Toronto Hydro
Demand Prediction

Data Sources

http://www.ieso.ca

20 CSV file contain all hydro demanded from 2003 to 2020

Date	Hour	Ontario Demand	Northwest	Northeast	Ottawa	East	Toronto	Essa	Bruce	Southwest	Niagara	West	Zone Total	Diff
2020-01-01	1	13219	523	1200	914	847	4718	902	64	2564	399	1290	13419	200
2020-01-01	2	12895	518	1190	887	826	4571	869	60	2504	384	1273	13082	187
2020-01-01	3	12554	519	1201	865	803	4443	839	60	2404	373	1260	12768	214
2020-01-01	4	12360	519	1183	852	789	4356	825	59	2406	361	1241	12591	231

https://openweathermap.org

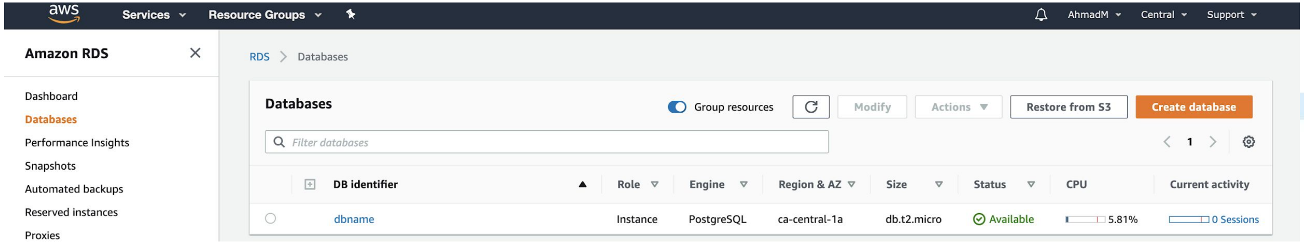
The temperature of Toronto including all features in same period of time.

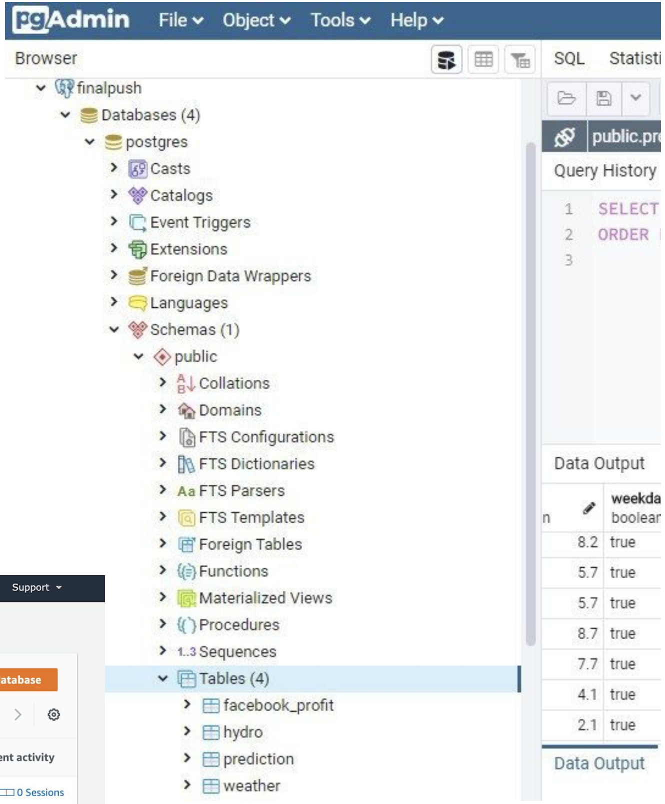
id	date	hour	dt	timezone	temp	feels_like	temp_min	temp_max	pressure	humidity	wind_speed	wind_deg	clouds_all	weather_main	weather_description
220537	2003-05-01	1	1051750800	-14400	7.52	1.21	3.32	9	1015	49	5.7	80	90	Clouds	overcast clouds
220538	2003-05-01	2	1051754400	-14400	7.03	1.53	3.52	8	1015	52	4.6	50	90	Rain	moderate rain
220539	2003-05-01	3	1051758000	-14400	6.57	-0.39	3.63	7.7	1014	65	7.2	50	90	Rain	light rain
220540	2003-05-01	4	1051761600	-14400	6.8	-1.47	3.65	8	1013	56	8.7	70	90	Clouds	overcast clouds

