Deep Neural Network for Weather Time Series Forecasting

Contents

1. Abstract

Forecasting future values of a time series plays an important role in nearly all fields of science and engineering, such as economics, finance, business intelligence and industrial applications, also in real world applications such as speech recognition, real time sign language translation, finance markets, weather forecast etc. Deep Learning algorithms are known to perform best when there is a massive dataset available for learning. Not every time series problem has massive dataset available. In that case advanced ML algorithms are available for time series applications. Because of the nature of time series analysis problem where two values of the same feature in two different time steps are considered as different features, the data size available for processing becomes larger. It is hard to decide which algorithms will perform better for a medium size dataset. The recommendation made in this project can be useful for anyone looking for best ML/DL algorithms for medium size time series problem dataset. I used Historical hourly Weather Data from Kaggle website. The dataset contains ~5 years of high temporal resolution (hourly measurements) data of various weather attributes, such as temperature, humidity, air pressure, etc. There is non-temporal data such as longitude and latitude of cities, which is also used in forecasting. Both Univariate and Multivariate time series analysis is done to collect the data for the recommendation.

2. Time Series Analysis

A time series is a sequence of numeric data observations collected over a period of time at regular intervals. The temporal dependency in time series cause two otherwise identical points of time to belong to different classes or predict different behavior. This characteristics generally increases the difficulty of analyzing them.

3. Weather Forecast

Weather forecast is among the most popular forecast problems. Weather forecast includes forecasting temperature, pressure, humidity, wind direction and wind speed. Unlike other time series datasets, weather data has unique features. There is season-to-season, year-to-year variability in the trends of weather data. The temperatures and Pressures are correlated. Wind speed and direction have similar attributes and changing patterns. So all these features could be separately predicted using univariate time series analysis techniques or could be used jointly to predict using multivariate time series techniques.

4. Univariate and Multivariate Time series Analysis

A univariate time series is a series with a single time-dependent variable. To predict the temperature for next few days, we look at the past values and try to extract a pattern. We would notice that the temperature is lower in the morning and at night, also we notice that it is colder during the months of November to January and warmer in April to June. In these observations we used only variable that is temperature. So this is called Univariate Time Series Analysis.

A Multivariate time series has more than one time-dependent variable. Each variable depends not only on its past values but also has some dependency on other variables. This dependency is used for forecasting future values. For example, temperature at any time depends on atmospheric pressure, humidity, wind speed, wind direction. To accurately predict the temperature, other variables should be considered too. This is called Multivariate Time Series Analysis.

5. Machine Learning for Time Series Analysis

There has been an extensive research done in machine learning for time series forecasting techniques. Several machine learning algorithms are used to solve time series forecast problems, such as Linear Regression, Random Forest, XGBRegressor, and Auto Regressive Integrated Moving Average (ARIMA). Weather Forecasting requires complex dynamic analysis of data from several past years which has variability from one year to another. Linear models such as LinearRegression, ARIMA cannot capture the non-linearity of the weather time series. Nonlinear Machine Learning models such as RandomForest and XGBRegressor perform better in precisely forecasting weather.

6. Historical Hourly Weather Dataset

The dataset contains ~5 years of high temporal resolution i.e. hourly measurements of six weather attributes: temperature, humidity, air pressure, wind direction, wind speed and general weather description of 30 US and Canadian cities and 6 Israeli cities. The dataset contains separate file for each weather attribute. Each file contains 36 cities as columns. Rows are time axis and time axis are same in all files for different weather attributes. The dataset also has non temporal data, the location of each city in term of longitude and latitude.

