Sparse Causal Temporal Modeling to Inform Power System Defense

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Overview

Smart Grid Defense and Major Influencers

Sparse Causal Temporal Methods

- **Lasso Granger**
- **Graphical Lasso**

Modelling Influence

Data Set

Experimental Set Up

Results

- **N50 per Node**
- **Single Feeder Single Week**
- **Predictive Accuracy**

Discussion

Smart Grid Defense and Major Influencers

Defense Against False Data Injection Attack

- Man –in-the-middle attack bypasses bad data detection in SCADA
- Undetectably manipulate state estimates: control electricity price, cascading blackouts
- Defense: Start from an initial set of nodes and gradually expand until entire set is observable

Partial Data Problem

- Need predictions in real time
- Some sensors systematically only provide partial data
- Need other sensors' data to perform prediction
- Which other sensors to use? Major Influencers

Protect Major Influencers

- Budget constraints allow securing only a fraction of nodes
- Incentivized to protect Major Influencers

Sparse Causal Temporal Methods

Regularized Regression Setting

$X \in \mathbb{R}^{m \times n}, y \in \mathbb{R}^n, \beta \in \mathbb{R}^d$

Objective: $\min_{\beta} f(\beta, X, y) + \lambda J(\beta)$

Lasso: $J(\beta) = \|\beta\|_1$

Squared error: $f(\beta, X, y) = \|y - X\beta\|_2^2$

Inherently Sparsity Inducing Regularization Term

Lasso Granger

- Combines Granger Causality and ℓ_1-norm regularization
- A time series $\boldsymbol{x}^i$ “Granger causes” another time series feature $\boldsymbol{x}^j$ if and only if using both $\boldsymbol{x}^i$’s and $\boldsymbol{x}^j$’s data leads to statistically significantly higher accuracy than predicting based solely on past values of $\boldsymbol{x}^j$
- Model dependencies between multiple time series
- Exhaustively trying pairs entails $O(n^2)$ tests, reduce the cost to by using Lasso regression: Lasso Granger

Sparse Causal Temporal Methods

Graphical Lasso

Graphical Models describe the topology of components in a complex probability model

- Components: Variables
- Topology: dependencies

Gaussian Graphical Models: Markov Random Fields of jointly Gaussian variables

$X \in \mathbb{R}^{m \times n}$: design matrix

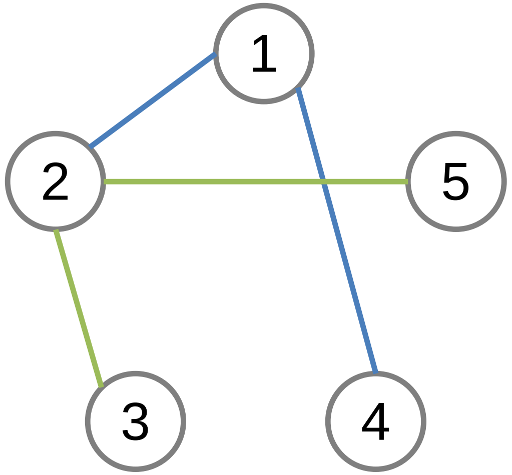
$\Sigma \in R^{nxn}$: covariance matrix

$\Omega = \Sigma^{-1}$: Inverse Covariance / Precision matrix

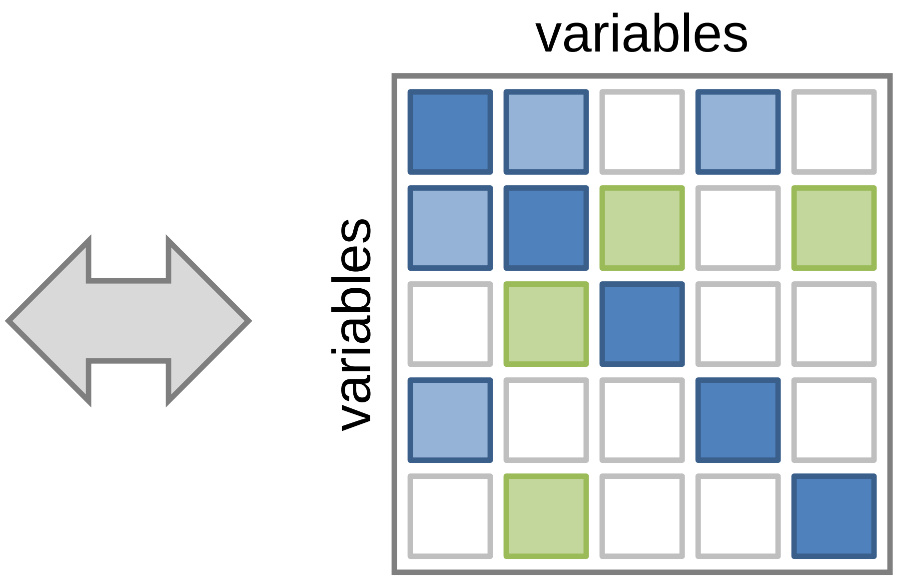
$\max \log det\Omega - tr(\Sigma\Omega) - \lambda||\Omega||_1$ (1)

