

# Long-Term Electricity Price Prediction



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# Objective

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Predict the monthly retail price of electricity **3-5 years** in advance.



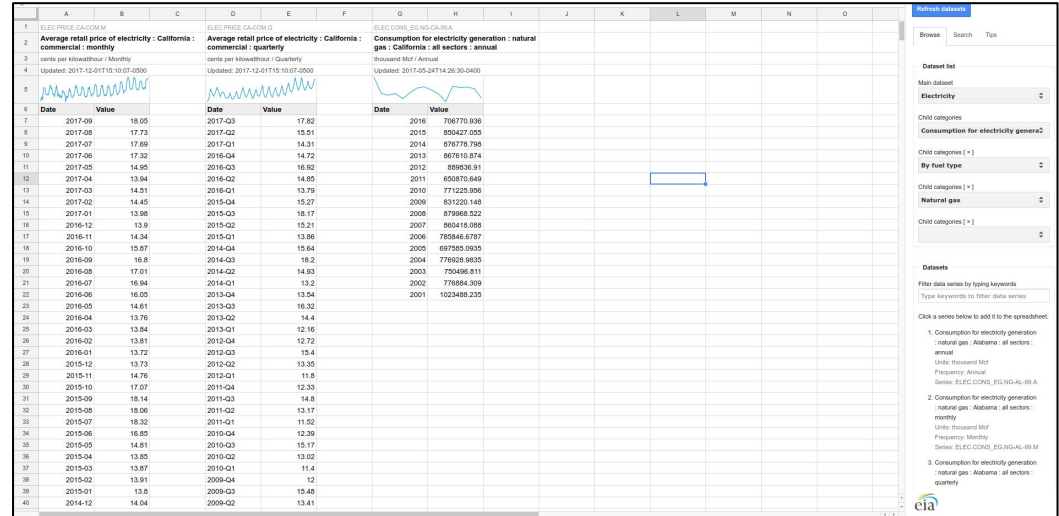
# Data Collection and Cleaning

## EIA "OpenData" Database

Biggest hiccup was finding enough data...

Spent majority of time selecting, cleaning, formatting, and merging data.

Up to last week we had 13 columns in our potential feature matrix. Now we have 78.