7. Deep Neural Networks

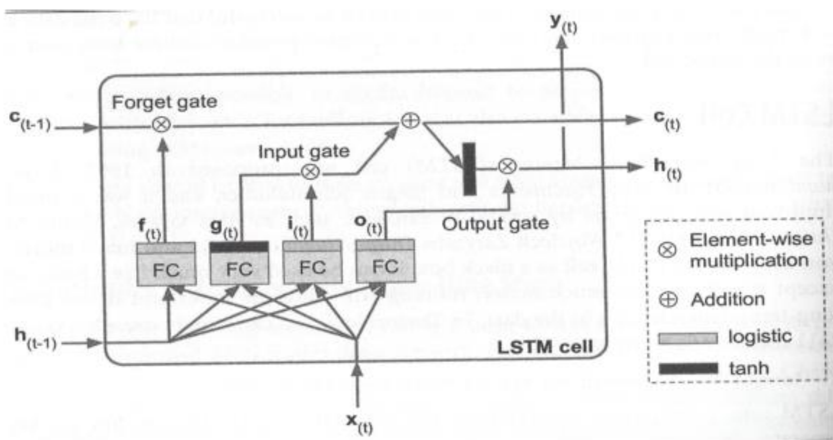
With the advent of Deep Learning algorithms, various supervised and unsupervised models are developed to analyze massive size time series data. Deep Learning is the general term for a series of multi-layer architecture neural networks. Several different Deep Learning approaches are there for time series analysis, such as Recurrent Neural Networks (RNN), The Long Short Term Memory (LSTM) neural network, Gated Recurrent Units (GRU), Stacked Auto Encoders, Multi-layer Perceptron (MLP) Regression. RNNs have shown their success in time series forecasting in recent years. However, they suffer from the problem of vanishing gradients and thus have difficulty capturing long term dependencies The LSTM and GRU have overcome this limitation and became very popular architectures for time series problems. LSTM neurons keep a context of memory within their pipeline to allow for tackling sequential and temporal problems without the issue of the vanishing gradient affecting their performance. The GRU model is simplified version of the LSTM model and performs just as well as LSTM which makes it popular architecture too for time series analysis.

8. The Long Short Term Memory networks

The Long Short Term Memory networks – usually just called "LSTMs" – are a special kind of Recurrent Neural Networks, introduced by Hochreiter & Schmidhuber (1997). Remembering information for long periods of time is practically the default behavior of LSTM networks, not something they struggle to learn!

Below the flow diagram of LSTM cell. The key idea is that the LSTM cell can learn to recognize an important input, store it in long term state, learn to preserve it for as long as it is needed and learn to extract it whenever it is needed. First the current input vector $x_{(t)}$ and the previous short term state $h_{(t-1)}$ are fed to the four fully connected layers. Each layer serves a different purpose.

- The main layer is the one which outputs $g_{(t)}$. This layer analyzes $x_{(t)}$ and $h_{(t-1)}$ and decides what is stored in the long term state.
- The three other layers are gate controllers for all 3 gates (input, forget and output).
  - The Forget gate controls which parts of the long term state should be erased
  - The input gate controls which part of $g_{(t)}$ should be added to the long term state.
  - The output gate controls which parts of the long term state should be read and output at this time step.
- As the long term state $c_{(t-1)}$ traverses the network from left to right, it first goes through a forget gate, dropping some memories, and then it adds some new memories selected by an input gate. The result $c_{(t)}$ is sent out. After the addition operation, the long term state is copied and passed through tanh function and then the result is filtered by the output gate. This produces the short term state $h_{(t)}$which is the cell's output for this time step $y_{(t)}$



Block Diagram of LSTM Cell

The equations below summarize how to compute the cell's long term states, short term states and outputs. Here Ws are the weight matrices and bs are the bias terms.

$$
\begin{aligned}
\mathbf{i}_{(t)} &= \sigma(\mathbf{W}_{xi}{}^T\mathbf{x}_{(t)} + \mathbf{W}_{hi}{}^T\mathbf{h}_{(t-1)} + \mathbf{b}_i)\\
\mathbf{f}_{(t)} &= \sigma(\mathbf{W}_{xf}{}^T\mathbf{x}_{(t)} + \mathbf{W}_{hf}{}^T\mathbf{h}_{(t-1)} + \mathbf{b}_f)\\
\mathbf{o}_{(t)} &= \sigma(\mathbf{W}_{xo}{}^T\mathbf{x}_{(t)} + \mathbf{W}_{ho}{}^T\mathbf{h}_{(t-1)} + \mathbf{b}_o)\\
\mathbf{g}_{(t)} &= (\mathbf{W}_{xg}{}^T\mathbf{x}_{(t)} + \mathbf{W}_{hg}{}^T\mathbf{h}_{(t-1)} + \mathbf{b}_g)\\
\mathbf{c}_{(t)} &= \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)}\\
\mathbf{y}_{(t)} &= \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes (\mathbf{c}_{(t)})
\end{aligned}
$$

9. Deep LSTM-MLP Model

The purpose of the exercise is to build a multi-variate prediction model that learns the relationships of the temporal weather variables such as temperature, pressure, humidity, wind direction and wind direction and non-temporal variables such as latitude and longitude of locations of cities using hourly historic data of 36 different cities. To compare the results, I built a deep LSTM MLP univariate prediction model to predict the Temperature also.

