DOE/OE Transmission Reliability Program

Grid Modernization LC, Cat 2:

Advanced Machine Learning for Synchrophasor Technology

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LANL+PNNL+LBNL+Columbia U+GridCons.

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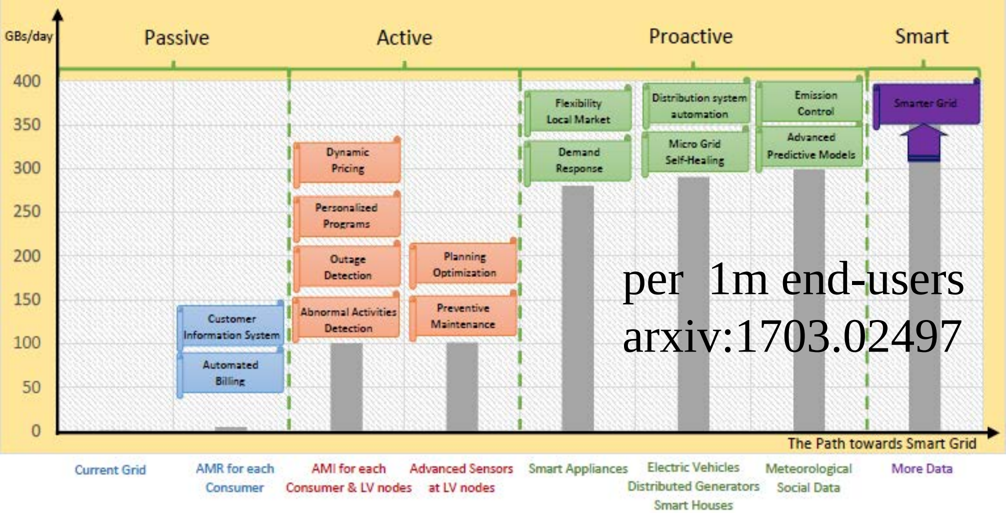
Why do we need to introduce Machine Learning techniques?

- New challenges for reliability
  - Deregulation (central -> local)
  - Variable Energy Resources
  - Passive -> Active (consumers)
  - "Reliability **indexes**" (20th century state of the art) cannot handle ever increasing uncertainty, fluctuations

- **Solution** = Data Analytics, Machine Learning
  - = software tools to handle all of the above
  - towards "ML-based reliability indexes"

- New **opportunities/drivers**
  - Better/new hardware
  - Smarter optimization/control
  - Better measurements = PMU +
  - More data



Aiming at (in 5-10 years)

Enhancing

real-time monitoring situational awareness and control

under changing system conditions

making

SCADA/PMU/data-driven and system-wide

Machine Learning (Applied Statistics) technology

a standard routine for power system utilities/practitioners

Expected outcome (in 3 years)

Machine Learning approaches

- to identify parameters of
  - transmission network (static & dynamic)
  - generators (with new controllers) & loads (passive & active)
- to detect network topology
- to estimate state (static & dynamic)

