Provable estimation in distribution grids: *physics-informed statistical learning* perspective

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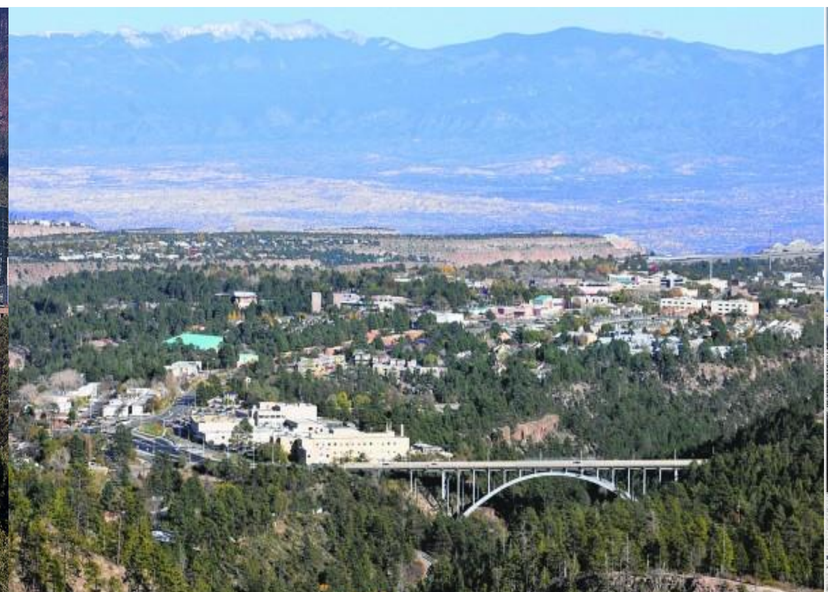
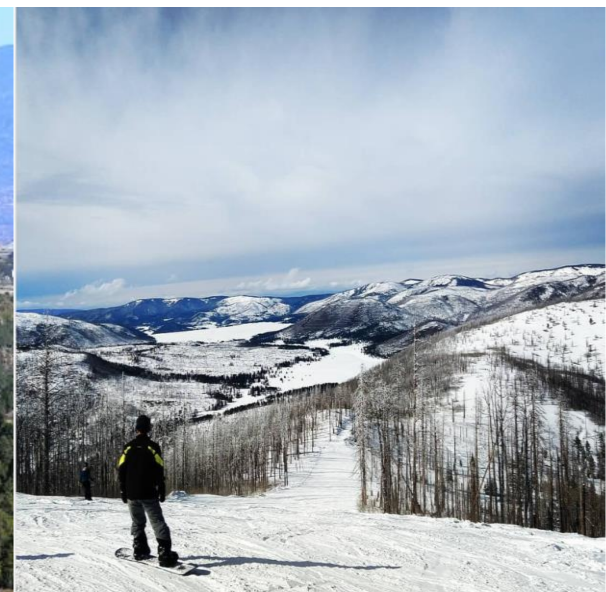
LANL

National Nuclear Security Administration
Operated by Los Alamos National Security, LLC for the U.S. Department of Energy's NNSA

Los Alamos National Lab

- Oldest DOE-NNSA Lab
- ~ 10,000 staff
- 7200 feet above sea level
- Ski-hill is 10 mins away
- Near Santa Fe, New Mexico





The Advanced Network Science Initiative   Overview   Projects   People   Publications   Software

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Los Alamos National Laboratory's Advanced Network Science Initiative.

- Los Alamos, NM
- Email
- GitHub
- YouTube

Overview

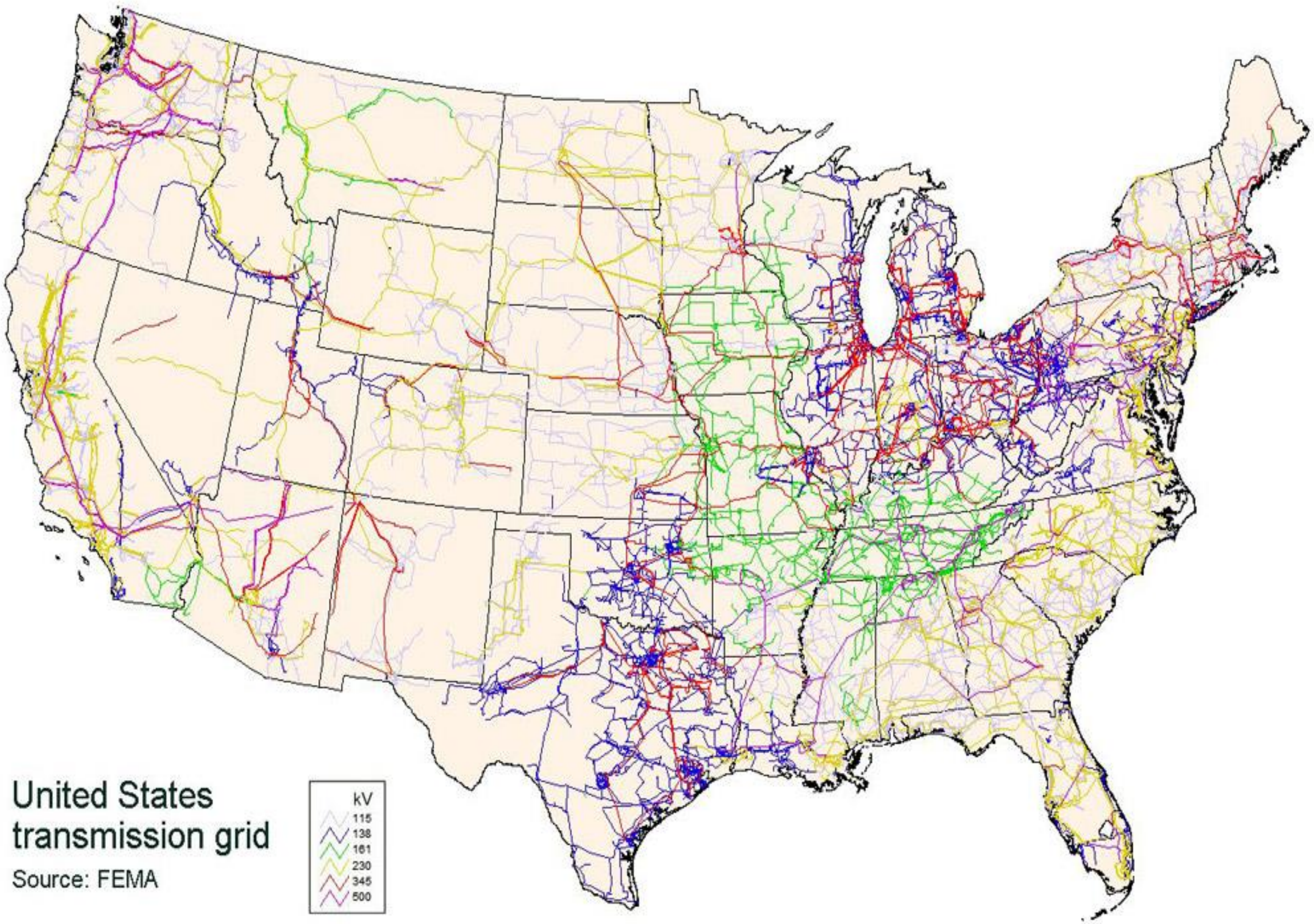
The Los Alamos National Laboratory's Advanced Network Science Initiative (ANSI) is an interdisciplinary initiative that enables fundamental and applied research to address long-term challenges in critical infrastructure design, operation, and security. The primary philosophy of ANSI is that combining insights from Theoretical Physics, Applied Mathematics, Computer Science, and Applied Engineering can result in novel computational methods that address a variety of emerging challenges in infrastructure networks.

Application Areas

To help motivate and inspire novel computational methods, ANSI studies a variety of challenging problems in critical infrastructure networks, such as *Analysis of Extreme Events*, *Network-base Machine Learning and Data Analytics, Control and*

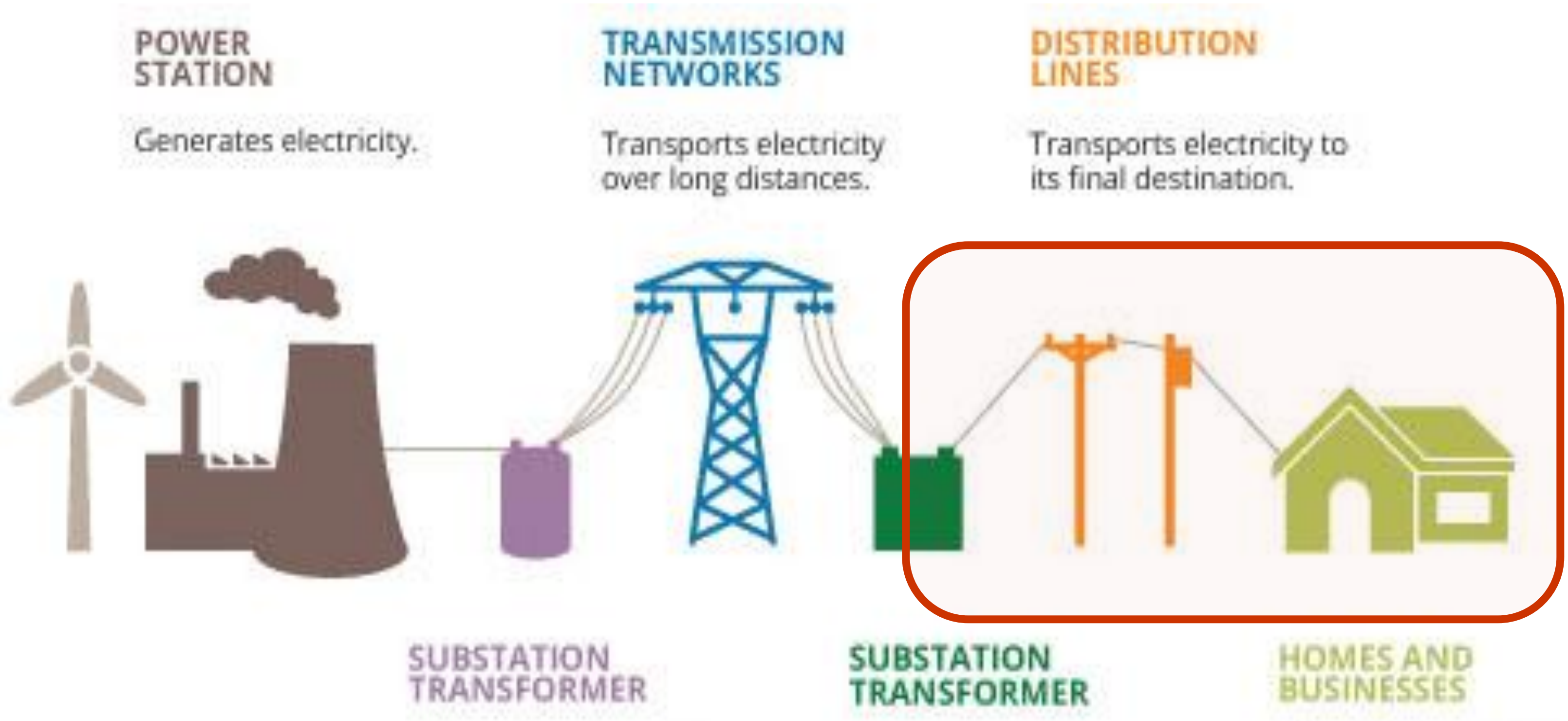
- ❖ Web: https://lanl-ansi.github.io/
- ❖ Email: deepjyoti@lanl.gov, for projects, post-doc, student positions.

Transmission Grid



Distribution Grid

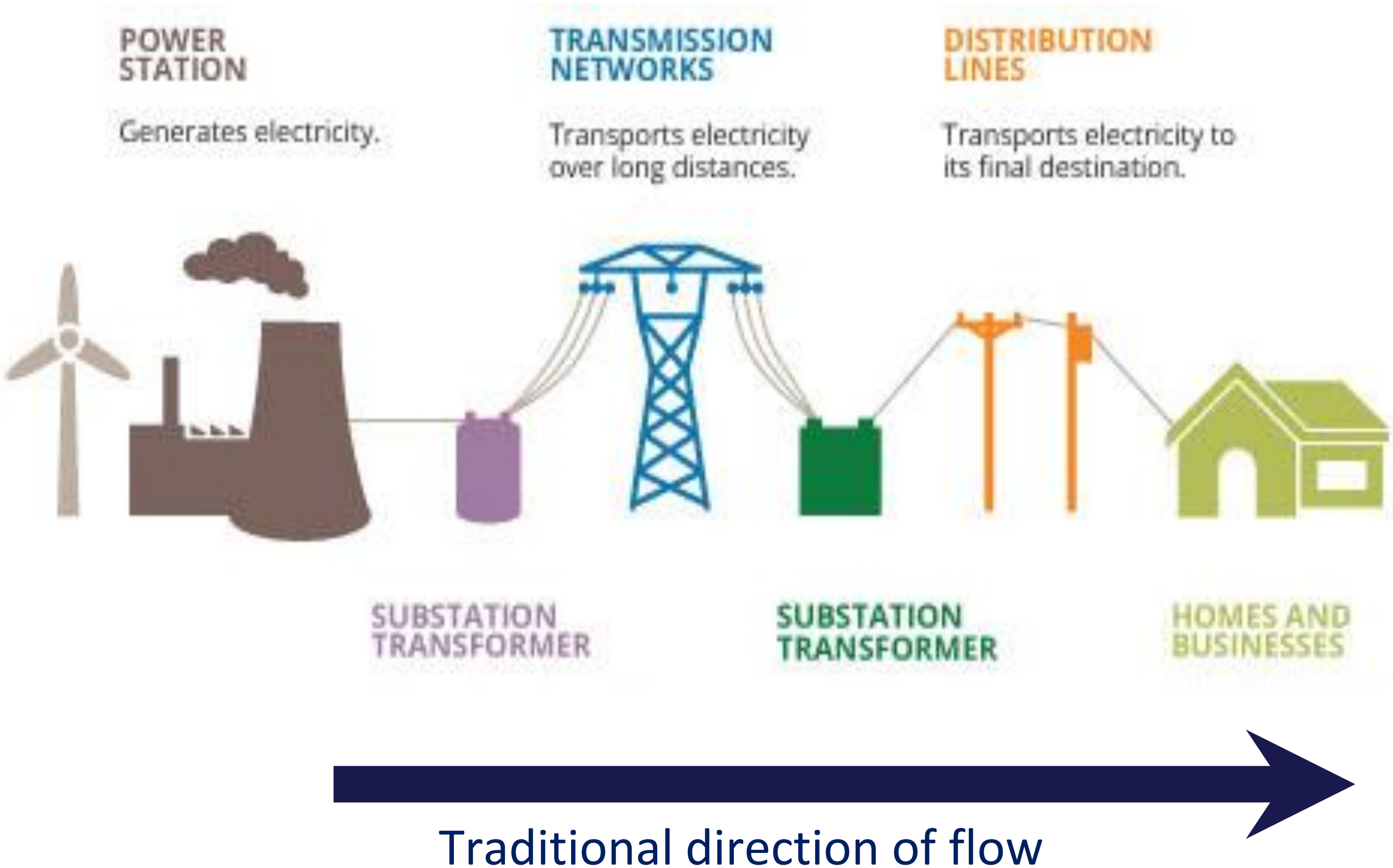
- Final Tier in electricity transfer



- Voltage: High → Medium → Low

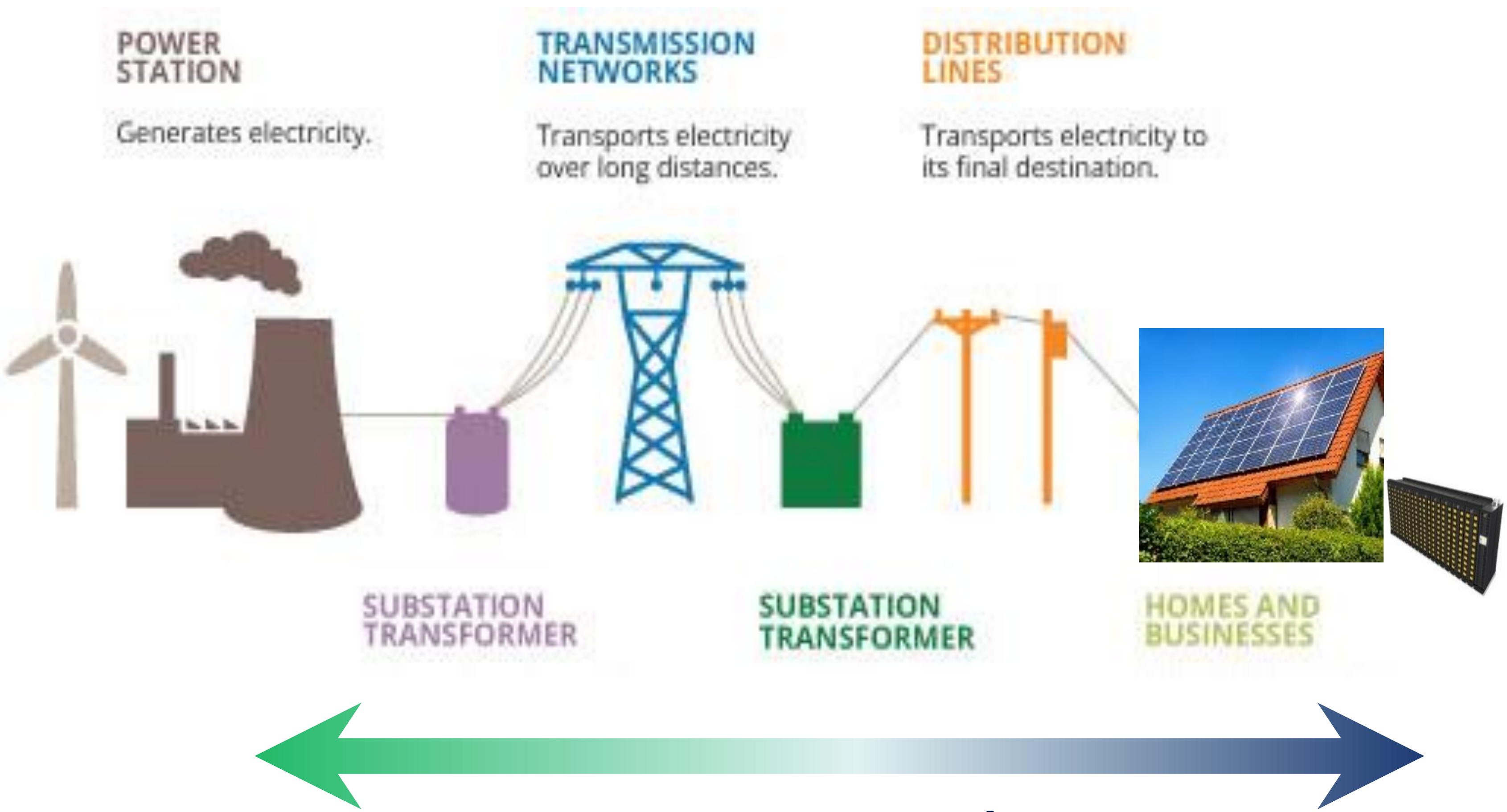
Distribution Grid

- Final Tier in electricity transfer



Distribution Grid

- Final Tier in electricity transfer



Current direction of flow → Issues

Grid Issues

Challenges

- Greater Variability/intermittent
- Lesser inertia/stability
- Needs real-time observability, control

Grid Issues

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- Greater Variability/intermittent
- Lesser inertia/stability
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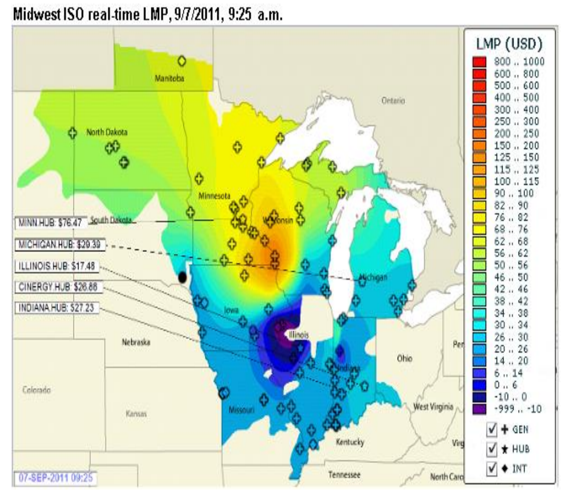
Use

- **Estimation**
- Optimization
- Resilience

Squirrel or cyber attack?