A. Network Architecture

The LSTM models are very efficient models for time series forecasting problems. Deep LSTM-MLP models consists 5 hidden layers of a block of stacked layers. Each block has LSTM layer, a batch normalization layer and a dropout layer. The temporal inputs are applied to first LSTM layer. The output of the last dropout layer and non-temporal inputs are applied to first MLP hidden layer. Network architecture includes several DNNs features such as ReLU activation function, Glorot weight initialization, Batch Normalization, Dropouts, Adam Optimizers.

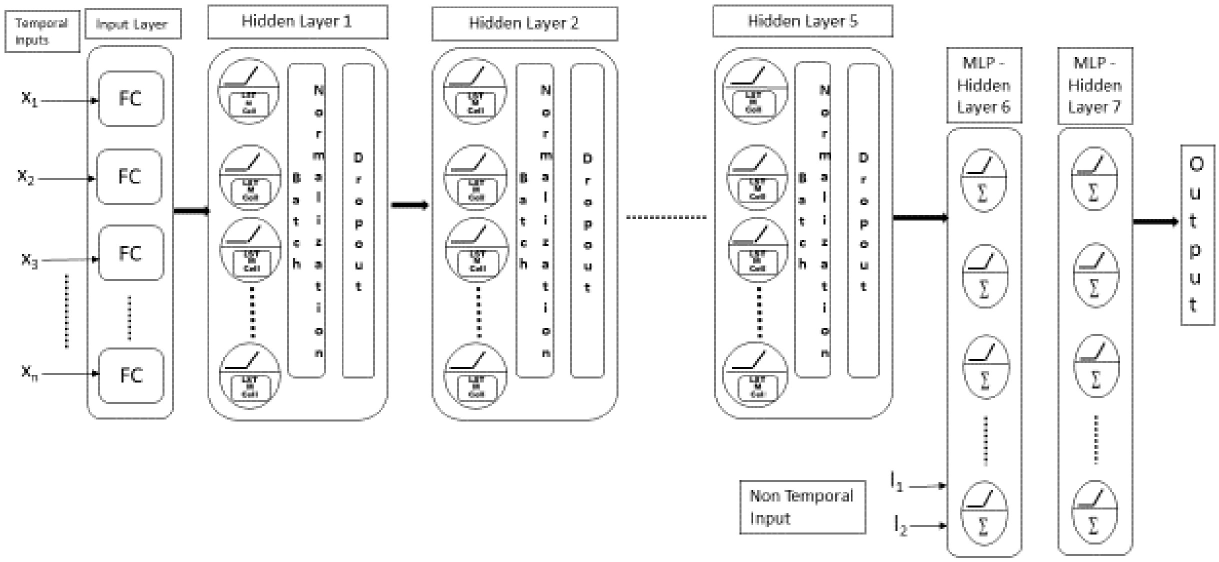
LSTM layers use Rectified Linear Unit (ReLU) activation function and Glorot weight initialization. Vanishing gradients and exploding gradients problems were empirically observed in DNNs for quite long time. Xavier Glorot and Yoshua Bengio in 2010 came up with ReLU activation function and Glorot or Xavier weight initialization strategy. They said that for the signal to flow properly, the variance of the outputs of each layer should be equal to the variance of the inputs. Also, gradients should have equal variance before and after flowing through a layer in reverse direction. ReLU activation function also has an advantage for being quite fast and perform better.

Good weight initialization and activation functions solve the vanishing/exploding gradient problem to some extent but don't guarantee that they won't come back in Deep Path of training in Neural Networks. Batch Normalization, is a technique consists of adding an operation in the model in each layer, simply zero-centering and normalizing the inputs, then scaling and shifting the results before they can be given as input to the next layer. The evaluation of mean and standard deviation of the input is done over the current mini batch hence called Batch Normalization.

Early Stopping is a technique used to avid over fitting of training data. During training model is evaluated at a regular interval and best performance is saved. Training is interrupted when its performance is not increased for a number of steps.

Dropout is another regularization technique for DNNs. At every training step, every neuron except the output neuron, has a probability p of being temporarily 'dropped out', meaning it will entirely ignored during this training step but it may be active during the next step.

