Machine learning with PMU data

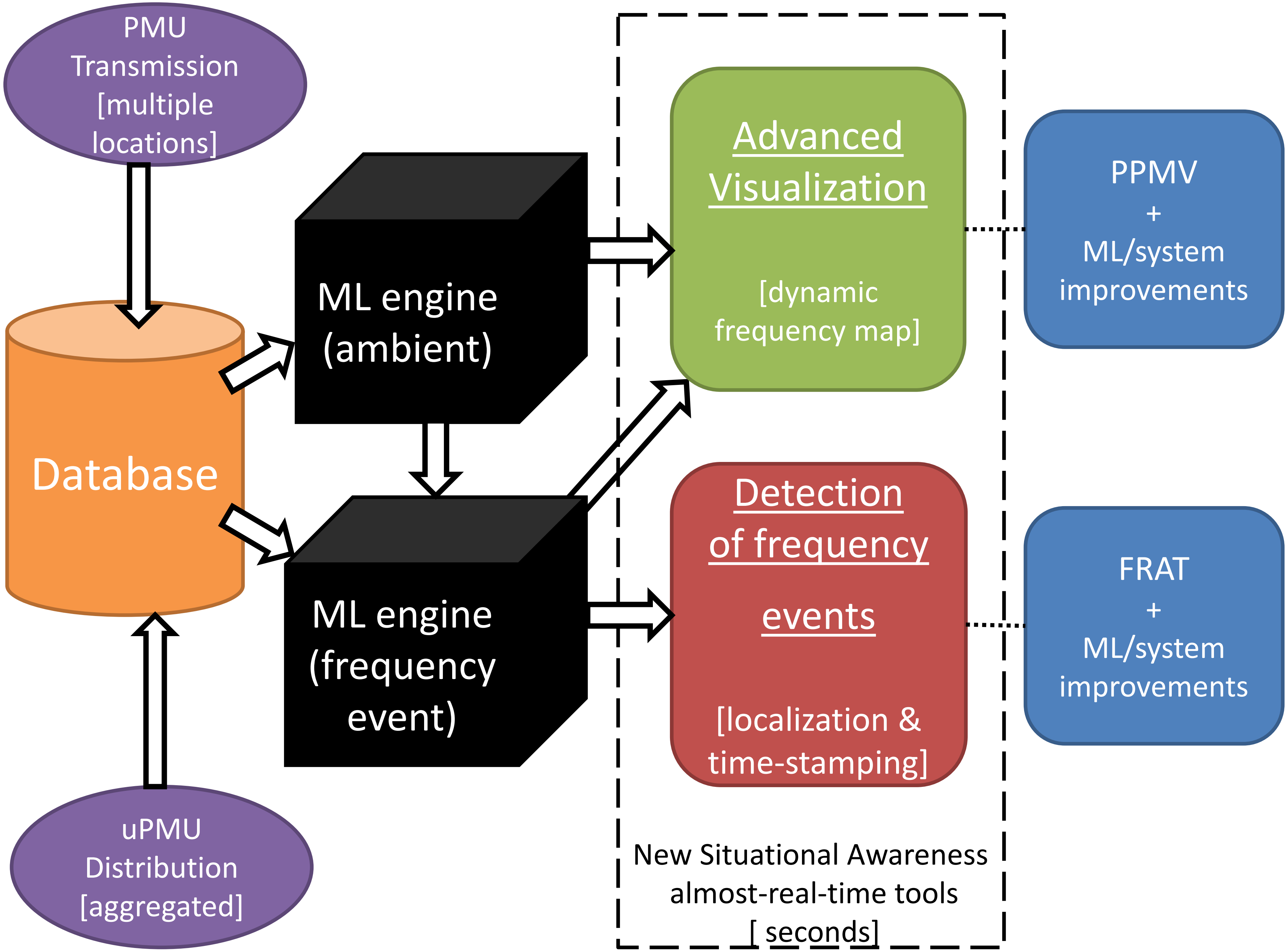
Columbia University:
Daniel Bienstock, Apurv Shukla, Mauro Escobar, Shuoguang Yang

LANL:
Seyoung Yun, Andrey Lokhov, Deepjyoti Deka, Sidhant Misra, Marc Vuffray, Michael Chertkov

GMLC, Cat 2

Advanced Machine Learning for Synchro-phasor Technology

- LANL
- PNNL
- LBNL
- Columbia U



PMU Transmission [multiple locations]

Database

uPMU Distribution [aggregated]

ML engine (ambient)

ML engine (frequency event)

Advanced Visualization

[dynamic frequency map]