Electricity markets:



Forest fires

Grid Issues

Challenges

- Greater Variability/intermittent
- Lesser inertia/stability
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Use

- **Estimation**
- Optimization
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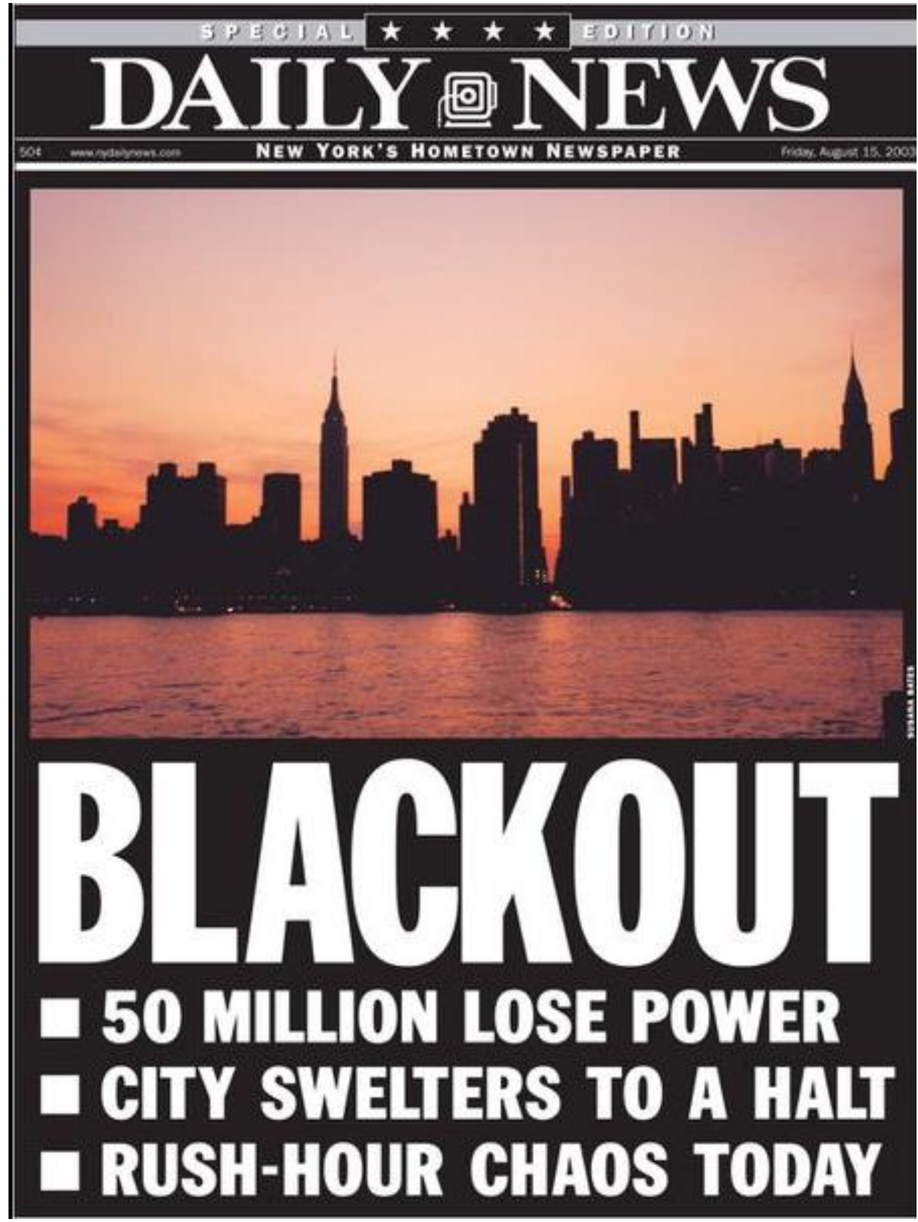
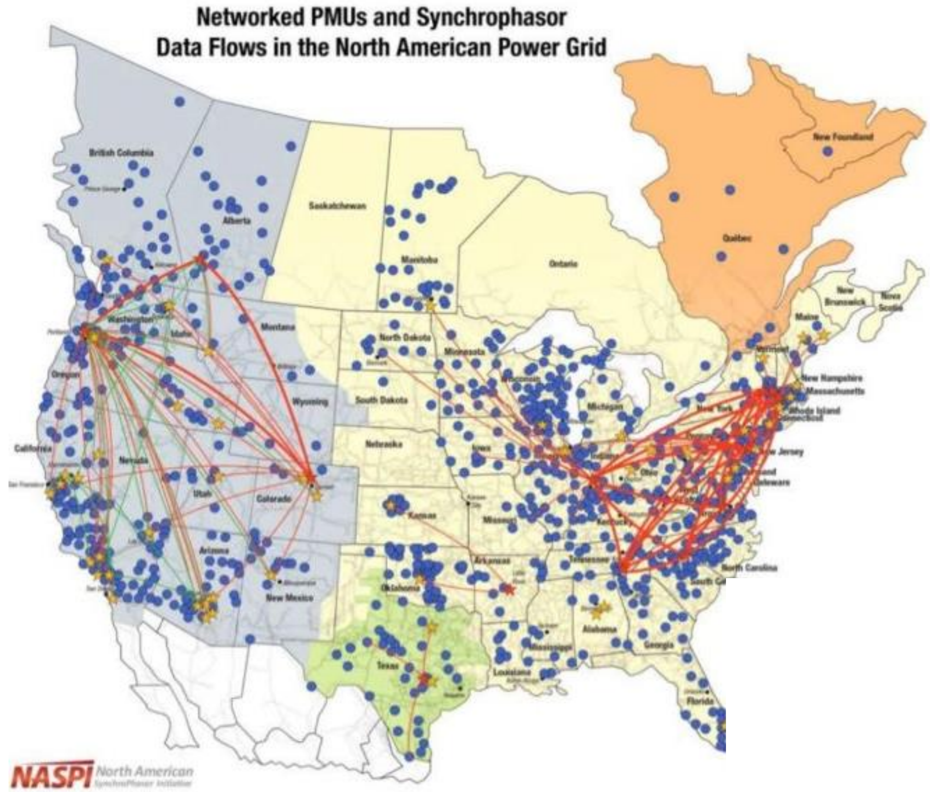


Grid Issues



Challenges

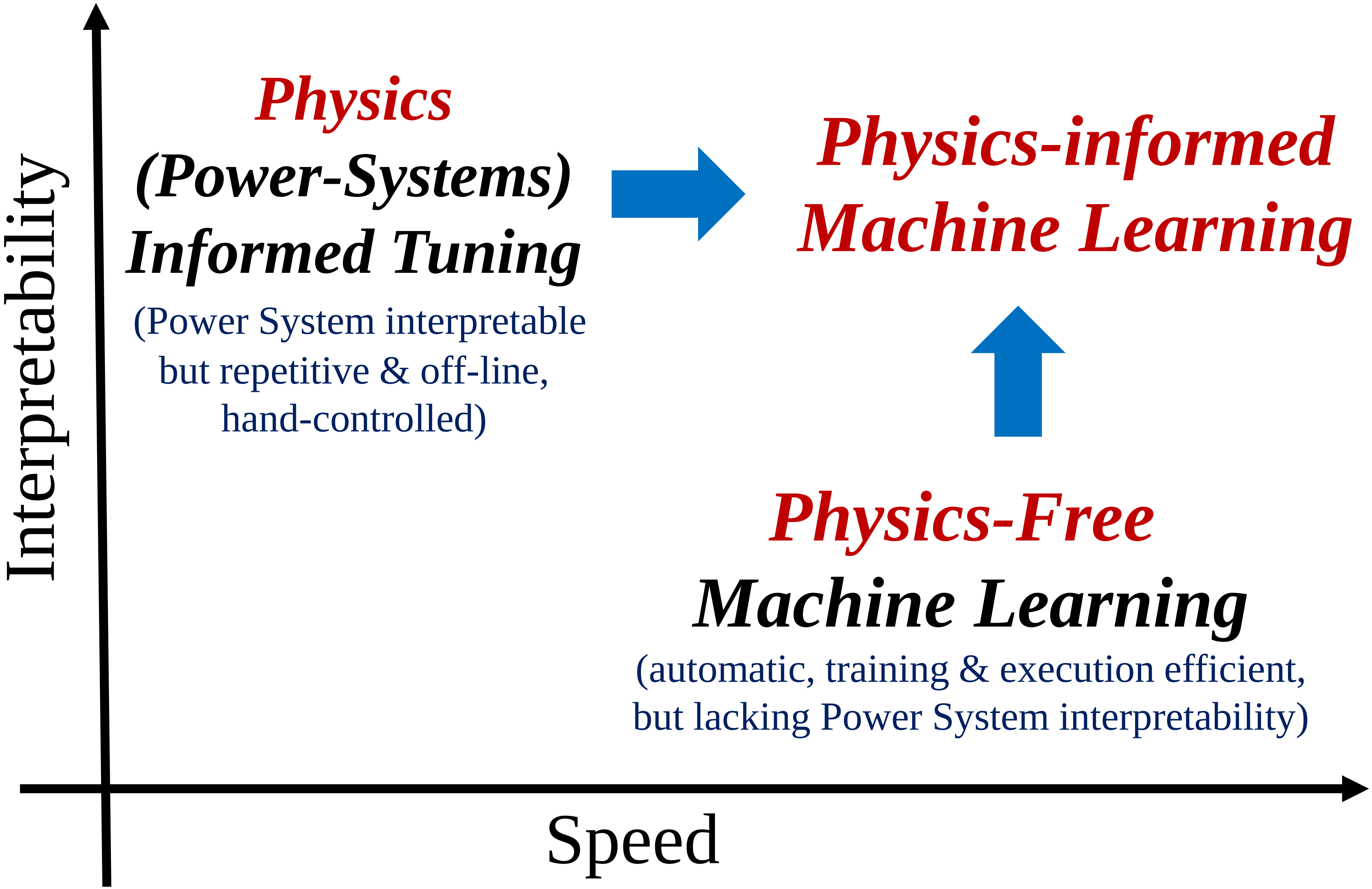
- Greater Variability/intermittent
- Lesser inertia/stability
- Needs real-time observability, control

Use

- **Estimation**
- Optimization
- Resilience

Solution

- Smart meters: PMUs, micro-PMUs, IoT
- Big Data: High fidelity measurements
- Over *2500* networked PMUs
- Sparse: Not everywhere in low voltage grids



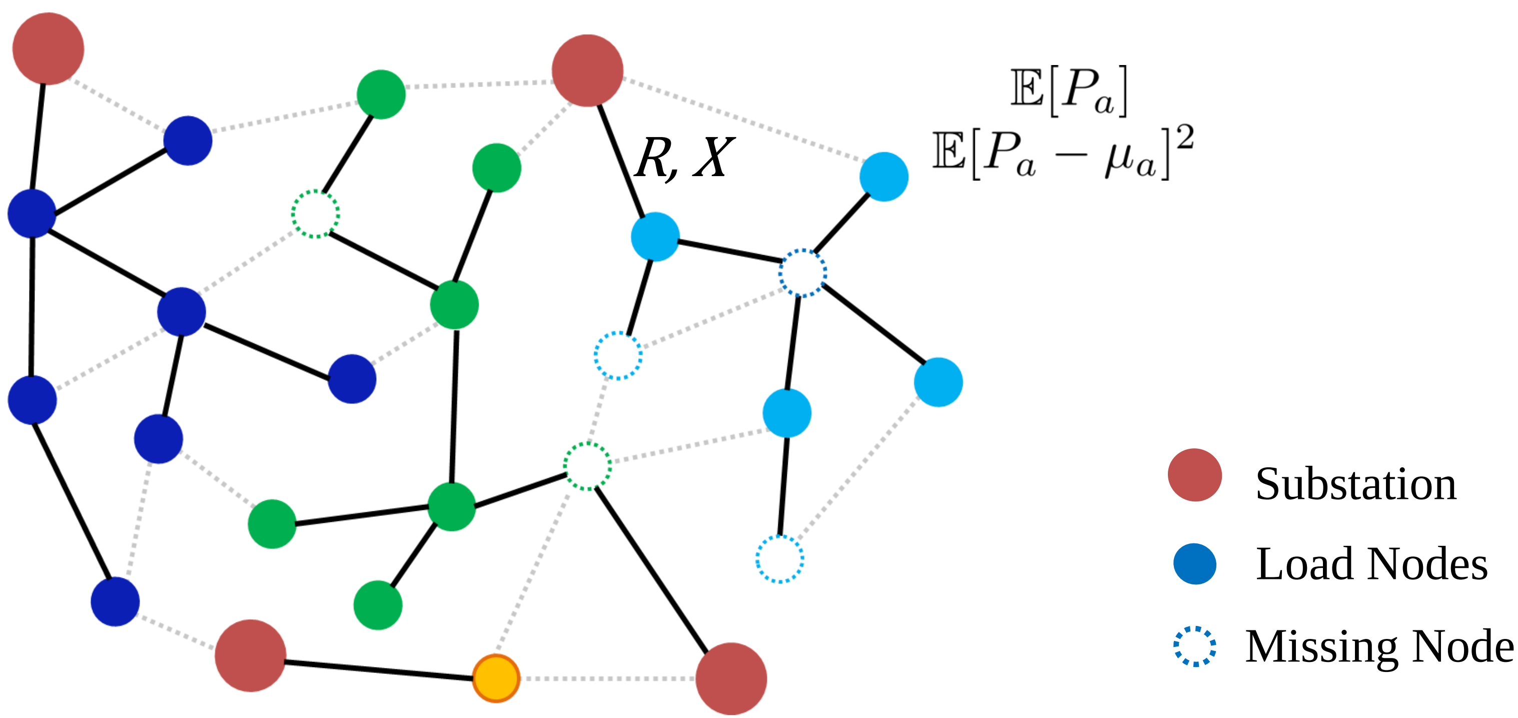
- Advantage: Provable results, Missing data extensions

Learning Problems in Distribution Grids

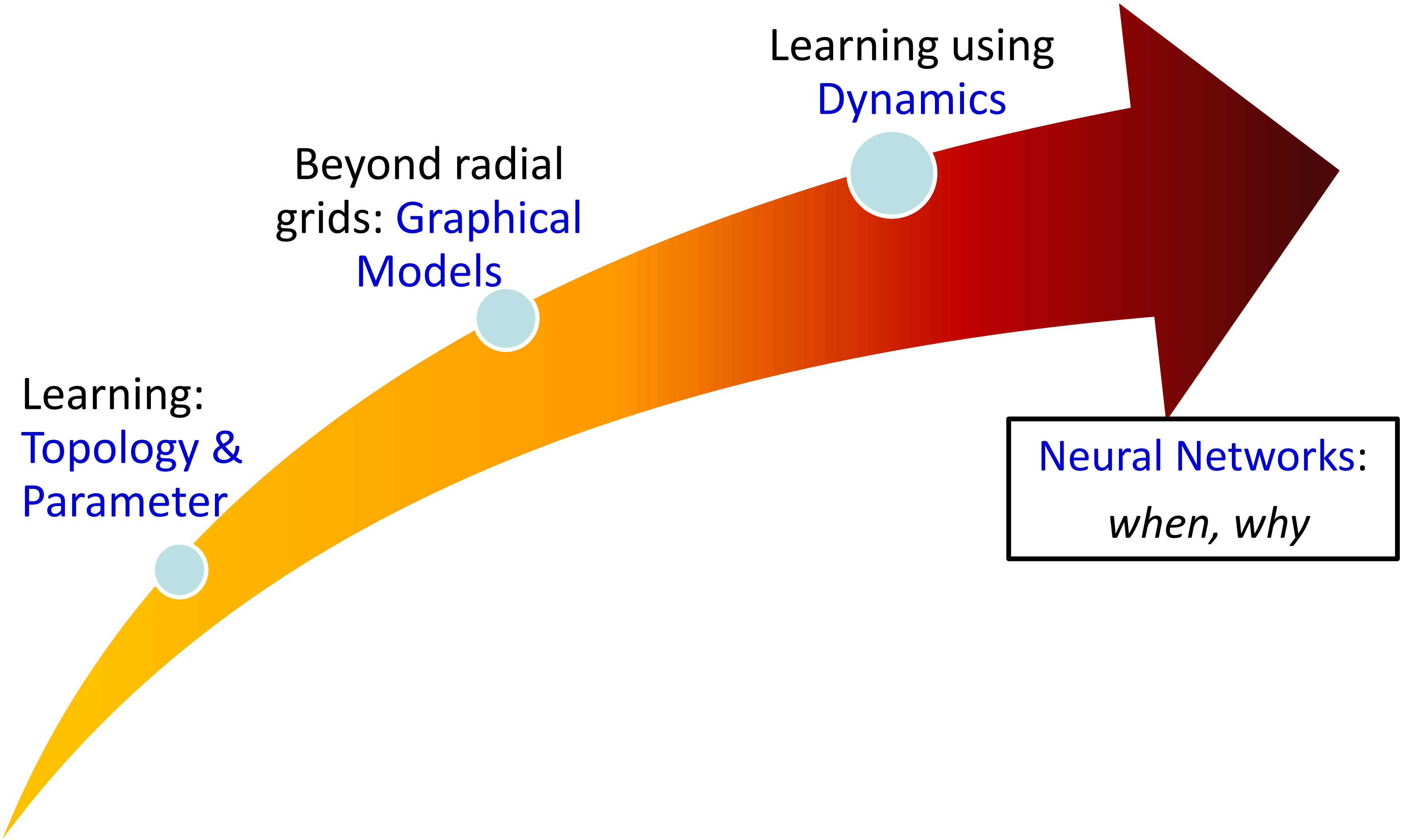
- Structure Learning
- Learning Line Impedances
- Incomplete observations

Theoretical guarantees:

what length of observations?
how much noise?
how much observability?

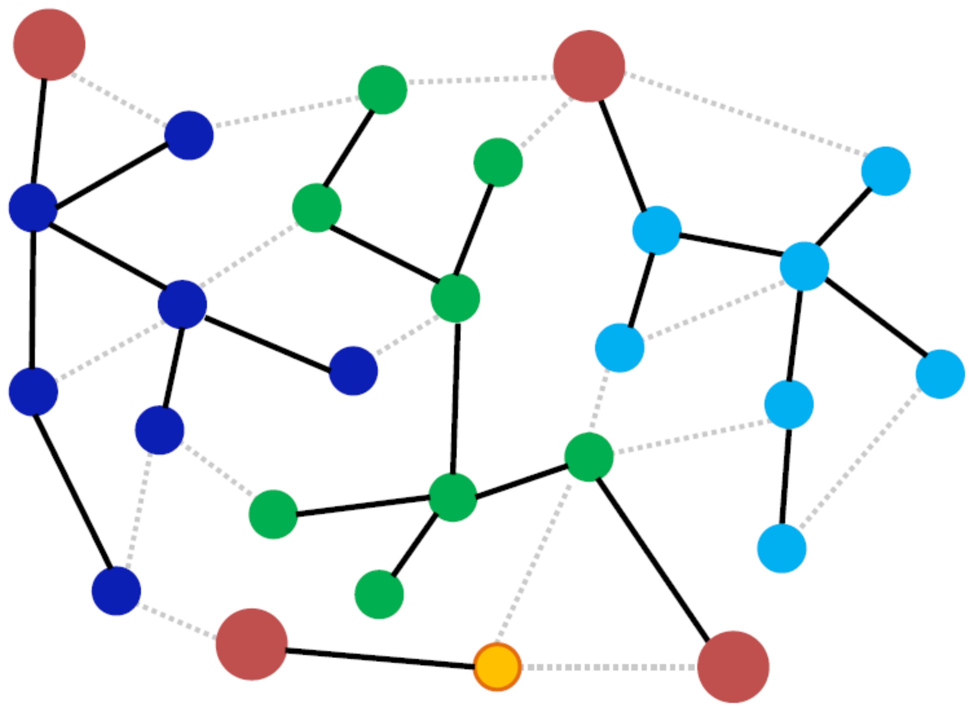


Data-driven problems



Physics-informed:

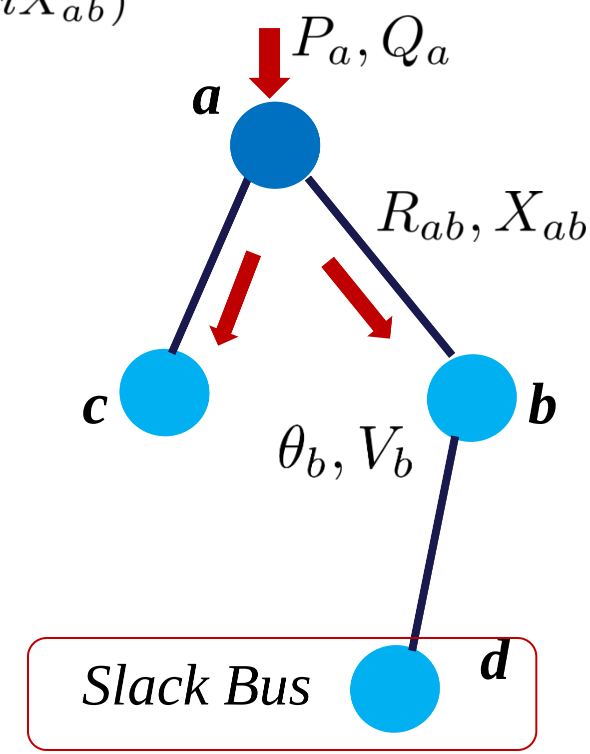
- Restrictions due to domain knowledge
    1. Structure of the grid: radial or large loops if meshed