normal/ambient

- develop taxonomy of events/anomalies
- localize events/anomalies

event

Demonstrate on models of utility partners

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Overall Project Objective

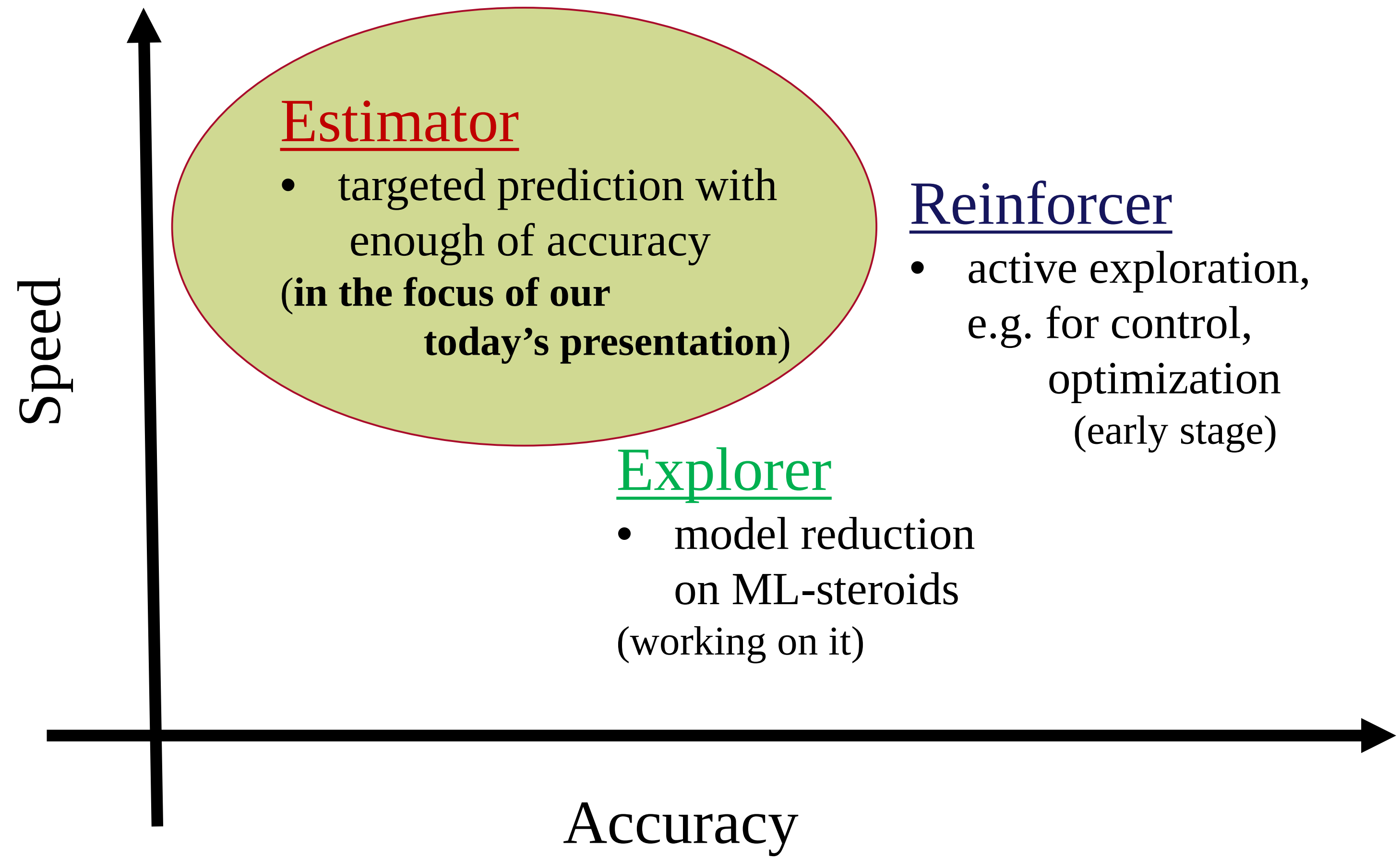
2016

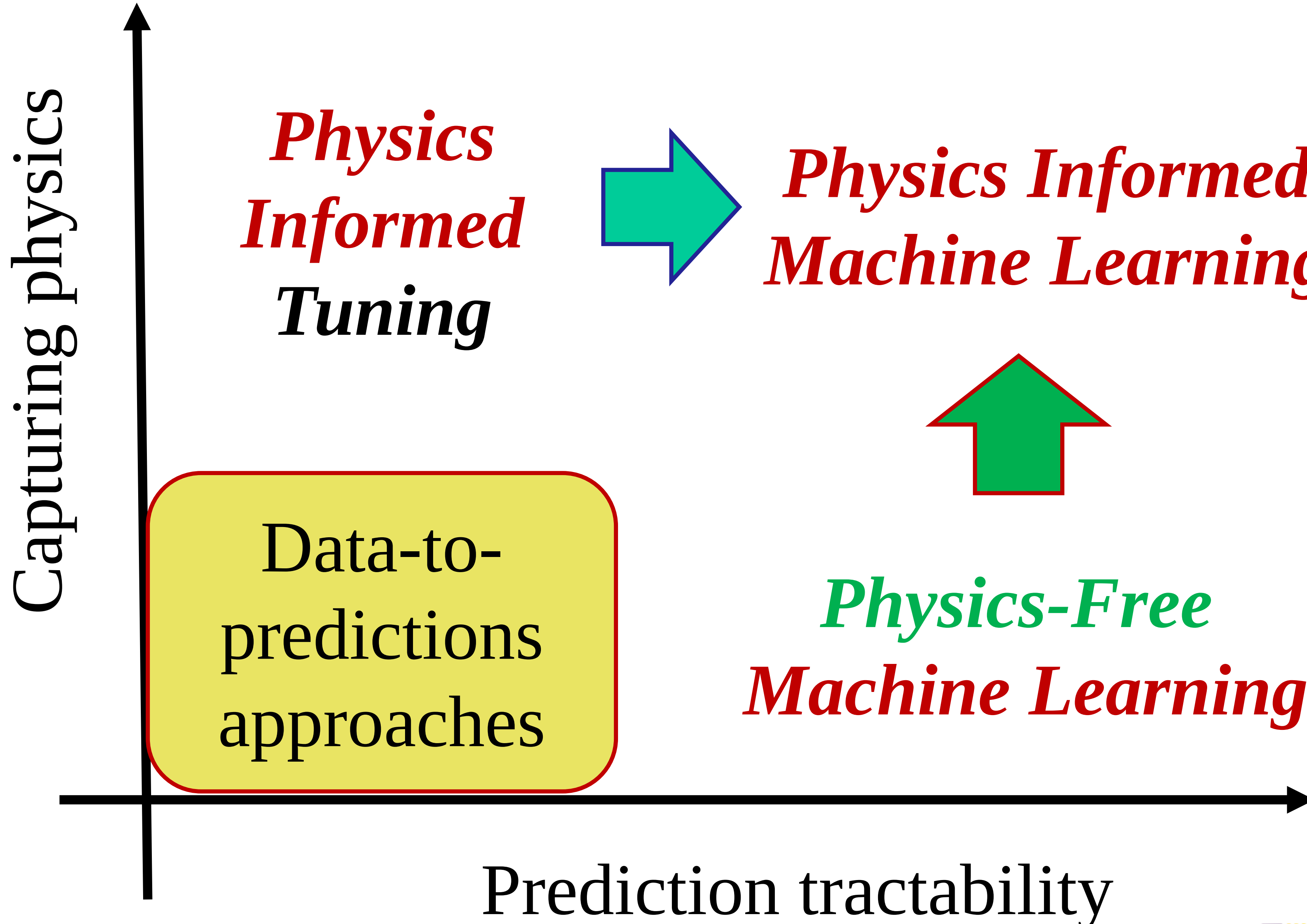
Expected Outcomes --- Machine Learning and Analytics (MLA) toolbox