Sparsity inducing regularization term

Graphical Lasso solves (1) by fitting a modified Lasso regression to each variable in a cyclical Fashion



Graph



Σ^{-1}: Precision matrix (Inverse covariance)

Modelling Influence

Dependency Matrix

- $S = \{s_1, \ldots, s_n\}$: Set of sensors which collect real time data
- Need to make predictions for each s_i
- $M \in \mathbb{R}^{n \times n}$, $M[i, j]$ reflects dependency of sensor s_i's time series data on sensor s_j's time series data
- Can be used as a look-up table to select most useful features for predicting s_i's time series data by choosing non-zero elements in the i-th row of M

Influence

- Use Dependency Matrix M to rank sensors by their degree of influence on other features
- Influence I^k of time series $\boldsymbol{x}^k$ defined as: $\mathrm{I}^{\mathrm{k}} = \Sigma_{j=1}^{n} M[k, j]$
- Obtain a ranking of time series features based on their Influence

Lasso Granger & Graphical Lasso both provide a Dependency Matrix

Data Set & Experimental Set-Up

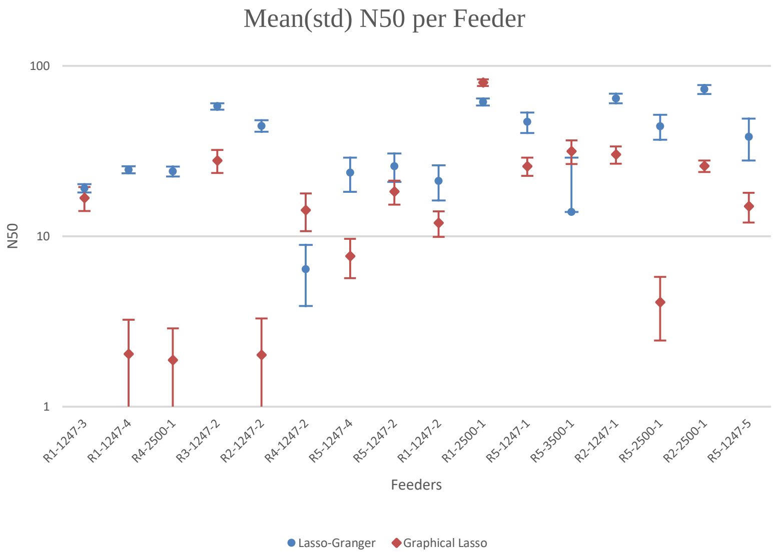
Feeders Data Set

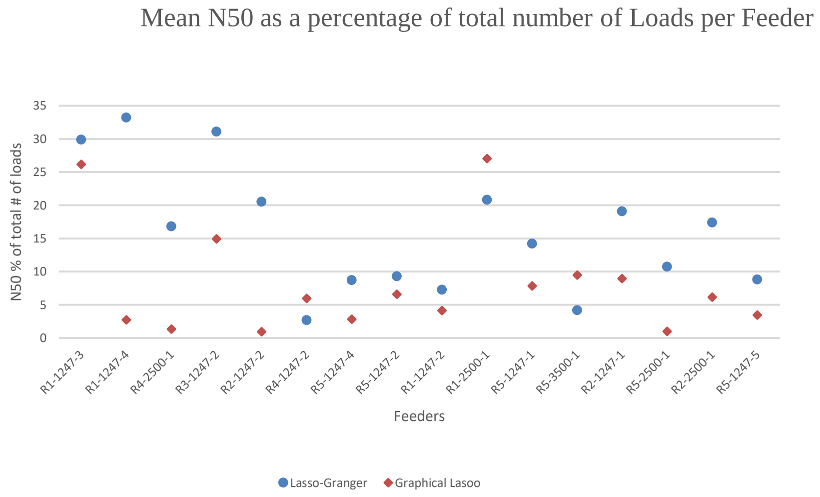
- Distribution nodes that connect substation to consumers
- Simulated with GridLab-D to study Photovoltaic Penetration
- Comprise 5 Geographical Regions
- 16 Feeders
- Each Feeder has Residential and Commercial loads, ranging from 64 to 436
- Averaged hourly values over one year – 8760 values per residential / commercial load

Experimental Set-Up

- For each Feeder: Use Data from first half of the week to learn two Dependency Matrices: Lasso-Granger, Graphical Lasso
- Determine globally most influential features using the Dependency Matrices using N50 statistic (number of features that contain 50% of the total weights)
- Use influential nodes' data to train Regression Trees on the first half of the week
- Use 24h data for training and a temporal horizon varying from 1h to 24h
- Use the learned Dependency Matrices and the Regression Tree models to test on the second half of the week
- Assess predictive accuracy by MAPE (mean absolute percentage error)
- Compare with ART, which is solely based on a node's own past time series data