# Correlation Analysis

For feature selection



0.00  
0.25  
0.50  
0.75  
1.00



# GDP

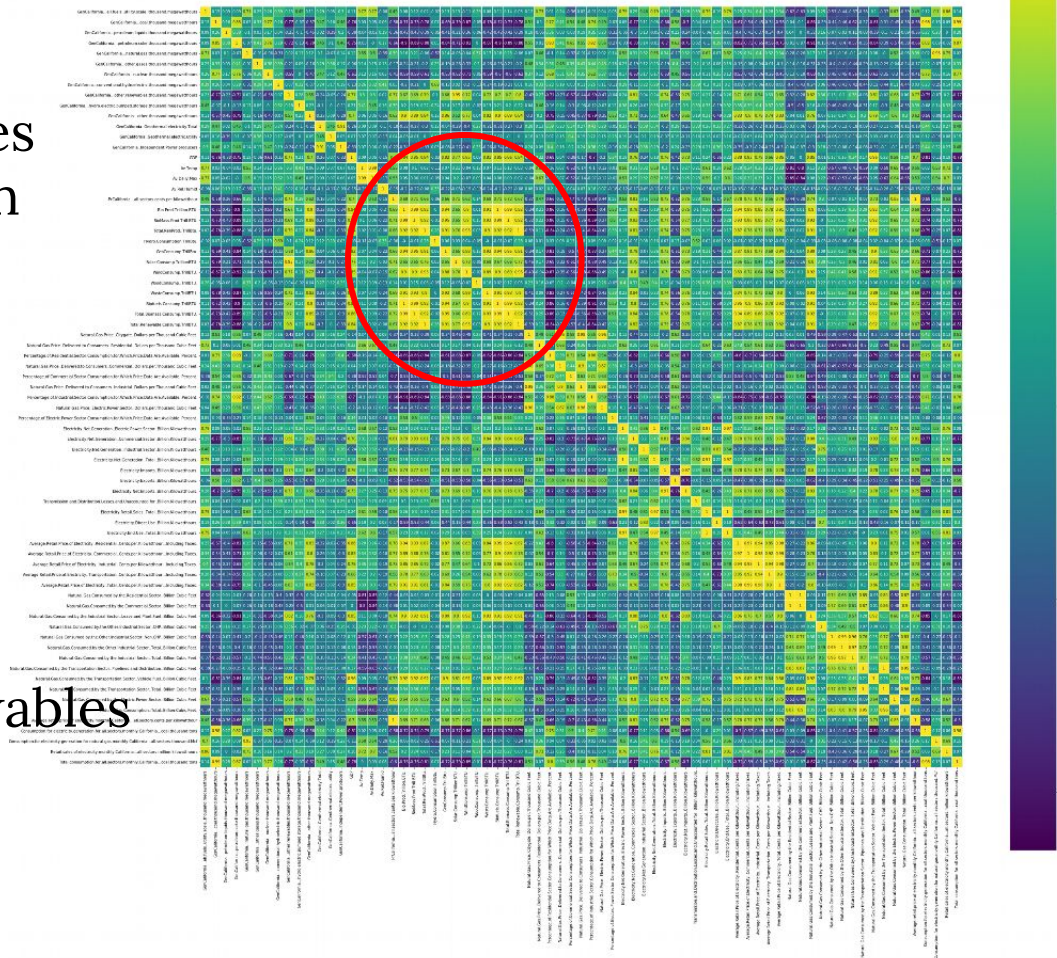
## Renewables Consumption

### ...and Average Retail Electricity Price



# Renewables Production

- Bio
- Geo
- Solar
- Wind
- Hydro
- Waste
- Total Renewables





# Natural Gas Price

# Electricity Price

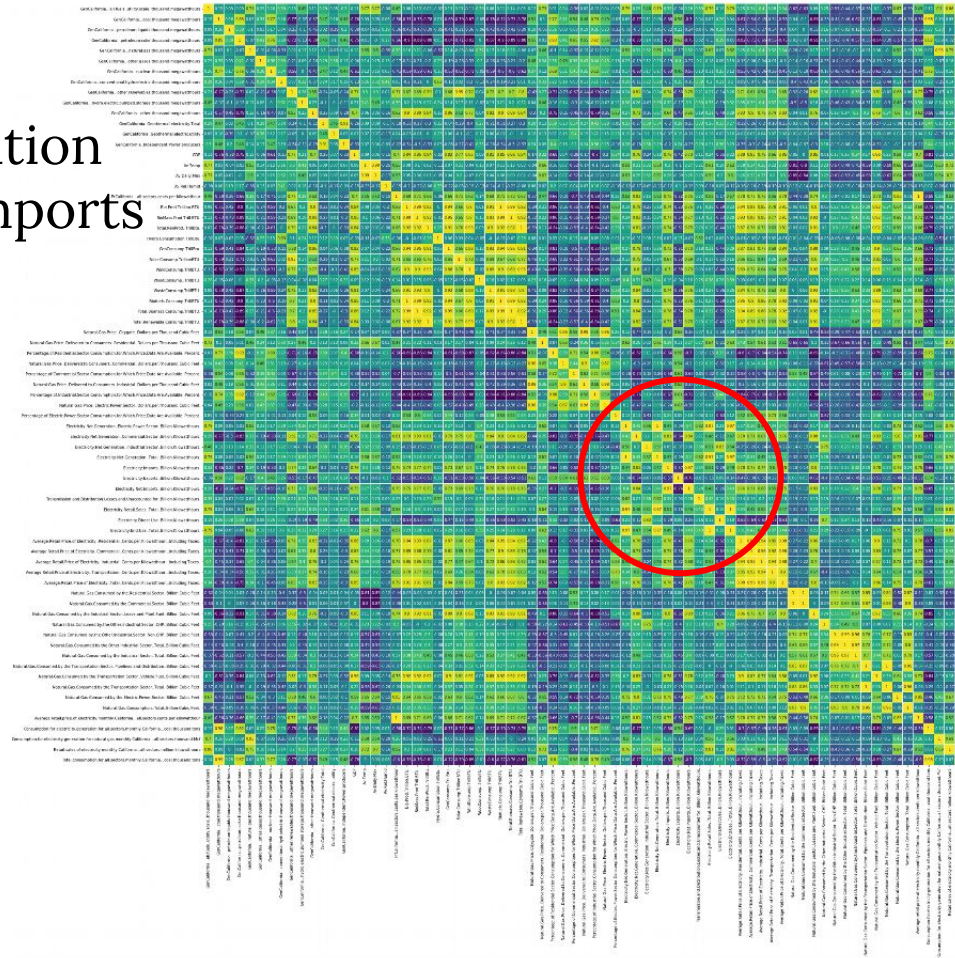
# Different Sectors

- Residential
- Commercial
- Industrial