Adam Optimizer (Adaptive moment estimation) is the most popular of all the adaptive learning rate algorithms. Algorithm calculates an exponential moving average of the gradient and the squared gradient and the parameters beta1 and beta2 control the decay rates of these moving averages. It requires less tuning of learning rate hyper-parameter which can simply be a default value of 0.001.



Block diagram of LSTM-MLP Deep Neural Network

B. Results Metrics

I used three metrics to compare the results. MAE, MSE and MAPE. MSE is used as the loss value for optimization during training to penalize the model for making predictions that differ greatly from the corresponding actual value. I see higher value of MAPE since MAPE grows unexpectedly large if the actual values are exceptionally small themselves. In our dataset, Wind Speed and Wind direction is close to zero for large number of samples.

C. Tools and Libraries

Different Python libraries are used for executing different Machine Learning and Deep Learning Models. LinearRegression and RandomForest from Sci-kit Learn, ARIMA model from Statsmodel, LSTM and MLP from Tensorflow Keras Functional APIs are used. The Keras functional API is the way to go for defining complex models, such as multi-output models, directed acyclic graphs, or models with shared layers. Tensorflow Estimator APIs used for seem less execution of Deep Neural Network (DNN) in distributed multi-server environment. Estimator is a high level Tensorflow API which facilitates building state of the art, highly scalable, complex models, which can be run on local host or on a distributed multi-server environment, on CPUs, GPUs or TPUs, without changing the model. A distributed VM in Google Cloud with 8 core CPUs, 52 GB memory and 2 GPUs is used to execute DNN models.

