In [0]:

```
## import required packages

# basic python libraries
import os, sys, math

# data handling
import pandas as pd # data processing, CSV file I/O, data manipulation as in SQL
pd.set_option('display.float_format', lambda x: '%.4f' % x)
import numpy as np # linear algebra

# graph plotting
import matplotlib.pyplot as plt
import matplotlib.ticker as tkr
import seaborn as sns
sns.set_context("paper", font_scale=1.3)
sns.set_style('white')
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()

# statistics
from scipy import stats
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import pacf

# machine learning
from sklearn.model_selection import train_test_split # to split the data into two parts
from sklearn.preprocessing import MinMaxScaler # for normalization
from sklearn.pipeline import Pipeline # pipeline making
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# deep learning
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.callbacks import EarlyStopping
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: more info.

In [0]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [0]:

```
# merged two columns 'Date' and 'Time' to 'datetime'
# convert those data to time-series type, by convert 'datetime' as an index
dataset_path = '/content/drive/My Drive/Colab Notebooks/household_power_consumption.csv'
df = pd.read_csv(dataset_path, parse_dates = True, index_col = 'datetime', low_memory = False)
```

In [0]:

```
df.head()
```

Out[0]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
datetime							

datetime	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
2006-12-16 17:24:00	4.2160	0.4180	234.8400	18.4000	0.0000	1.0000	17.0000
2006-12-16 17:25:00	5.3600	0.4360	233.6300	23.0000	0.0000	1.0000	16.0000
2006-12-16 17:26:00	5.3740	0.4980	233.2900	23.0000	0.0000	2.0000	17.0000
2006-12-16 17:27:00	5.3880	0.5020	233.7400	23.0000	0.0000	1.0000	17.0000
2006-12-16 17:28:00	3.6660	0.5280	235.6800	15.8000	0.0000	1.0000	17.0000

In [0]:

```
df.shape
```

Out[0]:

```
(2075259, 7)
```

In [0]:

```
# get values
dataset = df.Global_active_power.values
dataset = dataset.astype('float32')

# reshape
dataset = np.reshape(dataset, (-1, 1))

# normalize
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)

# split data
train_size = int(len(dataset) * 0.80)
test_size = len(dataset) - train_size
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
```

In [0]:

```
train
```

Out[0]:

```
array([[0.37479633],
       [0.47836325],
       [0.47963068],
       ...,
       [0.01828716],
       [0.02426218],
       [0.02335687]], dtype=float32)
```

In [0]:

```
test
```

Out[0]:

```
array([[0.02353793],
       [0.02335687],
       [0.02335687],
       ...,
       [0.07803731],
       [0.07767518],
       [0.07749411]], dtype=float32)
```

In [0]:

```
# convert an array of values into a dataset matrix
def create_dataset(dataset, look_back=1):
    X, Y = [], []
```

```
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        X.append(a)
        Y.append(dataset[i + look_back, 0])
    return np.array(X), np.array(Y)
```

In [0]:

```
# reshape into X=t and Y=t+1
look_back = 30
X_train, Y_train = create_dataset(train, look_back)
X_test, Y_test = create_dataset(test, look_back)
```

In [0]:

```
X_train.shape
```

Out[0]:

```
(1660176, 30)
```

In [0]:

```
# reshape input to be [samples, time steps, features]
X_train = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1]))
X_test = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))
```

In [0]:

```
X_train.shape
```

Out[0]:

```
(1660176, 1, 30)
```

In [0]:

```
model = Sequential()
model.add(LSTM(100, input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(Dropout(0.2))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')

history = model.fit(X_train, Y_train, epochs=20, batch_size=70, validation_data=(X_test, Y_test),
                    callbacks=[EarlyStopping(monitor='val_loss', patience=10)], verbose=1, shuffle=
False)

# Training Phase
model.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/ops/resource_variable_ops.py:1630: calling
BaseResourceVariable.__init__ (from tensorflow.python.ops.resource_variable_ops) with constraint i
s deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/ops/math_grad.py:1424: where (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 1660176 samples, validate on 415021 samples
Epoch 1/20
1660176/1660176 [==============================] - 147s 89us/sample - loss: 7.6127e-04 - val_loss:
3.9072e-04
Epoch 2/20
1660176/1660176 [==============================] - 143s 86us/sample - loss: 6.6105e-04 - val_loss:
3.8210e-04
Epoch 3/20
1660176/1660176 [==============================] - 143s 86us/sample - loss: 6.5152e-04 - val_loss:
3.8128e-04
```