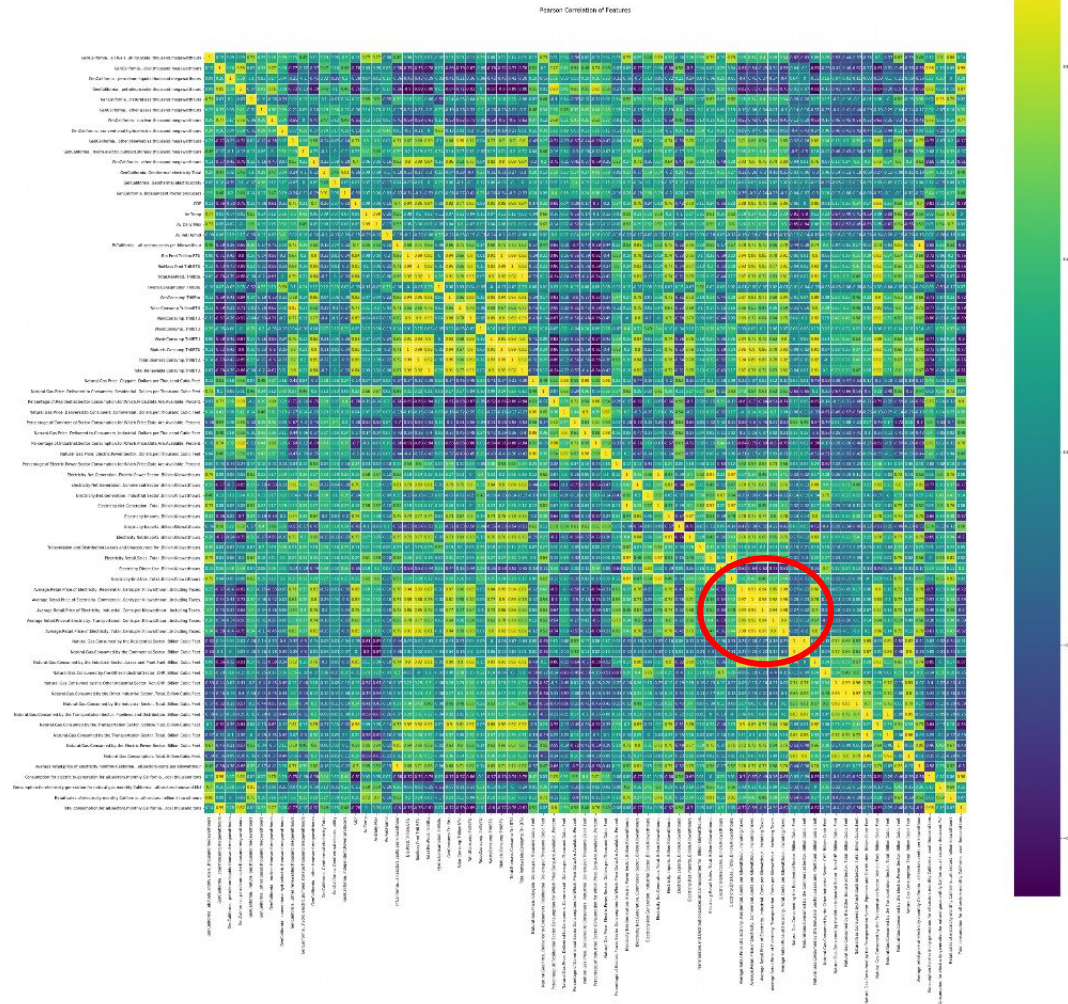




# Net Generation Exports/Imports in different sectors



## Different Sectors/ Units





# Natural Gas Consumption and Production by sector.



Petroleum  
Coke  
and Coal  
Generation

... And

Average  
Monthly  
Retail Price of  
Electricity

Person Correlation of Features



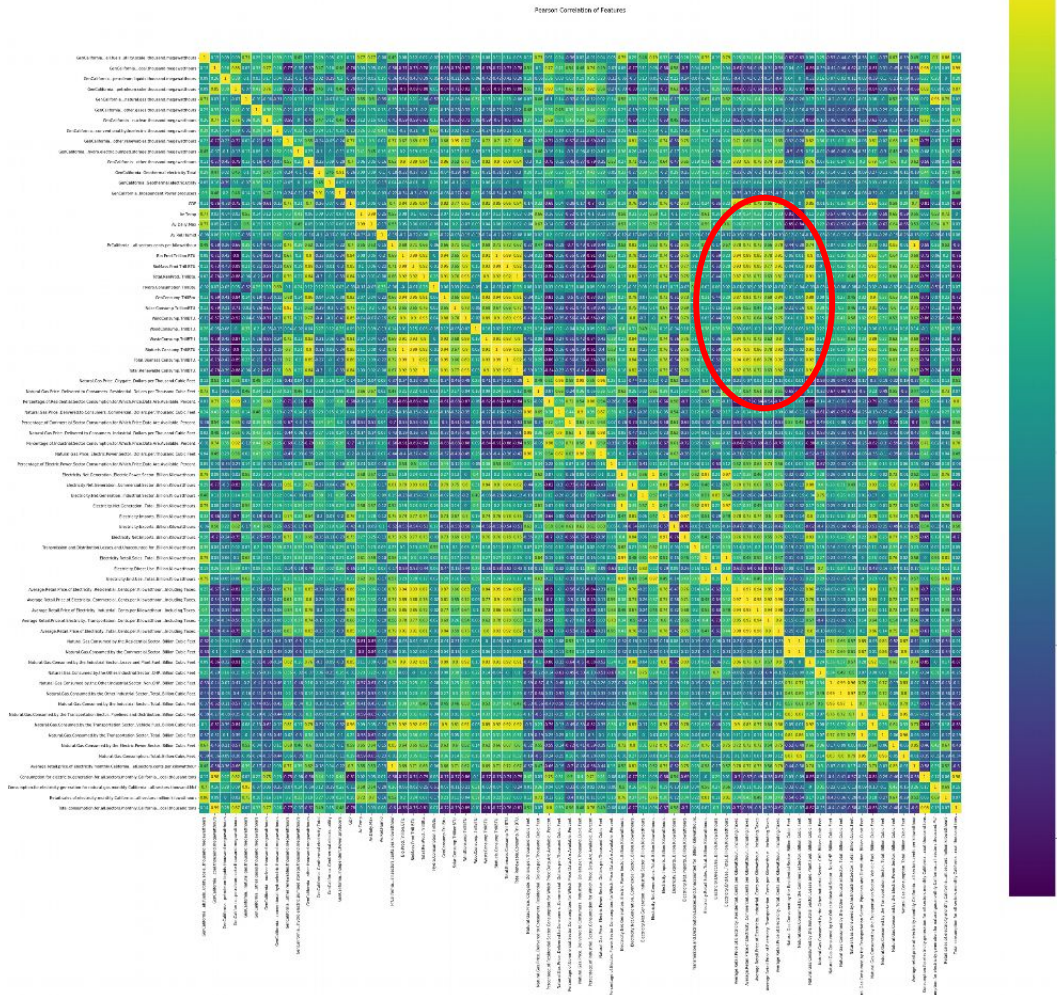


# Renewables Production and Consumption

- Bio
- Geo
- Solar
- Wind
- Hydro
- Waste
- Total  
Renewables

And...