Data Structure

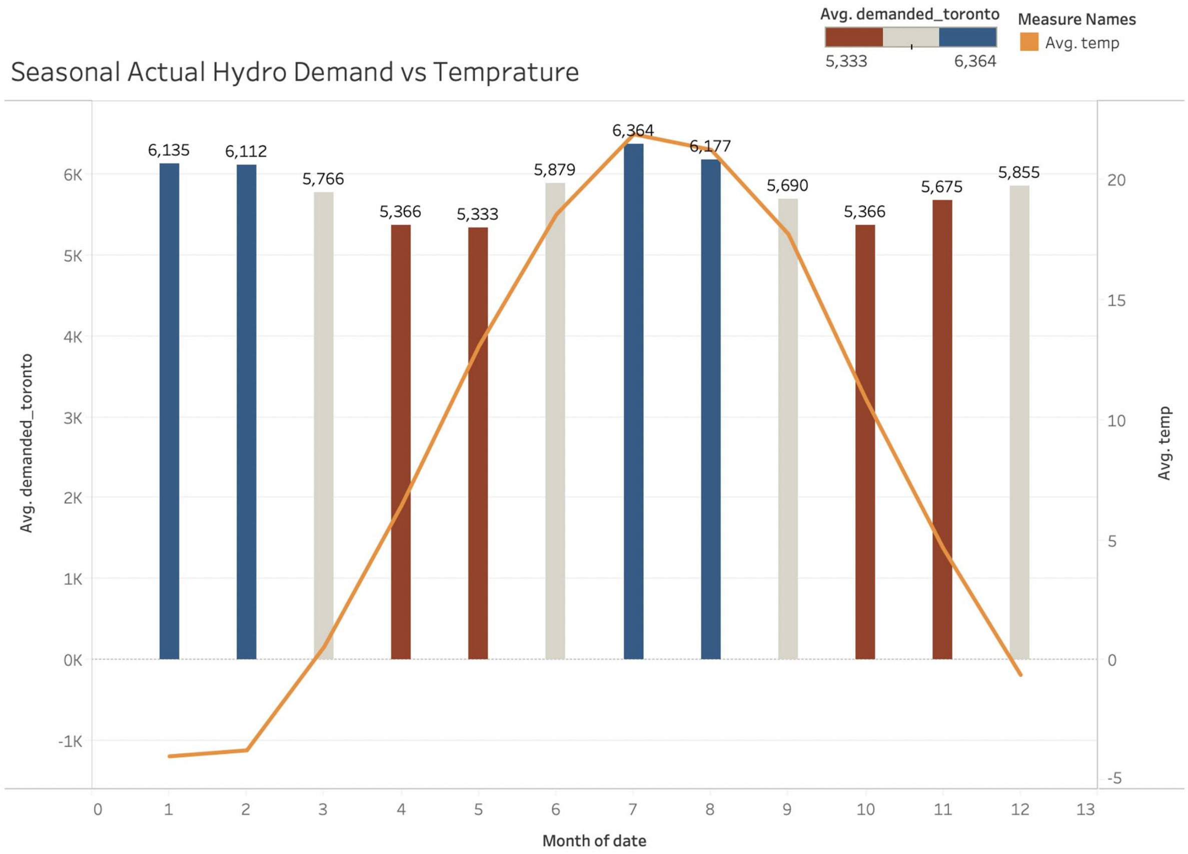
- Merging all CSVs from hydro to a single file in Python
- Cleaning all dataset such as converting UTC to GMT, splitting columns, etc.
- Uploading final data sources on to the AWS as a PostgreSQL.

```python
[1]: import os
     import glob
     import pandas as pd
     os.chdir("Resources")

[2]: extension = 'csv'
     all_filenames = [i for i in glob.glob('*.{}'.format(extension))]

[3]: combined_csv = pd.concat([pd.read_csv(f, skiprows=3) for f in all_filenames ])
     combined_csv.to_csv( "combined_csv.csv", index=False, encoding='utf-8-sig')
```





Basic Analysis



Facebook Prophet- Time Series

```
from fbprophet import Prophet
from datetime import datetime
from fbprophet.plot import plot_plotly
import plotly.offline as py
```

```
df = pd.read_csv('combined_csv2.csv')
df.head(2)
```

	Date	Hour	Time	Ontario Demand	Northwest	Northeast	Ottaw
0	2003-05-01	1	2003-05-01 00:59:59	13702	809	1284	96
1	2003-05-01	2	2003-05-01 01:59:59	13578	825	1283	92

```
new_df=df[['Time','Toronto']]
final_df = new_df.rename({'Time': 'ds', 'Toronto': 'y'}, axis=1)
final_df['Time'] = pd.to_datetime(df['Time'])
#sample=final_df.tail(26280)
final_df.head(2)
#sample.tail()
```

	ds	y	Time
0	2003-05-01 00:59:59	4422	2003-05-01 00:59:59
1	2003-05-01 01:59:59	4340	2003-05-01 01:59:59