Detection of frequency events

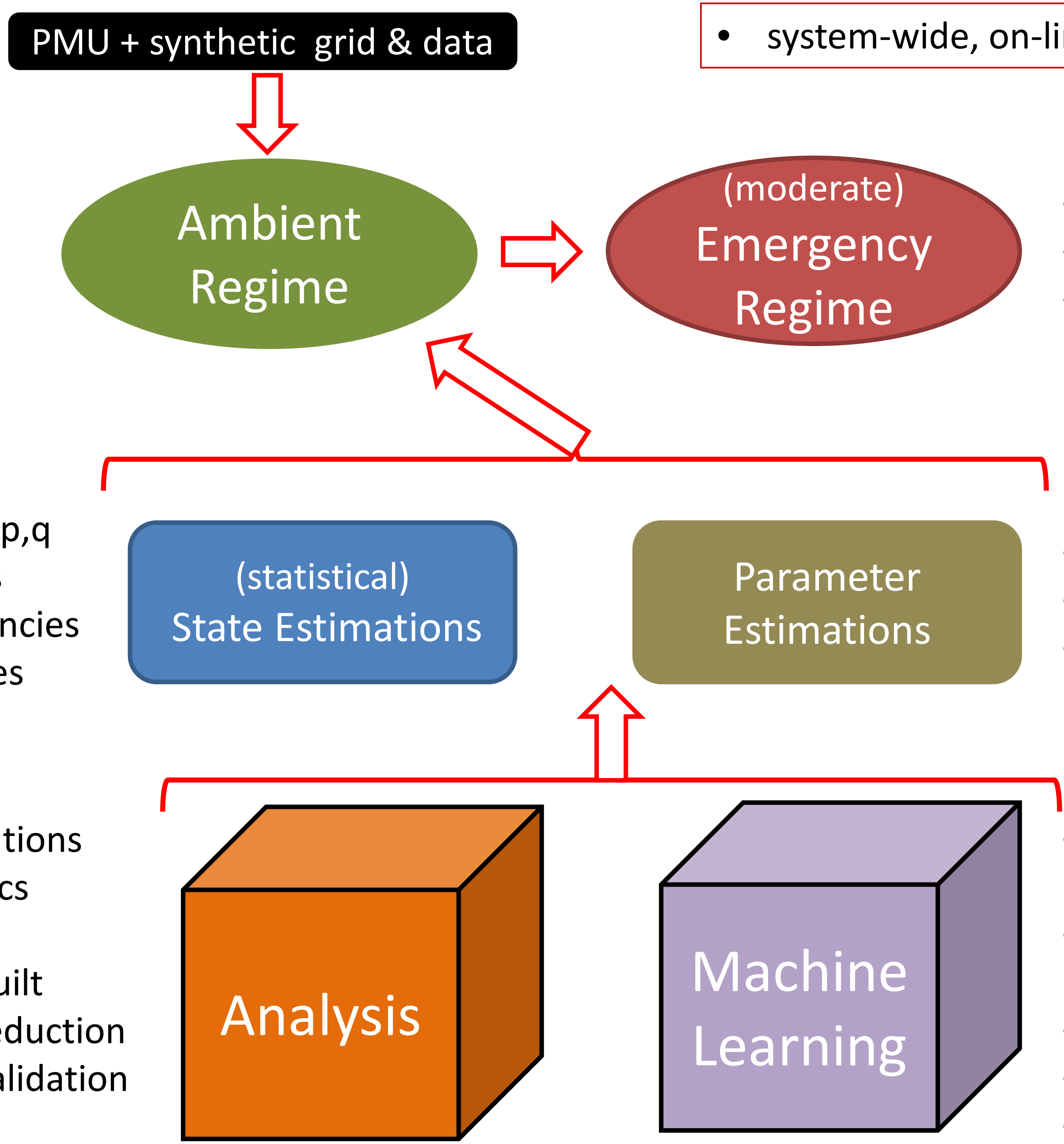
[localization & time-stamping]

PPMV + ML/system improvements

FRAT + ML/system improvements

New Situational Awareness almost-real-time tools [seconds]