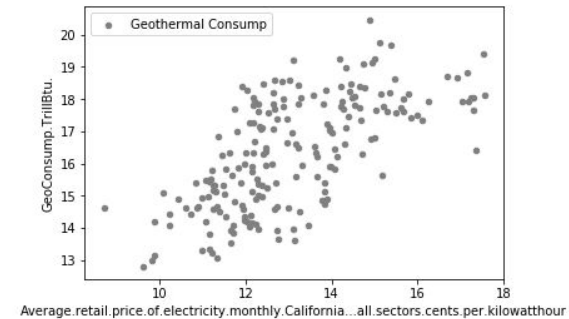
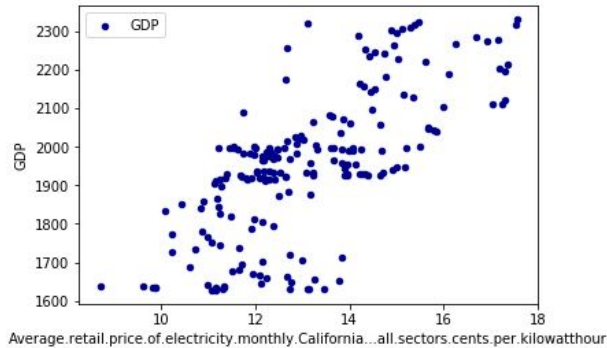
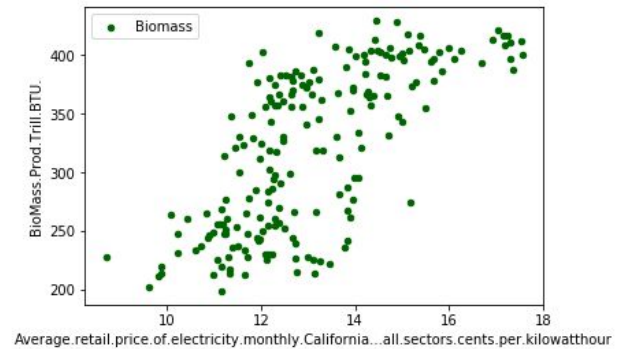
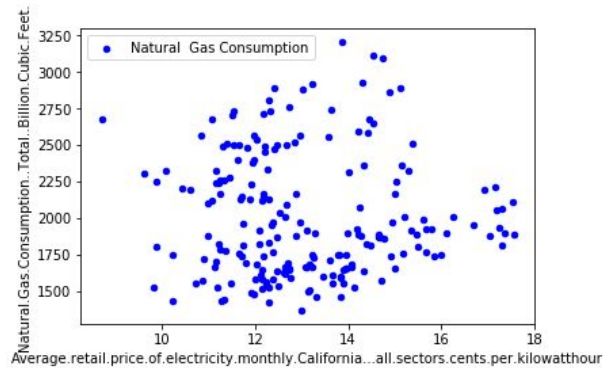
- Average  
Monthly  
Retail  
Electricity  
Price in  
different  
sectors.
- Electricity  
Import Price

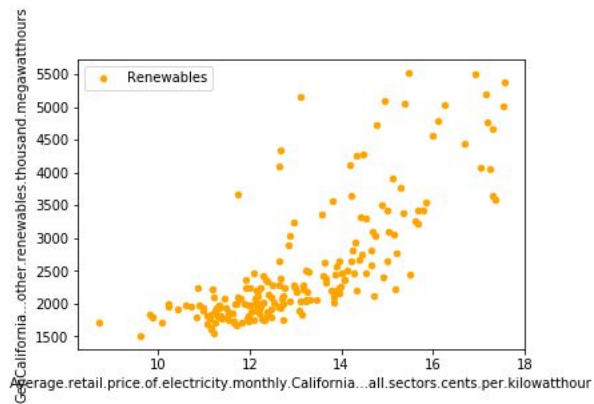
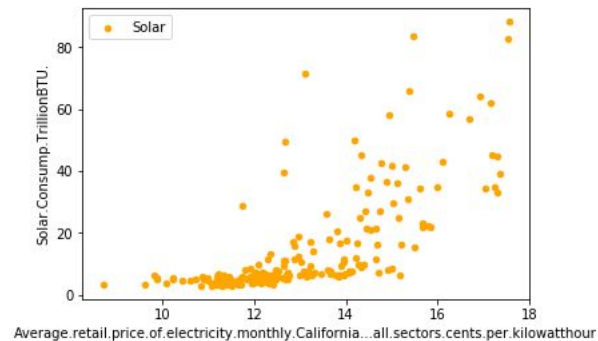
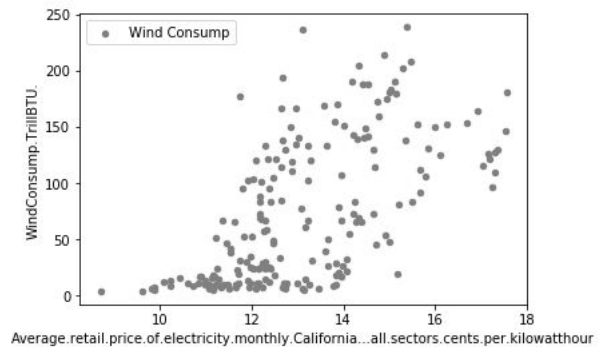




