CS584 – MACHINE LEARNING

FALL 2016

Electric Power Usage Forecasting

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Electric Power Usage Forecasting

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Task

With given weather data (temperature, wind, rain, humidity, precipitation, etc.) and past electricity usage (in terms of kw/hr.), predict future usage of power based on the weather conditions.

Electric power demand prediction is a necessary process for efficient resource management in a smart grid. If performed accurately it can save millions of dollars for power companies.

To predict the electric power load using various regression techniques like Locally Weighted Regression (LWR), Multilayer Perceptron (MLP), Kernel Ridge Regression (KRR) and Support Vector Regression (SVR). All methods have been applied to the Comed Electricity historical data for a period of 8 months. The hourly prediction is considered in each of the techniques.

Moreover, this project gives prediction of power load consumption based on the inputs provided and the day for which the prediction needs to be made.

Dataset

The power usage majorly depends upon the climatic conditions of the local area. The parameters that constitute the climatic conditions are temperature, wind chill, humidity, precipitation and wind speed.

Data source

The weather data was extracted from weather underground API. A python script was created to call the weather API and the corresponding interval data was extracted. The hour wise climatic data was extracted for a period of 8 months from 1st Jan 2016 to 31st Aug 2016.

http://api.wunderground.com/api/<API_DEVELOPER_KEY>/history_20160101/q/IL/Chicago.json

Target variable

The target data which is the power consumption for a period is extracted from the historical comed data. The data was extracted from the below link:

https://www.comed.com/customer-service/rates- pricing/retail-electricity-metering/Pages/historical-load- data.aspx

Features

Time of the day, temperature, wind chill, humidity, precipitation and wind speed

Data size

5850 instances and 6 features

Preprocessing

Weather data viz., date, time of the day, temperature, wind chill, humidity, precipitation and wind speed are extracted from weather underground API and the power usage for the same date and time hour is extracted from the comed historical data. All data is stored into 'weather_data.csv' under data folder.

Missing Values:

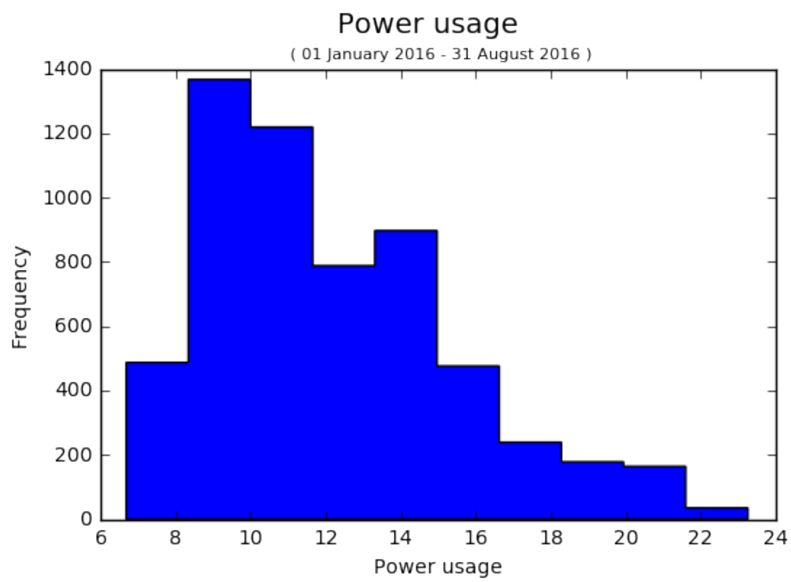
In case the values of the any of the feature elements were missing, the average of previous and next element in the same column is calculated and added to the missing feature.

Visualization

Target

In this project, the target variable is power usage.