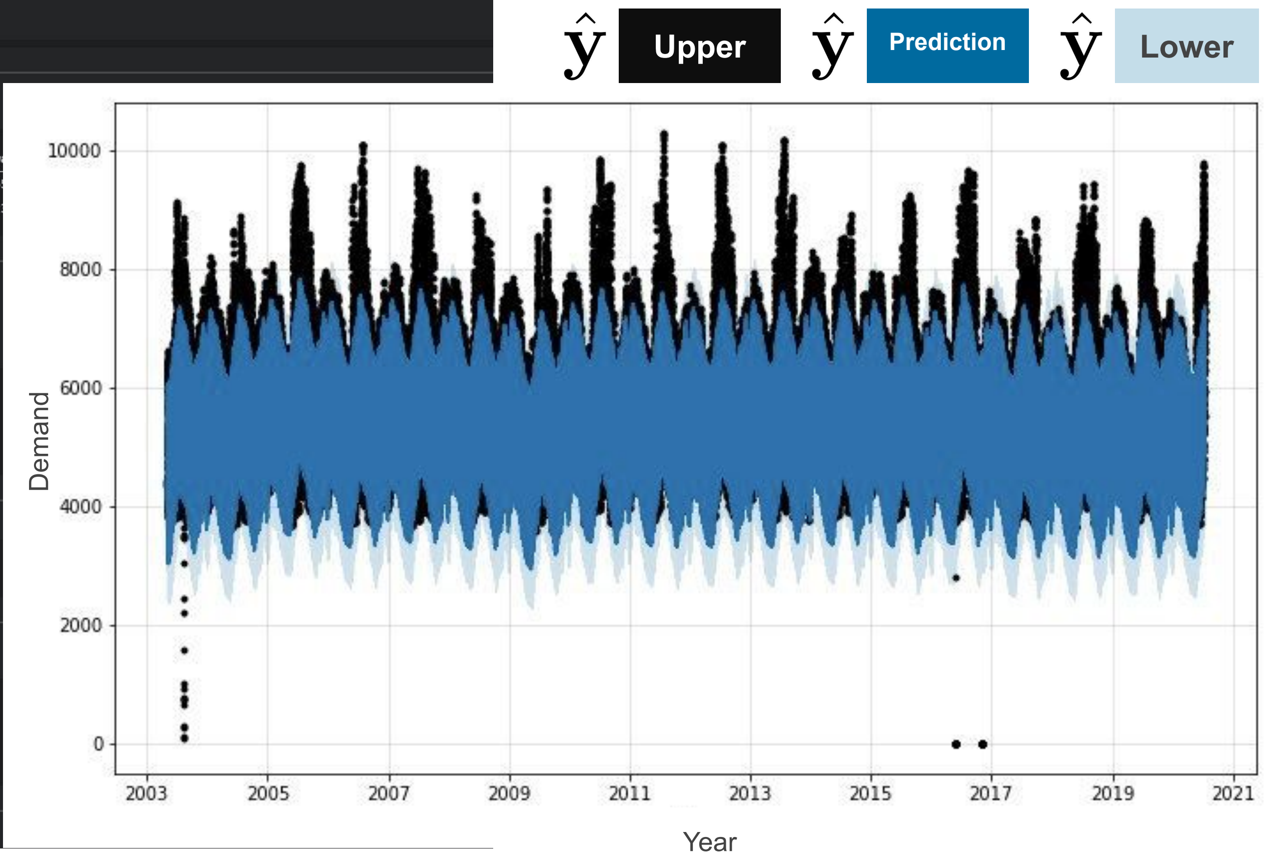
```
m = Prophet(yearly_seasonality=True)
m.fit(final_df)
```

<fbprophet.forecaster.Prophet at 0x132dae310>

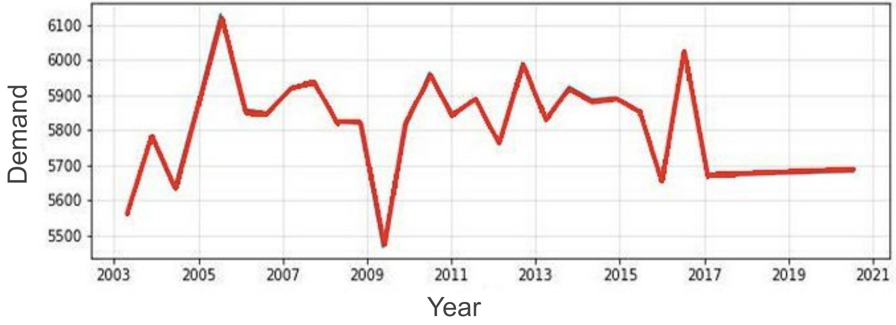
```
#future=pd.read_csv('predict.csv')
future = m.make_future_dataframe(freq="H",periods=72)
future.tail(2)
```

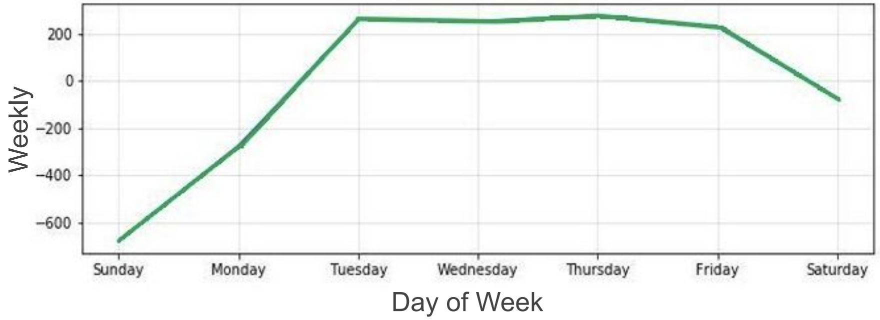
	ds
150838	2020-07-14 22:59:59
150839	2020-07-14 23:59:59