## Correlations Summary (Features)

- GDP (.7)
- Natural Gas Consumed by Industrial Sector (.74)
- Natural Gas Consumed by Electric Power Sector (.85)
- Net Electricity Imports (.75)
- Net Electricity Generation (.81)
- Renewables (.77)
  - Solar Consumption (.71)
  - Geothermal Consumption (.65)
  - Wind Consumption (.62)
  - Biofuels Production (.72)









# Prediction

Time Series



## Prediction with **Time Series**

- Time Series Prediction (Autoregressive Integrated Moving Average or ARIMA) for 3 years in advance – train 2000–2014, test 2014–2017, predict 2017–2020.
- ... for 5 years in advance – train 2000–2012, test 2012–2017, predict 2017–2022.

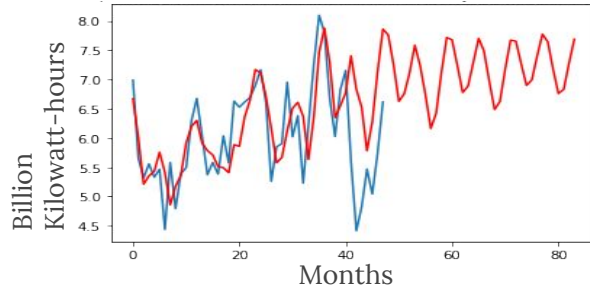


## **Time Series** Results

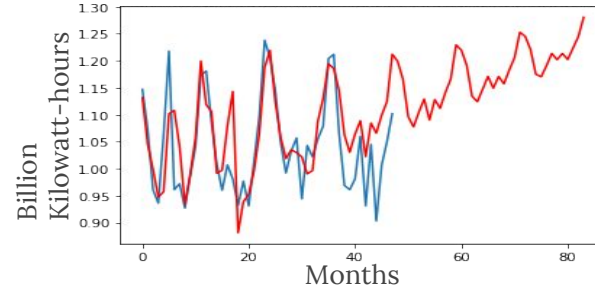
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- Time Series Prediction for 3 years performed superbly.
  - Considered Cross-validation, but discovered that doesn't work well with time series because it misses trends and captures other erroneous trends. Time series depends on history.
- Time Series for 5 years performed slightly worse, but still good.

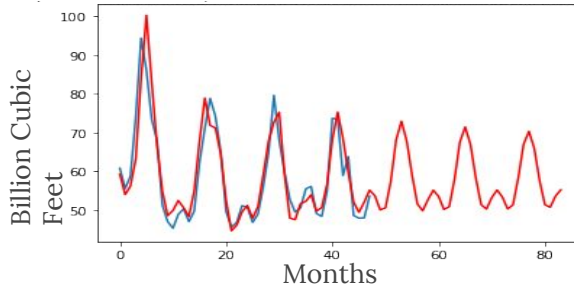
Electricity Imports (3 Years)



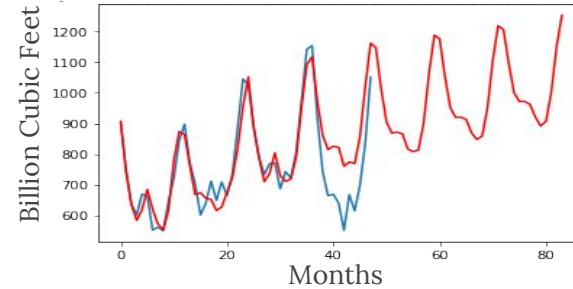
Net Commercial Generation (3 Years)



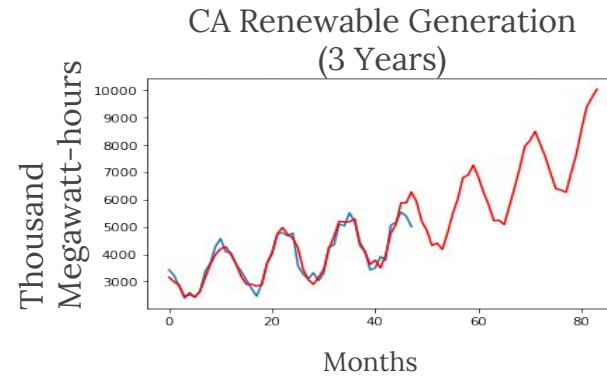
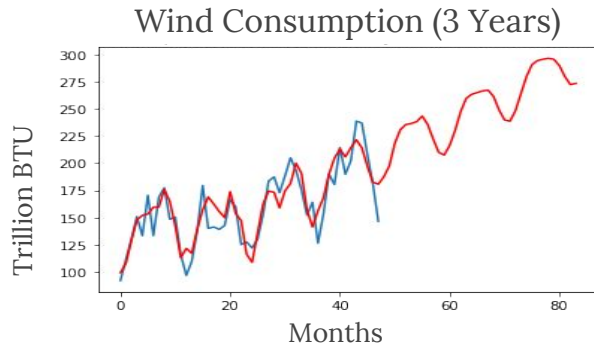
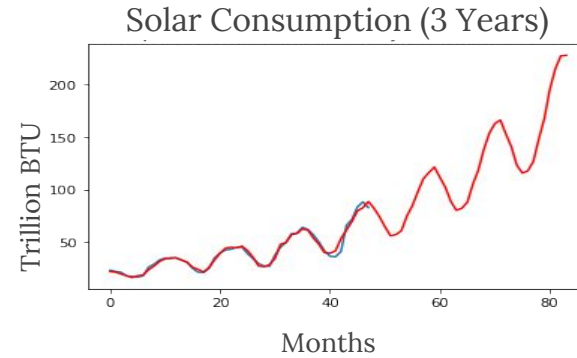
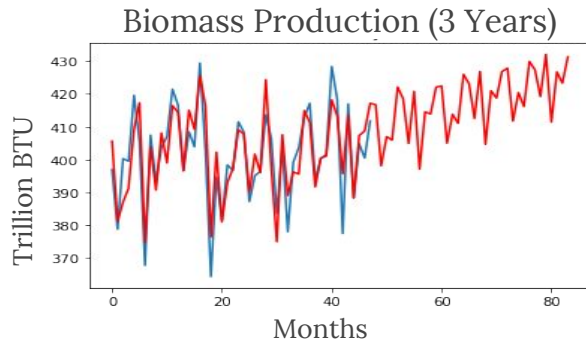
Natural Gas Consumed by Industrial Sector (3 Years)