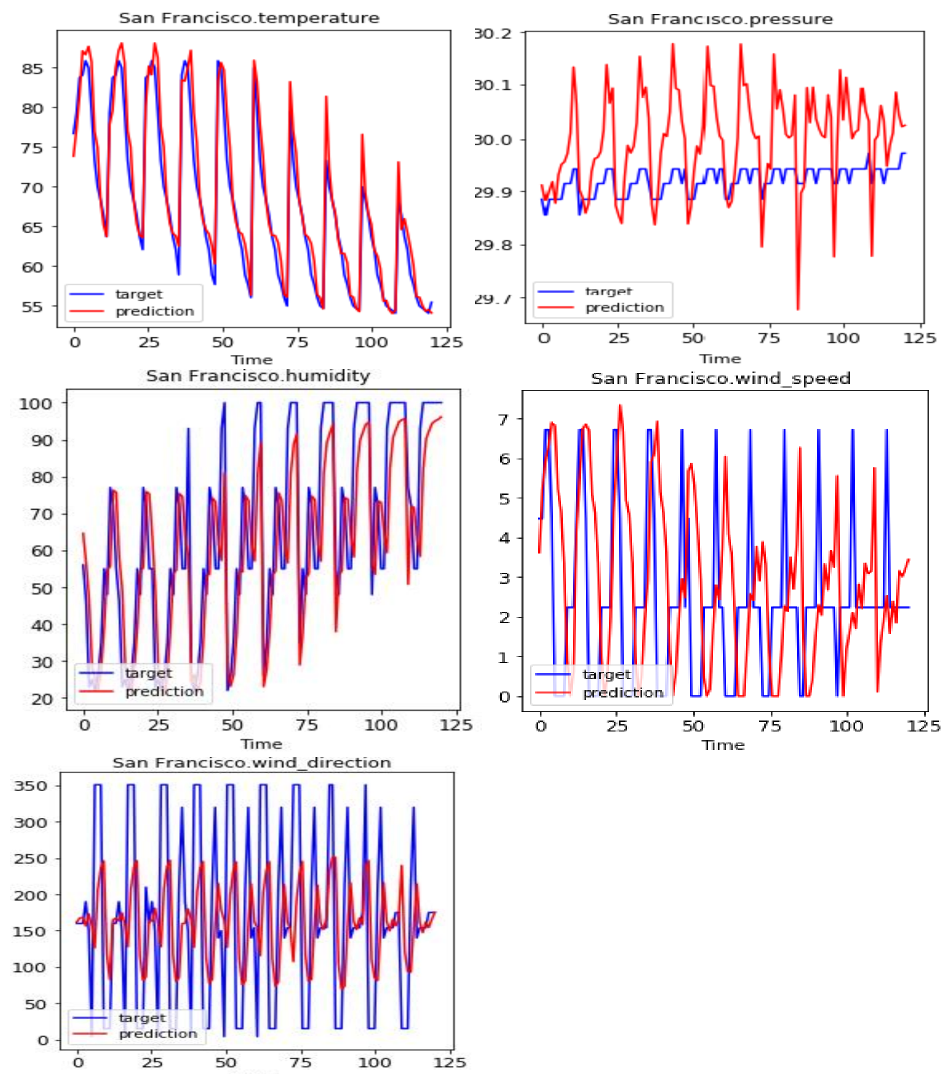
D. Experimental Details

The dataset contains weather features in scientific unit and not popular in everyday life. I converted Temperature in degree Fahrenheit, Pressure in inches of Mercury and wind speed in miles per hour. These features have physical properties and related to each other such as temperature and pressure are inversely proportional to each other, wind has speed and direction so can be represented by a vector. I considered these as data and not co-relating among them is considered during the analysis. The data is normalized with zero mean and unit variance. We perform 6 step ahead prediction for all the variables for univariate analysis and multivariate analysis.

10. Results

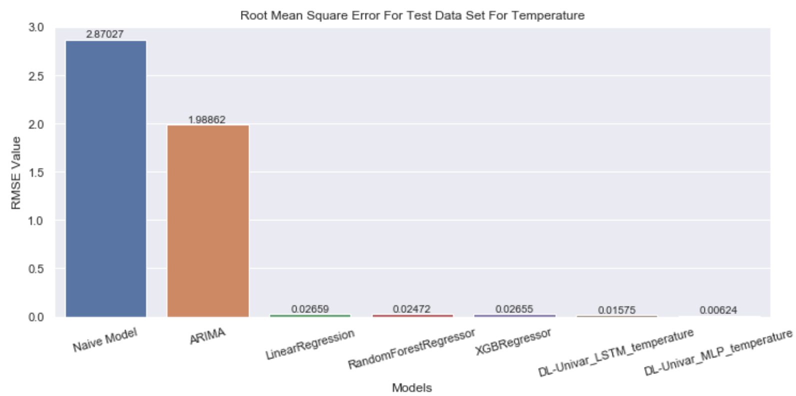
A. Qualitative Predictions

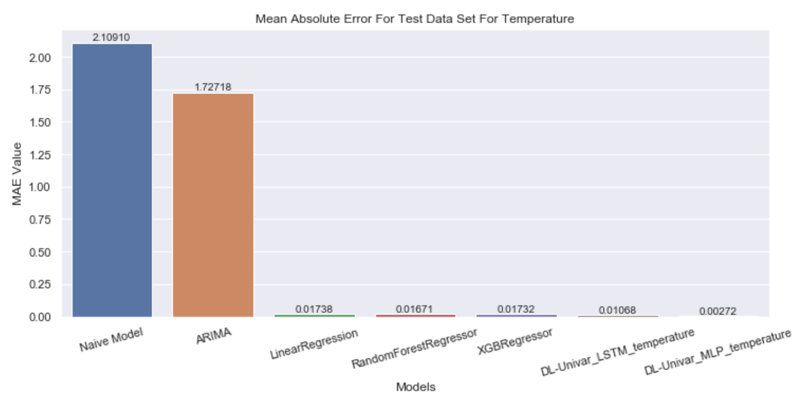
The Prediction plot for multivariate LSTM-MLP model of all 5 weather features for San Francisco from the weather dataset are shown below. The plot below show that Pressure and Wind Direction had higher variance and really low variance respectively and these were hard to predict. Temperature, Humidity and Wind Speed were relatively smooth and were easy to predict.



B. Aggregate Quantitative Performance

Figure below shows the values of RMSE, MAE and MAPE for uni-variable analysis of Temperature, I achieved on the hourly weather dataset. Clearly Deep Learning models Multi-Layer Perceptron (MLP) and Long Short Term Memory (LSTM) performed better Machine Learning Models for RMSE and MAE.