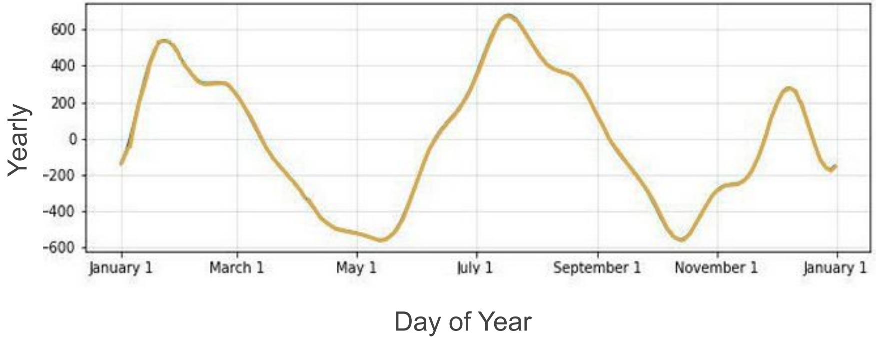
```
forecast = m.predict(future)
forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail(2)
```

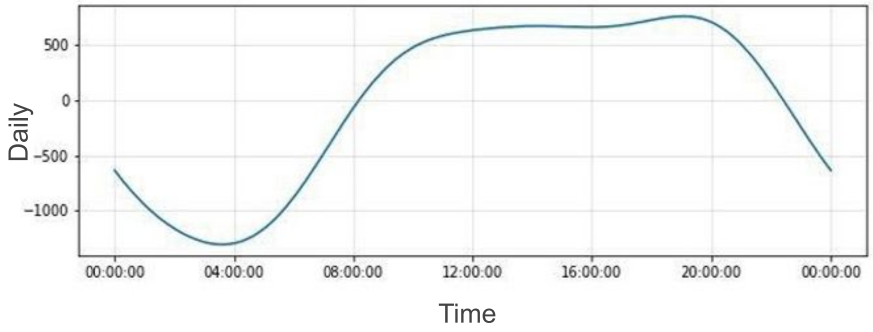


Facebook Prophet- Time Series









Machine Learning- Scikit Linear Regression

Linear_Regression_Model.ipynb

File Edit View Insert Runtime Tools Help

+ Code + Text

```
[ ] import pandas as pd
    %matplotlib inline
    import matplotlib.pyplot as plt
    import numpy as np
    from sqlalchemy import create_engine
    import sqlalchemy
    from sqlalchemy.ext.automap import automap_base
    from sqlalchemy.orm import Session
    from sqlalchemy import create_engine, func
    import datetime
```

HYDRO DATA

```
# Reading Hydro Data
engine  = create_engine('postgresql://postgres:postgres@dbname.cxw2xnixkpbl.ca-central-1.rds.amazonaws.com/postgres')

# Reflect an existing database into a new model
Base = automap_base()

# Reflect the tables
Base.prepare(engine, reflect=True)

# Save reference to the table
hydro = Base.classes.hydro
weather = Base.classes.weather
```

```
[ ] session = Session(engine)
    results = session.query(hydro.date,hydro.hour,hydro.demanded_toronto,hydro.weekday, hydro.previous_hour_demand, hydro.

    session.close()

    hydro = []
    for date, hour, demanded_toronto, weekday, previous_hour_demand, previous_day_demand in results:
        hydro_dict = {}
        hydro_dict["date"] = date
        hydro_dict["hour"] = hour
        hydro_dict["demanded_toronto"] = demanded_toronto
        hydro_dict["weekday"] = weekday
        hydro_dict["previous_hour_demand"] = previous_hour_demand
        hydro_dict["previous_day_demand"] = previous_day_demand

        hydro.append(hydro_dict)
```

