LSTM ON MISSING DATA.

Import Libraries

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
pd.set_option('display.float_format', lambda x: '%.4f' % x)
import seaborn as sns
sns.set_context("paper", font_scale=1.5)
sns.set_style('darkgrid')
import warnings
warnings.filterwarnings('ignore')
from time import time
import matplotlib.ticker as tkr
from scipy import stats
from statsmodels.tsa.stattools import adfuller
from sklearn import preprocessing
from statsmodels.tsa.stattools import pacf
%matplotlib inline
import math
import pickle
import keras
from keras.models import Sequential
from keras.models import model_from_json
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
from keras.layers import *
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from keras.callbacks import EarlyStopping
import pydot_ng as pydot
from keras.utils import plot_model
import time
```

```
Using TensorFlow backend.
```

Load the data

In [2]:

```
df = pd.read_csv('missing_data.csv', header=None, low_memory=False)
```

In [3]:

```
df.columns
```

Out[3]:

```
Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12], dtype='int64')
```

Here, we picked one column to represent the data since they are pretty much alike

In [4]:

```
df['2nd']=df[2]
```

In [5]:

```
df=df['2nd']
```

Finding the missing values and dropping them

In [6]:

```
df.isnull().sum()
```

Out[6]:

```
44725
```

In [7]:

```
df.dropna(inplace=True)
```

Feature extraction using timesteps

We are using the previous data values to determine the next one.

so the value at (t-1)s will be used to determine value at (t)s

we are employing 12 timesteps, so the previous 12 values will be used to determine the 13th values.

In [8]:

```
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)
```

Normalisation

Normalisation-this helps the model work better as they dont understand the context of the data, ages of people and heights of people are different context which the model cant understand. normalisation gives the values a particular to help the model understand the limits and context of the data.

In [9]:

```
dataset = df.values #numpy.ndarray
dataset = dataset.astype('float32')
dataset = np.reshape(dataset, (-1, 1))
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
train_size = int(len(dataset) * 0.80)
test_size = len(dataset) - train_size
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
```

we also performed some splitting activities to divide the data so we can test the model with a data that it has not seen.

In [10]:

```
look_back = 12
X_train, Y_train = create_dataset(train, look_back)
X_test, Y_test = create_dataset(test, look_back)
```

2D to 3D

LSTM input layer requires a 3D data. In DNN, 2D data was used as [samples,features]. it assumes the timesteps are the features but LSTM takes the timesteps into consideration. so the 3D data will now be [samples, time steps, features]

In [11]:

```
# 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]))
```

LSTM Model

In [12]:

```
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')

start=time.time()
history = model.fit(X_train, Y_train, epochs=20, batch_size=100, validation_data=(X_test, Y
                    callbacks=[EarlyStopping(monitor='val_loss', patience=10)], verbose=1,
end=time.time()
training_time=end-start
print(training_time)
```

```
Train on 1478567 samples, validate on 369632 samples
Epoch 1/20
1478567/1478567 [==============================] - 71s 48us/step - loss: 6.1
469e-04 - val_loss: 2.7317e-04
Epoch 2/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 3.0
470e-04 - val_loss: 2.4906e-04
Epoch 3/20
1478567/1478567 [==============================] - 69s 46us/step - loss: 2.8
353e-04 - val_loss: 2.2714e-04
Epoch 4/20
1478567/1478567 [==============================] - 68s 46us/step - loss: 2.6
375e-04 - val_loss: 2.0649e-04
Epoch 5/20
1478567/1478567 [==============================] - 70s 47us/step - loss: 2.4
779e-04 - val_loss: 1.9874e-04
Epoch 6/20
1478567/1478567 [==============================] - 69s 46us/step - loss: 2.4
177e-04 - val_loss: 1.8899e-04
Epoch 7/20
1478567/1478567 [==============================] - 68s 46us/step - loss: 2.3
979e-04 - val_loss: 1.8972e-04
Epoch 8/20
1478567/1478567 [==============================] - 68s 46us/step - loss: 2.3
869e-04 - val_loss: 1.8749e-04
Epoch 9/20
1478567/1478567 [==============================] - 74s 50us/step - loss: 2.3
779e-04 - val_loss: 1.8632e-04
Epoch 10/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 2.3
482e-04 - val_loss: 1.8558e-04
Epoch 11/20
1478567/1478567 [==============================] - 69s 46us/step - loss: 2.3
305e-04 - val_loss: 1.8654e-04
Epoch 12/20
1478567/1478567 [==============================] - 72s 49us/step - loss: 2.3
516e-04 - val_loss: 1.8532e-04
Epoch 13/20
1478567/1478567 [==============================] - 72s 49us/step - loss: 2.3
254e-04 - val_loss: 1.8505e-04
Epoch 14/20
1478567/1478567 [==============================] - 72s 49us/step - loss: 2.3
116e-04 - val_loss: 1.8454e-04
Epoch 15/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 2.3
343e-04 - val_loss: 1.8349e-04
```