Natural Gas Consumed by Electric Power Sector (3 Years)







Lag: 14

Coefficients: [-0.06925843 0.62417522 0.04481464 0.01982984 -0.02458993 0.02896534  
-0.03363928 0.08095022 -0.07569835 0.03176049 -0.02809795 0.29576012

0.33499937 -0.07588766 -0.21199173]

predicted=16.698876, expected=17.250000

predicted=16.086452, expected=17.300000

predicted=15.367021, expected=15.360000

predicted=14.276157, expected=15.160000

predicted=14.089079, expected=14.460000

predicted=14.078031, expected=14.550000

predicted=14.193885, expected=14.300000

predicted=13.466611, expected=14.220000

predicted=13.219550, expected=12.640000

predicted=14.530995, expected=14.760000

predicted=16.291482, expected=16.120000

predicted=17.084774, expected=17.310000

predicted=16.963351, expected=17.190000

predicted=16.362001, expected=17.360000

predicted=15.494480, expected=15.620000

predicted=14.713708, expected=15.030000

predicted=14.410178, expected=14.410000

predicted=14.484953, expected=14.740000

predicted=14.354295, expected=14.530000

predicted=13.910401, expected=13.340000

predicted=13.914972, expected=12.670000

predicted=14.993065, expected=14.940000

predicted=16.436993, expected=16.240000

predicted=17.233379, expected=16.930000

predicted=17.184642, expected=17.150000

predicted=16.586172, expected=16.680000

predicted=15.756495, expected=14.180000

predicted=15.066525, expected=14.990000

predicted=14.802596, expected=14.880000

predicted=14.799852, expected=15.120000

predicted=14.650228, expected=15.300000

predicted=14.362594, expected=15.390000

predicted=14.512454, expected=13.120000

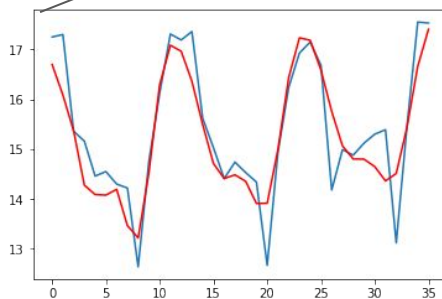
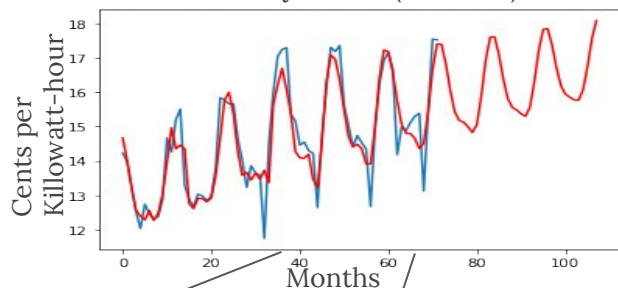
predicted=15.441955, expected=15.460000

predicted=16.661402, expected=17.550000

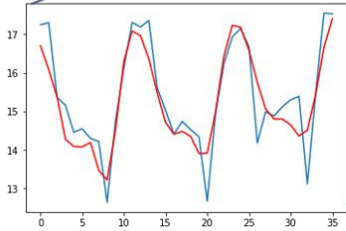
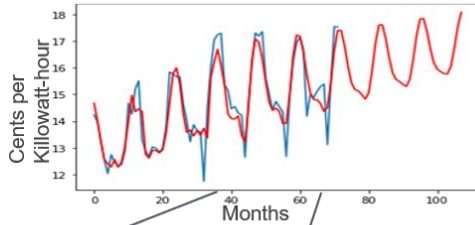
predicted=17.405589, expected=17.530000

Test MSE: 0.387

Average Monthly Retail  
Electricity Price (3 Years)

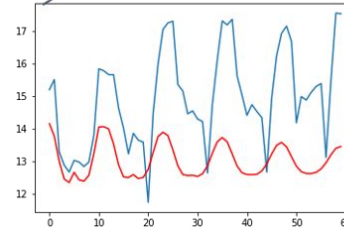
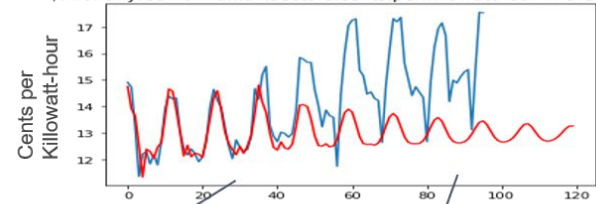


**Average Monthly  
Retail Electricity Price  
(3 Years)**



**MSE (Mean Square Error)=0.38**

**Average Monthly  
Retail Electricity Price  
(5 Years)**



**MSE (Mean Square Error)=4.972**



## Hand-Picked Features Model

Use Time Series to predict value of features in the future.