Physics-informed:

- Restrictions due to domain knowledge
  1. Structure of the grid: radial or large loops if meshed
  2. Flow Physics (Static regime)

$$P_a + \hat{i}Q_a = \sum_{(a,b)} V_a e^{\hat{i}\theta_a} \frac{(V_a e^{-\hat{i}\theta_a} - V_b e^{-\hat{i}\theta_b})}{(R_{ab} - \hat{i}X_{ab})}$$



- First order expansion: LinDist Flow

$$\theta = H_{1/X}^{-1} P - H_{1/R}^{-1} Q,$$
$$V = H_{1/R}^{-1} P + H_{1/X}^{-1} Q$$

- $H_{1/R} = M^T R^{-1} M$

wt. Laplacian matrix

Physics-informed:

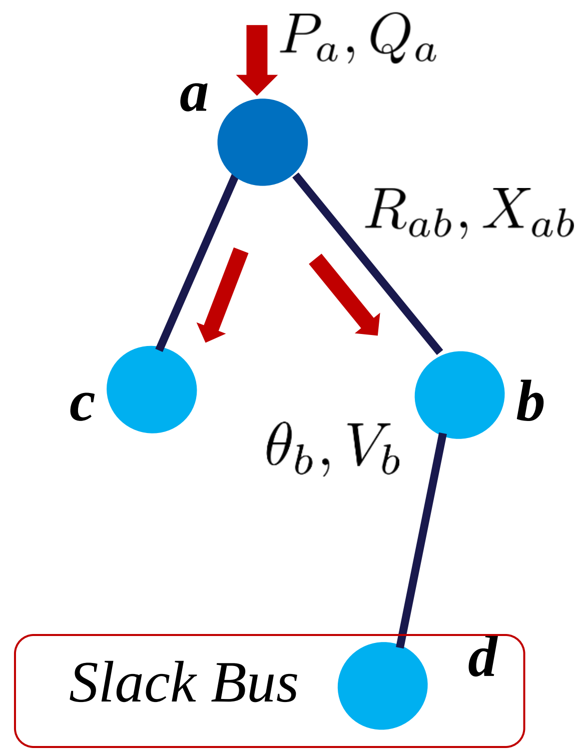
- Static Regime:
- LinDist Flow:

$$\theta = H_{1/X}^{-1} P - H_{1/R}^{-1} Q,$$
$$V = H_{1/R}^{-1} P + H_{1/X}^{-1} Q$$

- Dynamic Regime: Swing Equations

$$\underbrace{M_a \ddot{\theta}_a + D_a \dot{\theta}_a}_{\text{Dynamics of state variables}} = \sum_{(a,b) \text{ is edge}} \underbrace{B_{ab}(\theta_b - \theta_a) + P_a}_{\text{Net disturbance imbalance}}$$

- Frequency: $\omega_a = \dot{\theta}_a$
- Inertia (M) and Damping (D)



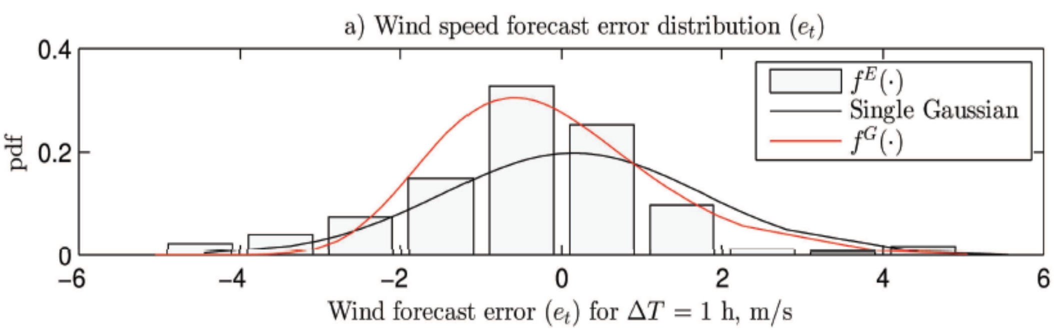
Physics-informed:

1. Structure of the grid:
    - radial or large loops
2. Flow Physics:
    - Static Regime (>1 m)
    - Dynamic Regime (<1 sec)

Statistical Learning:

- Properties of large/finite data

1. Sufficient statistics:
    - Means, covariances
2. Concentration bounds:
    - *How far are empirical estimates from true values?*



Dvorkin et al., Uncertainty Sets For Wind Power Generation, *PES Letters 2016*

If X_i are i.i.d,

$$\mathbb{P}[|\sum_i^n X_i - \sum_i^n E(X_i)| > t] < 2\exp\left(\frac{-2t^2}{nC^2}\right)$$

Chernoff, **Hoeffding**, Markov bounds

Physics-informed:

1. Structure of the grid
2. Flow Physics

Statistical Learning:

1. Sufficient statistics:
2. Concentration bounds:

Provable Learning solutions

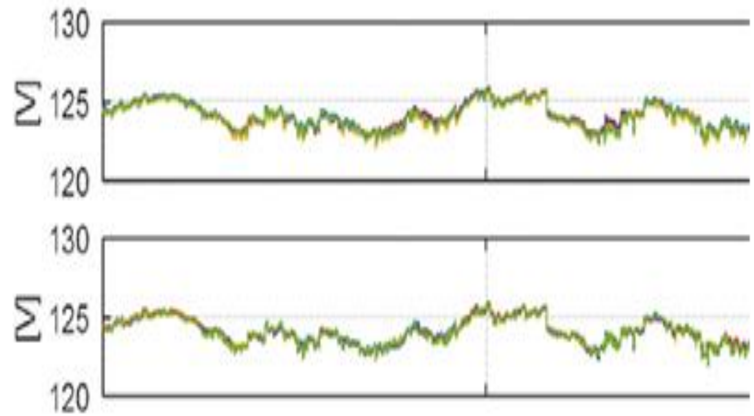
1. Estimation algorithm *consistent* at infinite samples.

2. Correct *with high probability* at finite samples/noise etc.

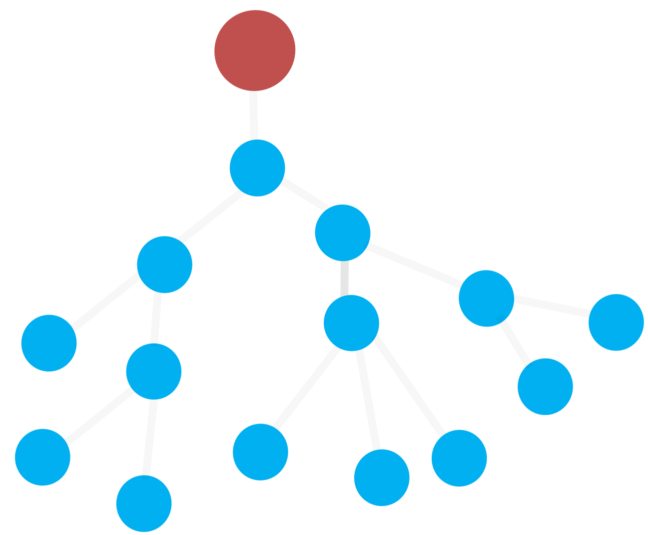
Learning with nodal voltages

- Data: Time-series Nodal voltages at all nodes (static regime)

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



- Unobserved: all lines
- Estimate: Operational Topology

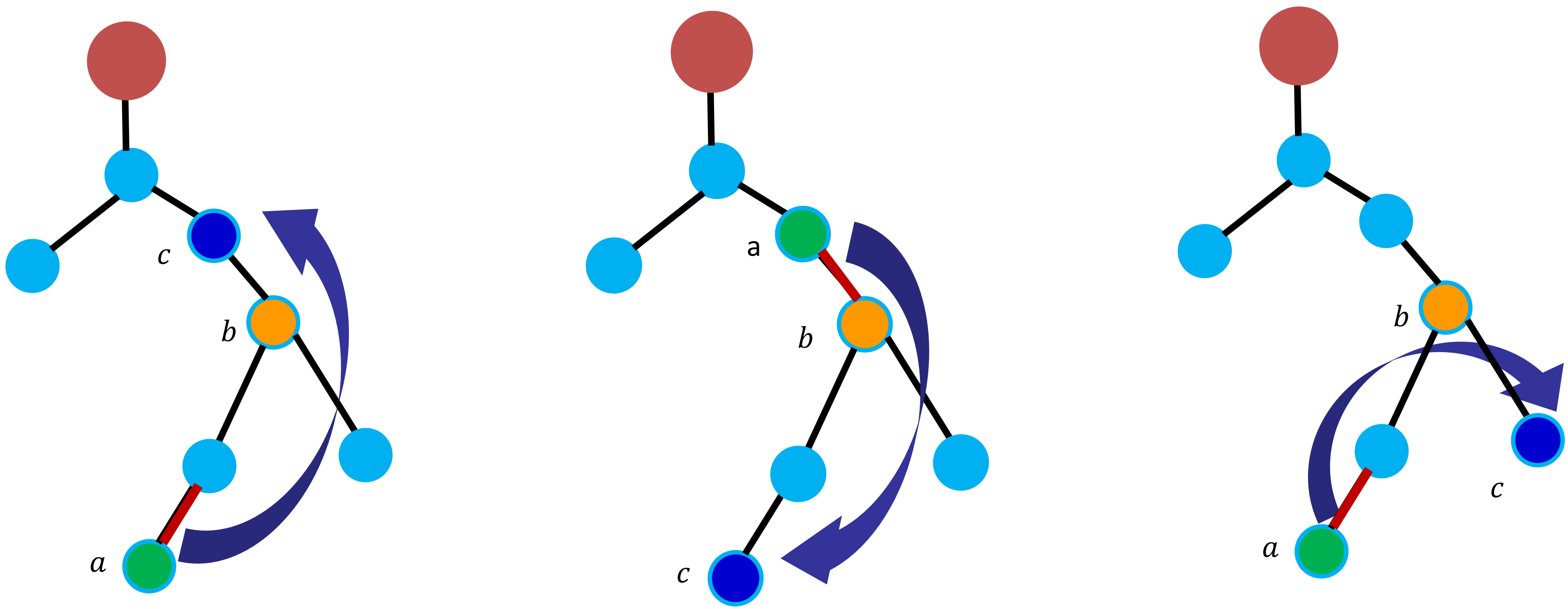


- Deka et al., Structure Learning in Distribution Networks, *IEEE Trans. Control of Networks,* 2017

Voltages in Radial Network

- ***Variance of voltage diff.:*** $\mathbb{E}[(V_a - \mu_{V_a}) - (V_k - \mu_{V_k})]^2$

- Minimum along any direction reached at nearest neighbor



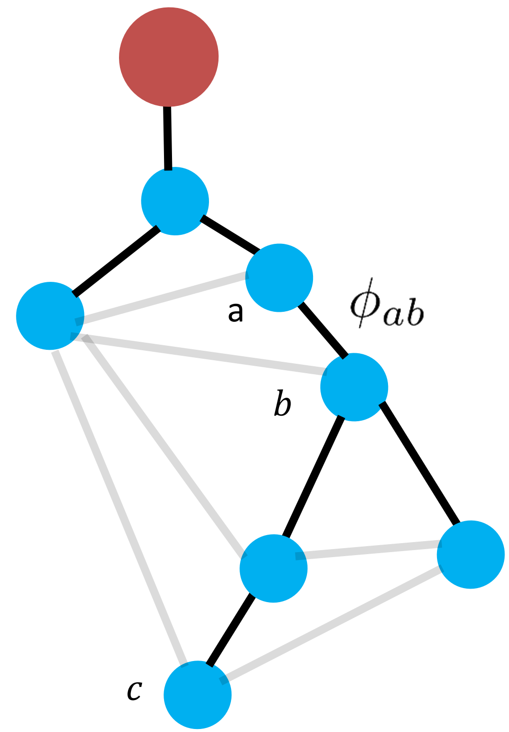
Topology Learning (No missing nodes)

Greedy Topology Learning:

1. 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)
- Computational complexity: O(|V|^2 log |V|)

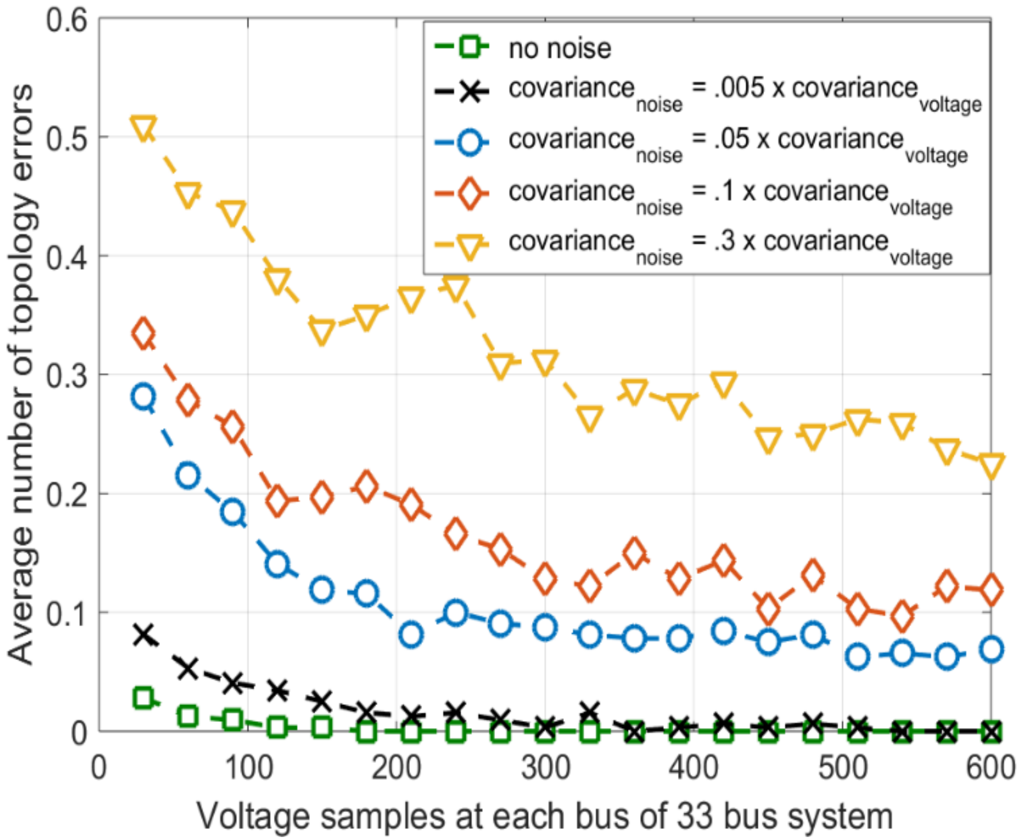


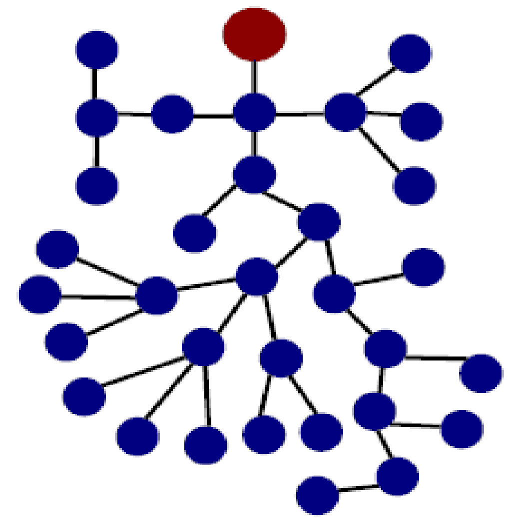
Sample Complexity :

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)