- Modeling of the system stochastic and dynamic phenomena
- New algorithms
  - State and Parameter estimation
  - Event localization
- Data-driven (synthetic → actual, PMU-measured)
- Validation and Integration into industry-grade platform(s)

2018

Physics (of Power Grid) Informed Machine Learning





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Project Highlights:

- Dynamic Parameter Identification

  (lead Dr. Lokhov – LANL)

- Detective   work with PMU data

  (lead Prof. Bienstock – Columbia U)

- More later today

  - 3-4pm "after NASPI" in the main conf. room
  also over webex

  everybody welcome !!

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Dynamic State Matrix Reconstruction

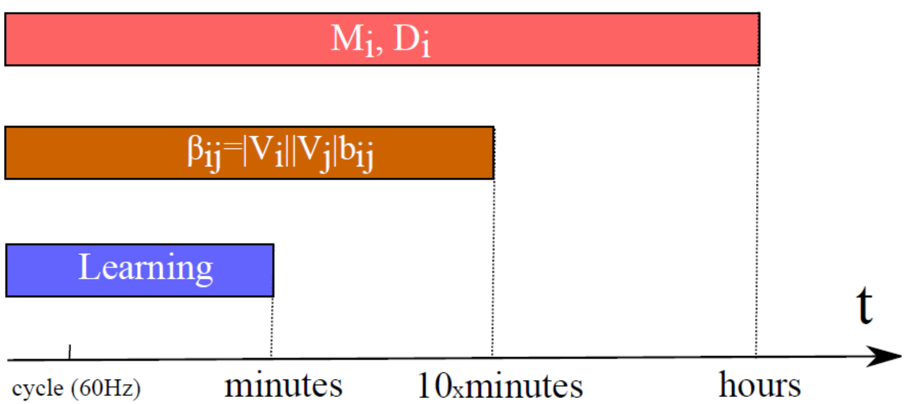
PI: Andrey Lokhov (LANL)

What: identification of parameters of dynamic swing equations:

$$M_i\dot{\omega}_i + D_i\omega_i = -\sum_{(i,j)\in\mathcal{E}} \beta_{ij}(\delta_i - \delta_j) + \delta P_i$$

$\delta_i = \theta_i - \theta_i^{(0)}$: phase deviations; $\delta P_i = P_i^{(m)} - P_i^{(e)}$: power deviations; and $\omega_i = \dot{\delta}_i$

Over **entire network** from real-time synchronized PMU measurements



Disadvantages of current practices:

- Semi-manual verification of parameters
- Usage of PMU data limited to rare events

Applications:

- Assessment of system stability
- Model validation & parameter calibration
- Detection of forced oscillations
- Further use in optimization & control