- system-wide, on-line, streaming



PMU + synthetic grid & data

Ambient Regime

(moderate) Emergency Regime

- EM waves
- Grid spectroscopy
- Event Localization

- in/out p,q
- phases
- frequencies
- voltages

(statistical) State Estimations

Parameter Estimations

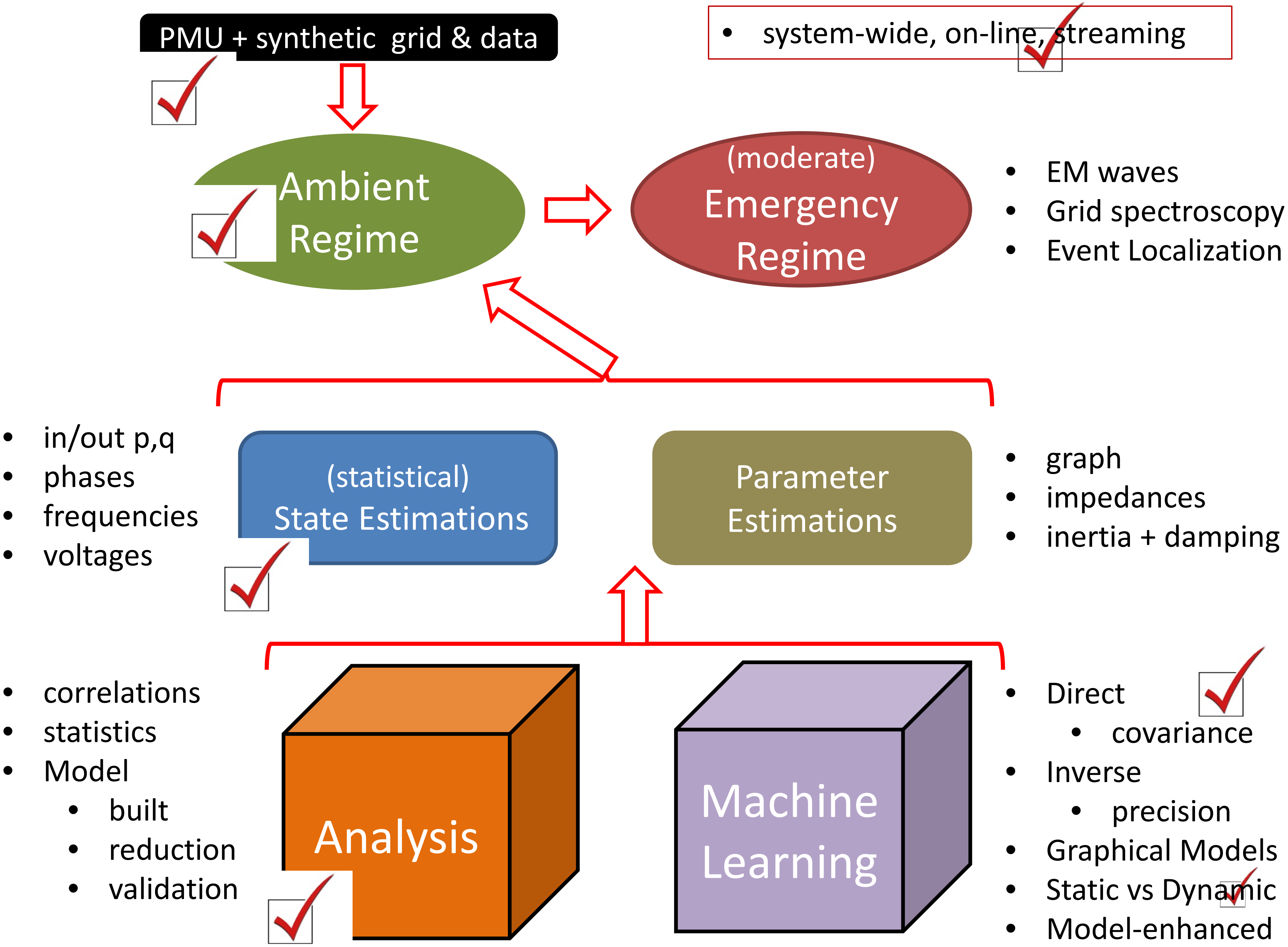
- graph
- impedances
- inertia + damping

- correlations
- statistics
- Model
  - built
  - reduction
  - validation

Analysis

Machine Learning

- Direct
  - covariance
- Inverse
  - precision
- Graphical Models
- Static vs Dynamic
- Model-enhanced



PMU + synthetic grid & data ☑

- system-wide, on-line, streaming ☑

☑ Ambient Regime

(moderate) Emergency Regime

- EM waves
- Grid spectroscopy
- Event Localization

- in/out p,q
- phases
- frequencies
- voltages

(statistical) State Estimations ☑

Parameter Estimations

- graph
- impedances
- inertia + damping

- correlations
- statistics
- Model
  - built
  - reduction
  - validation

Analysis ☑

Machine Learning

- Direct ☑
  - covariance
- Inverse
  - precision
- Graphical Models
- Static vs Dynamic ☑
- Model-enhanced