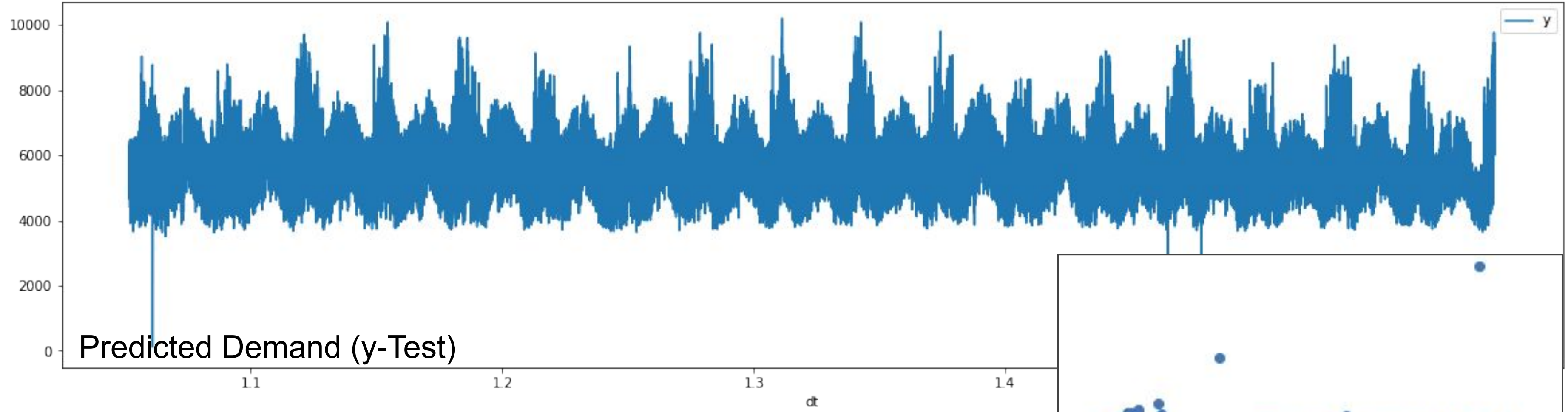
Linear_Regression_Model.ipynb

File Edit View Insert Runtime Tools Help All changes saved

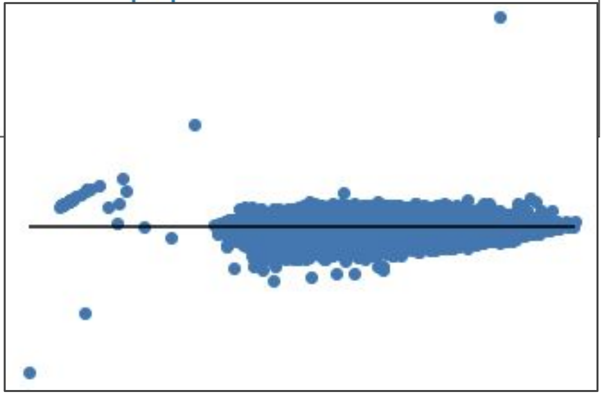
+ Code + Text

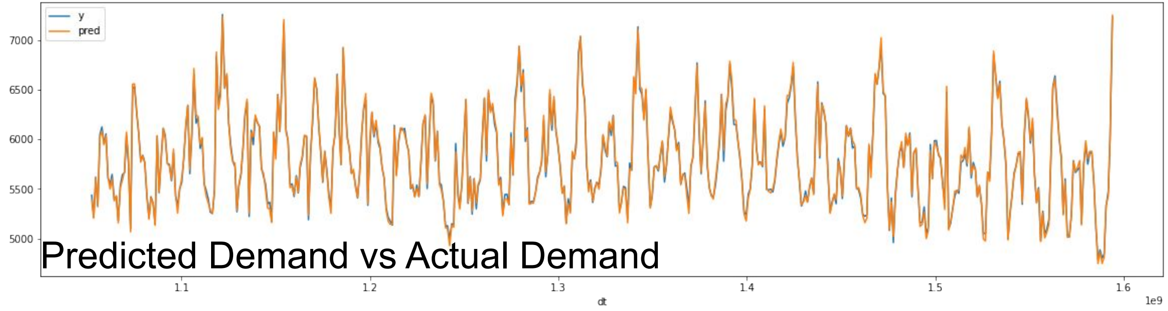
```
[ ] from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y, random

[ ] from sklearn.linear_model import LinearRegression
    model = LinearRegression()
    model.fit(X_train, y_train)

    LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, n

[ ] X_train

[ ] score = model.score(X_train, y_train)
    print(f"R2 Score: {score}")

    R2 Score: 0.9574600025557655

[ ] score = model.score(X_test, y_test)
    print(f"R2 Score: {score}")

    R2 Score: 0.9570905237024288
```

Machine Learning- Scikit Linear Regression



Predicted Demand (y-Test)





Predicted Demand vs Actual Demand

R2 Score: 0.9571

Machine Learning– Neural Network

TensorFlow

Neural_Network_Model.ipynb

File Edit View Insert Runtime Tools Help Last saved at 10:51 PM

+ Code + Text

```
[ ] # Function to create the keras model

    def build_model():
        model = keras.Sequential([
        layers.Dense(units=200, activation='relu', input_dim=X_train2.shape[1]),
        layers.Dense(units=200, activation='relu'),
        layers.Dense(units=1)
        ])

        optimizer = tf.keras.optimizers.RMSprop(0.001)

        model.compile(loss='mse',
                      optimizer=optimizer,
                      metrics=['mae', 'mse'])

        return model
```

```
[ ] # Create a model object
    model = build_model()
```

```
[ ] # Check the model
    model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 200)               2400
_________________________________________________________________
dense_1 (Dense)              (None, 200)               40200
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 201
=================================================================
Total params: 42,801
Trainable params: 42,801
Non-trainable params: 0
_________________________________________________________________
```

```
[ ] # save the model
    model.save( '/content/gdrive/My Drive/Final Project/HydroDemand_NeuralModel')
```

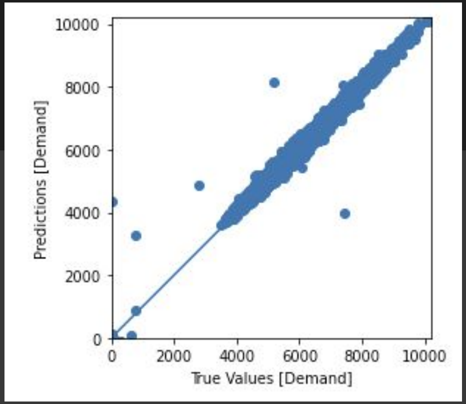
```
INFO:tensorflow:Assets written to: /content/gdrive/My Drive/Final Project/HydroDemand_NeuralModel/assets
```