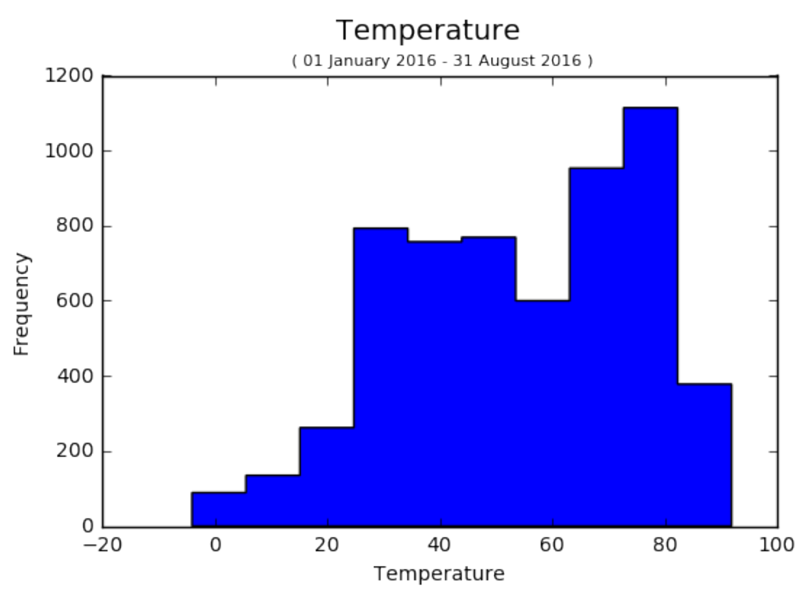
Mean: 12.1707113238
Variance: 10.8769157674



Features

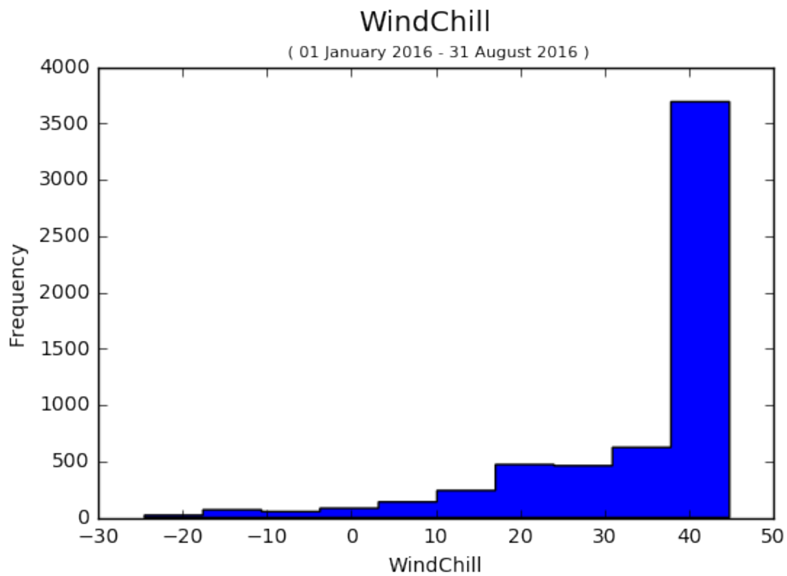
1. Temperature:

   Mean: 53.9151965812
   Variance: 457.261346842



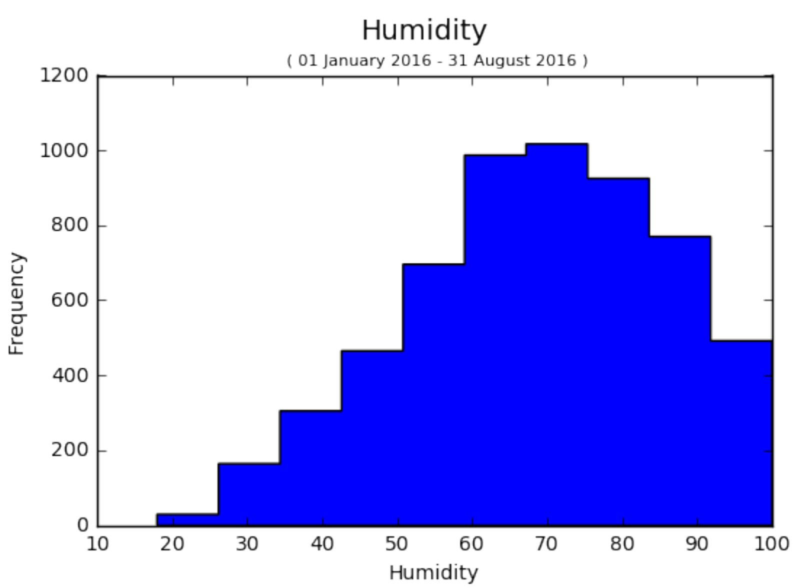
2. Wind Chill

Mean: 34.5562905983
Variance: 163.66808436



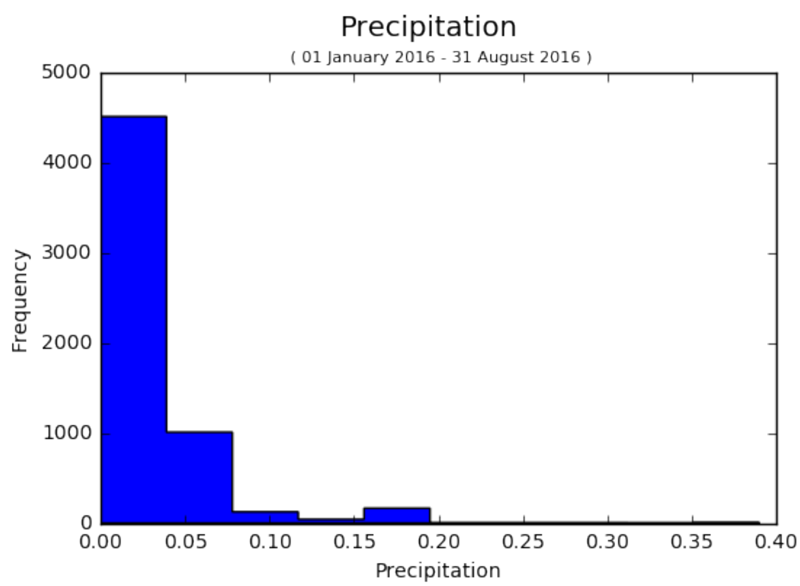
3. Humidity

Mean: 68.2991452991
Variance: 290.121794141



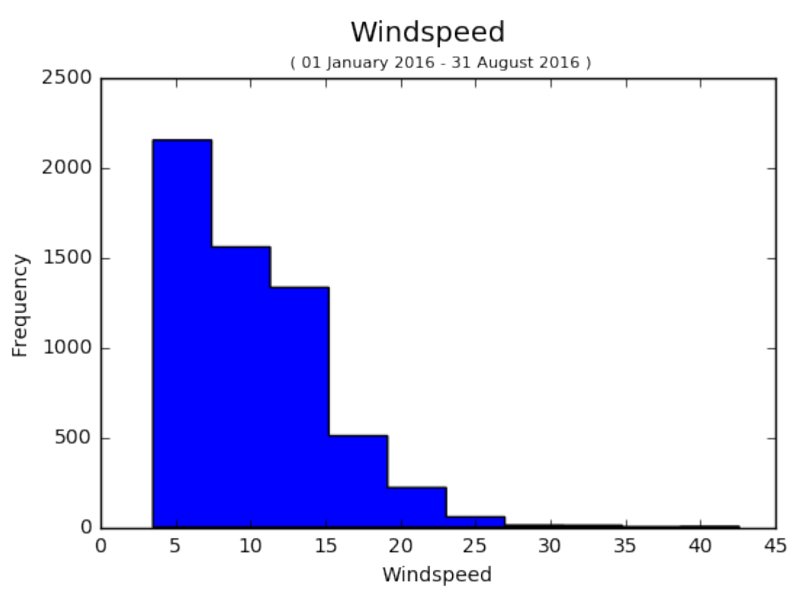
4. Precipitation

Mean: 0.0277982905983
Variance: 0.00100869093725



5. Wind Speed

Mean: 9.9944957265
Variance: 24.9118056004



Evaluation

Performance Measure

We used Negative Mean Absolute Error (MAE) and Negative Mean Square Error (MSE) to measure performance because -