Dynamic State Matrix Reconstruction

How: Maximum likelihood based regression with strong statistical guarantees

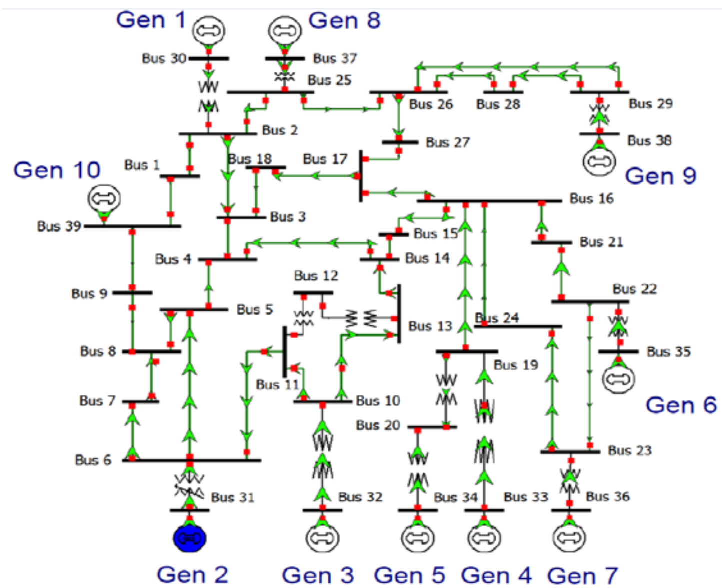
Important parameters:

number of data points T

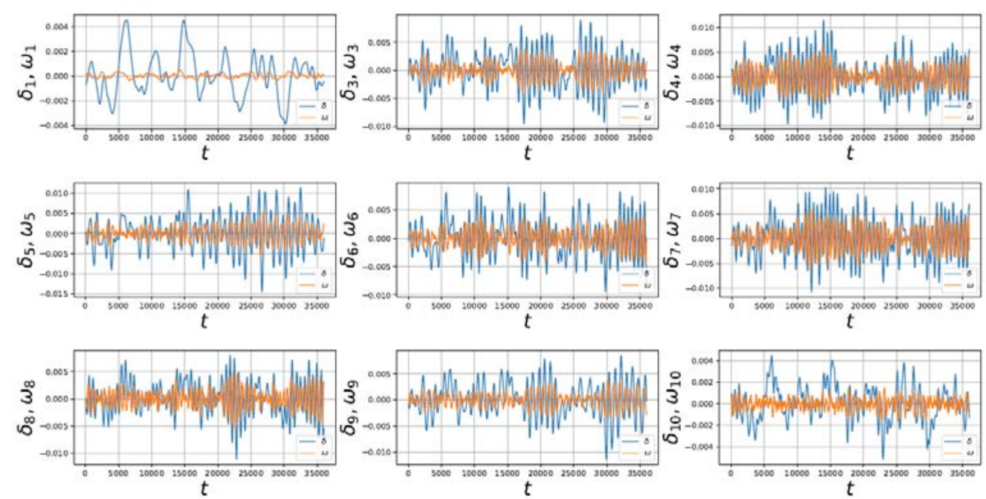
time difference between data points Δt

total observation time $t_{obs} = T\,\Delta t$

Theorem: expected parameter Estimation error decays as $1/\sqrt{t_{obs}}$ in the regime of validity of linearization



Synthetic PMU measurements time series:



Sampled at the smallest resolution Δt = 1/60 sec (1 cycle)

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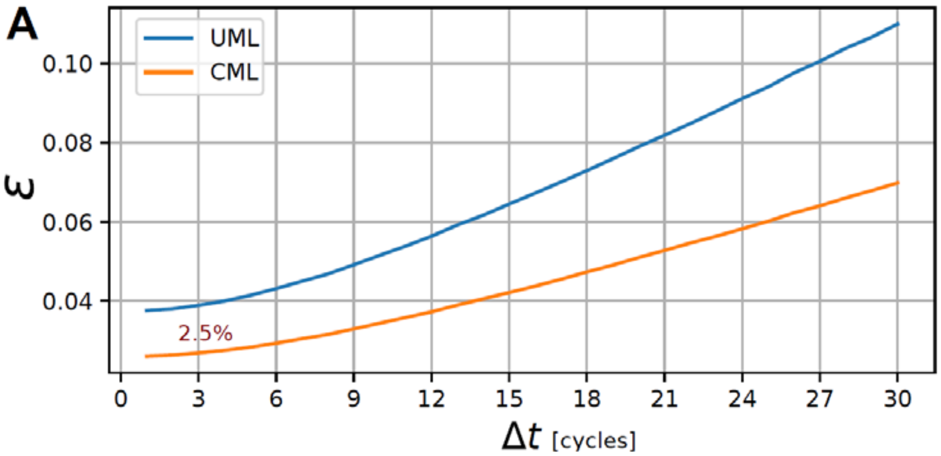
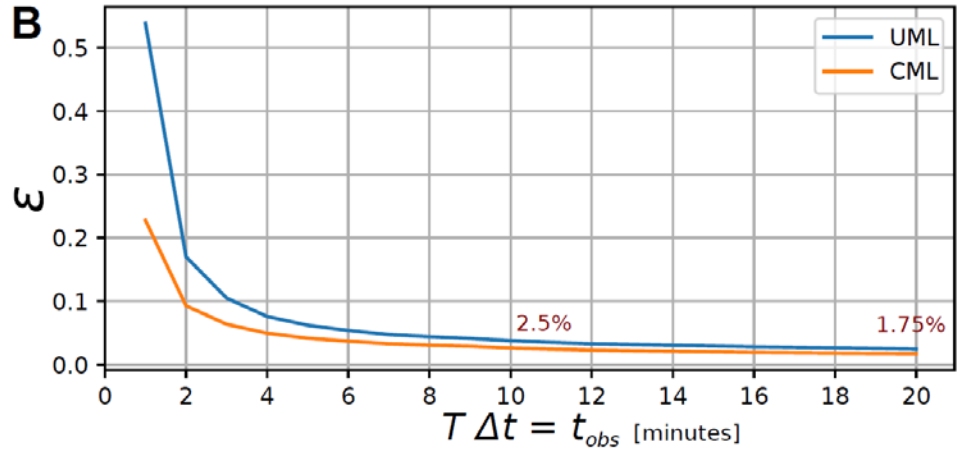
Dynamic State Matrix Reconstruction