Focus: learning structure from PMU data

- Normal regime
- Adversarial regime

Power Grid: Structure Learning

- Uses:
  - Real time control
  - Failure Identification
  - Optimizing flows

- Challenge:
  - Limited real-time breakers
  - Brute Force inefficient

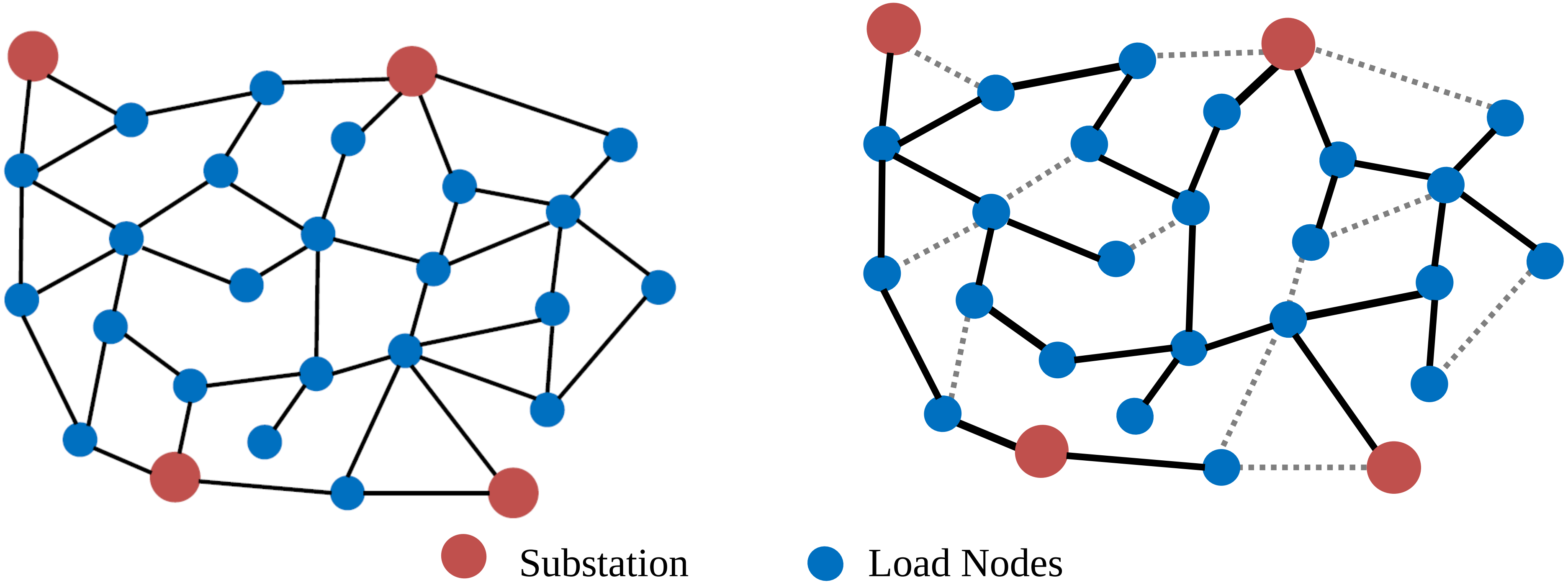
- Solution
  - Smart meters: PMUs, micro-PMUs, IoT
  - Big Data: High fidelity measurements

Grid ‘*Operational*’ Structure

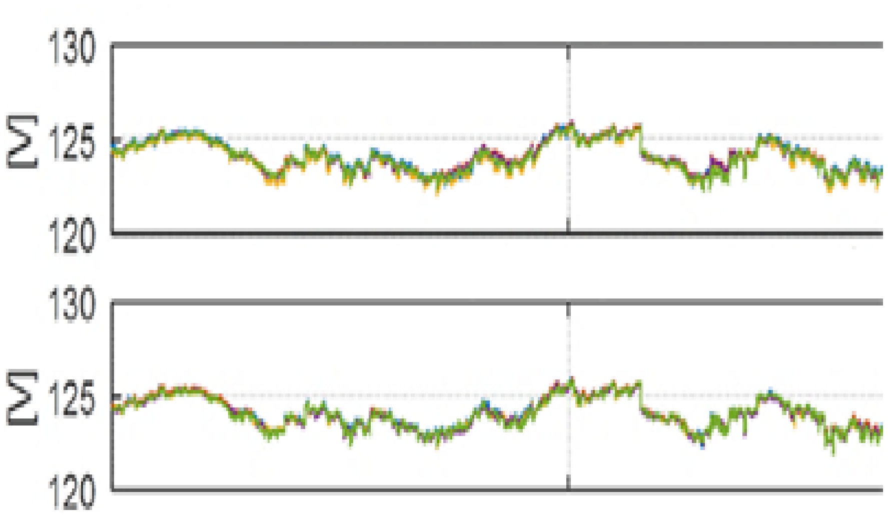
- Underlying Loopy network
- Switches/Relays decide structure