Effect of Noise



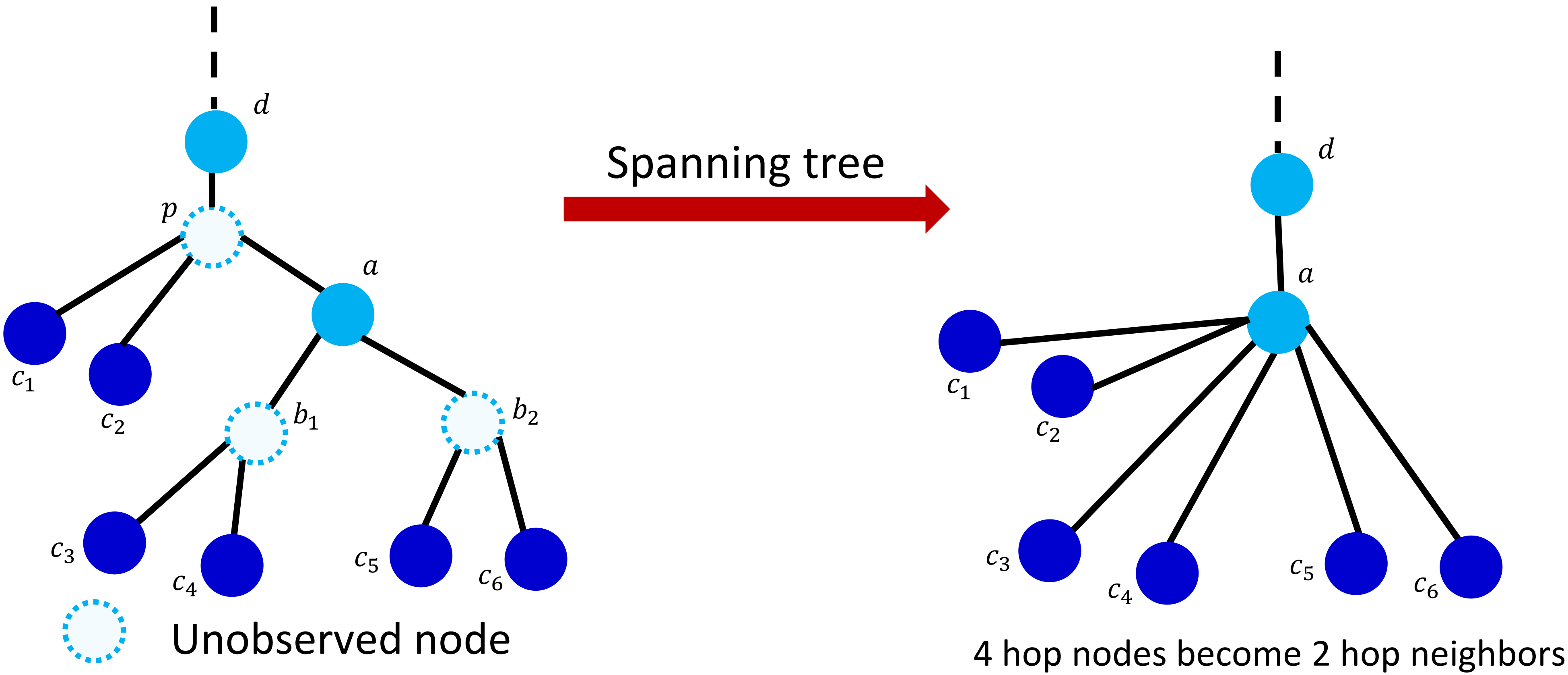


33-bus test system, Matpower

Reference: 12 KV substation voltage

Topology Learning with Missing Data

- *Missing nodes* that are *greater than 1 hop away* *(not adjacent)*



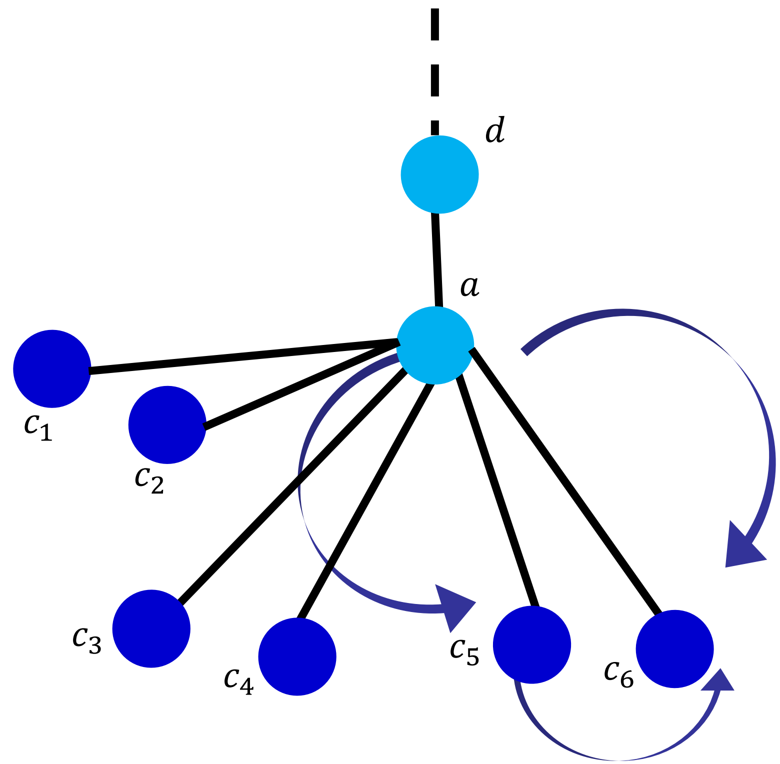
Topology Learning with Missing Data

- *Missing nodes* that are *greater than 1 hop away* *(not adjacent)*

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

Node triplets: $\left[\phi_{ac_i} + \phi_{ac_j} - \phi_{c_i c_j}\right]$

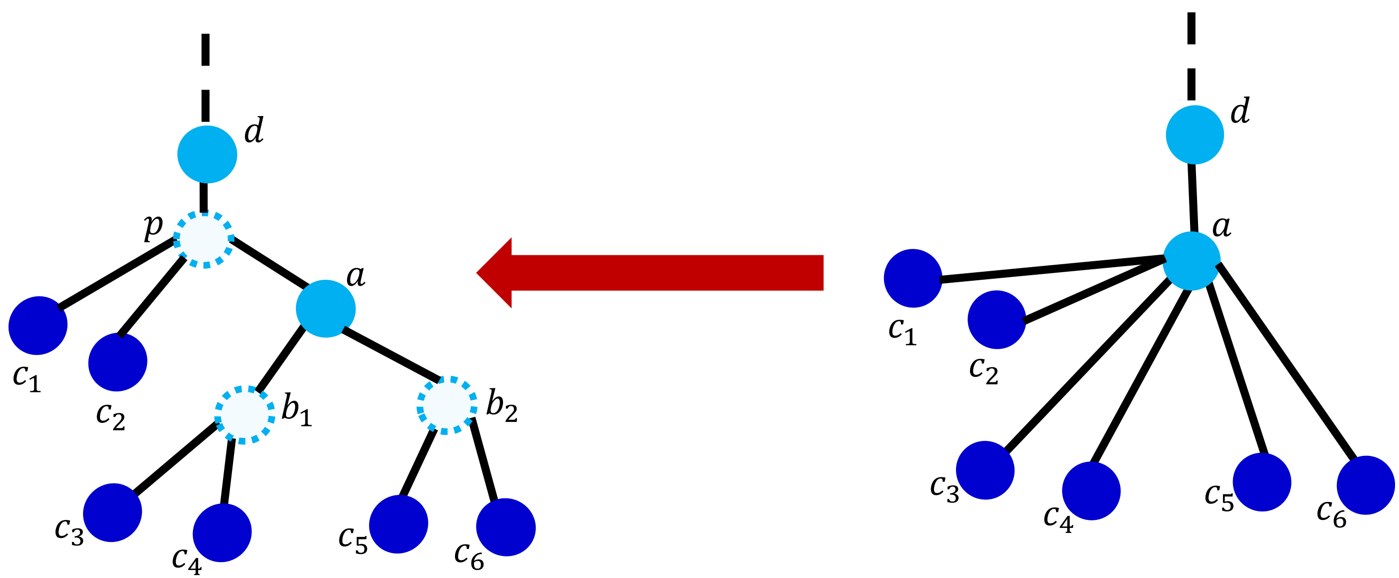
$$\begin{array}{c|cccccc}
 & \multicolumn{2}{c}{C_p} & \multicolumn{2}{c}{C_{b_1}} & \multicolumn{2}{c}{C_{b_2}} \\
\hline
C_p & + & + & (-) & (-) & (-) & (-) \\
 & + & + & (-) & (-) & (-) & (-) \\
C_{b_2} & (-) & (-) & + & + & 0 & 0 \\
 & (-) & (-) & + & + & 0 & 0 \\
C_{b_2} & (-) & (-) & 0 & 0 & + & + \\
 & (-) & (-) & 0 & 0 & + & +
\end{array}$$



- Deka et al., Joint Estimation of Topology and Injection Statistics with Missing Nodes, *IEEE Trans. Control of Networks, 2020*

Topology Learning with Missing Data

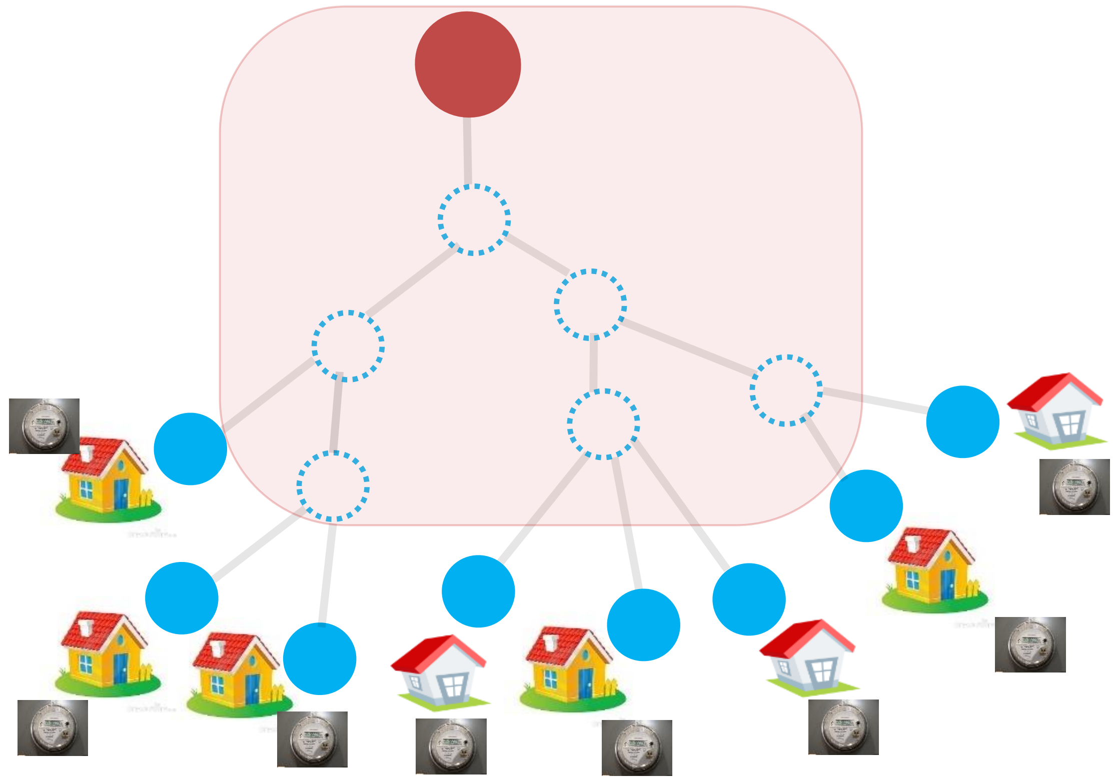
- *Missing nodes* that are *greater than 1 hop away* *(not adjacent)*
- Learning Algo:
  1. Construct spanning tree
  2. Cluster matrix $\left[\phi_{ac_i} + \phi_{ac_j} - \phi_{c_i c_j}\right]$
  3. Find missing parents and iterate.



- Deka et al., Joint Estimation of Topology and Injection Statistics with Missing Nodes, *IEEE Trans. Control of Networks, 2020*

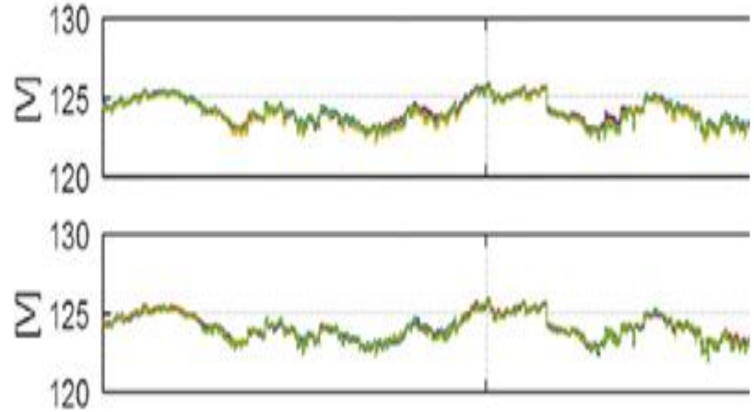
Learning with *end-users*

- Data: Time-series Nodal voltages **and injection samples** at leaves
- Unobserved: all intermediate nodes & lines
- Estimate: Operational Topology **+ Line Impedance**



End-user data

- Time-stamped voltage magnitudes (V)

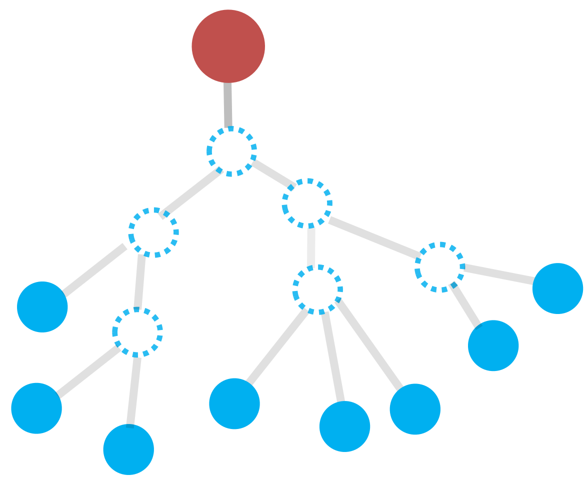


$$\mu_V = \mathbb{E}[V]$$
$$\Omega_V = \mathbb{E}[V - \mu_V][V - \mu_V]^T$$

- Time-stamped nodal active & reactive injections (P &Q)

$$\mu_P,\ \Omega_P,\ \mu_Q,\ \Omega_Q,\ \Omega_{PQ}$$

- Cross-covariances: Ω_{VP}, Ω_{VQ}



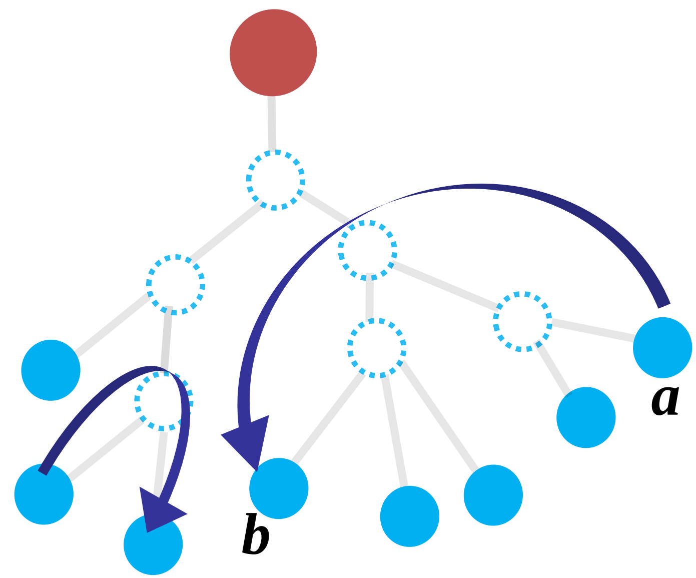
Learning with *end-users*

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

➢ Compute *effective impedances* between leaf pairs

$$R_{eff}(a,b) = H^{-1}_{1/R}(a,a) + H^{-1}_{1/R}(b,b) - 2H^{-1}_{1/R}(a,b)$$

➢ ***Recursive Grouping Algo*** (Anandkumar'11) to learn topology & distances from known effective impedances

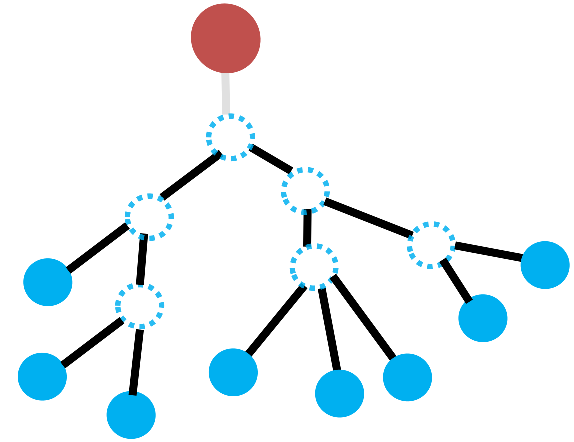


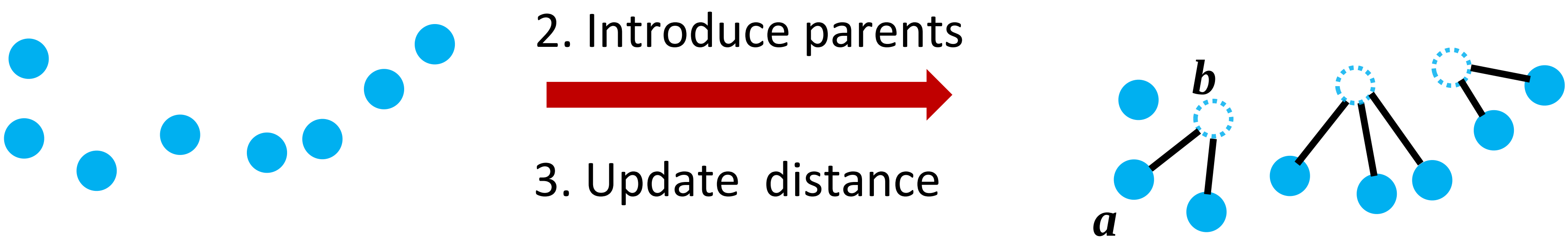
Recursive Grouping Algo

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

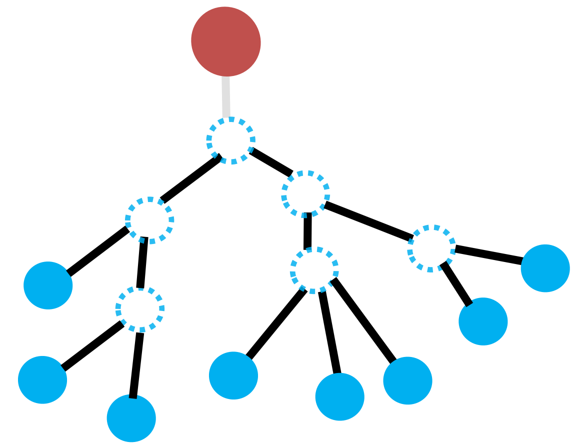
2. a is a leaf node and b is its parent iff

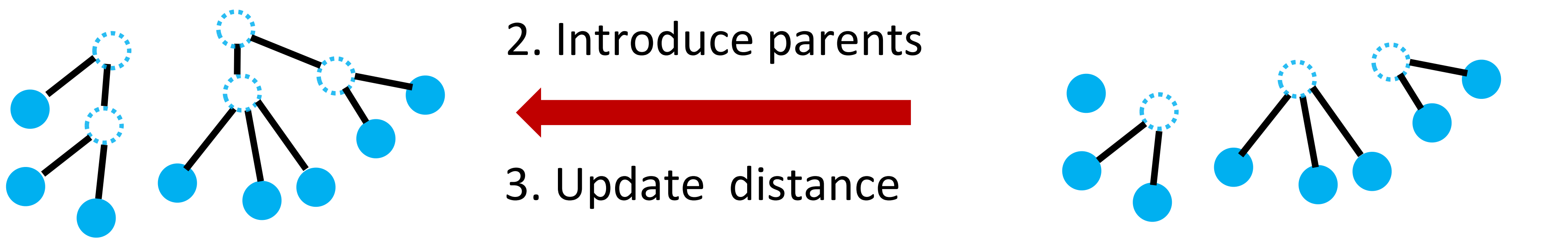
$d(a,c) - d(b,c) = d(a,b)$ for all $c \neq a, b$



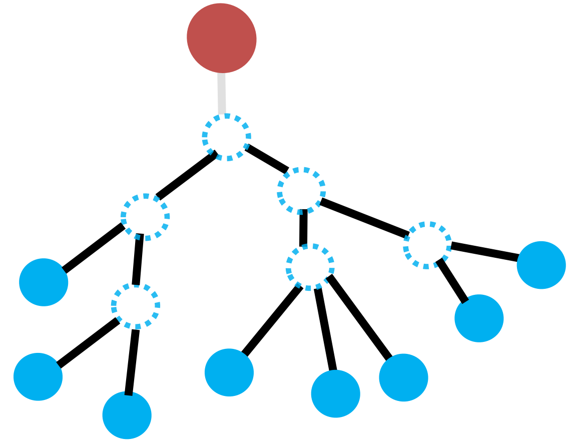


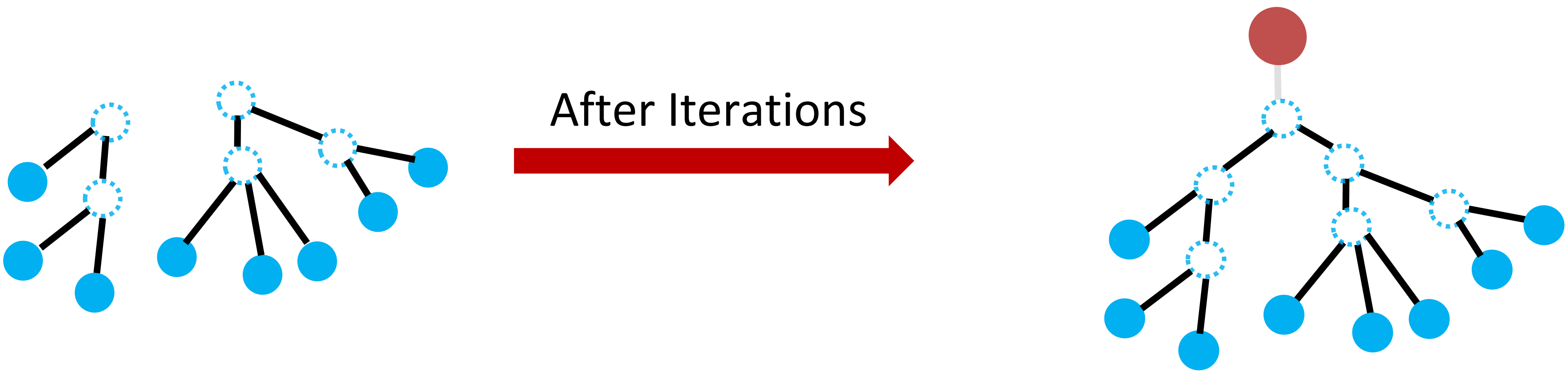
Recursive Grouping Algo





Recursive Grouping Algo





Estimating effective impedances

- Algorithm:

➢ Compute *effective impedances* between leaves

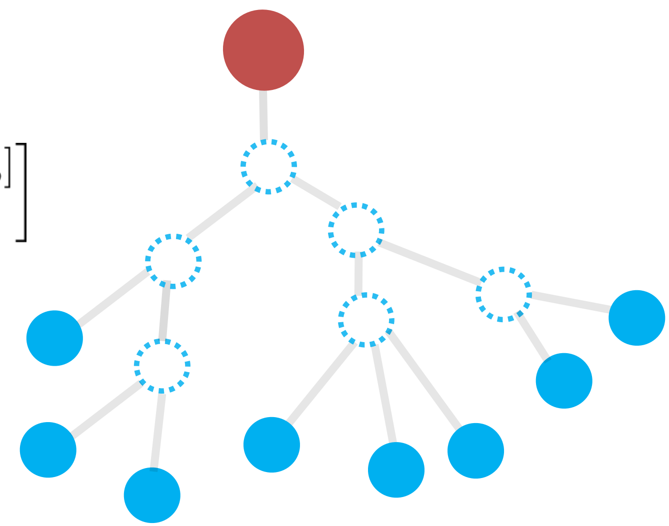
$$R_{eff}(a,b) = H^{-1}_{1/R}(a,a) + H^{-1}_{1/R}(b,b) - 2H^{-1}_{1/R}(a,b)$$

➢ Power Flow equations:

$$\begin{bmatrix}\mathbb{E}[v_{\mathcal{L}}p_{\mathcal{L}}^T] & \mathbb{E}[v_{\mathcal{L}}q_{\mathcal{L}}^T]\end{bmatrix} = \begin{bmatrix}H^{-1}_{1/r}(\mathcal{L},\mathcal{L}) & H^{-1}_{1/x}(\mathcal{L},\mathcal{L})\end{bmatrix}\begin{bmatrix}\mathbb{E}[p_{\mathcal{L}}p_{\mathcal{L}}^T] & \mathbb{E}[p_{\mathcal{L}}q_{\mathcal{L}}^T] \\ \mathbb{E}[q_{\mathcal{L}}p_{\mathcal{L}}^T] & \mathbb{E}[q_{\mathcal{L}}q_{\mathcal{L}}^T]\end{bmatrix}$$

