```
In [1]: from math import sqrt
        from numpy import concatenate
        from matplotlib import pyplot
        from pandas import read_csv
        from pandas import DataFrame
        from pandas import concat
        from sklearn.preprocessing import MinMaxScaler
        from sklearn.preprocessing import LabelEncoder
        from sklearn.metrics import mean squared error
        from keras.models import Sequential
        from keras.layers import Dense
        from keras.layers import LSTM
        import pandas as pd
        import numpy as np
In [2]: df_t= pd.read_csv('temperature.csv', index_col=0)
        df_h= pd.read_csv('humidity.csv', index_col=0)
        df p = pd.read csv('pressure.csv', index col=0)
        df_w = pd.read_csv('wind_speed.csv', index_col=0)
        df_h.columns
Out[2]: Index(['Vancouver', 'Portland', 'San Francisco', 'Seattle', 'Los Angeles',
                'San Diego', 'Las Vegas', 'Phoenix', 'Albuquerque', 'Denver',
                'San Antonio', 'Dallas', 'Houston', 'Kansas City', 'Minneapolis',
                'Saint Louis', 'Chicago', 'Nashville', 'Indianapolis', 'Atlanta',
                'Detroit', 'Jacksonville', 'Charlotte', 'Miami', 'Pittsburgh',
                'Toronto', 'Philadelphia', 'New York', 'Montreal', 'Boston',
                'Beersheba', 'Tel Aviv District', 'Eilat', 'Haifa', 'Nahariyya',
                'Jerusalem'],
               dtype='object')
In [5]: def normalize(data):
            data_mean = data.mean (axis=0)
            data_std = data.std (axis=0)
            return (data - data_mean) / data_std
In [7]: city = 'San Diego'
        tempog = df_t[city]
        temp = df_t[city].rename("temperature").to_frame(name='temperature')
        humid = df_h[city].rename("humidity").to_frame (name='humidity')
        press = df_p[city].rename("presure").to_frame (name='presure')
        wind = df w[city].rename("wind").to frame (name='wind')
        features = pd.concat([temp, press, humid, wind], axis=1)
        #features. index -time
        features = features.dropna()
        features
        featuresog = features
        featuresog
```

datetime				
2012-10-01 13:00:00	291.530000	1013.0	82.0	0.0
2012-10-01 14:00:00	291.533501	1013.0	81.0	0.0
2012-10-01 15:00:00	291.543355	1013.0	81.0	0.0
2012-10-01 16:00:00	291.553209	1013.0	81.0	0.0
2012-10-01 17:00:00	291.563063	1013.0	80.0	0.0
•••	•••		•••	
2017-11-29 20:00:00	292.150000	1017.0	72.0	2.0
2017-11-29 21:00:00	292.740000	1017.0	72.0	1.0
2017-11-29 22:00:00	292.580000	1016.0	68.0	2.0
2017-11-29 23:00:00	292.610000	1016.0	63.0	2.0
2017-11-30 00:00:00	291.400000	1017.0	72.0	2.0

44899 rows × 4 columns

```
In [9]: features = normalize(features.values)
  features= pd.DataFrame (features)
  features
```

Out[9]:		0	1	2	3
	0	0.222888	-0.528665	0.731908	-1.181374
	1	0.223482	-0.528665	0.680392	-1.181374
	2	0.225155	-0.528665	0.680392	-1.181374
	3	0.226829	-0.528665	0.680392	-1.181374
	4	0.228502	-0.528665	0.628876	-1.181374
	•••	•••			
	44894	0.328173	-0.061829	0.216750	0.162904
44	44895	0.428364	-0.061829	0.216750	-0.509235
	44896	0.401194	-0.178538	0.010687	0.162904
	44897	0.406288	-0.178538	-0.246892	0.162904
	44898	0.200812	-0.061829	0.216750	0.162904