Learning Problem:

- Estimate Configuration of Switches/Relays



Learning Methodology



***Probabilistic Graphical Model** for the nodal voltages*

- Static Regime: *Power Flow Equations*
- Dynamic Regime: *Swing Equations*

Adversarial regime (ongoing work)

- A fictional setting: an adversary controls some (few) grid resources
- Some overt physical changes have been made by the adversary
- Additionally the adversary alters some sensor data
- Adversary is intelligent and has computed these actions in advance

1. Can we even tell that something has happened?
2. And quickly?
3. Do we want to use a lot of data?
4. Or maybe not (data could be corrupted)?
5. Methodology: robust inverse optimization

Focus: learning covariance matrices for PMU data

- Covariance analysis is a major tool in risk planning

- Correlation patterns important: what is revealed?

- Counterpoint: principal components analysis (PCA) is an important perspective

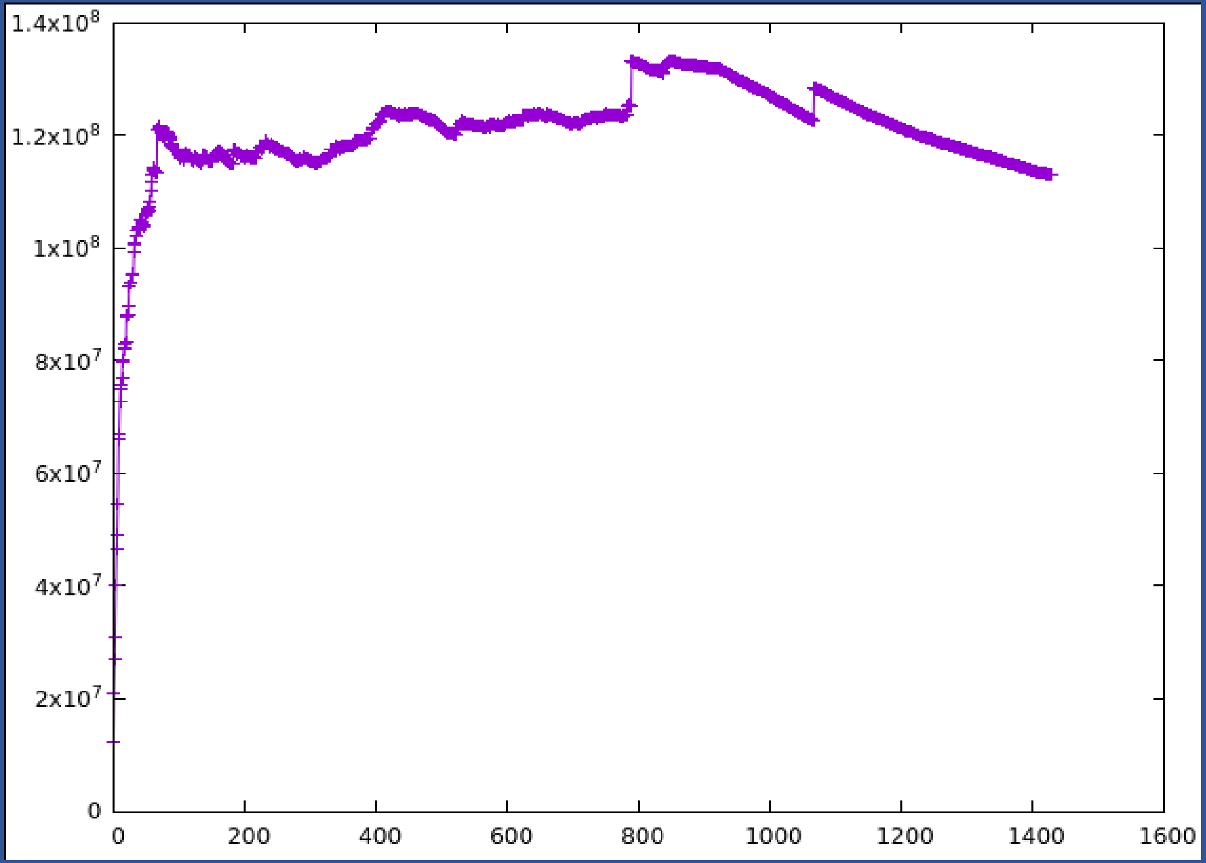
- A classical outlook: the factors revealed by PCA can be used in control algorithms, even though there is no overt “understanding” of the factors