➢ **Uncorrelated** Injections

$$\begin{bmatrix}\mathbb{E}[v_a p_b] & \mathbb{E}[v_a q_b]\end{bmatrix} = \begin{bmatrix}H^{-1}_{1/r}(a,b) & H^{-1}_{1/x}(a,b)\end{bmatrix}\begin{bmatrix}\mathbb{E}[p_b^2] & \mathbb{E}[p_b q_b] \\ \mathbb{E}[q_b p_b] & \mathbb{E}[q_b^2]\end{bmatrix}$$



– Two equations with 2 unknowns

Effect of Correlated Injection

- Algorithm:

➢ Compute *effective impedances* between leaves

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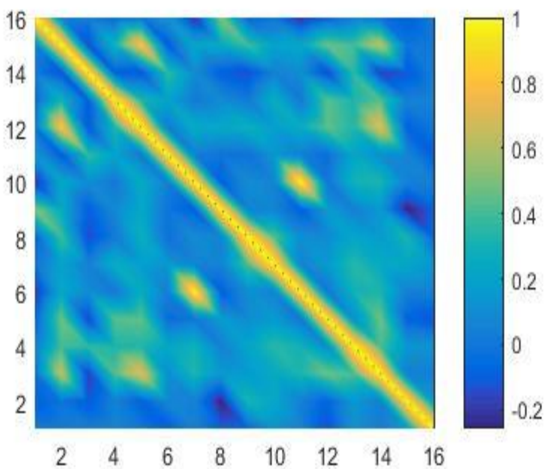
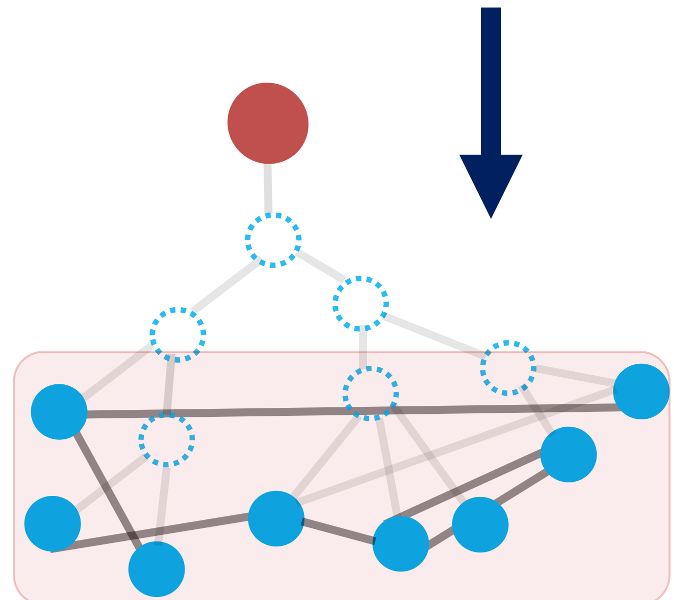
➢ Power Flow equations:

$$\begin{bmatrix}\mathbb{E}[v_{\mathcal{L}}p^T_{\mathcal{L}}] & \mathbb{E}[v_{\mathcal{L}}q^T_{\mathcal{L}}]\end{bmatrix} = \begin{bmatrix}H^{-1}_{1/r}(\mathcal{L},\mathcal{L}) & H^{-1}_{1/x}(\mathcal{L},\mathcal{L})\end{bmatrix}\begin{bmatrix}\mathbb{E}[p_{\mathcal{L}}p^T_{\mathcal{L}}] & \mathbb{E}[p_{\mathcal{L}}q^T_{\mathcal{L}}] \\ \mathbb{E}[q_{\mathcal{L}}p^T_{\mathcal{L}}] & \mathbb{E}[q_{\mathcal{L}}q^T_{\mathcal{L}}]\end{bmatrix}$$



DiSc data set,
Aalborg Univ,



Effect of Correlated Injection

- Algorithm:

➢ Compute *effective impedances* between leaves

$$R_{eff}(a,b) = H^{-1}_{1/R}(a,a) + H^{-1}_{1/R}(b,b) - 2H^{-1}_{1/R}(a,b)$$

➢ Correlated Injections

$$\begin{bmatrix}\mathbb{E}[v_{\mathcal{L}} p_{\mathcal{L}}^T] & \mathbb{E}[v_{\mathcal{L}} q_{\mathcal{L}}^T]\end{bmatrix} = \begin{bmatrix} H^{-1}_{1/r}(\mathcal{L},\mathcal{L}) & H^{-1}_{1/x}(\mathcal{L},\mathcal{L})\end{bmatrix} \begin{bmatrix}\mathbb{E}[p_{\mathcal{L}} p_{\mathcal{L}}^T] & \mathbb{E}[p_{\mathcal{L}} q_{\mathcal{L}}^T] \\ \mathbb{E}[q_{\mathcal{L}} p_{\mathcal{L}}^T] & \mathbb{E}[q_{\mathcal{L}} q_{\mathcal{L}}^T]\end{bmatrix}$$

➢ Computing inverse

➢ ML estimate (SPICE) for inverse:

$$\min_{\Omega \succ 0} -\det(\Omega) + \mathrm{tr}\Big(\mathbb{E}\big[[p_{\mathcal{L}}^T \; q_{\mathcal{L}}^T]^T [p_{\mathcal{L}}^T \; q_{\mathcal{L}}^T]\big]\Omega\Big) + \lambda|\Omega^-|_1$$

Sample Complexity

Uncorrelated :

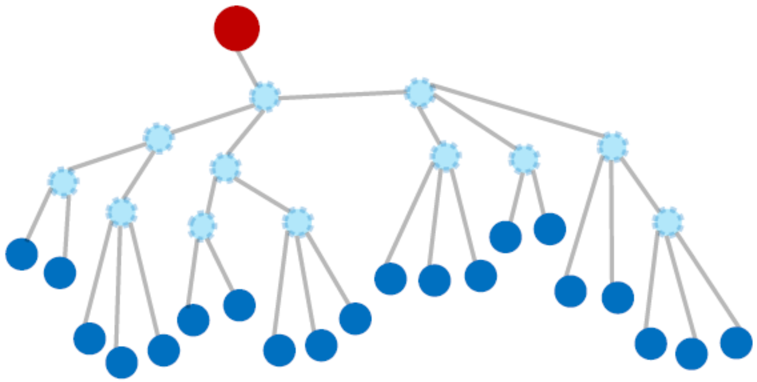
For a grid with constant depth and sub-Gaussian complex power injections, $O(|V|\log(|V|/\eta))$ samples recovers the true topology with probability $1-\eta$.

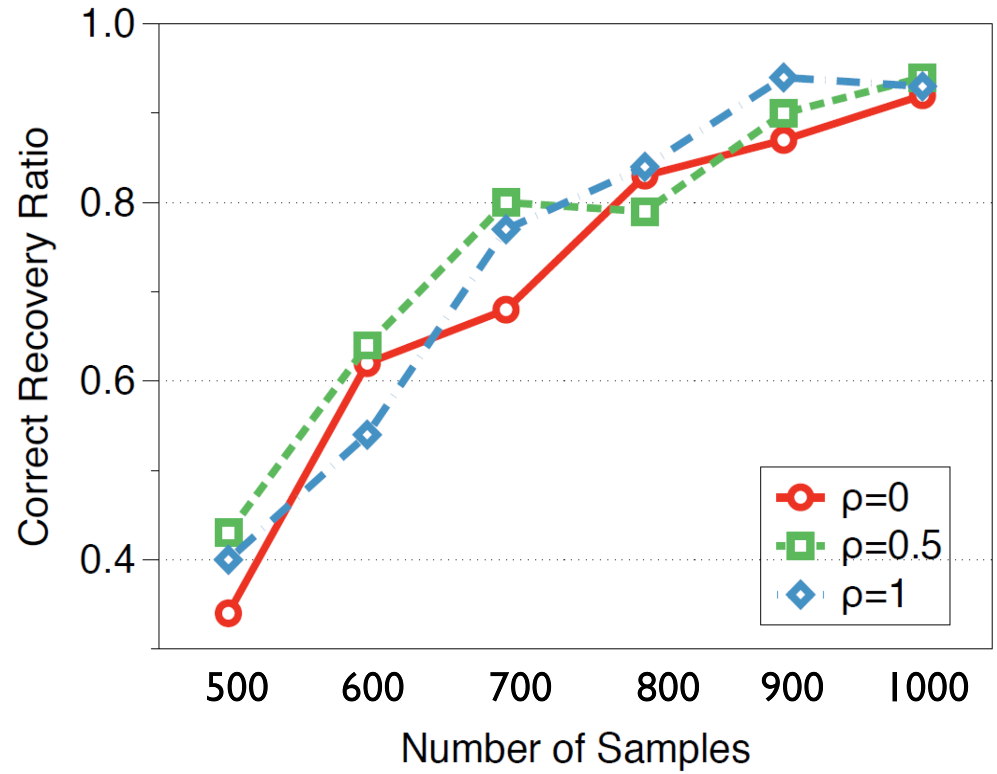
Correlated :

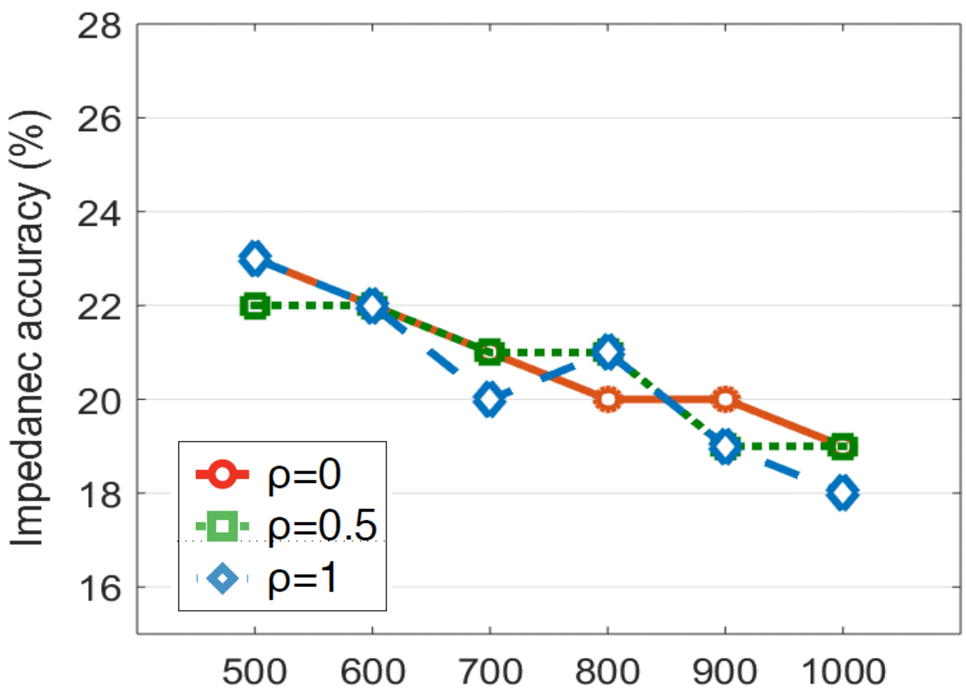
$O(|V|^2\log(|V|/\eta))$ samples recovers the true topology with probability $1-\eta$.

- Park et al., Learning with End-Users in Distribution Grids: Topology and Parameter Estimation, *IEEE Trans. Control of Networks, 2020*

Simulations: IEEE 33 bus graphs (Matpower samples)

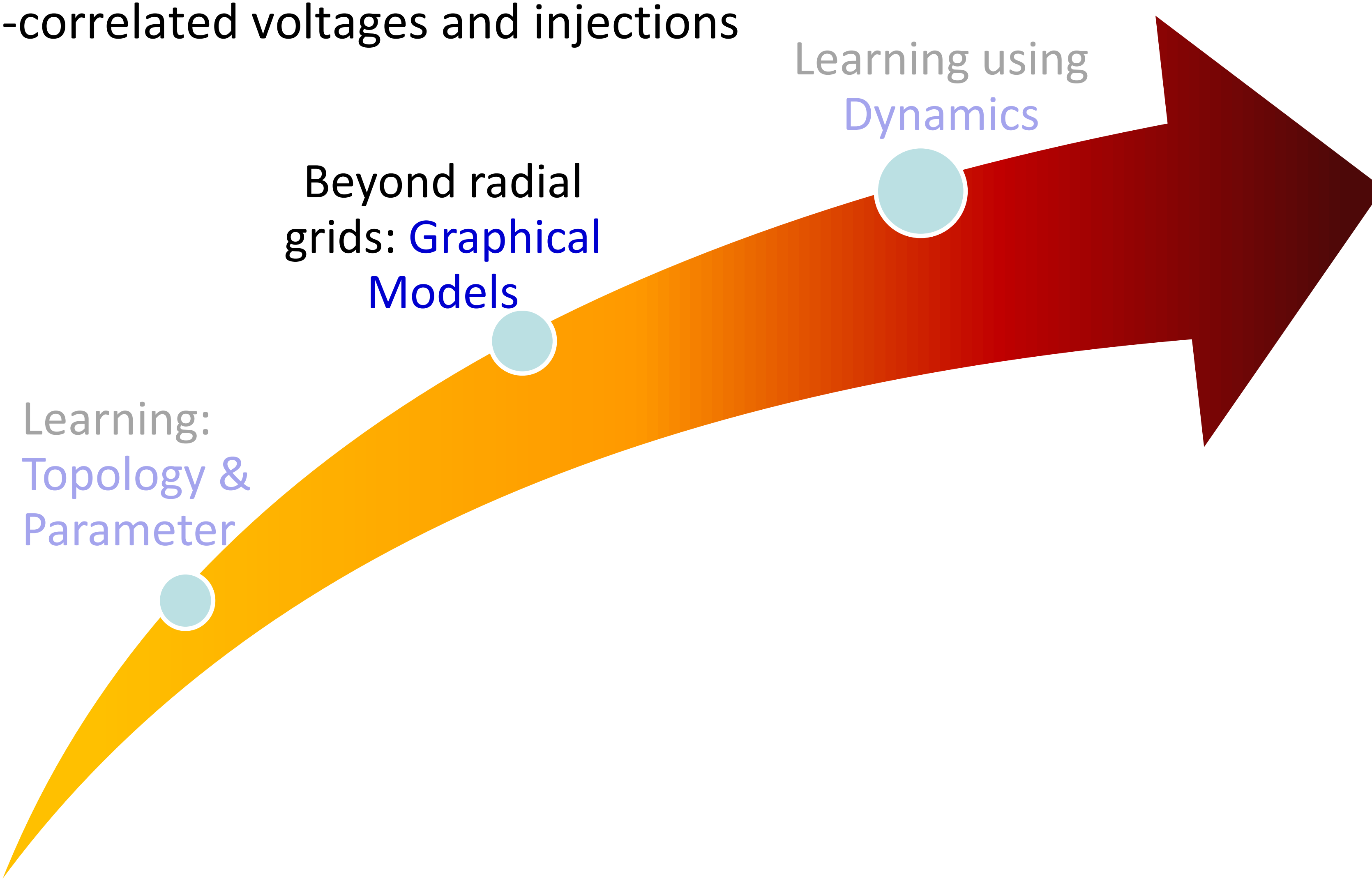




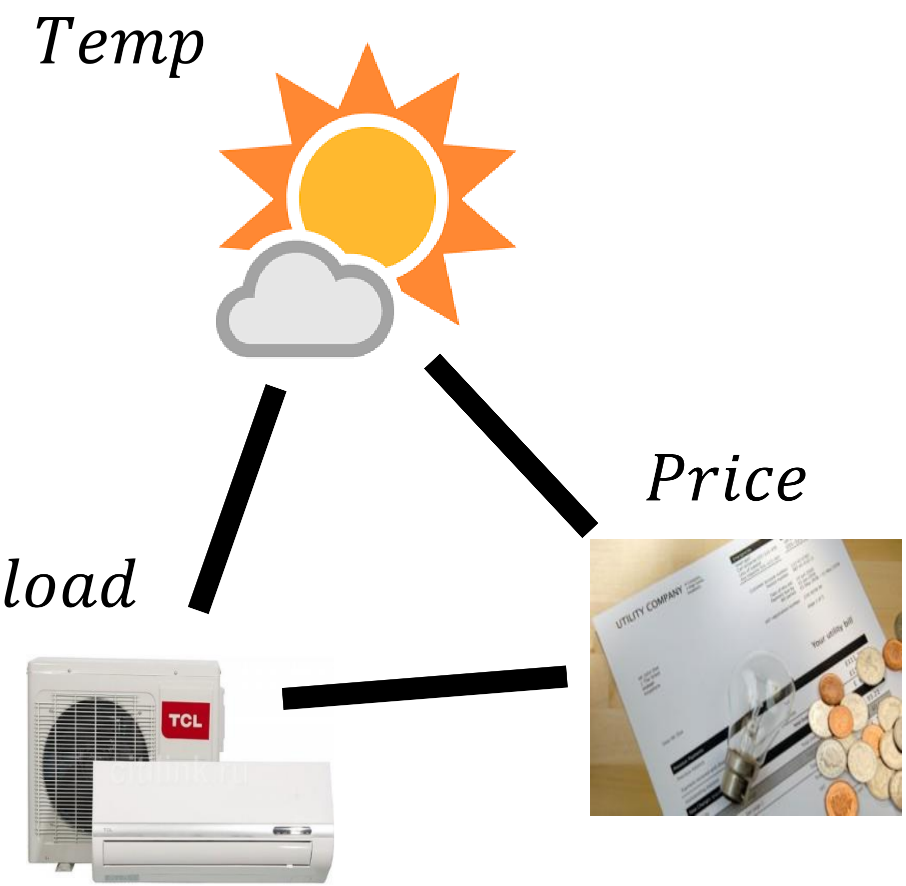


What about

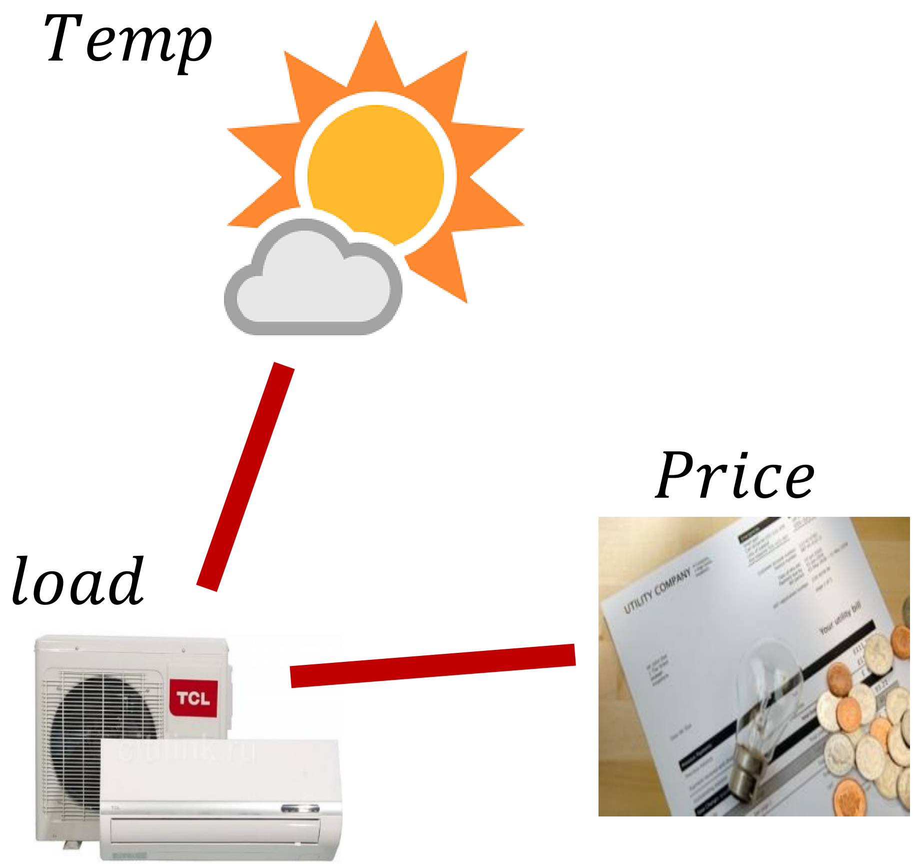
1. Loopy grids
2. Time-correlated voltages and injections