Neural_Network_Model.ipynb

File Edit View Insert Runtime Tools Help Last saved at 10:51 PM

+ Code + Text

```
[ ] # use model to predict using testing data
    test_predictions = model.predict(X_test2).flatten()

    a = plt.axes(aspect='equal')
    plt.scatter(y_test, test_predictions)
    plt.xlabel('True Values [Demand]')
    plt.ylabel('Predictions [Demand]')
    lims = [0, max(y_test)]
    plt.xlim(lims)
    plt.ylim(lims)
    _ = plt.plot(lims, lims)
```




```
[ ] plt.savefig('/content/drive/My Drive/Final Project/Neural_Prediction_Xtest.jpg')
```

```
<Figure size 432x288 with 0 Axes>
```

```
[ ] # model = keras.models.load_model('/content/drive/My Drive/Final Project/HydroDemand_NeuralModel/')
```

```
[ ] pred = model.predict(X_test2)
```

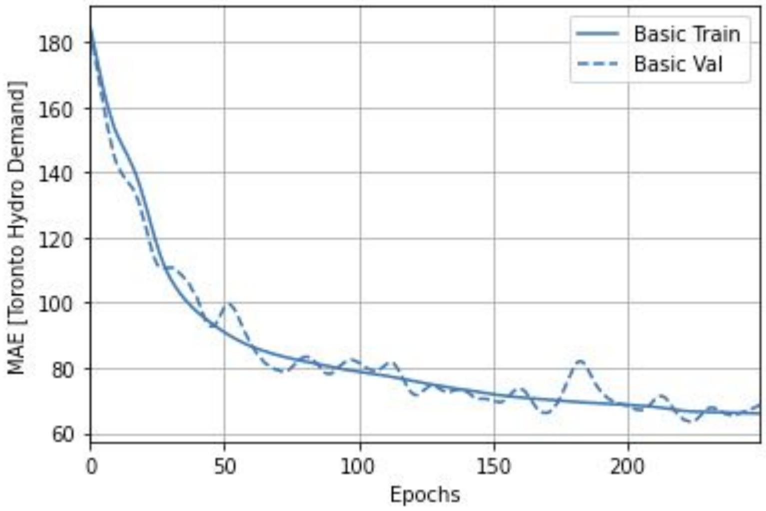
```
[ ] r2_score(y_test, pred)
```

```
0.9879894579676439
```

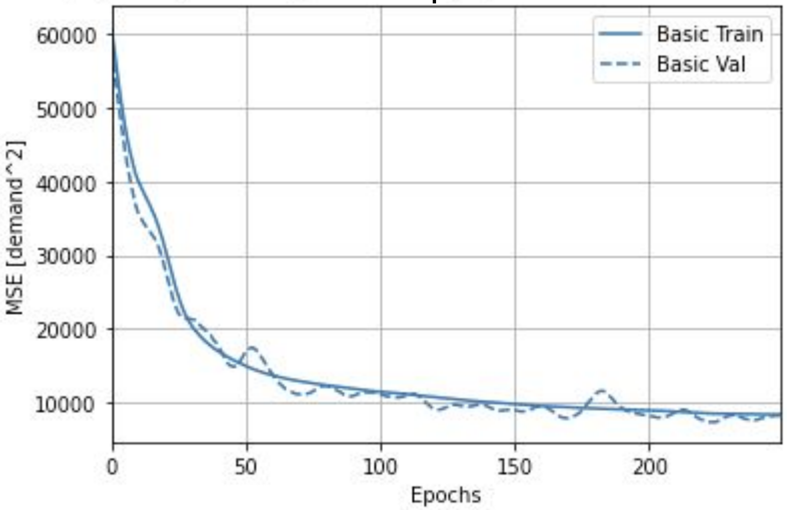
Machine Learning- Neural Network

TensorFlow

Mean Absolute Error



Mean Square Error



	loss	mae	mse	val_loss	val_mae	val_mse	epoch
245	8437.715820	65.906090	8437.715820	13518.171875	86.379005	13518.171875	245
246	8421.664062	66.187973	8421.664062	6475.656738	59.384483	6475.656738	246
247	8441.654297	66.013245	8441.654297	5915.229492	56.081337	5915.229492	247
248	8386.368164	65.855492	8386.368164	6543.145996	58.717964	6543.145996	248
249	8341.509766	65.975052	8341.509766	11230.646484	89.272881	11230.646484	249