Results: Empirical results on the error





Implementation:

near real-time matrix inversion (UML)

& least-squares optimization with **constraints** (CML) using standard optimization solvers

Advantages:

simple but principled and rigorous approach, allows for an easy inclusion of extensions:
slow parameter variation, uncertainty in topology, partial observations

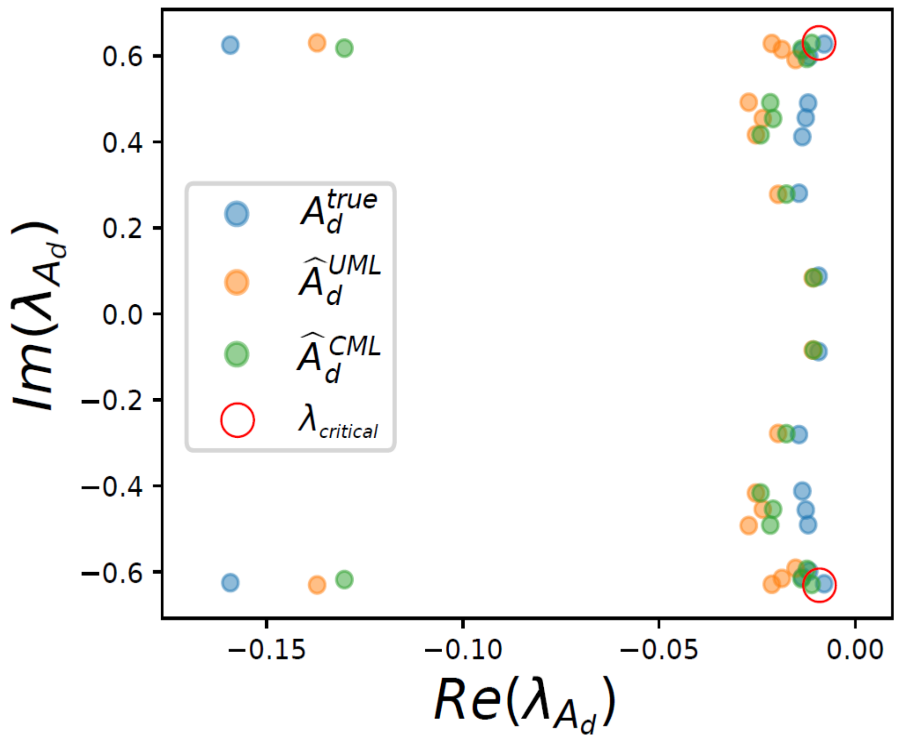
Dynamic State Matrix Reconstruction

Lokhov, Vuffray, Shemetov, Deka, Chertkov PSCC 2018

Path forward:

- Tests on real data
- Testing robustness to statistical models:
  - space & time correlations
  - non-Gaussianity
  - non-stationarity
  - higher-order models
- Learning statistics of loads
- Dealing with partial observations
  (CDC 2018, reduced model,
  more details 3-4 pm later today)
- Probing proximity to instability

Application: estimation of critical eigenvalues of Ad



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Dynamic State Matrix Reconstruction

NASPI application: detection and localization of forced oscillations

Leading existing efforts:

- Dan Trudnowski (Montana Tech): RMS energy method, energy flow
- Mani V. Venkatasubramanian (Washington State): data analytics, oscillation mode shape
- Slava Maslennikov (ISO New England): energy flow method