```
Epoch 16/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 2.3
091e-04 - val_loss: 1.8547e-04
Epoch 17/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 2.2
991e-04 - val_loss: 1.8795e-04
Epoch 18/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 2.3
083e-04 - val_loss: 1.8410e-04
Epoch 19/20
1478567/1478567 [==============================] - 70s 47us/step - loss: 2.2
730e-04 - val_loss: 1.8300e-04
Epoch 20/20
1478567/1478567 [==============================] - 69s 47us/step - loss: 2.2
866e-04 - val_loss: 1.8273e-04
1395.224143743515
```

In [13]:

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_1 (LSTM)                (None, 100)               45200     
_________________________________________________________________
dropout_1 (Dropout)          (None, 100)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101       
=================================================================
Total params: 45,301
Trainable params: 45,301
Non-trainable params: 0
_________________________________________________________________
```

Prediction

In [14]:

```
start=time.time()
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])
end=time.time()
prediction_time=end-start
print(prediction_time)
```

```
41.44150710105896
```

Measuring accuracy of the model

there is no way to use percentage accuracies to determine accuracies, instead we use MSE mean squared error, MASE mean absolute squared error. this errors simply show how far the the predicted values are from the actual values to show their competency when faced with real-world data.

In [15]:

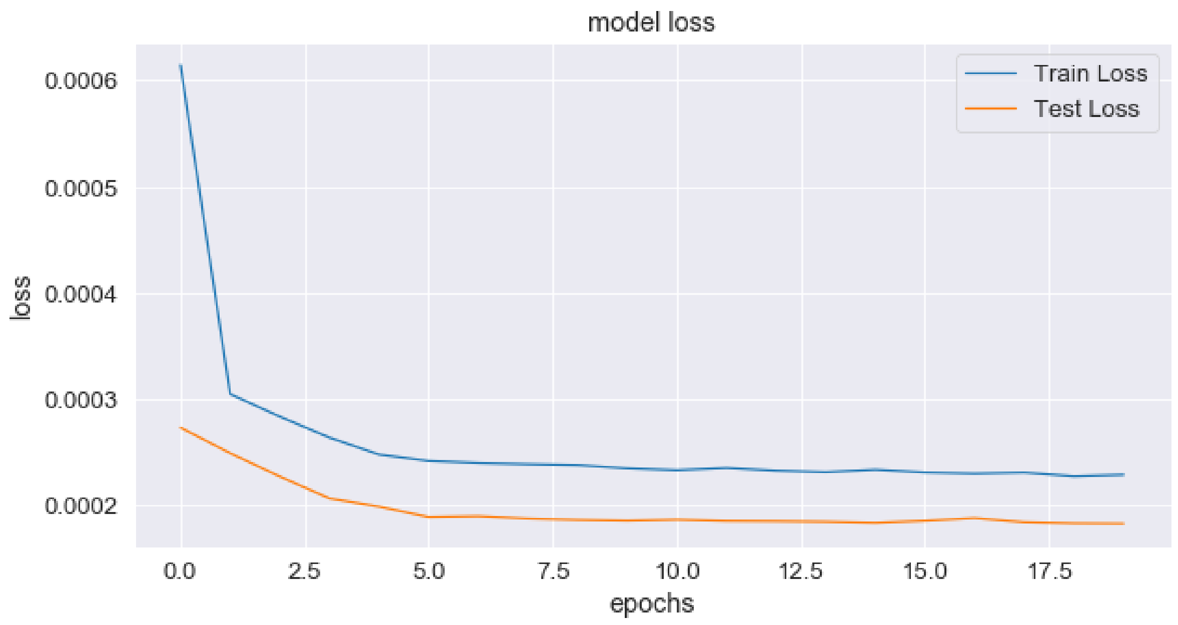
```
print('Train Mean Absolute Error:', mean_absolute_error(Y_train[0], train_predict[:,0]))
print('Train Root Mean Squared Error:',np.sqrt(mean_squared_error(Y_train[0], train_predict
print('Test Mean Absolute Error:', mean_absolute_error(Y_test[0], test_predict[:,0]))
print('Test Root Mean Squared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

```
Train Mean Absolute Error: 0.4637423628876297
Train Root Mean Squared Error: 2.365602304875661
Test Mean Absolute Error: 0.4058534146924971
Test Root Mean Squared Error: 2.233558904184524
```

Model losses when training the model and testing

In [16]:

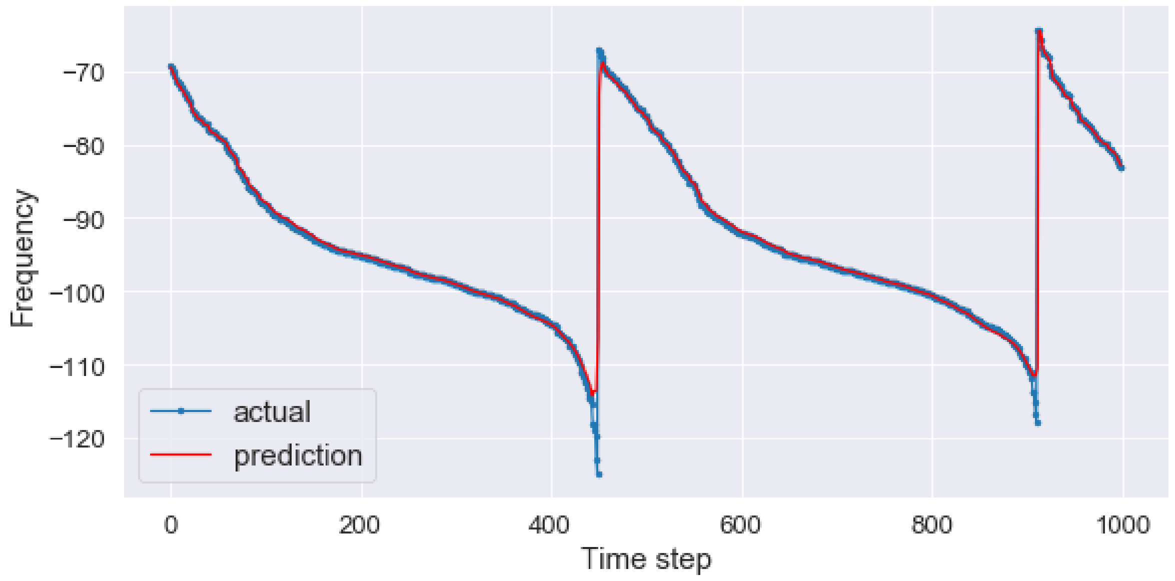
```
plt.figure(figsize=(10,5))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epochs')
plt.legend(loc='upper right')
plt.show()
```



Actual values vs Predicted values

In [17]:

```
aa=[x for x in range(1000)]
plt.figure(figsize=(8,4))
plt.plot(aa, Y_train[0][:1000], marker='.', label="actual")
plt.plot(aa, train_predict[:,0][:1000], '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('Frequency', size=15)
plt.xlabel('Time step', size=15)
plt.legend(fontsize=15)
plt.show()
```



Saving predicted data

In [18]:

```
sed=pd.DataFrame(test_predict)
sed.to_csv('missingLSTMpredict.csv', index=False)
```

Saving the model

In [19]:

```
filename = 'missing_model_LSTM.sav'
pickle.dump(model, open(filename, 'wb'))
```

In [20]:

```
model_json = model.to_json()
with open("missingLSTM_model.json", "w") as json_file:
    json_file.write(model_json)
# serialize weights to HDF5
model.save_weights("model.h5")
print("Saved model to disk")
```

```
Saved model to disk
```

Saving the normalisation model

the LSTM model was built on normalised data for better result. When attempting to predict new values, the data must be normalised before being sent to the model

In [21]:

```
filename = 'missing_LSTMscaler.sav'
pickle.dump(scaler, open(filename, 'wb'))
```

Loading the saved model

In [22]:

```
json_file = open('LSTM_model.json', 'r')
loaded_model_json = json_file.read()
json_file.close()
loaded_model = model_from_json(loaded_model_json)
# load weights into new model
loaded_model.load_weights("model.h5")
print("Loaded model from disk")
```

```
Loaded model from disk
```

In [23]:

```
look_back = 12
X_train, Y_train = create_dataset(train, look_back)
X_test, Y_test = create_dataset(test, look_back)
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]))
train_predict = loaded_model.predict(X_train)
test_predict = loaded_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
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[:,
```

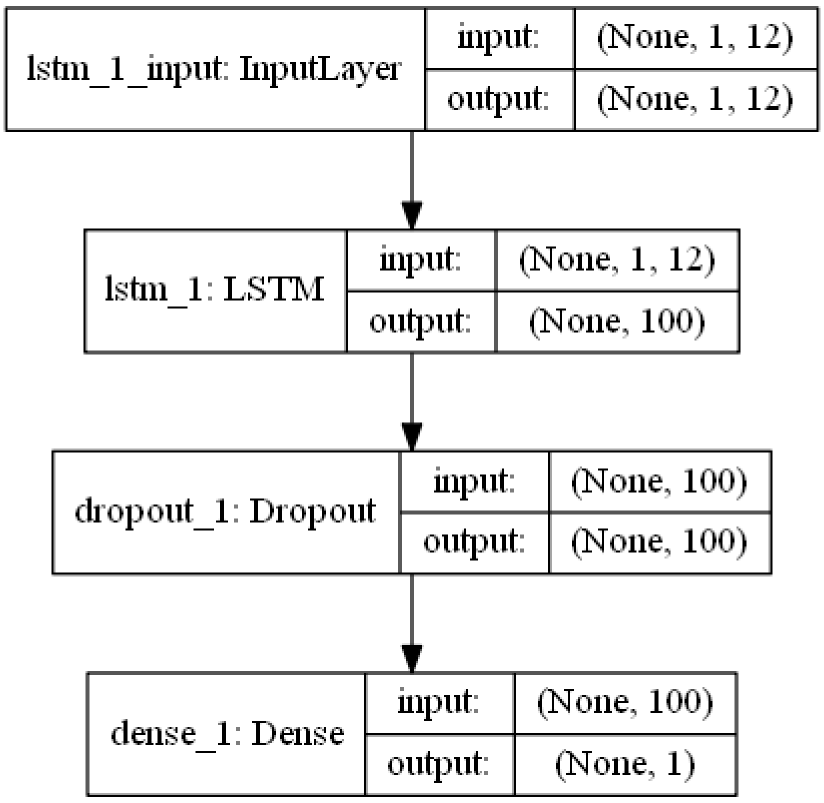
```
Train Mean Absolute Error: 0.4637423628876297
Train Root Mean Squared Error: 2.365602304875661
Test Mean Absolute Error: 0.4058534146924971
Test Root Mean Squared Error: 2.233558904184524
```

Visualisation of the Neural Network

In [24]:

```
plot_model(model, to_file='mod1.png', show_shapes=True)
```

Out[24]:



Model Parameters

- Epoch = 20
- Batch size = 100
- Dropout layers = 1
- Dropout = 0.2
- Hidden layers = 1
- Neurons = 100 in hidden layer, 1 in output layer

Observation	values
Train Mean Absolute Error	0.4637
Train Root Mean Squared Error	2.3656
Test Mean Absolute Error	0.4059
Test Root Mean Squared Error	2.2336
Training time	1395.2241
Prediction time	41.4415

Observation	LSTM	Improved LSTM
Train Mean Absolute Error	0.4637	0.3642
Train Root Mean Squared Error	2.3656	2.2711
Test Mean Absolute Error	0.4059	0.3061
Test Root Mean Squared Error	2.2336	2.1449
Training time	1395.2241	1868.2691
Prediction time	41.4415	56.9378

Models	Train Mean Absolute Error	Train Root Mean Squared Error	Test Mean Absolute Error	Test Root Mean Squared Error	Training time	Prediction time
DNN	0.4160	2.3057	0.3607	2.1937	374.9854	15.0671
Improved DNN	1.1289	2.5515	1.0850	2.4479	1088.0616	28.2217
LSTM	0.4637	2.3656	0.4059	2.2336	1395.2241	41.4415
Improved LSTM	0.3642	2.2711	0.3061	2.1449	1868.2691	56.9378