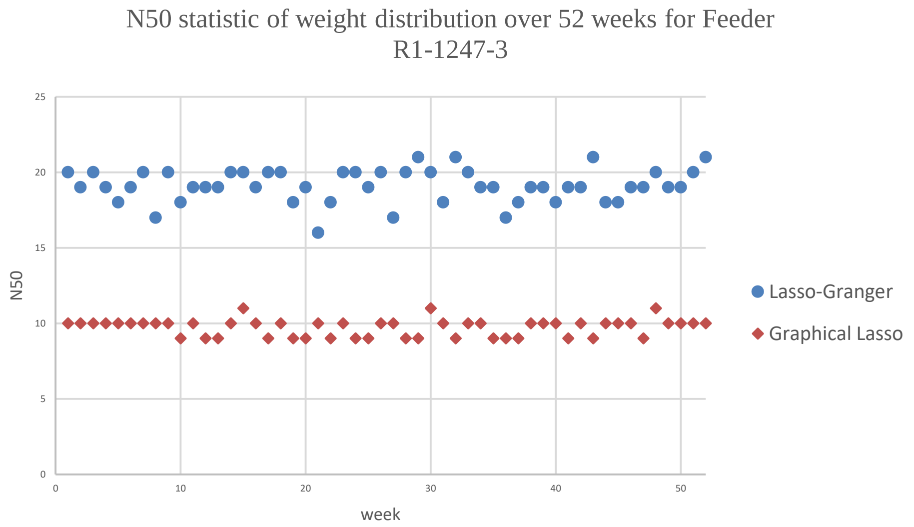
Results

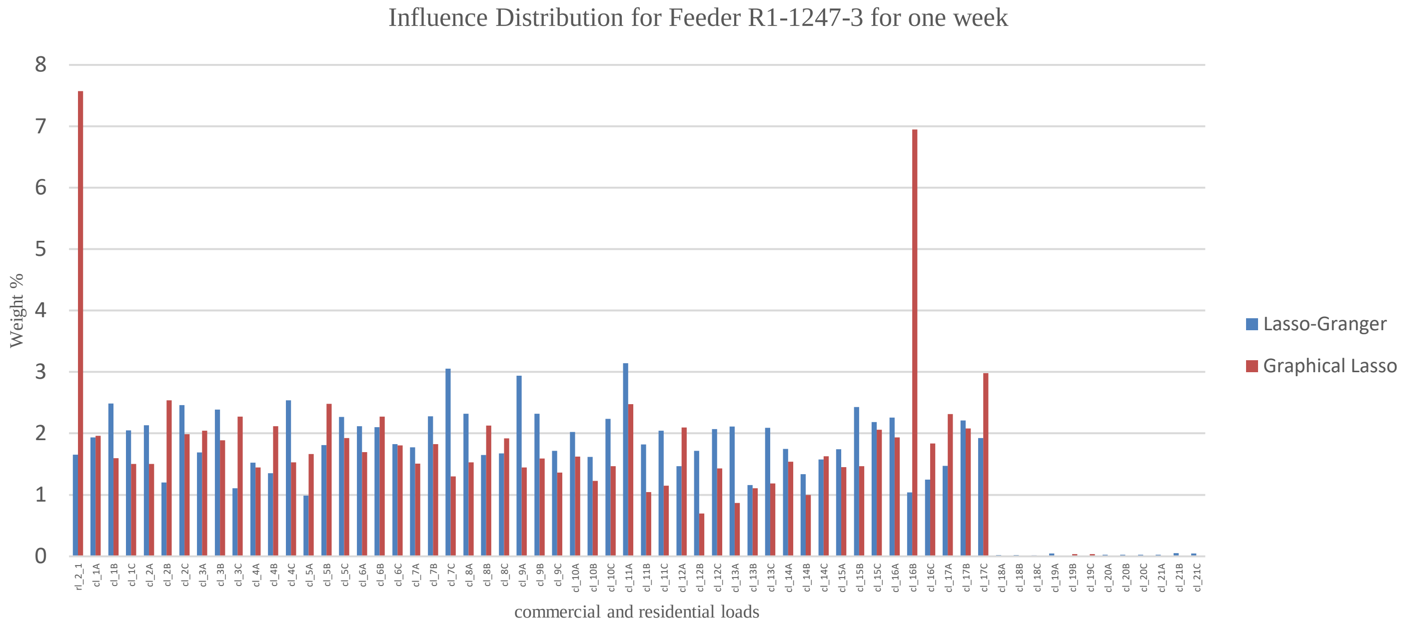




N50 calculated for Lasso Granger learned structure deviates less from the mean

Results





Lasso-Granger returns a N50 that amounts to larger set of nodes than that of Graphical Lasso