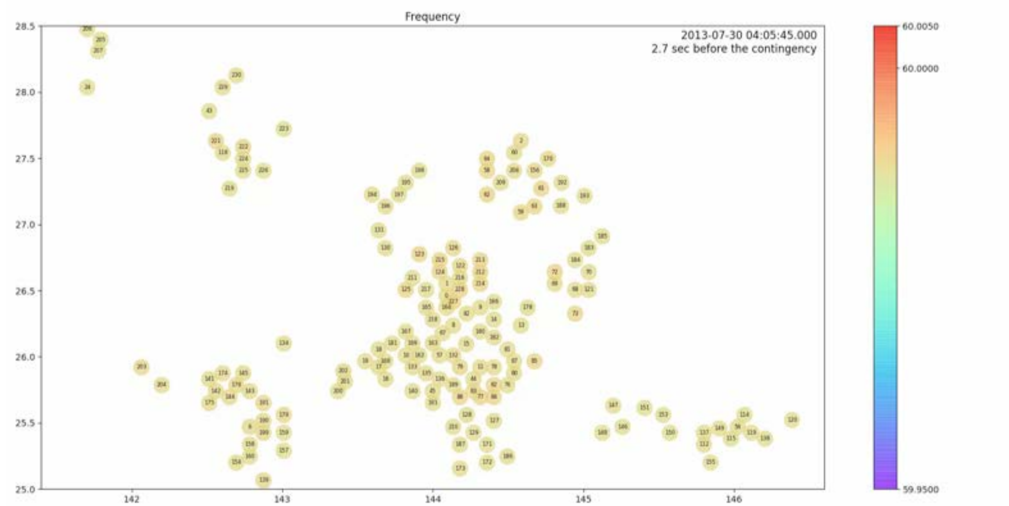
Principle difficulties:

- Hardness of accurate networked localization if oscillations excite one of the natural modes

Approach based on proposed machine learning techniques:

- Learning parameters of dynamic swing equations
- Explicit inclusion of low-frequency forcing sources
- Identification of modes in the system
- Network based localization

"Detective" approach with Real PMU data
(Daniel Bienstock, Columbia University)



What:

- See what we can do with real data, e.g.
- Basic, practical statistics
- Localize, time stamp events
- Classify events
  - Physics + Optimization
- Develop On-line algorithms

PMU data (historical):

- Midwest Utility
- 200 nodes, 2 years

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"Detective" approach with Real PMU data (PI: Daniel Bienstock, Columbia University)

How [basic statistics]:

- Finding "uneventful" periods
- frequency, phases, voltages
- Subtract sliding mean(s), normalized, with superimposed standard deviations

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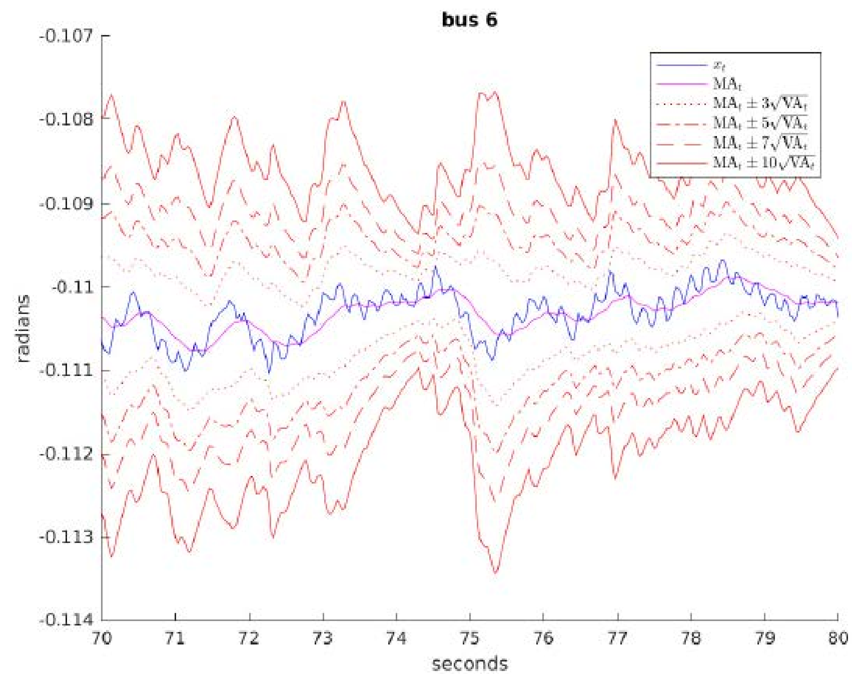

Figure 1: There is an event between seconds 74 and 75 for $K = 3$.