```
Epoch 4/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.4457e-04 - val_loss:
3.8121e-04
Epoch 5/20
1660176/1660176 [==============================] - 143s 86us/sample - loss: 6.3955e-04 - val_loss:
3.8077e-04
Epoch 6/20
1660176/1660176 [==============================] - 140s 84us/sample - loss: 6.3599e-04 - val_loss:
3.7879e-04
Epoch 7/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.3294e-04 - val_loss:
3.7910e-04
Epoch 8/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.3259e-04 - val_loss:
3.8040e-04
Epoch 9/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.2957e-04 - val_loss:
3.7856e-04
Epoch 10/20
1660176/1660176 [==============================] - 140s 84us/sample - loss: 6.2859e-04 - val_loss:
3.7893e-04
Epoch 11/20
1660176/1660176 [==============================] - 142s 85us/sample - loss: 6.2709e-04 - val_loss:
3.7889e-04
Epoch 12/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.2660e-04 - val_loss:
3.7908e-04
Epoch 13/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.2703e-04 - val_loss:
3.7688e-04
Epoch 14/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.2496e-04 - val_loss:
3.7752e-04
Epoch 15/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.2749e-04 - val_loss:
3.7643e-04
Epoch 16/20
1660176/1660176 [==============================] - 141s 85us/sample - loss: 6.2341e-04 - val_loss:
3.7625e-04
Epoch 17/20
1660176/1660176 [==============================] - 139s 84us/sample - loss: 6.2443e-04 - val_loss:
3.7648e-04
Epoch 18/20
1660176/1660176 [==============================] - 140s 84us/sample - loss: 6.2086e-04 - val_loss:
3.7602e-04
Epoch 19/20
1660176/1660176 [==============================] - 139s 84us/sample - loss: 6.2279e-04 - val_loss:
3.7554e-04
Epoch 20/20
1660176/1660176 [==============================] - 138s 83us/sample - loss: 6.2243e-04 - val_loss:
3.7543e-04
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm (LSTM)                  (None, 100)               52400     
_________________________________________________________________
dropout (Dropout)            (None, 100)               0         
_________________________________________________________________
dense (Dense)                (None, 1)                 101       
=================================================================
Total params: 52,501
Trainable params: 52,501
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

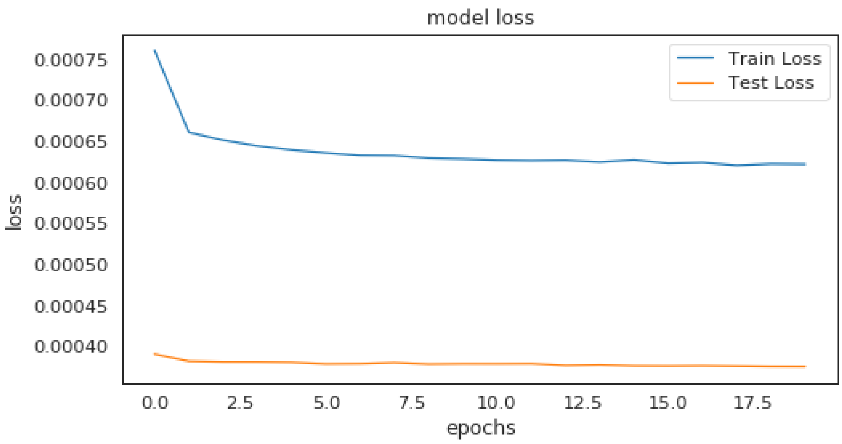
```
# make predictions
train_predict = model.predict(X_train)
test_predict = model.predict(X_test)
# invert predictions
train_predict = scaler.inverse_transform(train_predict)
Y_train = scaler.inverse_transform([Y_train])
test_predict = scaler.inverse_transform(test_predict)
Y_test = scaler.inverse_transform([Y_test])
```

```
print('Train Mean Absolute Error:', mean_absolute_error(Y_train[0], train_predict[:,0]))
print('Train Root Mean Squared Error:',np.sqrt(mean_squared_error(Y_train[0],
train_predict[:,0])))
print('Test Mean Absolute Error:', mean_absolute_error(Y_test[0], test_predict[:,0]))
print('Test Root Mean Squared Error:',np.sqrt(mean_squared_error(Y_test[0], test_predict[:,0])))
```

```
Train Mean Absolute Error: 0.10317662910811236
Train Root Mean Squared Error: 0.26531286633953105
Test Mean Absolute Error: 0.08504515461079583
Test Root Mean Squared Error: 0.21402822123636867
```

In [0]:

```
plt.figure(figsize=(8,4))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epochs')
plt.legend(loc='upper right')
plt.show();
```



In [0]:

```
aa=[x for x in range(200)]
plt.figure(figsize=(8,4))
plt.plot(aa, Y_test[0][:200], marker='.', label="actual")
plt.plot(aa, test_predict[:,0][:200], 'r', label="prediction")
# plt.tick_params(left=False, labelleft=True) #remove ticks
plt.tight_layout()
sns.despine(top=True)
plt.subplots_adjust(left=0.07)
plt.ylabel('Global_active_power', size=15)
plt.xlabel('Time step', size=15)
plt.legend(fontsize=15)
plt.show();
```