R2 Score: 0.9880

Tableau- Final Analysis

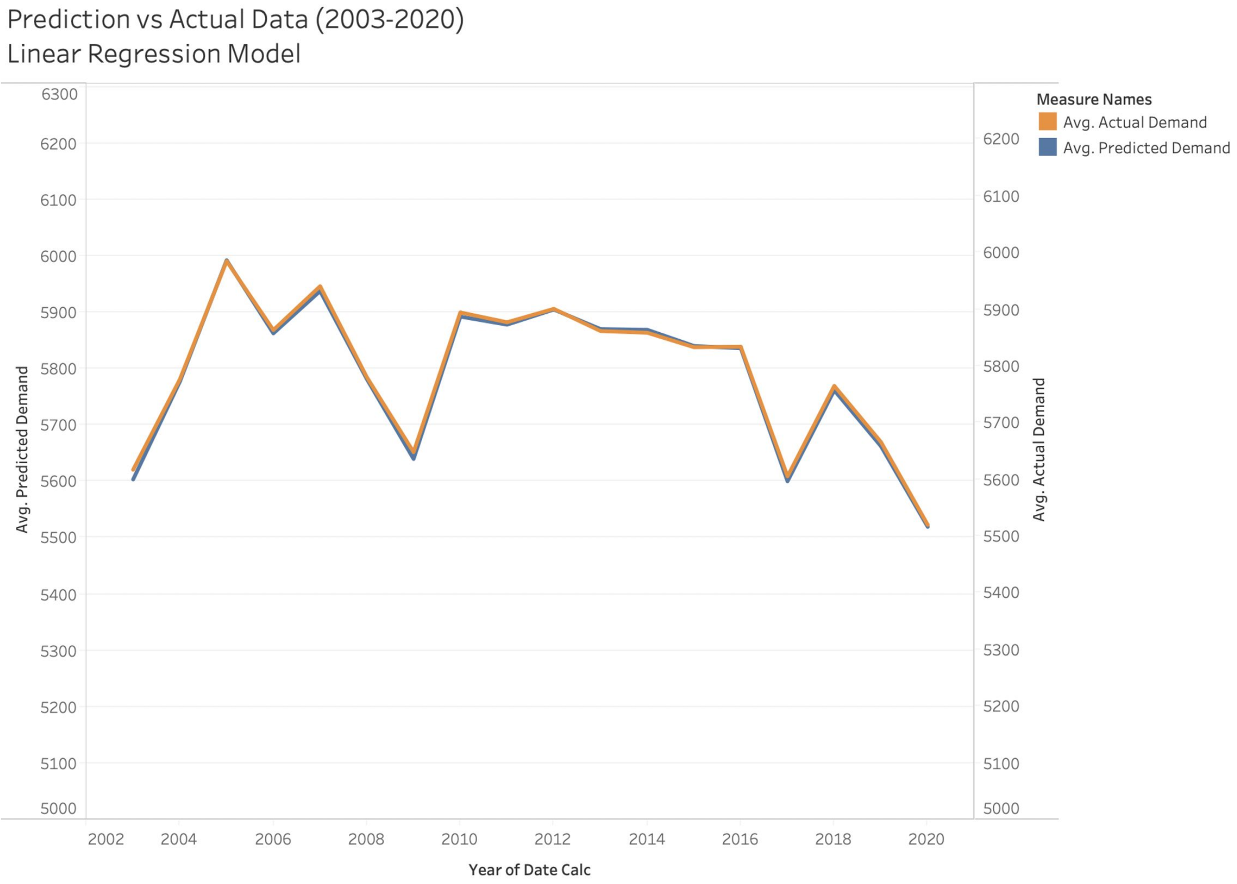


Tableau- Final Analysis