- Both mean squared error (MSE) and mean absolute error (MAE) are used in predictive modeling.
- MAE is more robust to outliers since it does not make use of square.
- MSE is more useful if we are concerned about large errors whose consequences are much bigger than equivalent smaller ones.

Regressors

- ***Locally Weighted Regression (LWR)***

  LWR model is very similar to simple regression model, the only difference is that we are introducing a weight matrix W. Once we have the weight matrix we can find the model parameters as follows:

  $$\beta=(X'WX)-1X'WY$$

  To get the prediction we need to multiply betas with our inputs X_0 , $\hat{y} = \beta X_0$.

- ***MLP Regression***

  This technique is a feedforward neural network model that helps to maps the input set into an output set using the hidden layer that is defined between the two. In our approach we have considered a single hidden layer fully connected to the input and output layer thus predicting the output as required.

- ***Kernel Ridge Regression***

  Kernel ridge regression (KRR) combines Ridge Regression (linear least squares with l2-norm regularization) with the kernel trick. It thus learns a linear function in the space induced by the respective kernel and the data.

- ***Support Vector Regression***

  Support vector machine (SVM) is a popular machine learning tool for classification and regression. SVM regression is considered a nonparametric technique because it relies on kernel functions.

Evaluation Strategy

Regressors are evaluated with **10-fold cross validation.** Again, they are evaluated with one-day input to predict the hourly power usage of that particular day and calculated mean square error and mean absolute error for predicted power usage with expected power usage.

Performance Results

Model	Parameters	Performance
Locally Weighted Regression (LWR)	-	Negative MAE : 2.74760190769 Negative MSE : 13.76786027565
MLP regression	hidden_layer_sizes = 50, alpha=0.0007, random_state=1, activation='identity', warm_start=True	Negative MAE : 2.107882568 Negative MSE : 6.92295378724
Kernel Ridge Regression - Laplacian	kernel='laplacian', alpha=0.1, gamma=0.1	Negative MAE : 1.57358798053 Negative MSE : 5.67602351394
Support Vector Regression - RBF	kernel='rbf', C=1e3	Negative MAE : 1.322480129185 Negative MSE : 5.00180266547

Table - 10-fold cross validation Results

Discussion

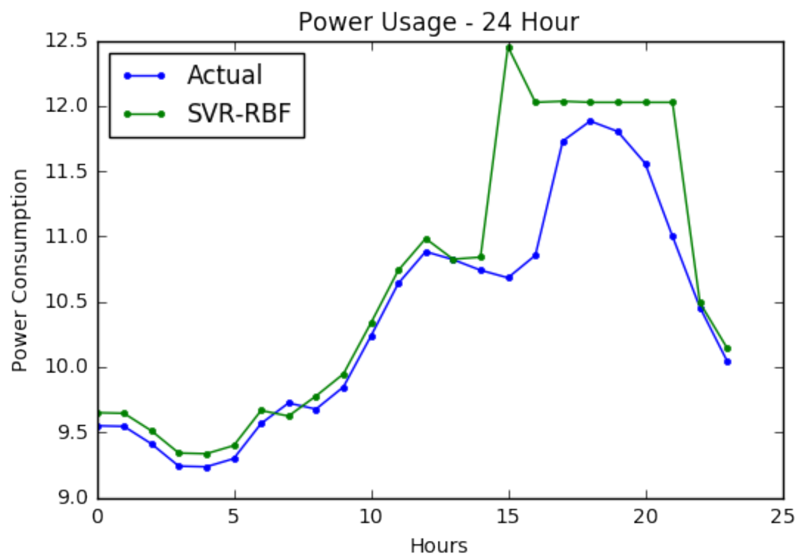
Considering performance measures, Mean Absolute Error (MAE) and Mean Square Error (MSE), we can say that support vector regression gives best result with parameters kernel='rbf', C=1e3.