Experiment using data from an industry partner

- Approx. 200 PMUs
- Consider voltage magnitude output for one day
- Compute covariance matrix since start of day until each minute of the day

First day: “Frobenius norm” = sum of eigenvalues

A measure of total volatility

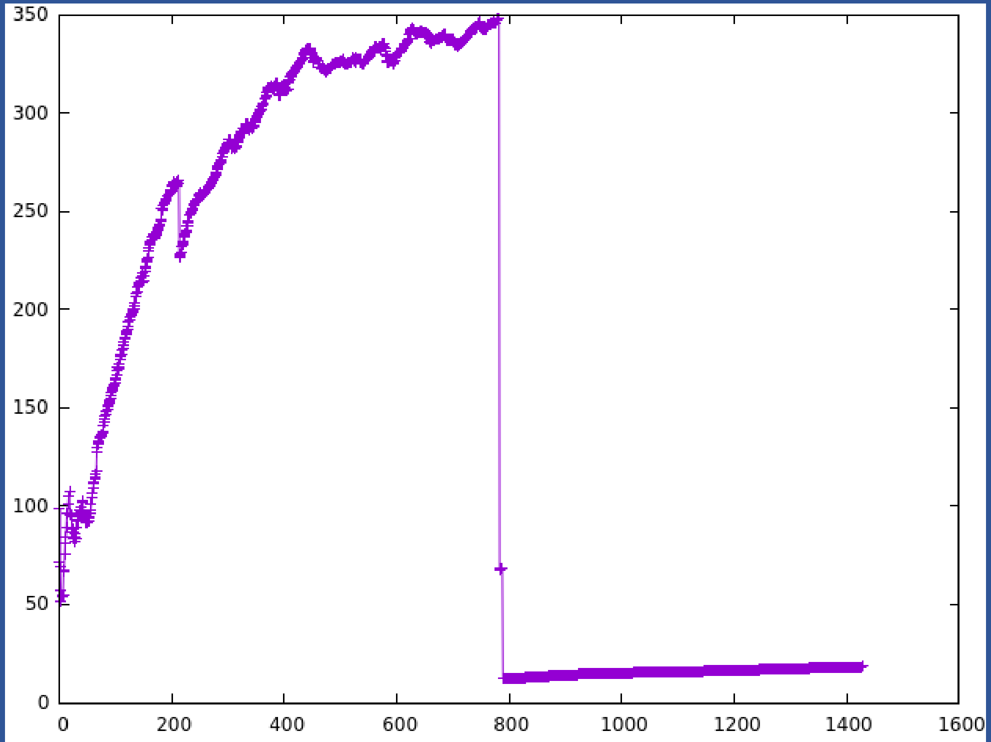


Volatility rises rapidly in the early morning and then stabilizes

What is that jump around minute 800 ~ 1:45 PM ?

Ratio of largest to second largest eigenvalue

A measure of ***lack*** of diversity in volatility



Ratio rises in the morning, stabilizes and then …

What is that jump around minute 800 ~ 1:45 PM ?