−1
cy
84
86
16
74
05
22

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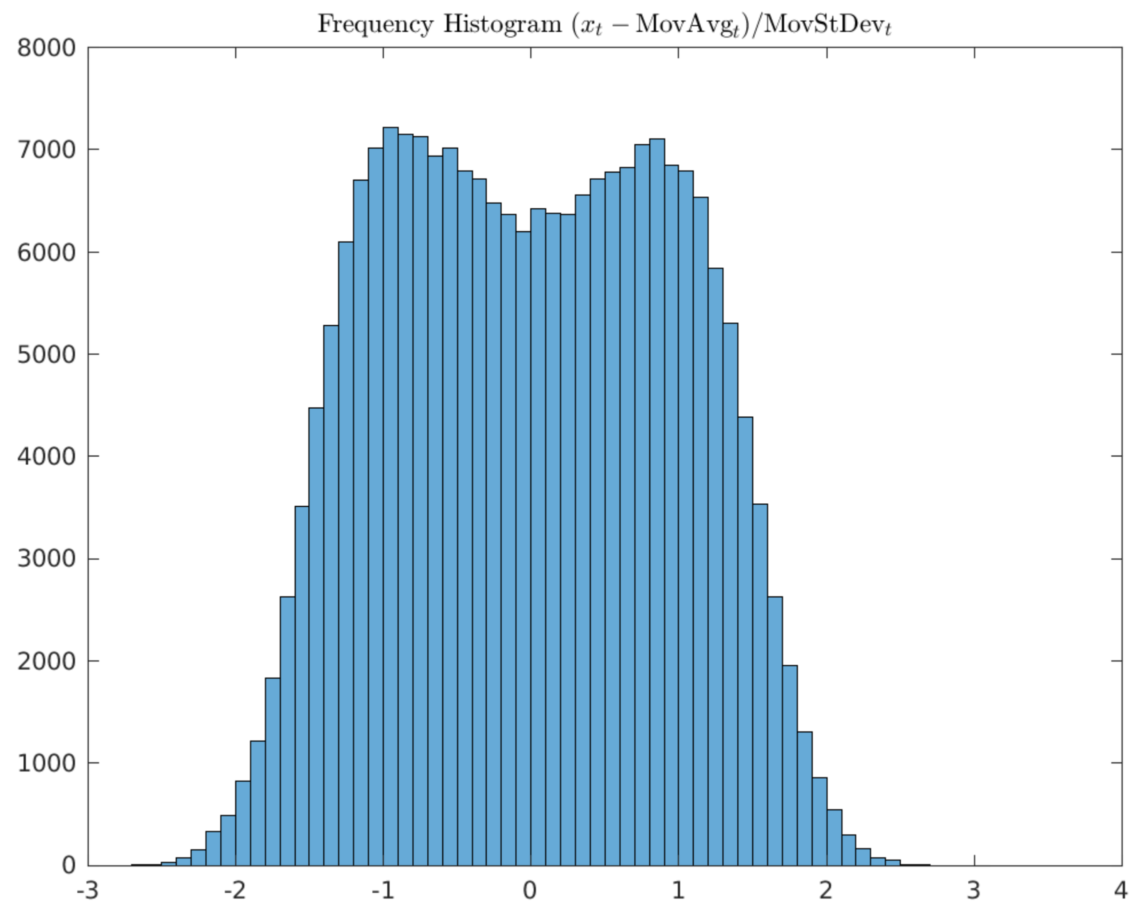
"Detective" approach with Real PMU data
(PI: Daniel Bienstock, Columbia University)

How [basic statistics]:

- Subtract sliding mean normalized, with superimposed standard deviations
- Gaussianity test fails



"Detective" approach with Real PMU data
(PI: Daniel Bienstock, Columbia University)