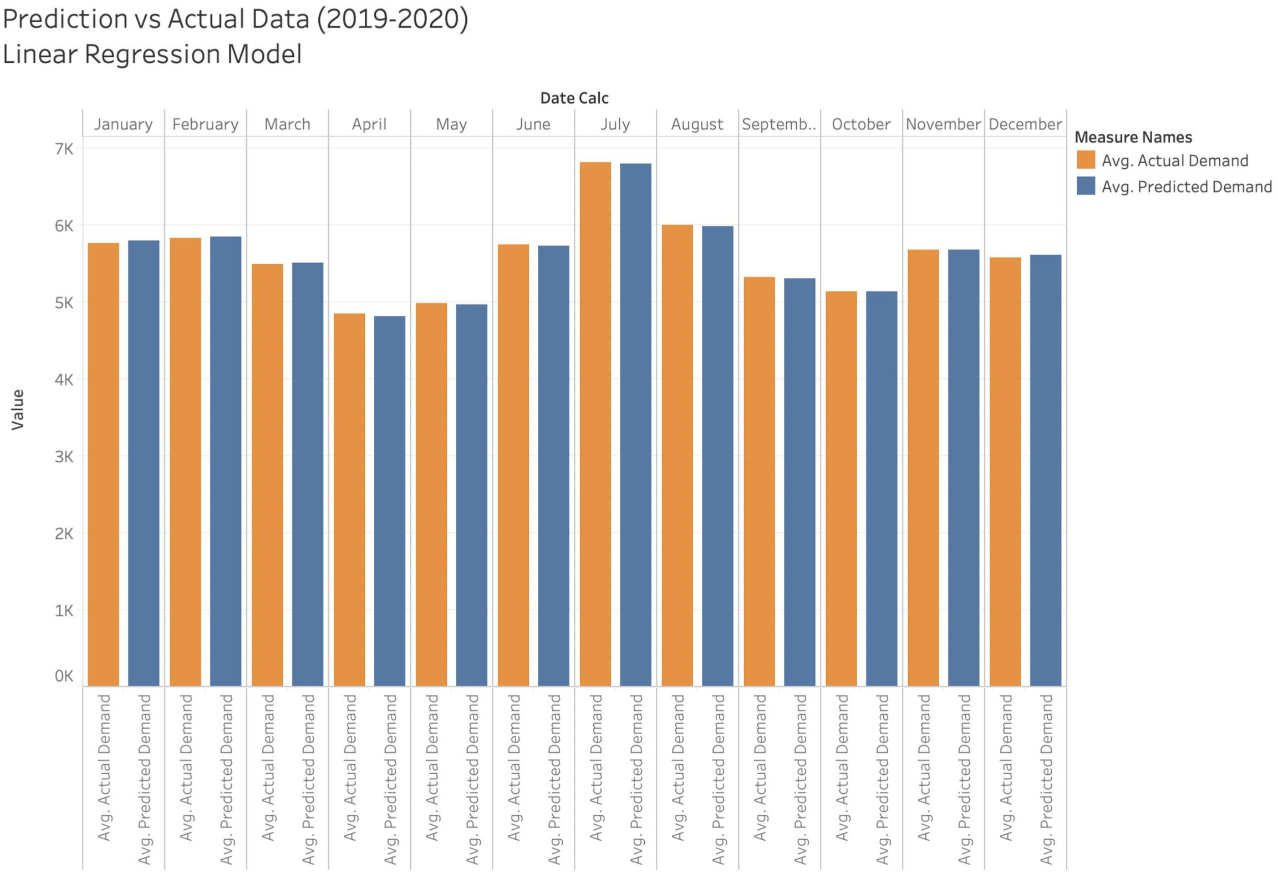


Tableau- Final Analysis

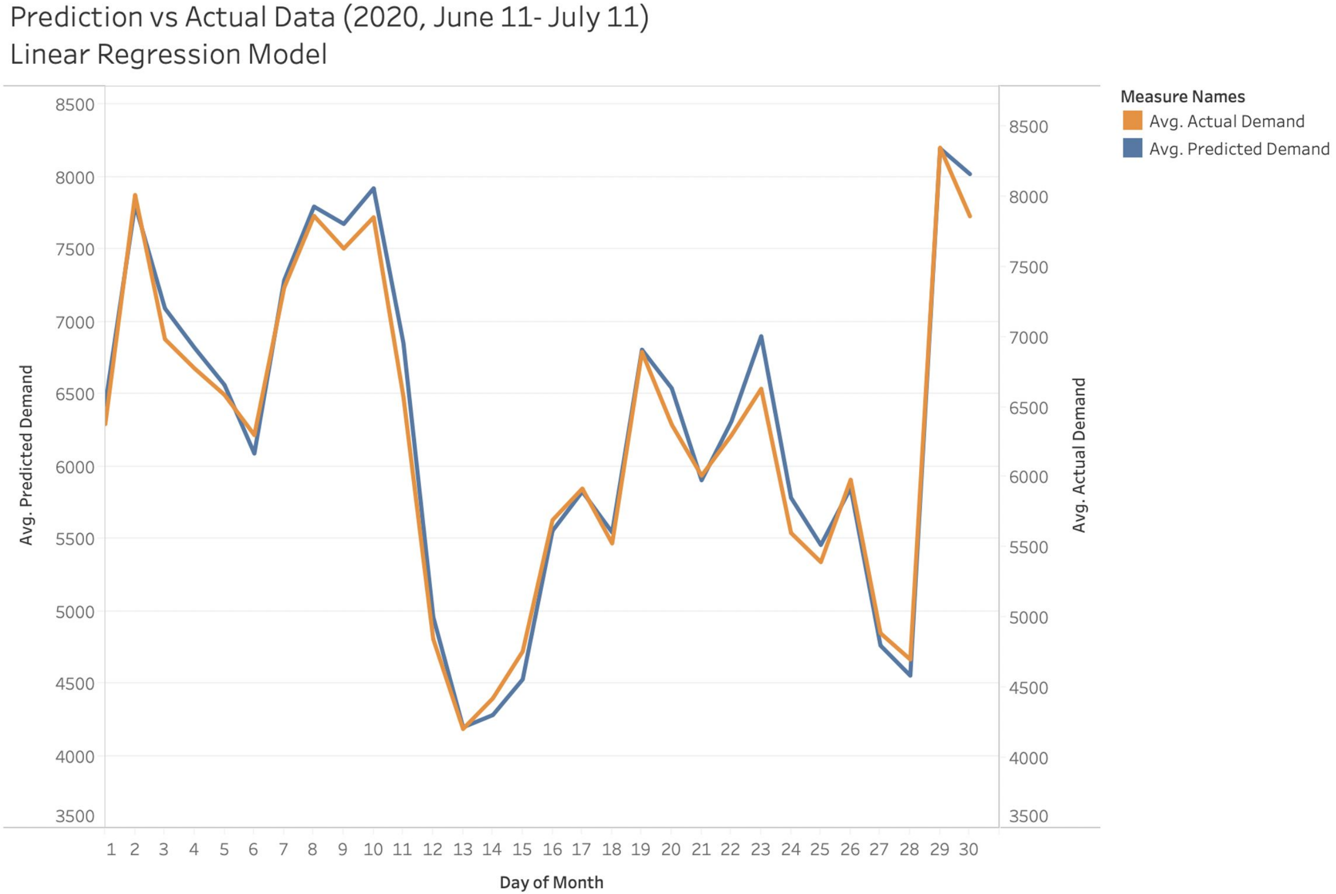


Tableau- Final Analysis