7-th week, Graphical Lasso zeros-out last 12 influence weights. Lasso-Granger weights more evenly distributed.

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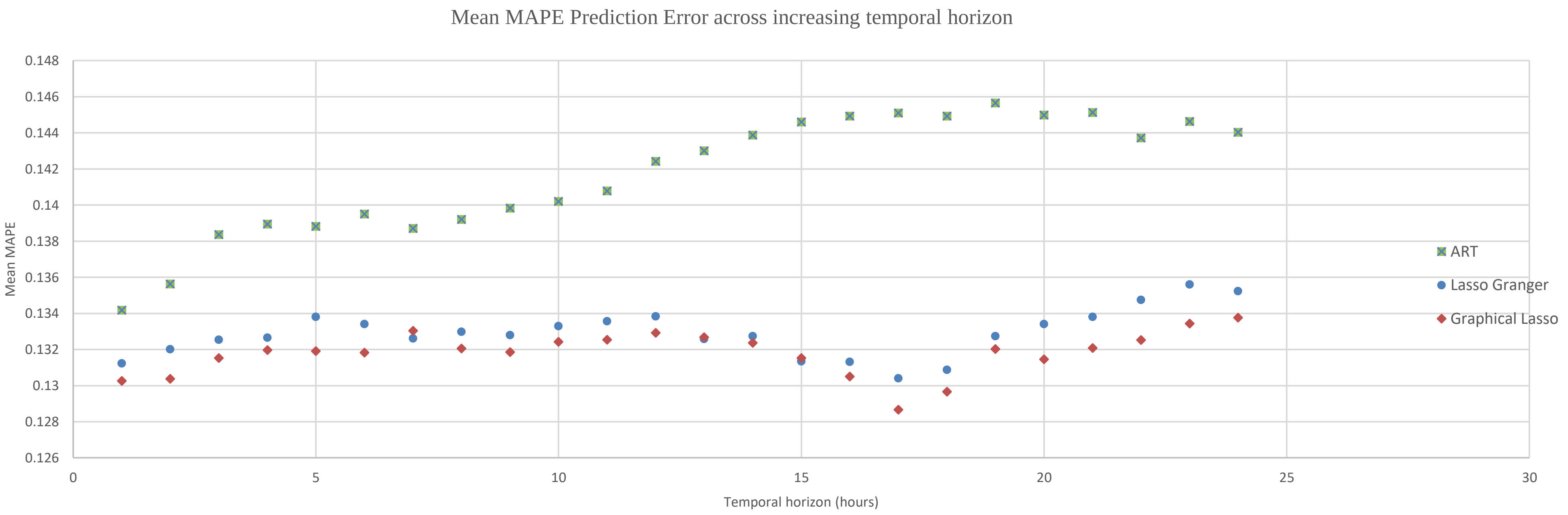
Results