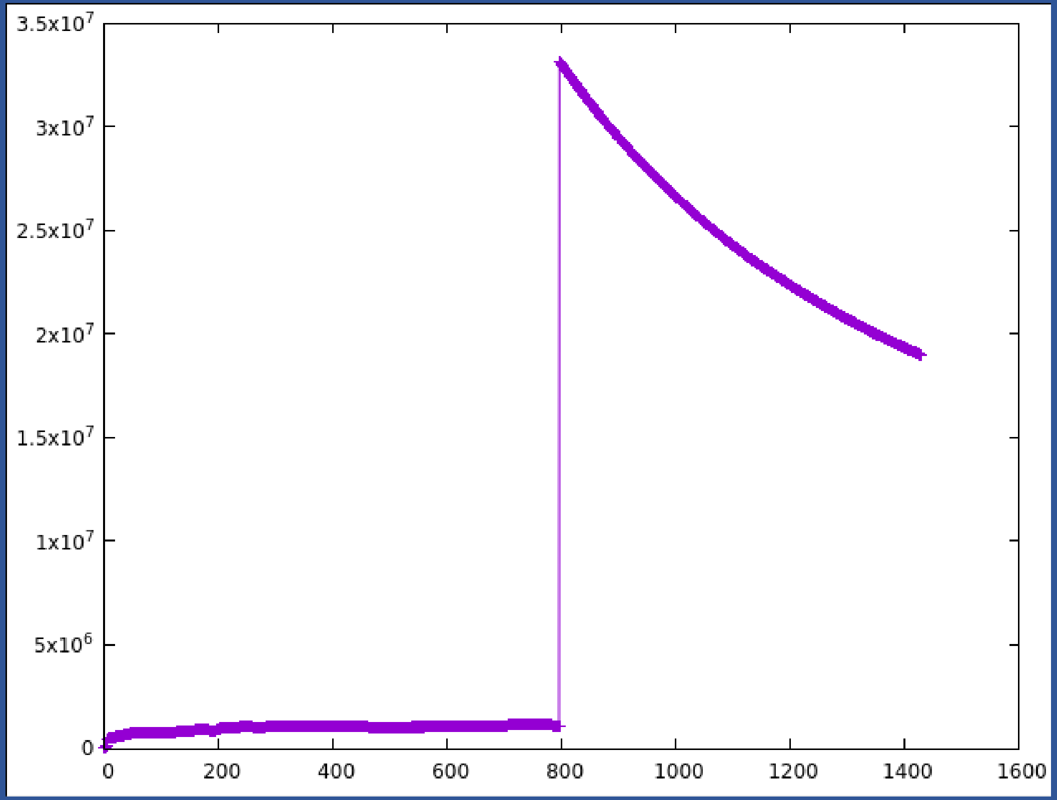
LET’S REPEAT THE EXPERIMENT

But using a different day

A day with some voltage oscillations

Second day: “Frobenius norm” = sum of eigenvalues

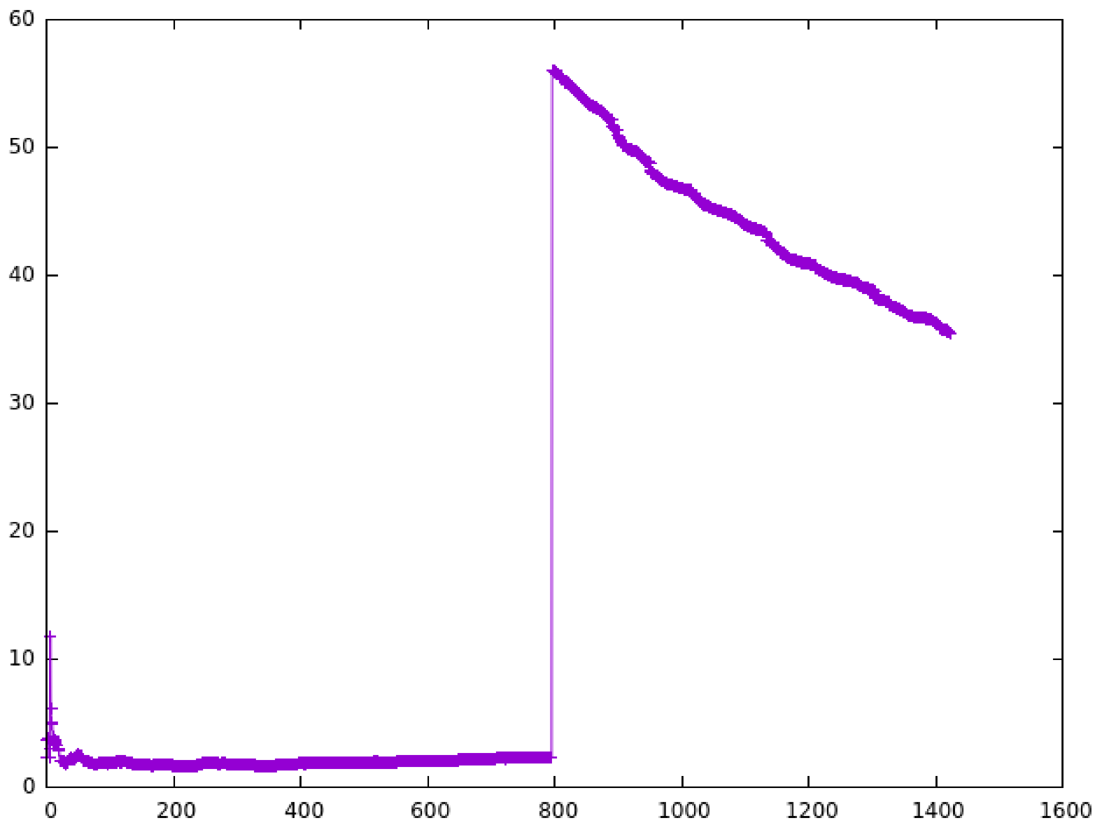
A measure of total volatility



Volatility low until minute 800, then a large jump

Ratio of largest to second largest eigenvalue

A measure of ***lack*** of diversity in volatility

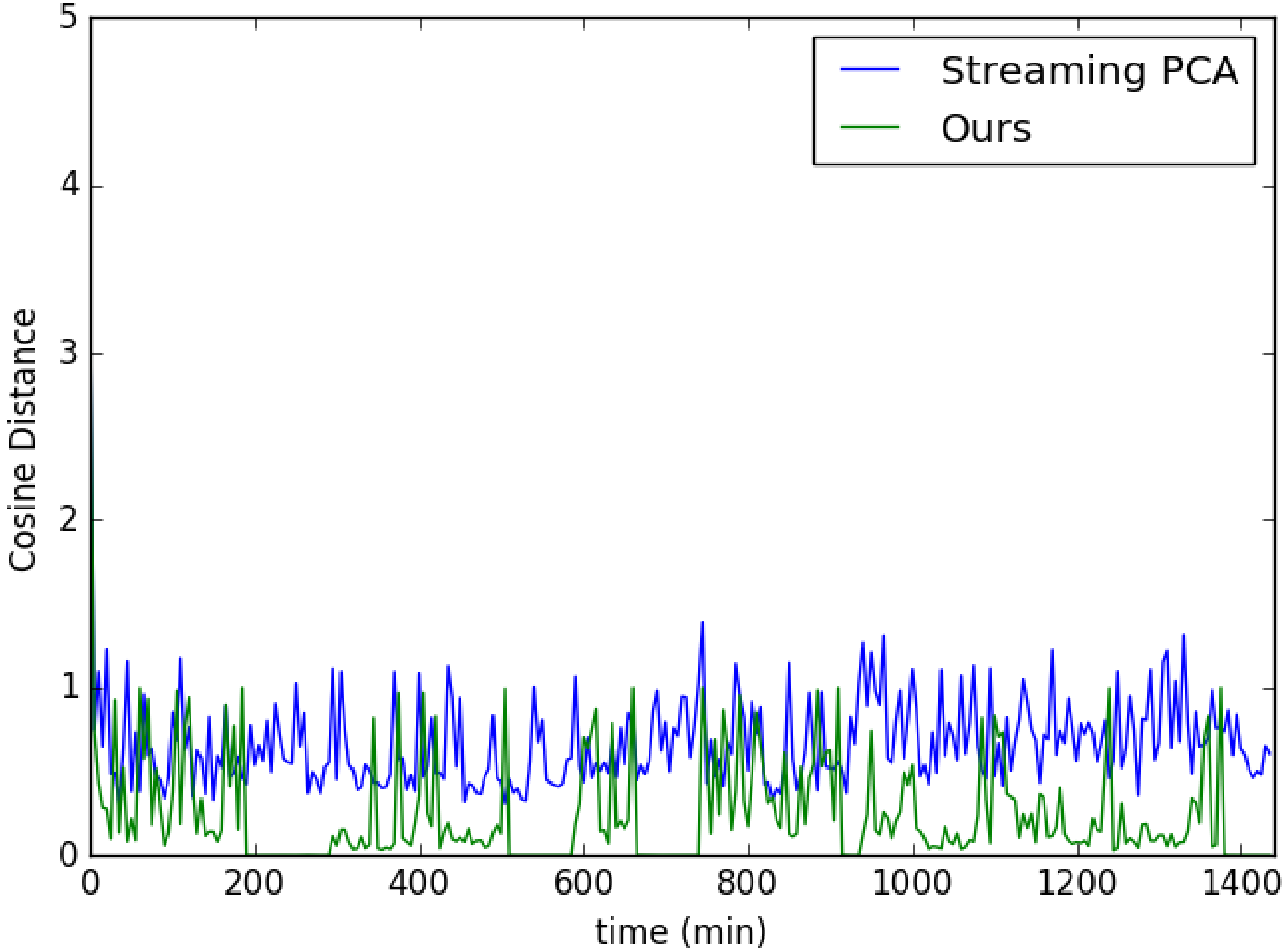


Ratio close to 1.0 until minute 800 …

Jump suggests a decrease in volatility diversity

FOCUS: fast, online estimation of covariance matrices from streaming data

- Exact covariance computation is slow and requires many samples to converge
- Can we quickly obtain an approximate estimate of the covariance matrix – actually what we care about is PCA
- Methodology: “sketching” algorithms
- Goal is to estimate the top eigenvalues/eigenvectors quickly


Streaming PCA
Ours
Cosine Distance
0
1
2
3
4
5
0
200
400
600
800
1000
1200
1400
time (min)