Probabilistic Distribution → Graphical Model



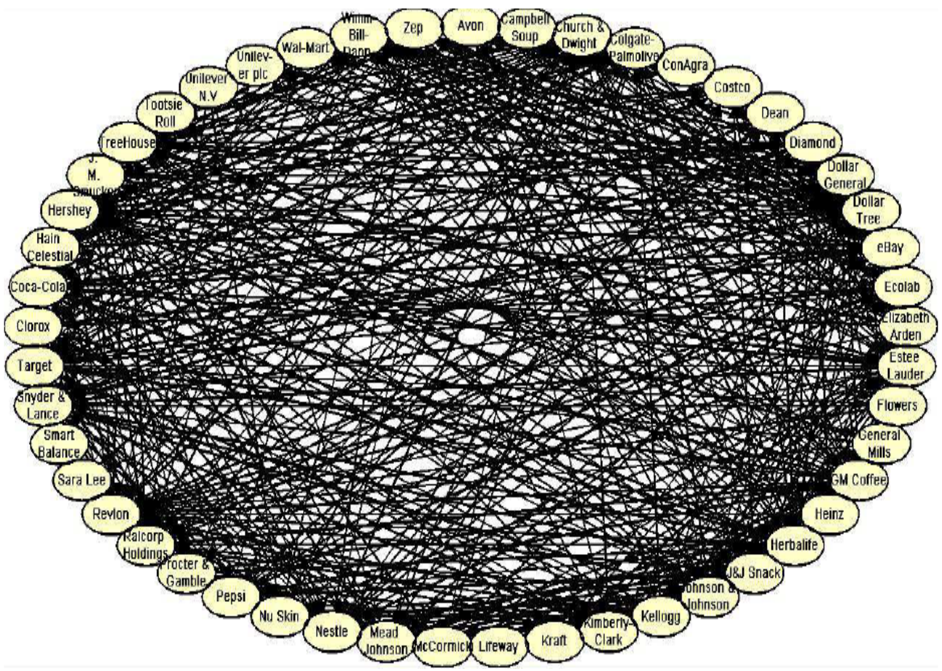
Correlation



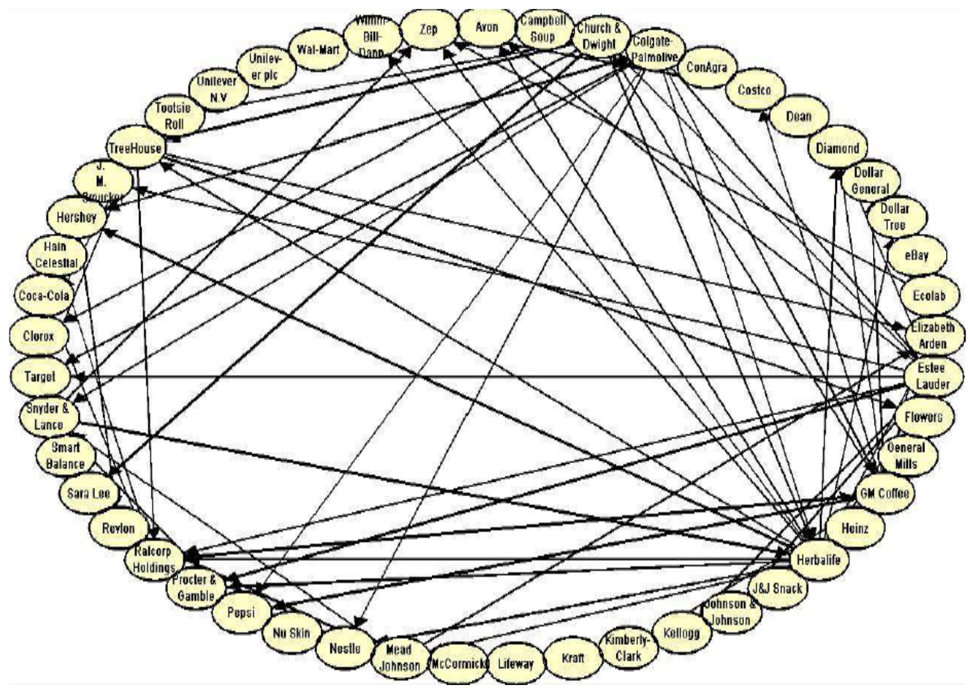
Conditional Dependence

Probabilistic Distribution → Graphical Model

- Graphical Model: Graphical Factorization of Distribution
- Think **Inverse Correlation** instead of **Correlation**



Correlation of stock prices



Graphical Model of stock prices

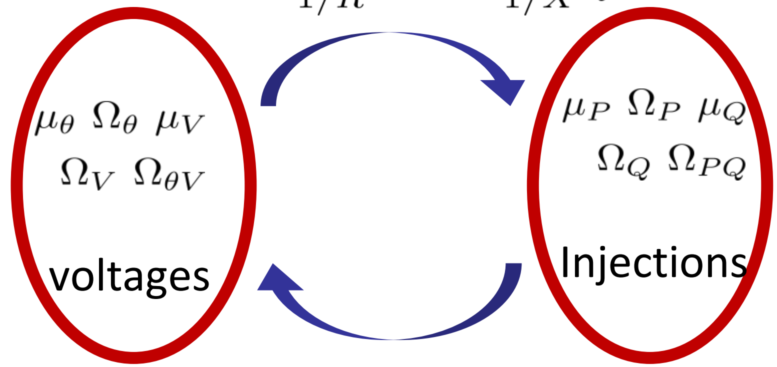
Probabilistic Distribution of Nodal Voltages

- Distribution of injections:

$$\mathcal{P}(P) = \prod_{a\in\mathcal{V}} \mathcal{P}_a(P_a)$$

$$\theta = H^{-1}_{1/X}P - H^{-1}_{1/R}Q,$$

$$v = H^{-1}_{1/R}P + H^{-1}_{1/X}Q$$



- Distribution of voltages:

$$\mathcal{P}(V,\theta) = \frac{1}{|J_P(V,\theta)|}\prod_{a\in\mathcal{V}} \mathcal{P}_a(P_a)$$

$$= \frac{1}{|J_P(V,\theta)|}\prod_{a\in\mathcal{V}} \mathcal{P}_a\left(\sum_{b:\{a,b\}\in\mathcal{E}} V_a(V_a^* - V_b^*)/z_{ab}^*\right)$$

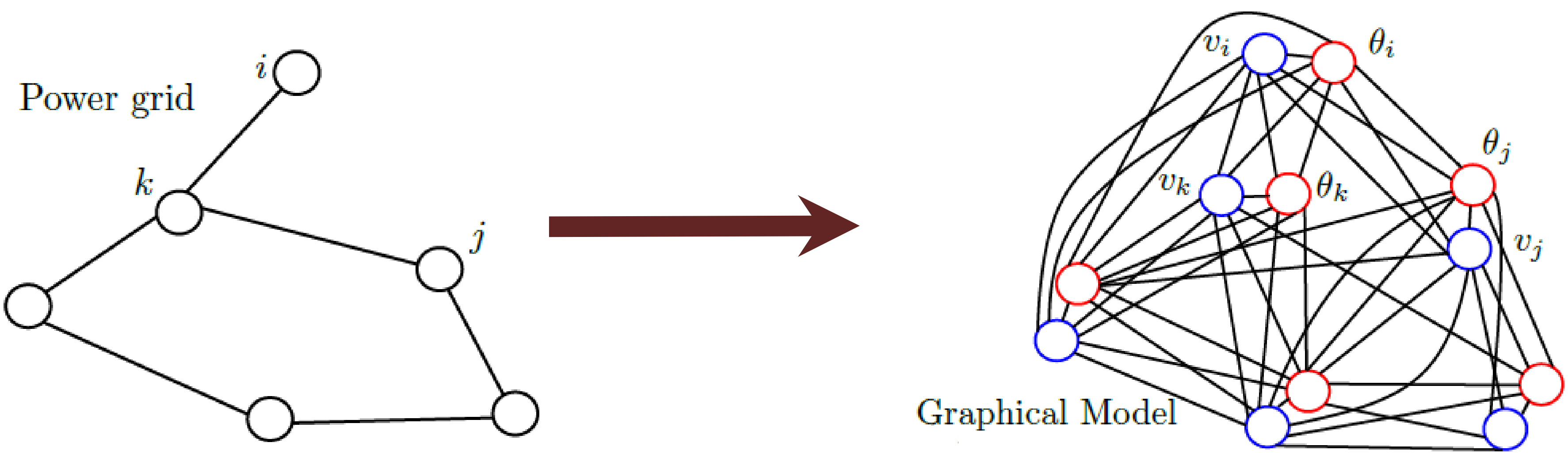
Jacobian $J_P(V,\theta) = (\frac{\partial V,\theta}{\partial P,Q})$

Graphical Model of Voltages

- Distribution $\mathcal{P}(V,\theta)$ with

$$\theta = H^{-1}_{1/X}P - H^{-1}_{1/R}Q,$$
$$v = H^{-1}_{1/R}P + H^{-1}_{1/X}Q$$

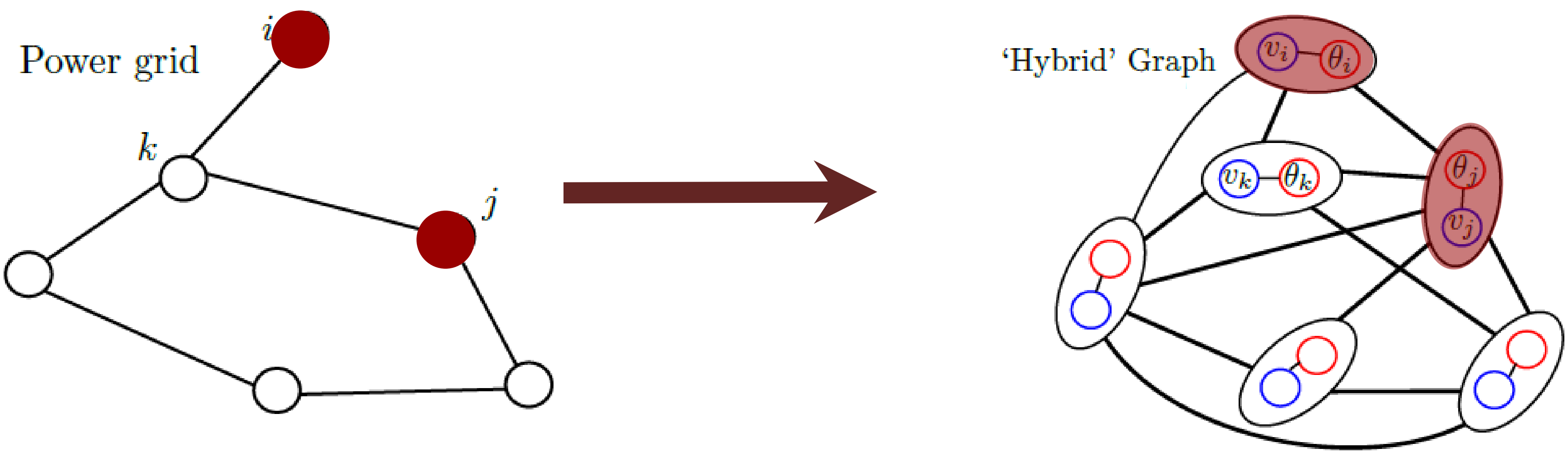
- Graphical Model: *between voltage, phase*



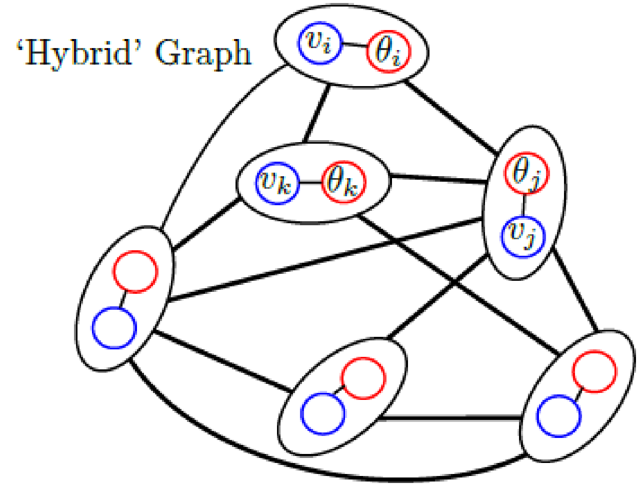
Graphical Model of Voltages

- Distribution $\mathcal{P}(V, \theta)$

- **Graphical Model:** Topology Edges + *2-hop neighbors*



Graphical Model Estimation



- Variables: (V, θ)
- Gaussian voltage fluctuations
- **Inverse covariance** $\Sigma^{-1}_{(V,\theta)}$ gives graphical model

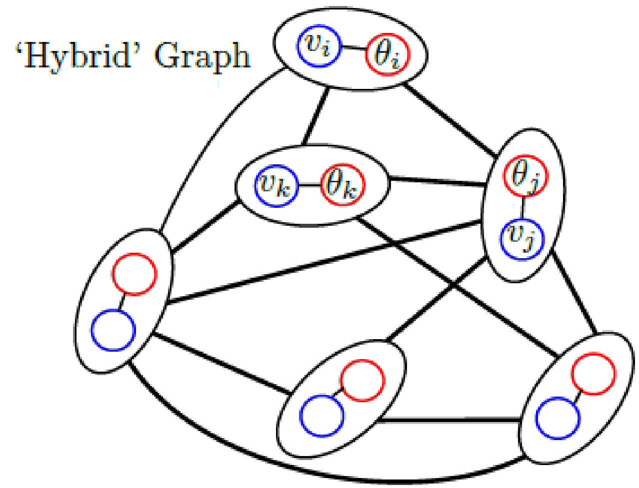
- Graphical Lasso:
  (Yuan & Lin, 2007)

$$\arg\min_{S} -\log\det S + \langle S, \sum_k x^k {x^k}^T / n \rangle + \lambda \|S\|_1$$

- Neighborhood Lasso:
  (Meinshausen, 2006)

$$\arg\min_{\substack{\beta_{ij} \\ j \neq i}} \mathbb{E} \left[x_i - \sum_{j \neq i} \beta_{ij} x_j \right]^2 + \lambda \left\| \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \vdots \\ \vdots \end{bmatrix} \right\|_1$$

Graphical Model → Topology estimation

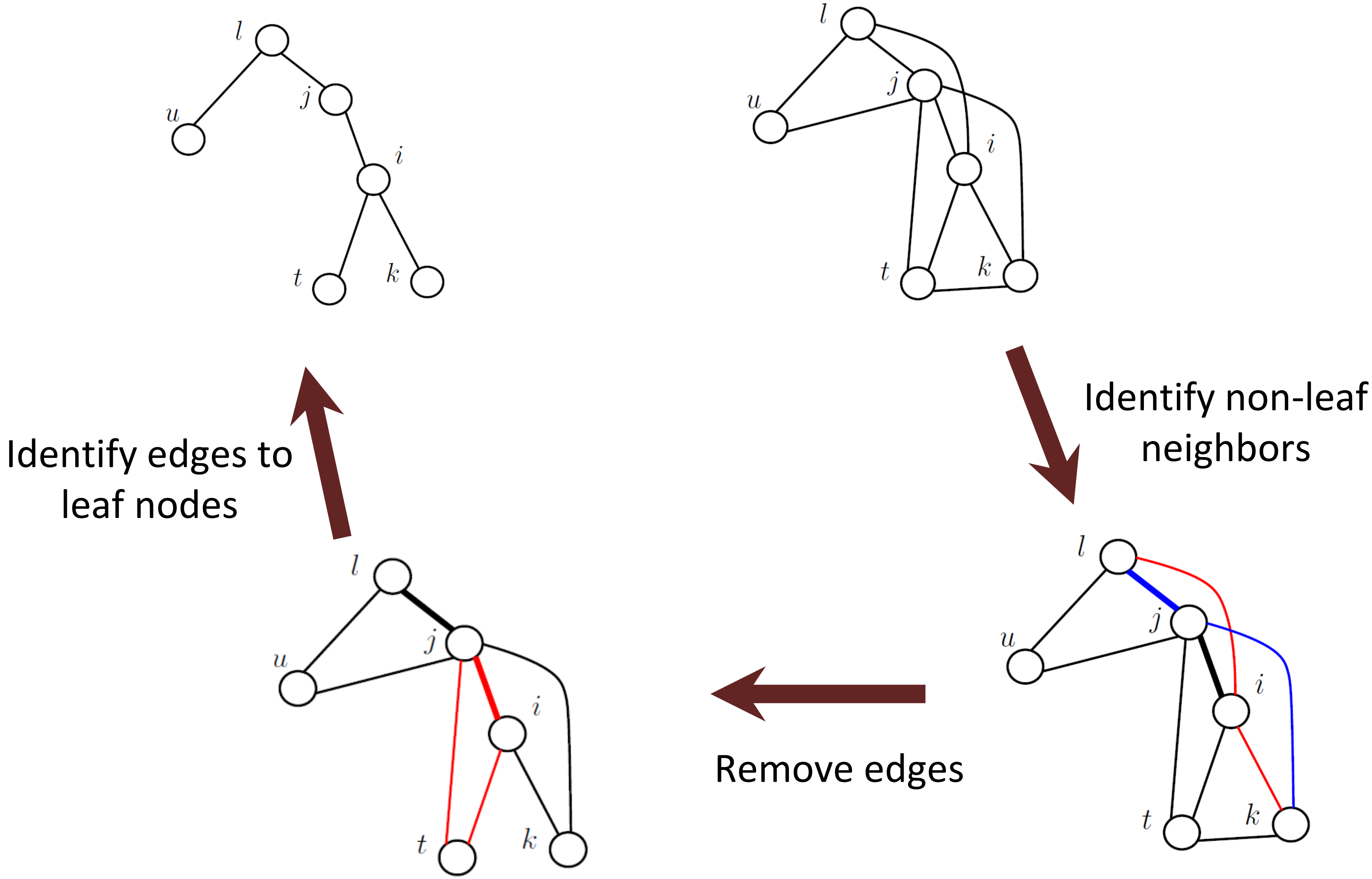


- How to distinguish true edges??
- Two schemes:
  - Neighborhood Counting
  - Thresholding
- Exact for radial networks
- Restrictions for loopy/meshed grids

- Deka et al., Graphical Models in Meshed Distribution Grids: Topology estimation, change detection & limitations, *IEEE Trans. Power Systems, 2020*

Graphical Model → Topology estimation

- Neighborhood Counting:



Graphical Model → Topology estimation

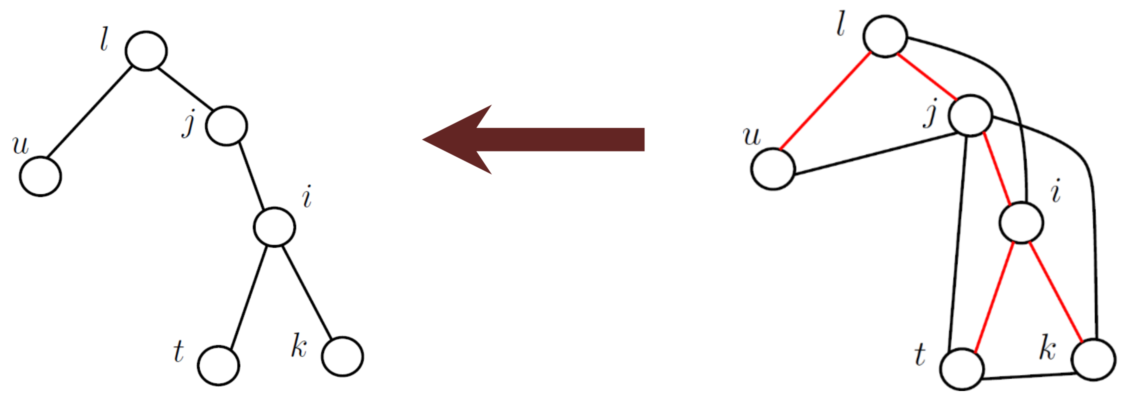
- Neighborhood Counting: topological separability

- Loopy Grid:
    - Recovers exact topology if cycle length greater than 6

- Deka et al., Graphical Models in Meshed Distribution Grids: Topology estimation, change detection & limitations, *IEEE Trans. Smart Grid, 2020*

Graphical Model → Topology estimation

- Thresholding:



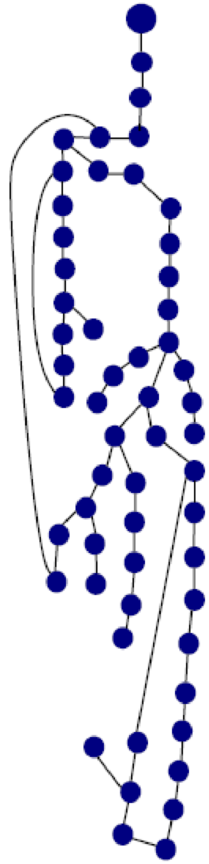
- True edges have $\Sigma_{\theta\theta}^{-1}(i,j) + \Sigma_{VV}^{-1}(i,j) < \tau_2 < 0$