Even from the first hour, the latter two models lead to lower MAPE and the difference becomes more pronounced as the temporal horizon increases to 17 hours look-ahead.

Discussion

- Other feature's data lead to better short term and long term Prediction
- Graphical Lasso – Probabilistic models incorporation into SmartGrid prediction
- Fast methods – Real Time Prediction – Large Datasets
- Comparison of the methods i. Optimality ii. Predictive Accuracy
- Budget Restrictions – Calibrating cutoff percentage of weights

End of Presentation

Thank you

Portland Crime Dataset

- 213 days worth of data (latest uploaded data)
- Clustering location points based on Euclidean distance
- Limitations of clustering based on location: ignoring other similarities between locations
- Modelling Dependencies between clusters using Graphical Models

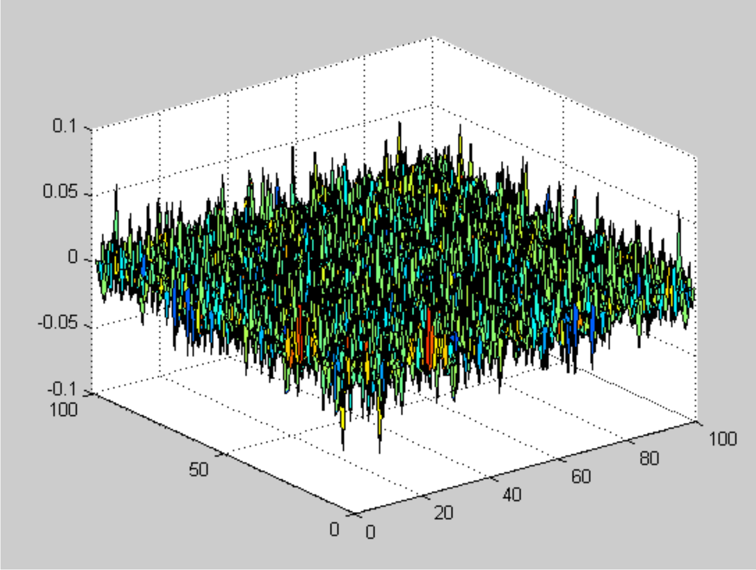
- Graphical Models Used: Graphical Lasso, Variable Selection Structure Learning, Multitask Structure Learning

$$\max_{\boldsymbol{\Omega} \succ 0} \left(\log\det \boldsymbol{\Omega} - \langle \widehat{\boldsymbol{\Sigma}}, \boldsymbol{\Omega} \rangle - \rho \|\boldsymbol{\Omega}\|_1 - \tau \|\boldsymbol{\Omega}\|_{1,p} \right)$$

$$\max_{(\forall k)\boldsymbol{\Omega}^{(k)} \succ 0} \left(\sum_k T^{(k)} \ell_{\widehat{\boldsymbol{\Sigma}}^{(k)}}(\boldsymbol{\Omega}^{(k)}) - \rho \|\boldsymbol{\Omega}\|_{1,\infty} \right)$$

- Graphical Models allow measuring likelihood of Data according to the model
- Variable Selection Consistently leads to models with the highest likelihood
- **Pipeline:**
- Cluster locations into 100 clusters
- Learn a Structure for 2 weeks
- Train Regression models using major influencers to predict next two weeks
- In the training, hyperparameters are learned: number of influencers & regression parameters
- Test on the next month

Portland Crime Dataset



- Lasso Regression: Mean Pearson Correlation – 0.2165

- Elastic Net Regression: Mean Pearson Correlation – 0.4507

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}(\|y - X\beta\|^2 + \lambda_2\|\beta\|^2 + \lambda_1\|\beta\|_1).$$

- Support Vector Regression: Mean Pearson Correlation – 0.05