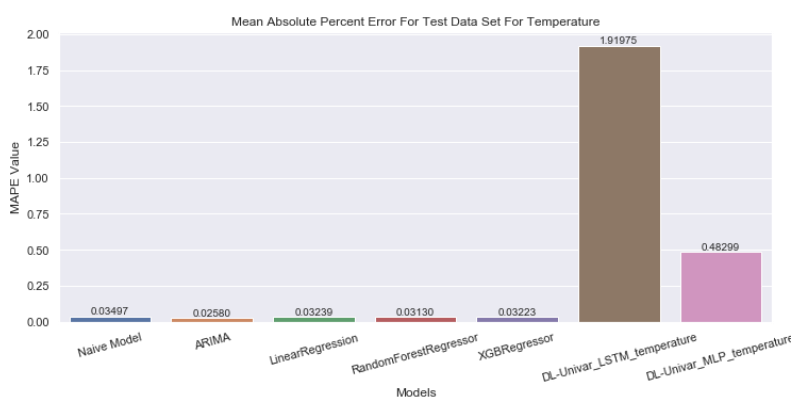
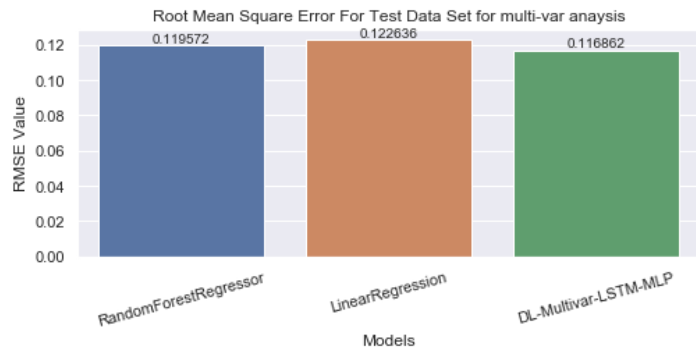
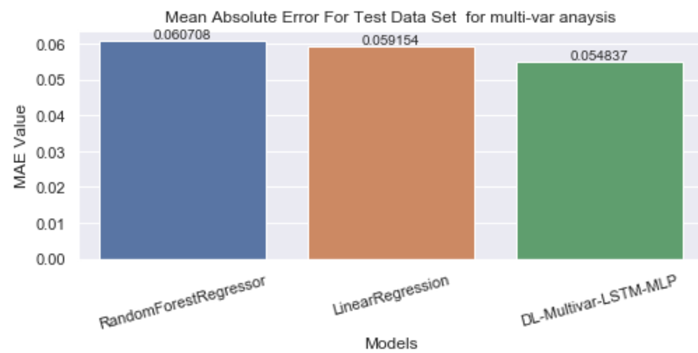
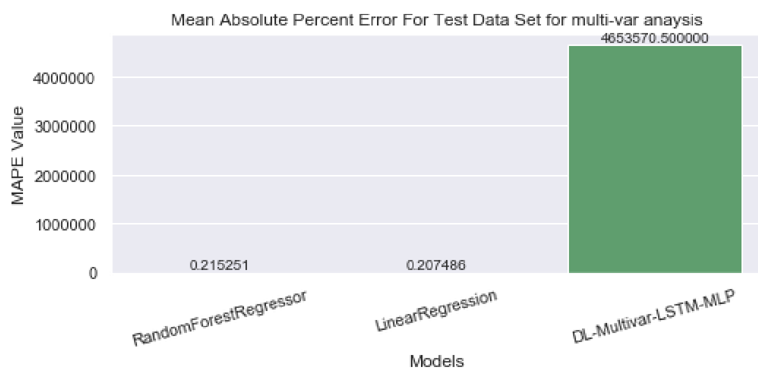


Figure below shows the values of RMSE, MAE and MAPE for multi-variable analysis of 5 weather features, I achieved on the hourly weather dataset. Clearly Deep Learning model LSTM-MLP performed better than Machine Learning Models for RMSE and MAE.







11. Conclusion

In this work, I presented a new model, LSTM-MLP, for multivariate time-series prediction by combining the multiple layers of LSTM cells and multiple layers of MLP layers. The idea is to use multiple LSTM layer to capture long term and short term memories of temporal weather data. Then combine that memory of non-temporal data in MLP layers to generate final predictions. I compared the results with several Machine Learning models. Both LSTM model for univariate and LSTM-MLP model for multivariate analysis performed better than traditional machine learning model. As I increase the number of steps ahead I want to make the predictions, the complexity of the model and time require to train the model increases. Deep Learning models with distributed networking can perform better and make analysis faster.

12. References:

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