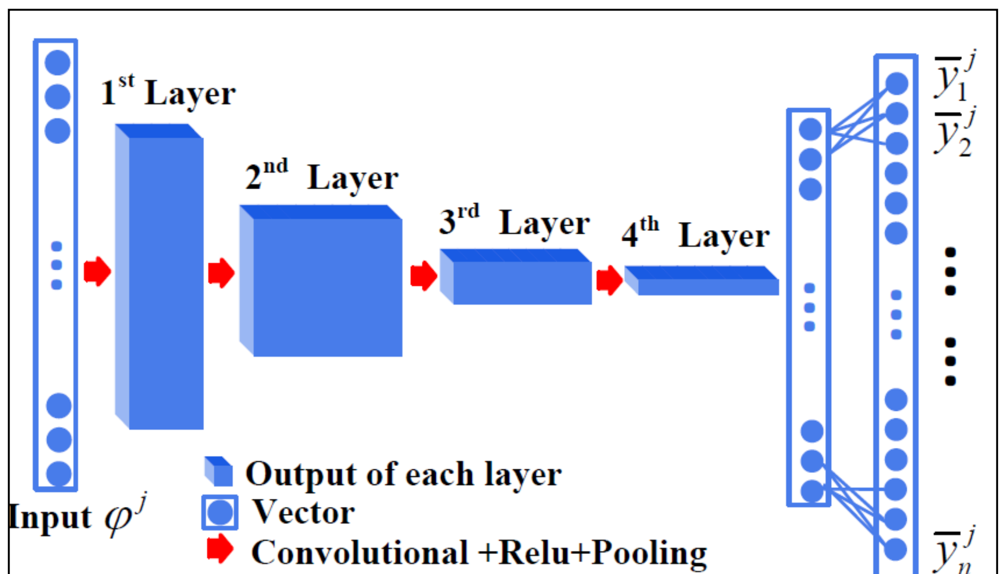


Fig. 1: IEEE 68-bus system with five coherence groups [19].

Outage Localization in Transmission Grid

- Data: Nodal voltages from few buses
- Goal: Learn locations from historical data
- Method: Use **right features** → Convolutional Neural Network (CNN)





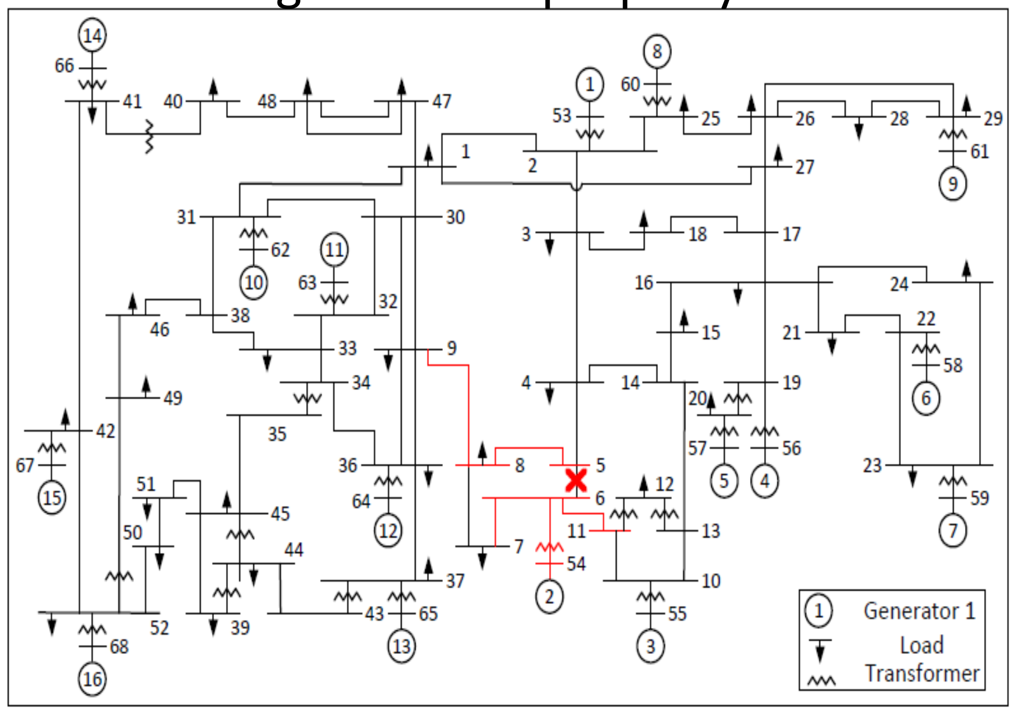
Outage Localization in Transmission Grid