<u>How   [basic statistics]:</u>

- Subtract sliding mean(s), normalized, with superimposed standard deviations

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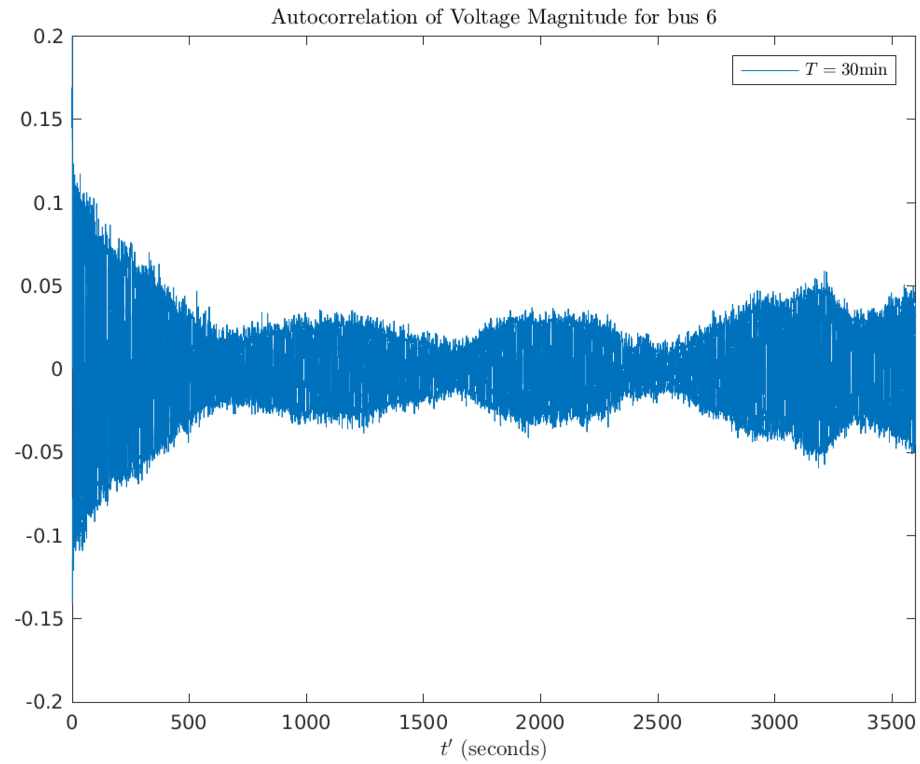

- Auto-correlation -> multi-scale, sustainable oscillations

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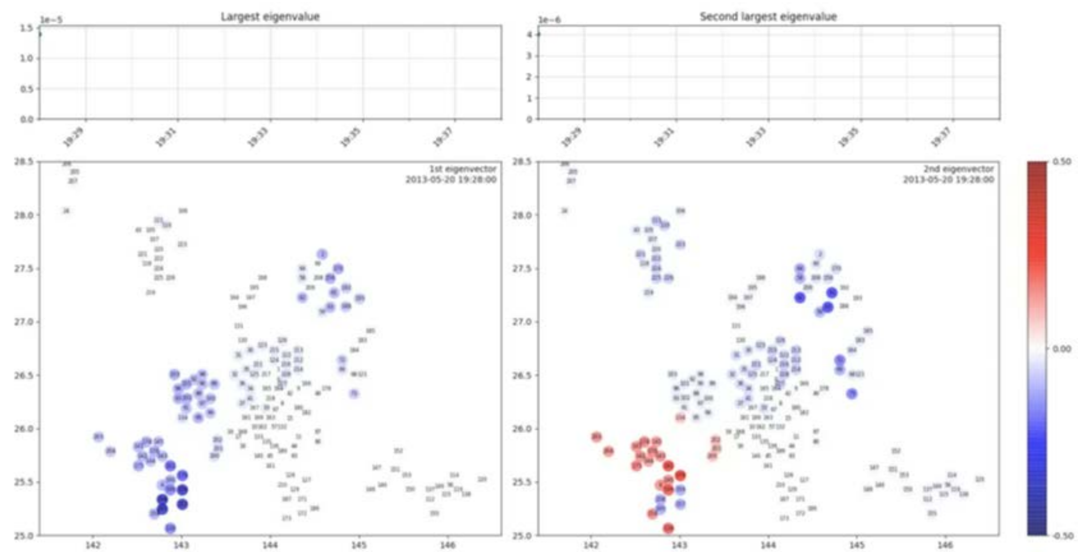
"Detective" approach with Real PMU data
(PI: Daniel Bienstock, Columbia University)

How:

- Analysis of covariances
  = PCA +
- Tracking it on-line
- "Light" version
  = streaming PCA
  - see data only once
    don't store
    (Non-Stationary Streaming PCA,
    Shukla, Yun and Bienstock, NIPS 2017)



“Detective” approach with Real PMU data (PI: Daniel Bienstock, Columbia University)

Work in Progress [Path Forward]:

- Spatio-temporal correlations

  (towards good features for clustering)

  - Time-delayed PCA
- Automatic separation of jumps, transients, ambient fluctuations
- Towards automatic on-line classification of events

  [line, generator, transformer; forced/transient; inside/outside the area]

  - Cluster algorithms with features from the PCA analysis
  - Auto-encoders, LTVSM +++

    Deep Learning versions = “nonlinear PCA”

Other projects (pipeline)

PMU based **Machine Learning** **[fast algorithms]** for:

- Topology & parameter reconstruction
- Failures in areas with low observability
- Higher order models of generators (calibration, reduced modeling)
- Aggregated dynamics & statistics of distribution networks
- Physics-preserving graph reduction
- Cloud based framework + validation …

- Looking for your feedback + collaborations within NASPI
- Please join us 3-4 pm (in the main room) for further discussions

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