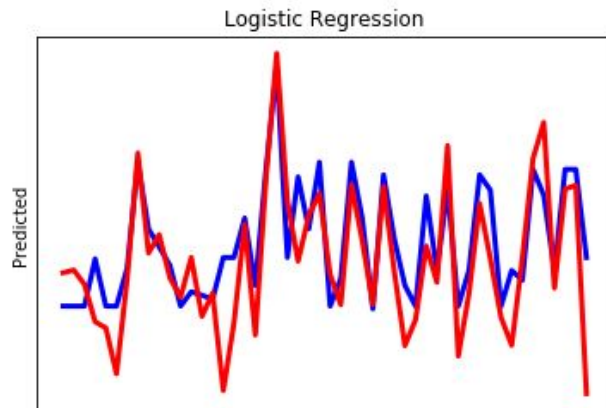
Train a model with the highest-correlated features.

Apply coefficients of tuned algorithm as weights to projected features.



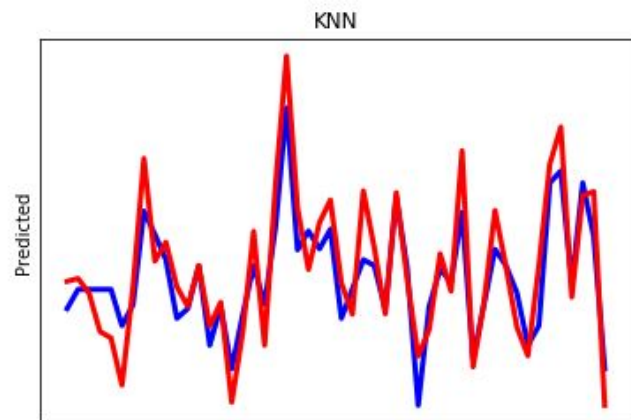


# Logistic Regression



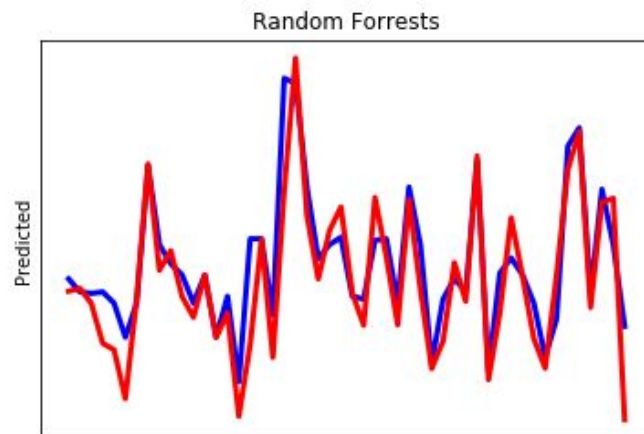


# KNN





# Random Forests





# Conclusions

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## 3-Year Prediction

Time series model performed superbly.

Will investigate trained model with projected feature data next.

## 5-Year Prediction

Time series model did not perform great, but tuned model with time series predicted feature data performed much better.



# Conclusions

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So many factors:

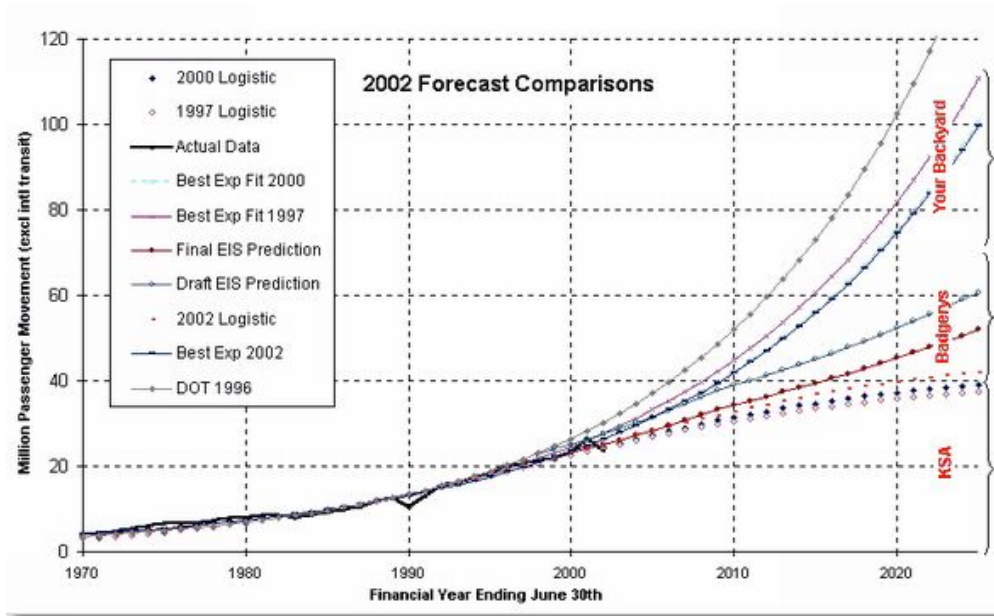
- Political Climate
- Economic Climate
- Corporate Decisions
- Weather and Climate Patterns (next week at best)
- Usage Patterns (next week at best)
- OPEC
- Foreign Policy

One really hard aspect of this problem (and one of the main reasons nobody has really solved this problem) is that these factors pretty much cannot be predicted, and, unfortunately, they affect prices pretty drastically.