Support Vector Regression (SVR) and Kernel Ridge Regression (KKR) almost gives similar performance. But, Locally Weighted Regression (LWR) and MLP regression are not preforming good if we compare them with SVR or KRR. This might be because of some parameter change.

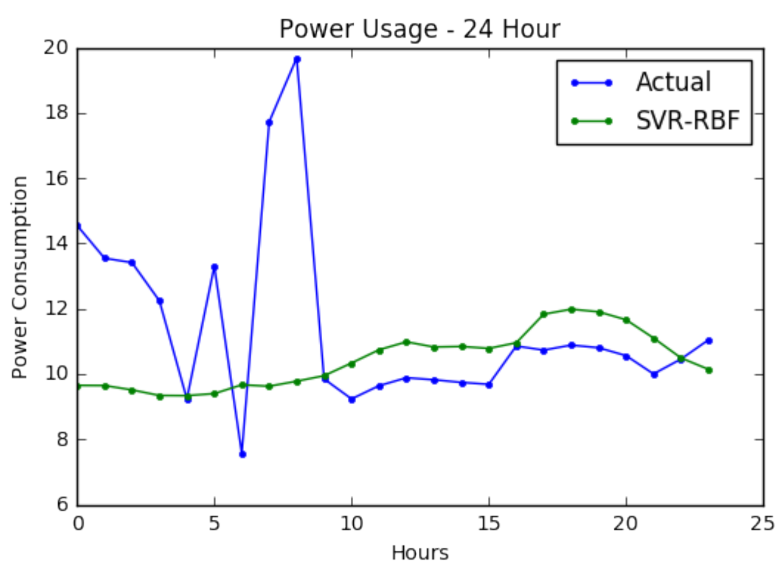
For given input data of single day, the performance is not that good. This means that models are not performing well with new weather data. I think this can be over done by giving more train data to the model.

Interesting/Unexpected Results

- If there is sudden huge change in weather condition, then the model does not gives accurate prediction.



- And sometimes it is difficult to predict power usage based on weather, there are other factors that also affect power usage, for example, festivals, events.



- This might be because the model is not trained with enough data that it cannot understand these sudden changes in weather or any circumstantial changes.

Conclusion

Power consumption prediction is important and if used efficiently can save huge amount of money in terms of resource management required for the electricity supply. Number of regression techniques can be applied to predict the power usage. This will help various energy power plants to generate and supply optimal energy. The various regression models work as required to predict the data with each of them using the best fit parameters to predict the power consumption.

References

[1] Machine Learning Techniques for Short-Term Electric Power Demand Prediction- [Fernando Mateo, Juan J. Carrasc, M´onica Mill´an-Giraldo, Abderrahim Sellami, Pablo Escandell-Montero, Jos´e M. Mart´ınez-Mart´ınez and Emilio Soria-Olivas]

[2] Ge, Y., Flueck, A.J., Kim, D.-K., Ahn, J.-B., Lee, J.- D, and Kwon, D.-Y, " An Event-Oriented Method for Online Load Modeling Based on Synchrophasor Data," in Smart Grid, IEEE transactions, 2015, volume: PP, Issue: 99.

[3] Ge, Y., Flueck, A.J., Kim, D.-K., Ahn, J.-B., Lee, J.- D, and Kwon, D.-Y, "Power System Real-time Event Detection and Associated Data Archival Reduction Based on Synchrophasor," in Smart Grid, IEEE transactions, 2015, volume: PP, Issue: 99.