- Data: Nodal voltages from few buses
- Goal: Learn locations from historical data
- Method: Use **right features** → Convolutional Neural Network (CNN)

ARC: Average Rank of Correct

The ratio of measured buses	7 %	10 %	15 %
Total number of buses	5	8	10
ARC	2.3	1.8	1.5

Neighborhood property



Conclusion:

Machine Learning works if system physics used *correctly*

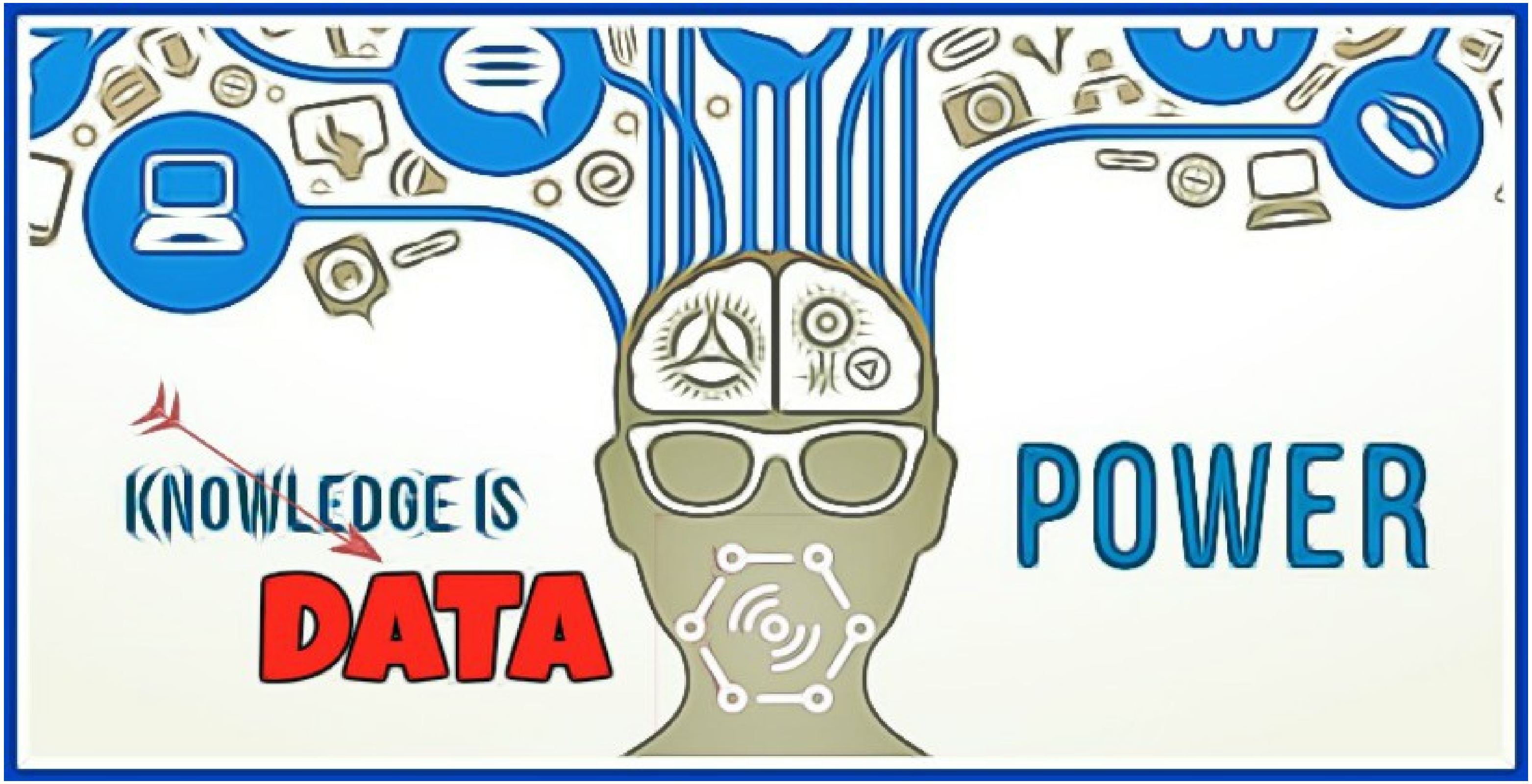
Collaborators:

LANL:	Michael Chertkov	Scott Backhaus
Students:	Sejun Park (KAIST)	Wenting Li (RPI)

Support from:

Center for Nonlinear Studies

GRID MODERNIZATION INITIATIVE
U.S. Department of Energy



Plea: *Please share/give **real-world** data*

a. International ??

b. Synthetic data grants ??

c. Large-scale competition → ARPA –E OPF challenge??