TEXAS
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Electric Load Forecasting

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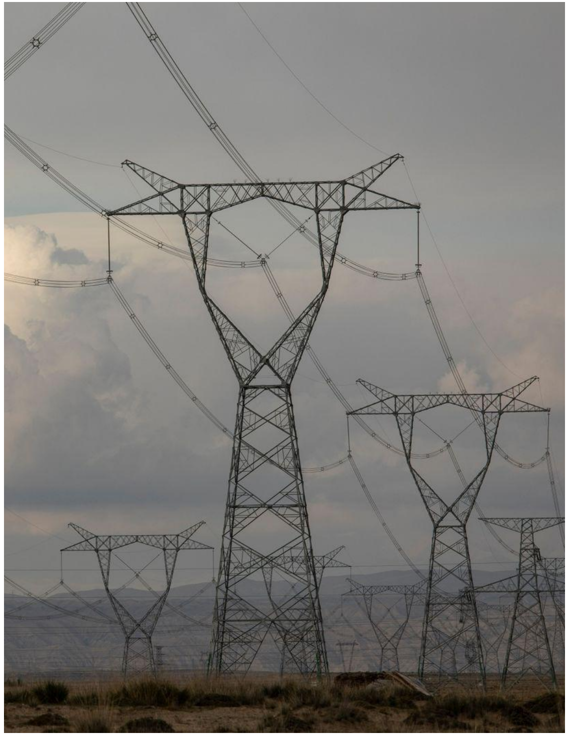
Introduction

- Applied machine learning project in domain of electric load forecasting
  - Critical for short, medium, and long term optimal control and operation of electric power systems
  - Can also be applied in the areas of utility capacity planning in regulated territory, Independent System Operator (ISO) planning in non-regulated territory, and may be a key part of energy systems analysis for a diverse set of applications

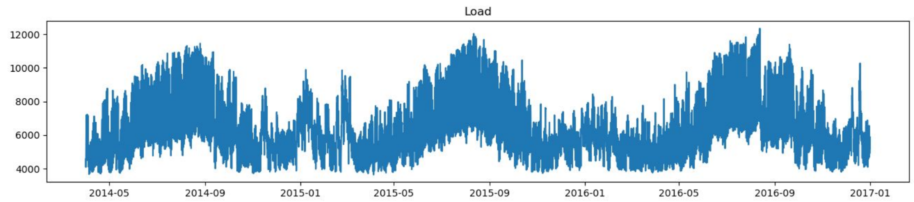
- We survey state of machine learning techniques applied in the space
  - Build models, create our best load forecasting model for a selected dataset
  - Benchmark performance of all applied models
  - Review theoretical underpinnings of the applied models

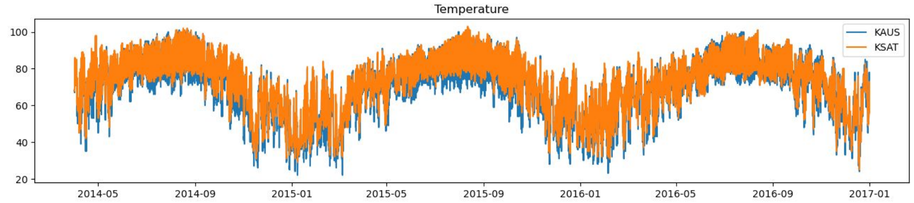
- Accuracy is important both on average and at the extremes



Data

- Endogenous
  - Electric load was sourced from the Electricity and Reliability Commission of Texas (ERCOT).
- Exogenous
  - Climate data from the National Oceanic and Atmospheric Administration (NOAA)
- Both datasets were available at hourly granularity
- Focused on the South Central ERCOT load zone, weather stations at Austin Bergstrom, San Antonio airport





Model - Multiple Linear Regression (MLR)

- Two distinct MLR models were applied
- Simple model
  - Incorporating only temperatures as exogenous variables
- Complex model
  - Adds humidity, binary encoded terms reflecting time series seasonality as exogenous variables (month, day of week, hour of day)
  - Interactions between terms
- Sets baseline for comparison to other models

Complexity	Train/Test	RMSE
Simple	Train	1410.454
Simple	Test	1464.745
Complex	Train	308.5117
Complex	Test	319.0298

Model - Transformer

- Selected due to high compatibility with time series data

- Data was inputted as a sliding window input
  - Hypertuned over providing 24 and 48 hour windows (TR)
- Implemented a single transformer encoder architecture
- Hypertuned the following parameters:
  - Encoder Layers (EL): [1, 4, 8]
  - Number of Heads (NH): [1, 5]
  - Dropout Percentage (D): [0, 0.1, 0.2]
  - Learning Rate (LR): [1e-3, 1e-4]
  - Max Epochs (ME): [10, 20]

EL	NH	D	LR	ME	TR	RMSE
1	1	0.0	1e-3	10	24	1706.72
1	1	0.0	1e-2	10	24	1706.99
4	1	0.0	1e-2	10	24	1707.05
4	1	0.2	1e-4	10	24	1707.32
8	1	0.0	1e-4	10	24	1707.38

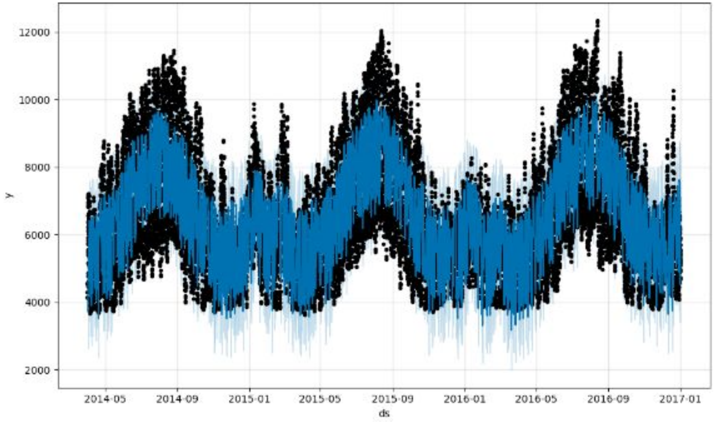
Model - META: *Prophet*

- Selected to show of what the state of the art models could do

- Ultimately trying to solve the equation:
  $y(t) = g(t) + s(t) + h(t) + e$

- $g(t)$ is the trend function for non-periodic changes
- $s(t)$ is the periodic changes
- $h(t)$ is the effects of holidays
- e is the irreducible error

- Testing two versions:
  - Only training on timeseries (no weather info) information
  - Training on all information



Data Trained on	Train/Test	RMSE
Timeseries	Train	2150.635
Timeseries	Test	2220.895
All	Train	2150.140
All	Test	2225.565

Discussion / Conclusion

- Best model:
  - MLR

- Lack of Data:
  - Incorporated 3 years of data
  - Only included 2 sources of weather data

- Surprised by SOA Model Results
  - Maybe because of same reasons why Transformers didn't perform as well

  - Incorrect usage of model

Best Respective Model	**RMSE**
MLR	319.029
Transformer	1706.72
META: *Prophet*	2220.895