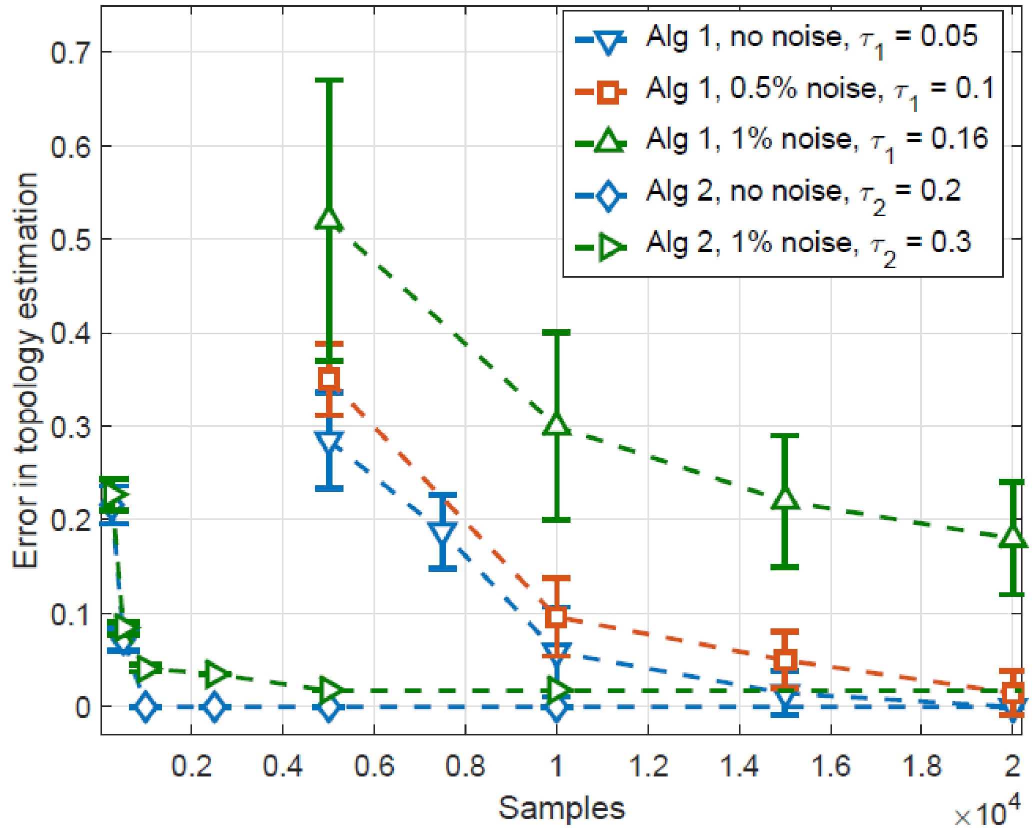
- Loopy Grid:
  - Recovers topology if cycle length greater than 3 (no triangles)

- Deka et al., Graphical Models in Meshed Distribution Grids: Topology estimation, change detection & limitations, *IEEE Trans. Smart Grid, 2020*

Graphical Model → Topology estimation

- Alg1: counting
- Alg2: thresholding
- 56 bus system

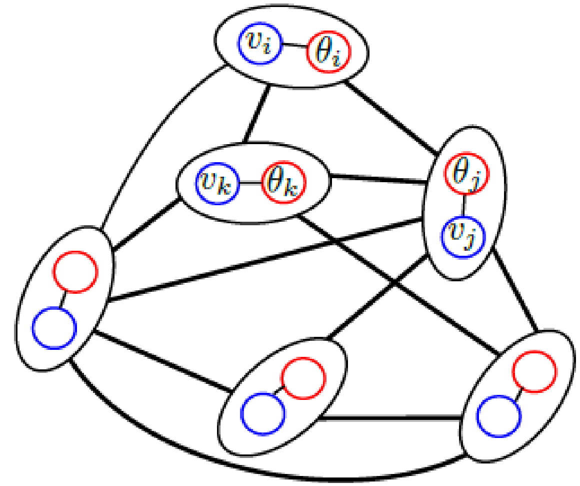


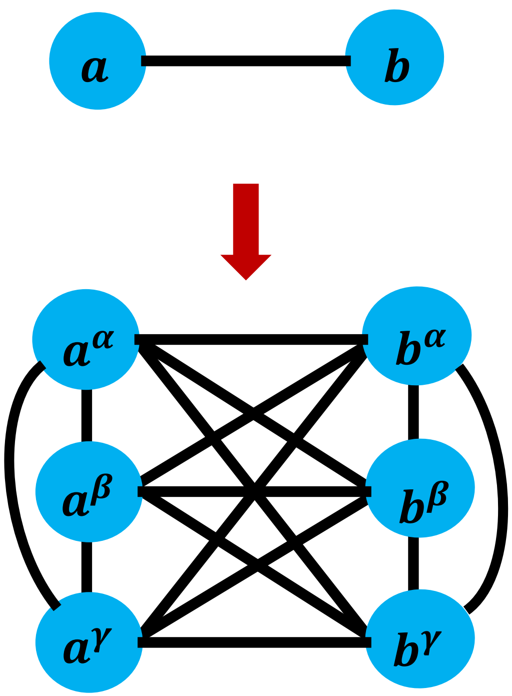


- Deka et al., Graphical Models in Meshed Distribution Grids: Topology estimation, change detection & limitations, *IEEE Trans. Smart Grid, 2020*

Graphical Model → Topology estimation

- Extends to ***3-phase unbalanced system***
- Deka et al., Topology estimation using graphical models in multi-phase power distribution grids, *IEEE Trans. Power Systems, 2020*





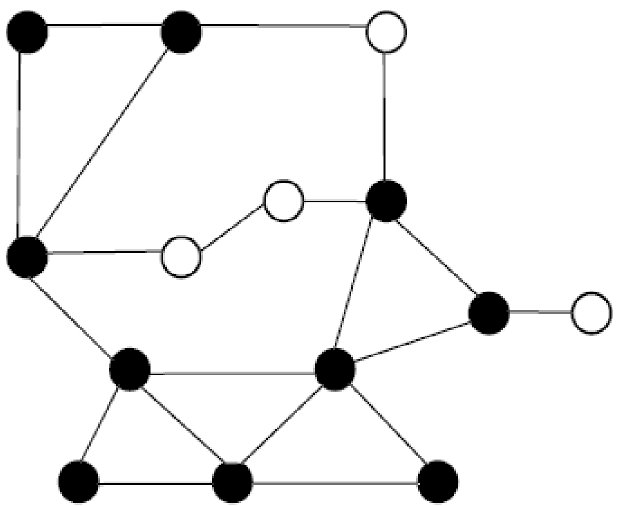
Messy!!

$$\mathcal{P}(V^\dagger) = \frac{1}{|J_P(V^\dagger)|}\prod_{i\in\mathcal{V}} \mathcal{P}_i(\hat{P}_i)$$

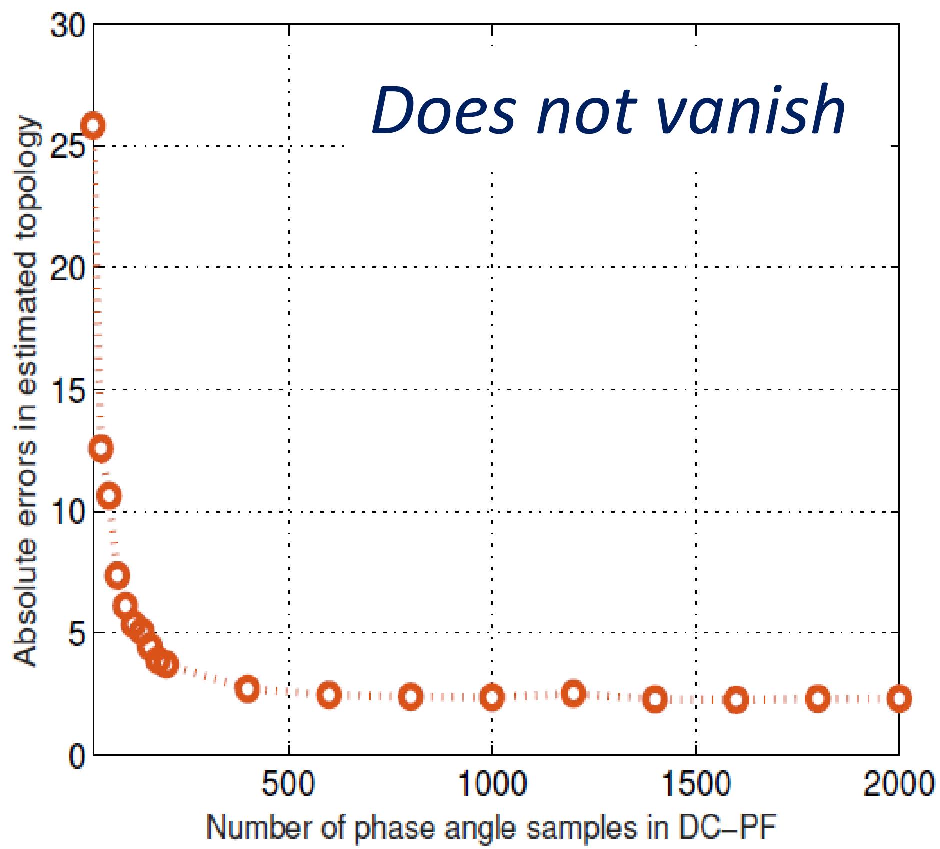
$$= \frac{1}{|J_P(V^\dagger)|}\prod_{i\in\mathcal{V}} \mathcal{P}_i\left(\sum_{j:(ij)\in\mathcal{E}}\begin{bmatrix}\sum_{\beta\in\{a,b,c\}} e^{\tilde{i}\theta^{a\beta}_{ref}}(V_i^a - V_j^\beta)Y_{ij}^{a\beta}\\ \sum_{\beta\in\{a,b,c\}} e^{\tilde{i}\theta^{b\beta}_{ref}}(V_i^b - V_j^\beta)Y_{ij}^{b\beta}\\ \sum_{\beta\in\{a,b,c\}} e^{\tilde{i}\theta^{c\beta}_{ref}}(V_i^c - V_j^\beta)Y_{ij}^{c\beta}\end{bmatrix}\right)$$

What about

- General Grids with triangles??
- Temporal Correlations??

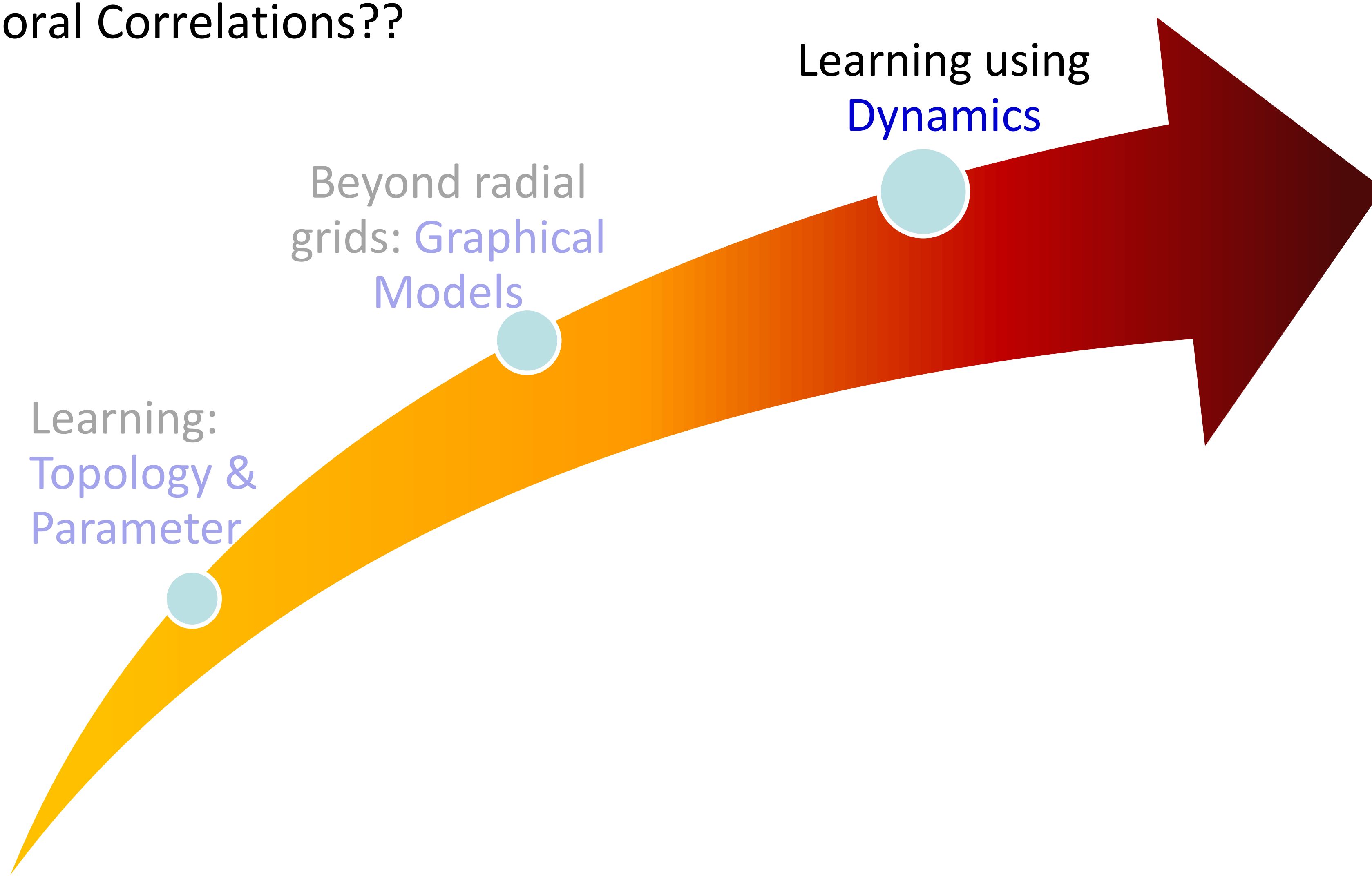


IEEE 14 bus



What about

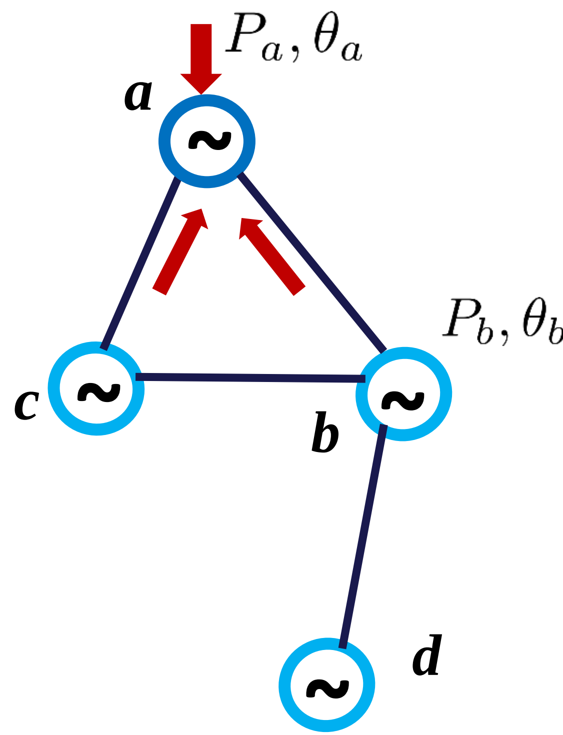
- General Grids with triangles??
- Temporal Correlations??



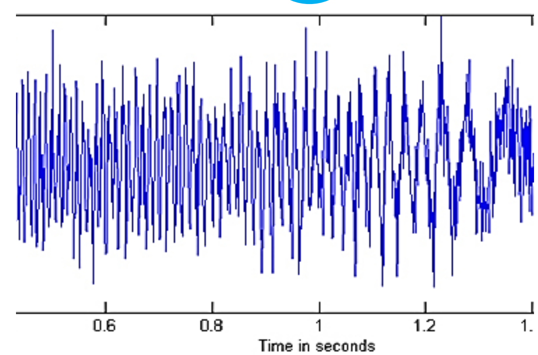
Dynamic Regime: Swing Equations

- Fluctuations due to ambient noise in injections:

$$\underbrace{M_a\ddot{\theta}_a + D_a\dot{\theta}_a}_{\text{Dynamics of phase angles}} = \underbrace{\sum_{(a,b)\text{ is edge}} B_{ab}(\theta_b - \theta_a) + P_a}_{\text{Net power imbalance}}$$



- Frequency $\omega_a = \dot{\theta}_a$
- Inertia (M) and Damping (D) from synchronous machines.
- Stochastic noise P_a



Power Flow

- General Form:

$$0 = \sum_{(a,b) \text{ is edge}} B_{ab}(\theta_b - \theta_a) + P_a$$

- Graphical Model:

Inverse **Correlation Matrix**

$$\Sigma_\theta = \mathbb{E}[\theta(t)\theta(t)^T]$$

Invert

$$\Sigma_\theta^{-1}$$

Swing equation

$$M_a\ddot{\theta}_a + D_a\dot{\theta}_a = \sum_{(a,b) \text{ is edge}} B_{ab}(\theta_b - \theta_a) + P_a$$

Inverse **Power Spectral Density**

$$\Sigma_\theta(r) = \mathbb{E}[\theta(t)\theta(t-r)^T]$$

Fourier Transform of delayed correlation

Invert

$$\Omega_\theta^{-1}(j\omega)$$

Power Flow

- General Form:

$$0 = \sum_{(a,b)\text{ is edge}} B_{ab}(\theta_b - \theta_a) + P_a$$

- Graphical Model:

Inverse **Correlation Matrix**

- Finite samples:

Neighborhood Lasso
(Meinshausen, 2006)

$$\arg\min_{\substack{\beta_{ij}\\ j\neq i}} \mathbb{E}\left[\theta_i - \sum_{j\neq i} \beta_{ij}\theta_j\right]^2 + \lambda \begin{Vmatrix} \beta_{i1} \\ \beta_{i2} \\ \vdots \\ \vdots \end{Vmatrix}_1$$

Swing equation

$$M_a\ddot{\theta}_a + D_a\dot{\theta}_a = \sum_{(a,b)\text{ is edge}} B_{ab}(\theta_b - \theta_a) + P_a$$

Inverse **Power Spectral Density**

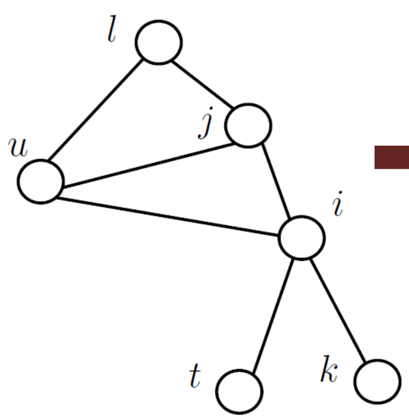
→ **Wiener Filter (non-causal)**
(Wiener, Kolmogorov 1950)

$$\arg\min_{\beta^r_{ij}, j\neq i} \mathbb{E}\left[\theta_i(t) - \sum_{\substack{j\neq a\\ -\infty<r<\infty}} \beta^r_{ij}\theta_j(t-r)\right]^2 + \lambda \begin{Vmatrix} \vec{\beta}_{i1} \\ \vec{\beta}_{i2} \\ \vdots \\ \vdots \end{Vmatrix}_{(2,1)}$$

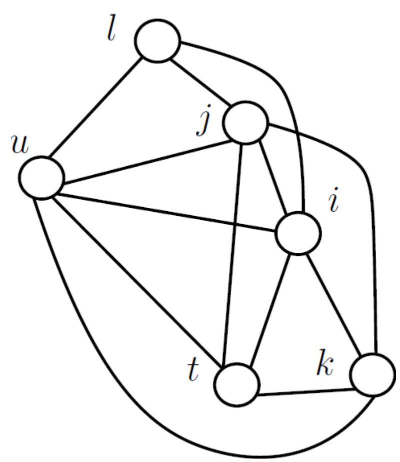
Learning in dynamic regime:

- Graphical Model of voltages: Topology Edges + *2-hop neighbors*
- Dynamic regime (inverse power spectral density):
  - Neighborhood counting (cycle length > 6)
- Inverse PSD: ($\Omega_\theta^{-1}(j\omega)$ is function of frequency)