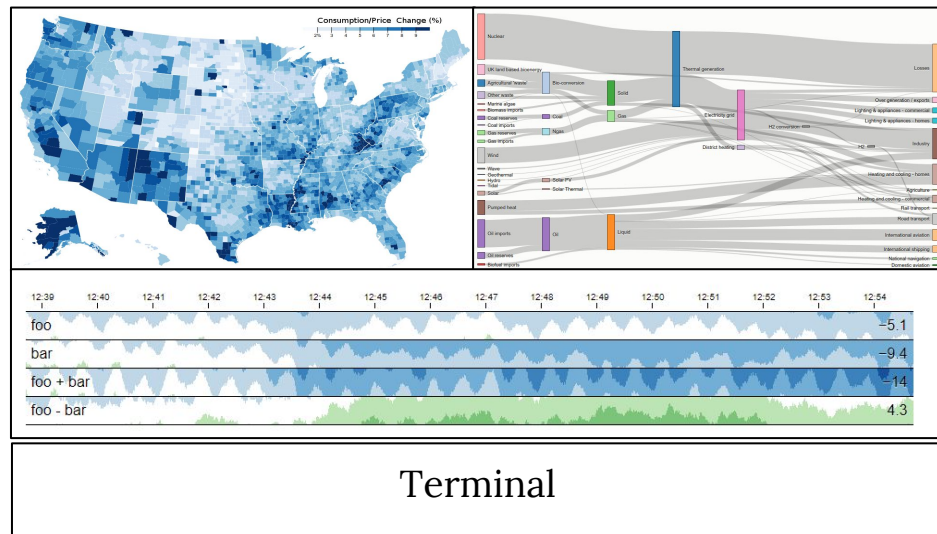
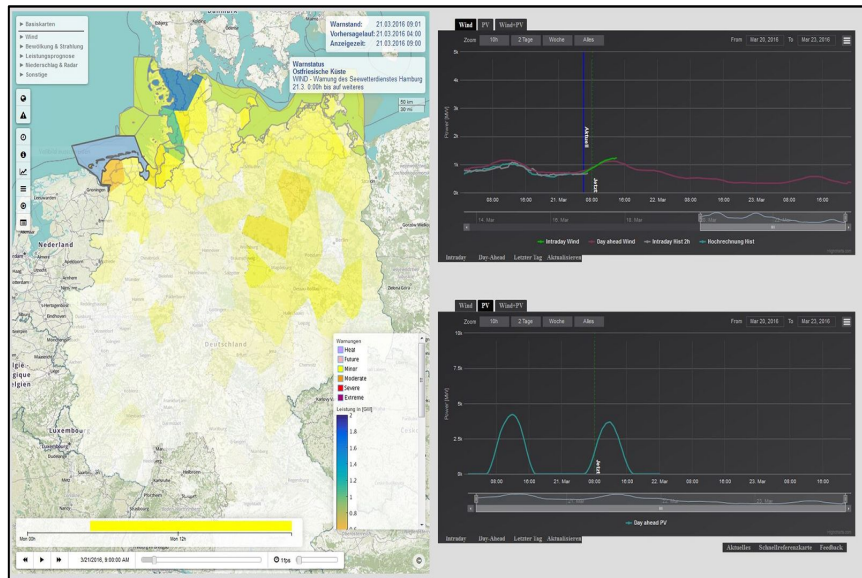




# Conclusions



Perturbance Flexible + Confidence Intervals



Terminal

Visualization





# Technical Components

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## Interface

Interactive Interface  
Online Learning  
Perturbance-Flexible  
Front End  
User Domain  
Knowledge Input  
Real Time Data  
Visualization

## Prediction

Linear Regression  
Time Series  
Random Forest  
Regressor  
Vector autoregressive  
model (ARIMA)  
Linear Dynamic Systems  
Gaussian State Space  
Models

## Techniques

Synthetic Data  
Augmentation  
Automated Database  
Query and processing  
(Pipelining)  
Online Learning  
Cross Validation



## Next Steps

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Try a new fuzzy model for more precise time series prediction (maybe tweak Random Forest)

Provide perturbation flexibility with confidence intervals (and a way to quantify perturbations).

Develop User Interface, reason about user domain knowledge input, look into online learning with constant feedback into pipeline, and find more data.



## Reference

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[1] A. Liaw and M. Wiener (2002). **Classification and Regression by randomForest**. R News 2(3), 18--22.

[2] Jason Brownlee (January, 2th, 2017 ) **Autoregression Models for Time Series Forecasting With Python**  
<https://machinelearningmastery.com/autoregression-models-time-series-forecasting-python/>

[3] Statsmodels <http://www.statsmodels.org/stable/index.html>





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# Thanks!

*Any questions ?*