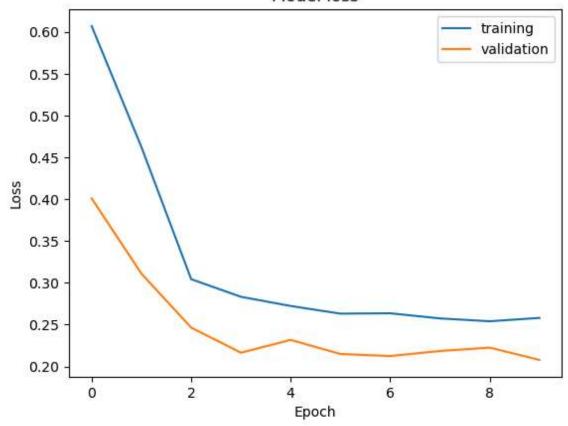
44899 rows × 4 columns

```
In [11]: training_size = int(0.8 * features.shape[0])
   train_data = features.loc[0: training_size - 1]
   val_data = features.loc[training_size:]
```

```
In [13]: start = 432 + 36
        end = start + training size
        x_train = train_data.values
        y_train = features.iloc[start:end][[0]]
        sequence_length = int(432 / 6)
In [15]: from tensorflow import keras
        dataset_train = keras. preprocessing.timeseries_dataset_from_array(
            data=x_train,
            targets =y_train,
            sequence length=sequence length,
            sampling rate=6,
            batch_size=64,
In [17]: x_val_end = len(val_data) - start
        label start = training size + start
        x_val = val_data.iloc[:x_val_end] [[i for i in range(4)]].values
        y val = features.iloc[label start:][[0]]
        dataset_val = keras.preprocessing.timeseries_dataset_from_array(
            x_val,
            y_val,
            sequence length=sequence length,
            sampling_rate=6,
            batch size=64,
In [19]: for batch in dataset_train. take (1):
            inputs, targets = batch
        inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
        lstm_out = keras.layers.LSTM(32)(inputs)
        outputs = keras.layers.Dense (1)(lstm_out)
        model = keras.Model (name="Weather_forcaster", inputs=inputs, outputs = outputs)
        model.compile(optimizer = keras.optimizers.Adam (learning_rate=0.001), loss="mse"
        model. summary()
       Model: "Weather_forcaster"
        Layer (type)
                                  Output Shape
                                                           Param #
       ______
        input_1 (InputLayer)
                                 [(None, 72, 4)]
        1stm (LSTM)
                                  (None, 32)
                                                           4736
        dense (Dense)
                                  (None, 1)
                                                           33
       ______
       Total params: 4769 (18.63 KB)
       Trainable params: 4769 (18.63 KB)
       Non-trainable params: 0 (0.00 Byte)
In [21]: history = model.fit(
            dataset train,
            epochs=10,
            validation data=dataset val
        )
```

```
Epoch 1/10
    s: 0.4010
    Epoch 2/10
    0.3110
    Epoch 3/10
    555/555 [============] - 7s 13ms/step - loss: 0.3044 - val loss:
    0.2465
    Epoch 4/10
    0.2165
    Epoch 5/10
    555/555 [============= ] - 7s 13ms/step - loss: 0.2723 - val loss:
    0.2318
    Epoch 6/10
    555/555 [=============] - 7s 13ms/step - loss: 0.2632 - val_loss:
    0.2149
    Epoch 7/10
    555/555 [============] - 7s 12ms/step - loss: 0.2636 - val_loss:
    0.2125
    Epoch 8/10
    0.2185
    Epoch 9/10
    555/555 [============] - 7s 13ms/step - loss: 0.2541 - val_loss:
    0.2225
    Epoch 10/10
    0.2079
In [27]: import matplotlib.pyplot as plt
     plt.plot(history.history['loss'])
     plt.plot(history.history['val_loss'])
     plt.title('Model loss')
     plt.ylabel('Loss')
     plt.xlabel('Epoch')
     plt.legend (['training', 'validation'], loc='upper right')
     plt.show()
```

Model loss



```
In [31]: dataset = featuresog.values
   dataset = dataset.astype('float32')
   scaler = MinMaxScaler (feature_range=(0, 1))
   dataset = scaler.fit_transform(dataset)
   #print('dataset. shape', dataset.shape)
   num_of_features = len(features.columns)
   print('Number of features', num_of_features)

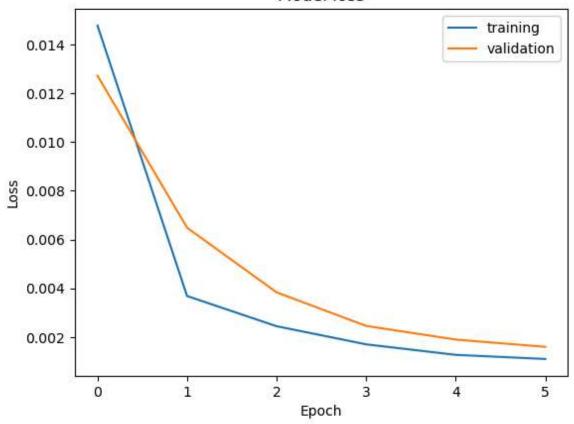
look_back = sequence_length
```

Number of features 4

```
In [45]: train_size_percent= 0.80
         pred col = featuresog.columns.get loc("temperature")
         print(pred col)
         #function to split the data
         def create_dataset(dataset, pred_col, look_back=1):
             dataX, dataY = [], []
             for i in range(len(dataset)-look_back-1):
                 a = dataset [i: (i+look_back), :]
                 dataX.append(a)
                 dataY.append(dataset [i + look_back, pred_col])
             return np.array(dataX), np.array(dataY)
         train_size = int(len(dataset) * train_size_percent)
         test_size = len(dataset) - train_size
         train, test = dataset [0: train_size, :], dataset [train_size: len(dataset), :]
         trainX, trainY = create_dataset (train, pred_col, look_back=look_back)
         testX, testY = create_dataset (test, pred_col, look_back=look_back)
         # reshape input to be [samples, time steps, features]
         trainX = np.reshape(trainX, (trainX.shape[0], look_back, num_of_features))
         testX = np.reshape(testX, (testX. shape[0], look_back, num_of_features))
         print('Training dataset length', len(train))
```

```
print('Testing dataset length ', len(test))
      print('look_back', look_back)
     Training dataset length 35919
     Testing dataset length 8980
     look_back 72
In [49]: expr_name = 'expr_4'
      # Look back = 24*120 # 60 days, as each entry is for 1 hour
      lstm_layers = 64 # 64
      epochs = 6 \# 6
      batch_size = 128 #128
      model = Sequential()
      model.add(LSTM(lstm layers, input shape=(look back,num of features)))
      model.add(Dense(1))
      model.compile(loss='mean_squared_error', optimizer='adam')
      history= model.fit(trainX,trainY,validation_split=0.30, epochs=epochs, batch_size
     Epoch 1/6
     s: 0.0127
     Epoch 2/6
     0.0065
     Epoch 3/6
     0.0038
     Epoch 4/6
     0.0025
     Epoch 5/6
     197/197 [================== ] - 6s 33ms/step - loss: 0.0013 - val_loss:
     0.0019
     Epoch 6/6
     0.0016
In [51]: plt.plot(history.history['loss'])
      plt.plot(history.history['val_loss'])
      plt.title('Model loss')
      plt.ylabel('Loss')
      plt.xlabel('Epoch')
      plt.legend (['training', 'validation'], loc='upper right')
      plt.show()
```

Model loss



```
In [77]: import math
         trainPredict = model.predict(trainX)
         testPredict = model.predict(testX)
         #Get something which has as many features as dataset
         trainPredict_extended = np.zeros((len(trainPredict), num_of_features))
         #Put the predictions there
         trainPredict_extended[:, pred_col] = trainPredict[:,0]
         #Inverse transform it and select the 3rd column.
         trainPredict = scaler.inverse_transform(trainPredict_extended) [:,pred_col]
         #Get something which has as many features as dataset
         testPredict_extended = np.zeros((len(testPredict), num_of_features))
         #Put the predictions there
         testPredict_extended[:,pred_col] = testPredict[:,0]
         #Inverse transform it and select the pred_coL column.
         testPredict = scaler.inverse_transform(testPredict_extended)[:,pred_col]
         trainY_extended = np.zeros((len(trainY), num_of_features))
         trainY_extended[:, pred_col]=trainY
         trainY = scaler.inverse_transform(trainY_extended) [:, pred_col]
         testY_extended = np.zeros((len(testY), num_of_features))
         testY_extended[:, pred_col]-testY
         testY = scaler.inverse_transform(testY_extended) [:, pred_col]
         #calculate root mean squared error
         trainscore_RMSE = math.sqrt(mean_squared_error(trainY, trainPredict))
         testscore_RMSE = math.sqrt(mean_squared_error(testY, testPredict))
         #calculate absolute mean error
         trainScore_MAE= np.sum(np.absolute (trainY - trainPredict))/len(trainY)
         testScore_MAE= np.sum(np.absolute (testY - testPredict))/len (testY)
```

```
#shift train predictions for plotting
         trainPredictPlot = np.empty_like(dataset)
         trainPredictPlot[:, :]= np.nan
         trainPredictPlot[look_back: len(trainPredict)+look_back, pred_col] = trainPredict
         #shift test predictions for plotting
         testPredictPlot = np.empty_like(dataset)
         testPredictPlot[:, :]= np.nan
         testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, pred_col] = tes
         #contruct pandas dataframe for plotting
         time df = pd.DataFrame(featuresog.index)
         time_df['Actual'] = scaler.inverse_transform(dataset)[:, pred_col]
         df1= pd.DataFrame (trainPredictPlot[:,pred_col], columns=['Train'])
         df2= pd.DataFrame(testPredictPlot[:,pred_col], columns=['Test'])
         time_df2= pd.concat([time_df, df1, df2], axis=1, sort=False)
         # print(time df2)
         time_df2.set_index('datetime', inplace=True)
        1121/1121 [========= ] - 6s 5ms/step
        279/279 [=========== ] - 1s 5ms/step
In [83]:
         print(trainscore RMSE)
         print(testscore_RMSE)
        3431172313701.46
        26.11277553072241
In [87]: fig, ax = plt.subplots(figsize=(15,7))
         time_df2.plot(ax=ax, rot=90,alpha=0.7)
         plt.xlabel('Timestamp')
         plt.ylabel('Temperature Value')
         plt.title('Temperature Prediction')
         plt.savefig(expr_name + '.png', bbox_inches = "tight")
                                            Temperature Prediction
               Actual
               Train
         310
         300
       Temperature Value
6
0
         280
```

2015-01-25 19:00:00

Timestamn

2016-03-17 12:00:00

2017-05-09 22:00:00

2013-12-01 19:00:00

270