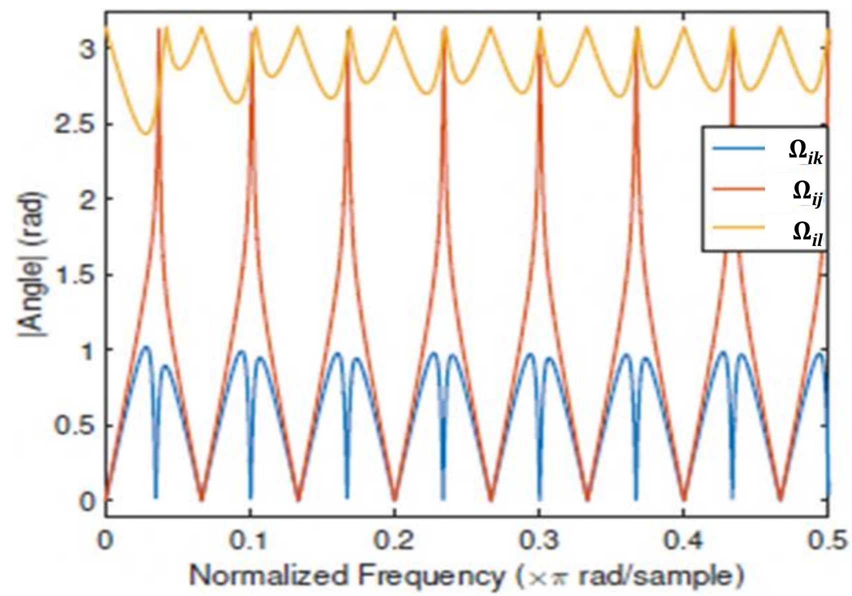
❑ Phase remains **constant** for spurious edges at all frequency



Topology

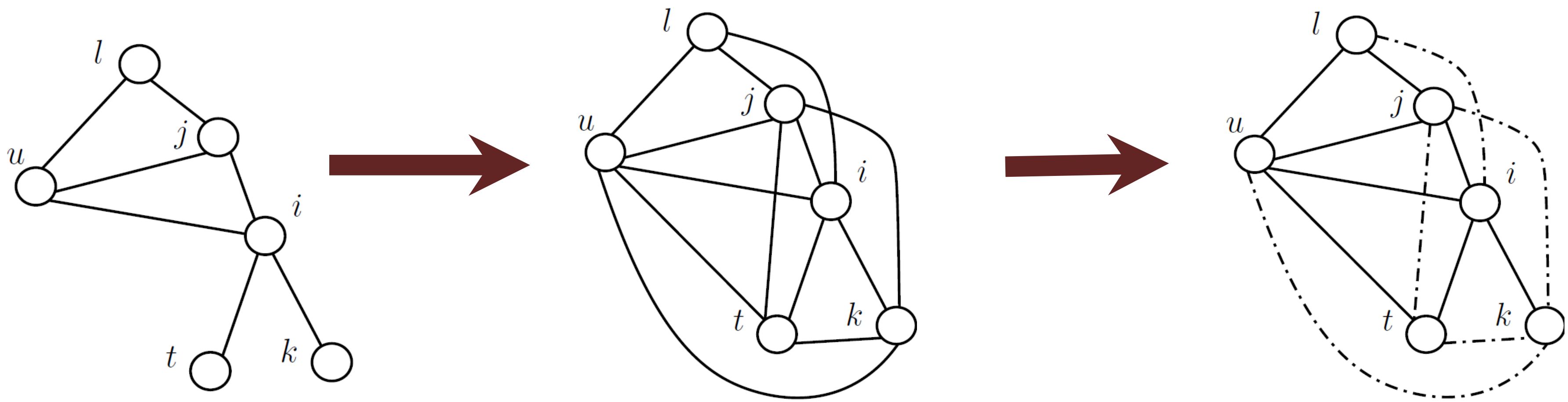


Graphical Model



Learning in dynamic regime:

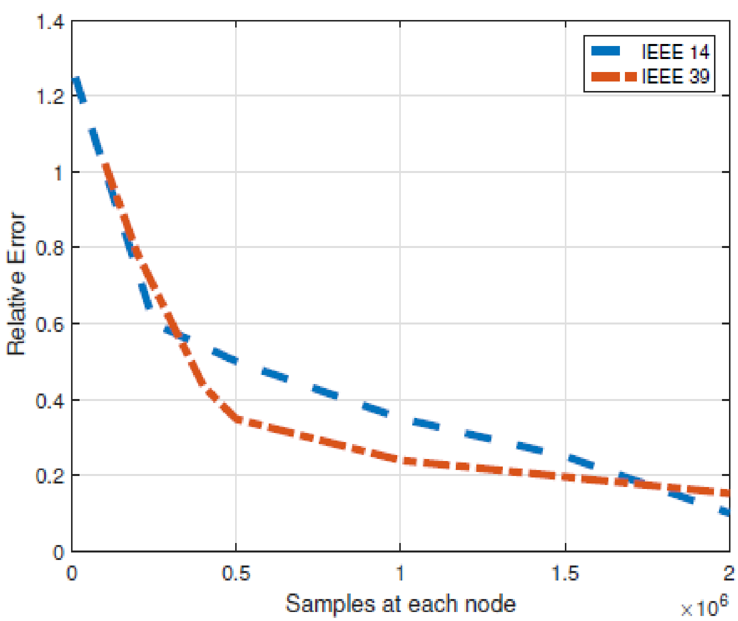
- Graphical Model of voltages: Topology Edges + *2-hop neighbors*
- Dynamic regime (inverse power spectral density):
  - Neighborhood counting (cycle length > 6)
  - Phase based edge detection (all graphs)
  - Holds for colored **(WSS or cyclo-stationary)** inputs
  - S. Talukdar et al., Physics-informed learning in linear dynamical systems, *Automatica,* 2020.

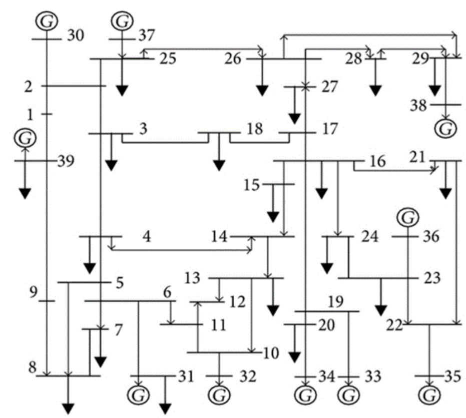


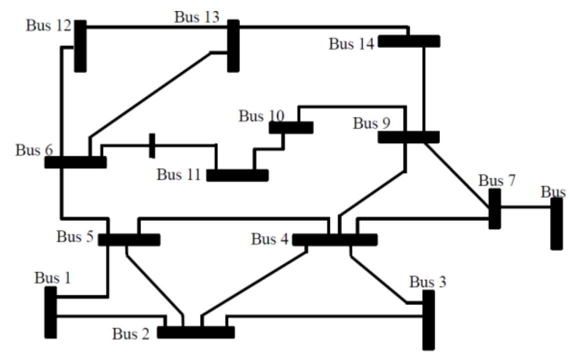
Topology   Graphical Model   Pruned model

Learning in dynamic regime:

- Graphical Model of voltages: Topology Edges + *2-hop neighbors*
- Dynamic regime (inverse power spectral density):
  - **Phase based edge detection** (all graphs)
  - Any linear dynamical system: Eg. Buildings
  - S. Talukdar et al., Physics-informed learning in linear dynamical systems, *Automatica,* 2020.







Learning in dynamic regime:

- Graphical Model of voltages: Topology Edges + *2-hop neighbors*
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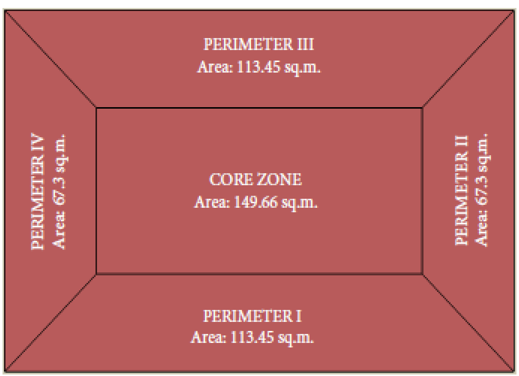
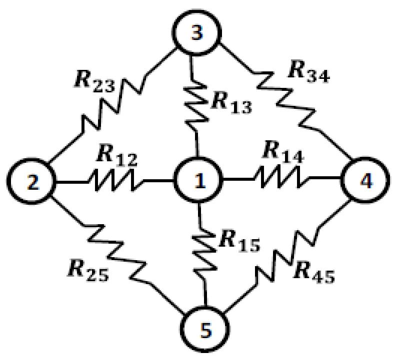
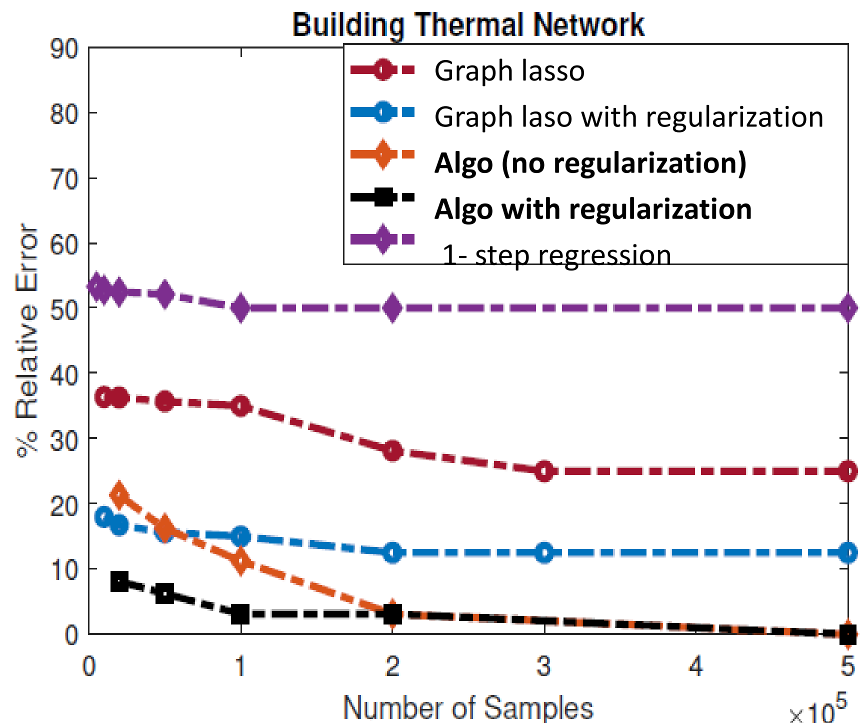


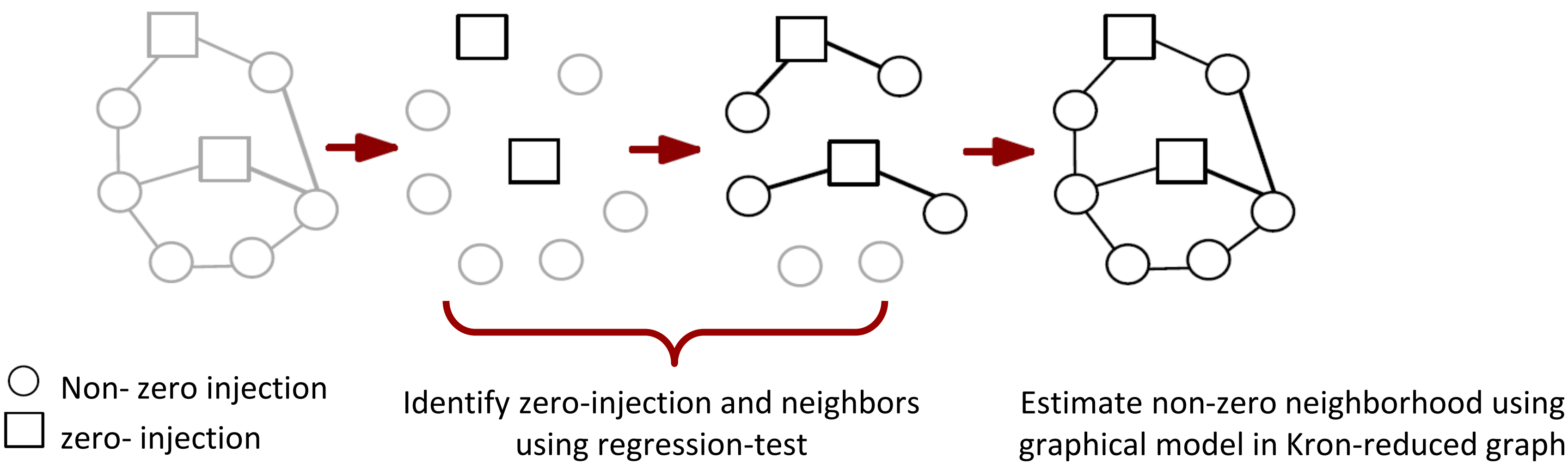




Learning in *under-excited* grids:

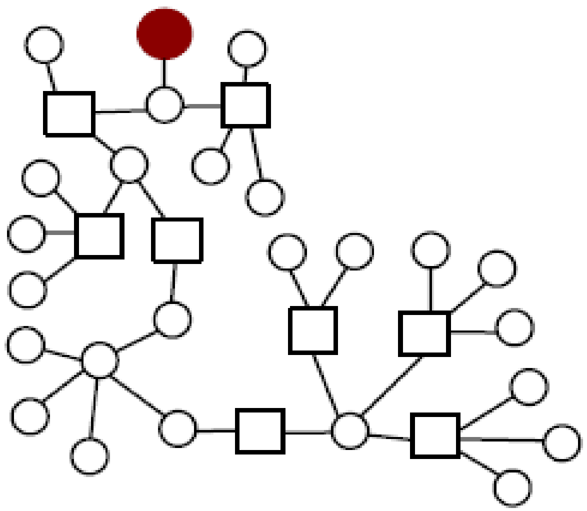
- Graphical Model of voltages: static or dynamic
  - Uses *inverse* voltage covariance or power spectral density
  - Needs fluctuations at all nodes ($\Sigma^{-1}_{(P,Q)} \Rightarrow \Sigma^{-1}_{(V,\theta)}$ to be defined)
  - What if zero-injection buses exist?

- Learning when 0-injection buses not adjacent



- Deka et al, Tractable learning in under-excited power grids, *arxiv pre-print, 2020.*

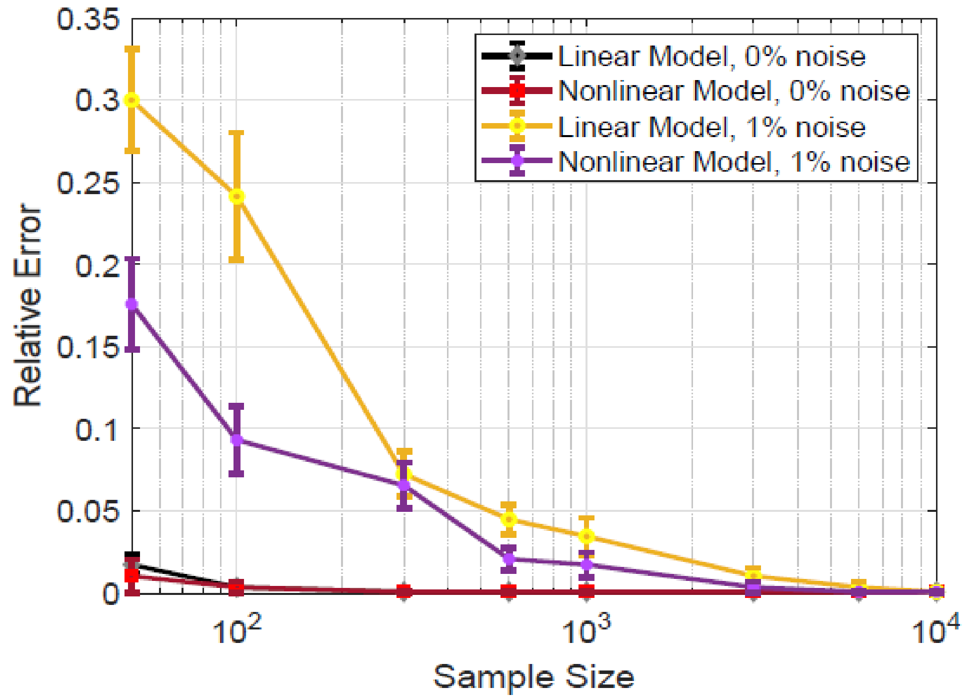
Learning in *under-excited* grids:



33 bus system

◯ Non- zero injection

☐ zero- injection



- Deka et al, Tractable learning in under-excited power grids, *arxiv pre-print, 2020.*

Practical Applications:

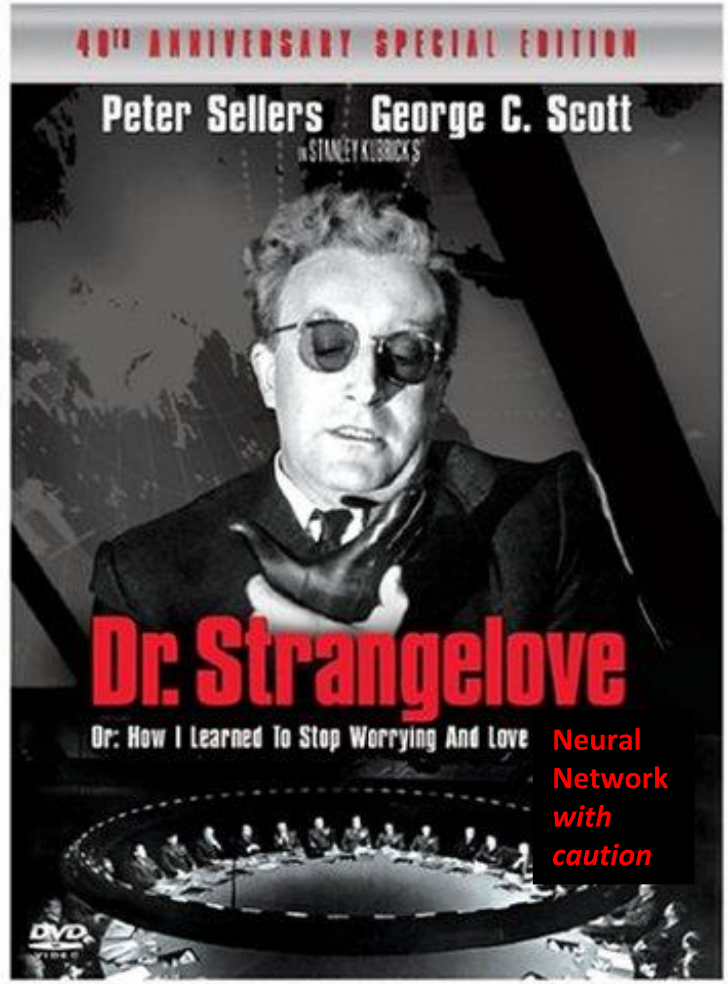
- Use tractable/provable algorithms as a starting point
- Additional constraints from real data:
  - Prior structures /impedance values (monitor change instead)
  - Use threshold selection based on historical data
  - Learn noise levels

- **Data-driven guided by real-data:**
  - Matt Reno, Yang Wang, Ram Rajagopal, Reza Arghandeh, Sascha von Meier, Vijay Arya
- **Direct Samples not statistics:** (regression or active probing based)
  - Steven Low, Vassilis Kekatos, Guido Cavraro
- **Statistical change detection:**
  - Anuradha Annaswamy, Alejandro Garcia

When such methods do not work well?

- Non-linearity makes linear approximations inadequate
  - Kernel based methods (George Giannakis)
  - Koopman operators
  - Neural networks- physics-informed (Yue Zhang)

- Use case where NN works well:
  - Fault detection/ localization



- Wenting Li et al., Real-time Faulted Line Localization and PMU Placement in Power Systems through Convolutional Neural Networks, *IEEE Trans. Power Systems, 2019.*

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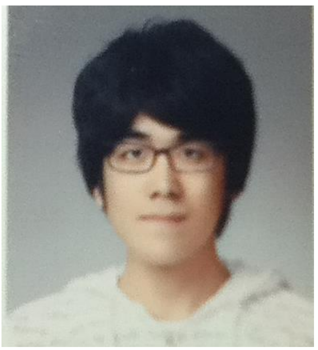
Minnesota

Sidhant Misra
LANL



Sejun Park
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Saurav Talukdar
Google

Harish Doddi
Minnesota

Wenting Li
LANL

Support:

Center for Nonlinear Studies

GRID MODERNIZATION INITIATIVE
U.S. Department of Energy

The Advanced Network Science Initiative

Overview Projects People Publications Software

Los Alamos National Laboratory's Advanced Network Science Initiative.

Los Alamos, NM

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Overview

The Los Alamos National Laboratory's Advanced Network Science Initiative (ANSI) is an interdisciplinary initiative that enables fundamental and applied research to address long-term challenges in critical infrastructure design, operation, and security. The primary philosophy of ANSI is that combining insights from Theoretical Physics, Applied Mathematics, Computer Science, and Applied Engineering can result in novel computational methods that address a variety of emerging challenges in infrastructure networks.

Application Areas

To help motivate and inspire novel computational methods, ANSI studies a variety of challenging problems in critical infrastructure networks, such as *Analysis of Extreme Events*, *Network base Machine Learning and Data Analytics, Control and*

- Web: https://lanl-ansi.github.io/
- Email: deepjyoti@lanl.gov, for projects, post-doc, student positions.

The Advanced Network Science Initiative | Overview | Projects | People | Publications | Software

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- YouTube

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Thank You. *Questions!*

Ans: