BD_24_Summative - Final Rev 2

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1 Summative - Dieter Gebert

Final toughts at the end

This exercise will go through a simulated streaming data workflow, as seen in the streaming data module. But it will be more complex, and closer to what a real world scenario might look like. You will need to - Investigate the incoming data - Create an appropriate database to store the incoming records - Write code to process records one by one as they arrive, including - Printing warnings when any reading goes above a predefined threshold - Storing the incoming data in a database - Write code to analyse the stored data in a scalable manner - Display relevant information in a dashboard

1.1 Create an appropriate database

Each incoming record will look something like the following:

{'Device_ID': 9,
'Temp1': 33.01235436945101,
'Temp2': 46.313589806396116,
'Temp3': 16.506177184725505,
'Temp_Ambient': 23.782493817278034}

Each device is assigned an integer ID. Every device has multiple sensors, and reports the readings from each sensor as a float. Each call to gen_data.getReading() returns a time (an integer here to make things easier) and a record that follows the same pattern as above.

Create a database to store the incoming data. Include a time field for the time that the data arrives. If you create the database with python, show the code here, otherwise include any bash or sql code you run. You may wish to come back and add additional fields to make later analysis easier.

1.2 Store and process the incoming data

As each record arrives (i.e. each loop of the for loop), you must - Store the record in the database you created above - Use either moving windows or exponential averaging to keep track each sensor value for each device. Print out the values at the end of the loop - Print a warning if any reported temperature exceeds 100 degrees for the first time for that device

```
In [1]: import pandas as pd
        import numpy as np
```

```
In [2]: import gen_data

        # Your code here for any initializations you may need

        temp1_ave = 0
        temp2_ave = 0
        temp3_ave = 0
        temp_am_ave = 0

        window1 = []
        window2 = []
        window3 = []
        windowA = []

        window_t1_sd = 0
        window_t1_av = 0
        window_t2_sd = 0
        window_t2_av = 0
        window_t3_sd = 0
        window_t3_av = 0
        window_ta_sd = 0
        window_ta_av = 0

        df = pd.DataFrame(columns=['Time', 'Device_ID', 'Temp1', 'Temp1_ave', 'Temp1_sd',
                                                         'Temp2', 'Temp2_ave', 'Temp2_sd',
                                                         'Temp3', 'Temp3_ave', 'Temp3_sd',
                                                         'Temp_Ambient', 'Temp_Am_ave', 'Temp_Am_

        for i in range(2000): # Hint: make this lower for testing origional value: 20000

            # The simulated data arriving - don't change this
            arrival_time, record = gen_data.getReading()

            # Your code here
            temp1_ave = temp1_ave*0.75 + record['Temp1']*0.25
            temp2_ave = temp2_ave*0.75 + record['Temp2']*0.25
            temp3_ave = temp3_ave*0.75 + record['Temp3']*0.25
            temp_am_avg = temp_am_ave*0.75 + record['Temp_Ambient']*0.25

            # Window for temp1
            window1.append(temp1_ave) # Add the temp1_ave to our moving window
            if len(window1)>10: # Keep the window size from growing beyond 10:
                del(window1[0]) # If the window is >10 items, delete the oldest
            window_t1_sd = np.std(window1) # Calculate the standard deviation of the ten items i
            window_t1_av = np.mean(window1) # Calculate the mean of the last ten readings

            # Window for temp2
            window2.append(temp2_ave) # Add the temp2_ave to our moving window
```

```
        if len(window2)>10: # Keep the window size from growing beyond 10:
            del(window2[0]) # If the window is >10 items, delete the oldest
        window_t2_sd = np.std(window2) # Calculate the standard deviation of the ten items i
        window_t2_av = np.mean(window2) # Calculate the mean of the last ten readings

        # Window for temp3
        window3.append(temp3_ave) # Add the temp3_ave to our moving window
        if len(window3)>10: # Keep the window size from growing beyond 10:
            del(window3[0]) # If the window is >10 items, delete the oldest
        window_t3_sd = np.std(window3) # Calculate the standard deviation of the ten items i
        window_t3_av = np.mean(window3) # Calculate the mean of the last ten readings

        # Window for temp_ambient
        windowA.append(temp_am_avg) # Add the temp_am_ave to our moving window
        if len(windowA)>10: # Keep the window size from growing beyond 10:
            del(windowA[0]) # If the window is >10 items, delete the oldest
        window_ta_sd = np.std(windowA) # Calculate the standard deviation of the ten items i
        window_ta_av = np.mean(windowA) # Calculate the mean of the last ten readings


        # Writing simulated data to df
        df = pd.concat([df, pd.DataFrame([{'Time': arrival_time, 'Device_ID': record['Device
                                   'Temp1':record['Temp1'],'Temp1_ave':window_t1_av,
                                   'Temp2':record['Temp2'],'Temp2_ave':window_t2_av,
                                   'Temp3':record['Temp3'],'Temp3_ave':window_t3_av,
                                   'Temp_Ambient':record['Temp_Ambient'],'Temp_Am_av

    # Going though the df to check for Temperatures that are out of bound
    for g in range(4):
        if df.iloc[g][1] >= 100 :
            print('Warning! Deive ID:', df.iloc[g][0],'Temp1 is above 100 řC. Reading: ', df
        elif df.iloc[g][2] >= 100 :
            print('Warning! Deive ID:', df.iloc[g][0],'Temp2 is above 100 řC. Reading: ', df
        elif df.iloc[g][3] >= 100 :
            print('Warning! Deive ID:', df.iloc[g][0],'Temp3 is above 100 řC. Reading: ', df
        elif df.iloc[g][4] >= 100 :
            print('Warning! Deive ID:', df.iloc[g][0],'Temp_Ambient is above 100 řC. Reading
```

I did not like the arrival_time recorded so I used the index as my arrival time instead

```
In [3]: df.reset_index(level=0, inplace=True)
```

create a datetime from the index

- epoch conversion - the origion is fixed though
- re-arrange the df

```
In [4]: df['Date'] = pd.to_datetime(df['index'], unit='s', origin = '2018-07-22')
```

```
df = df[['Date', 'Device_ID', 'Temp1', 'Temp1_ave', 'Temp1_sd',
                              'Temp2', 'Temp2_ave', 'Temp2_sd',
                              'Temp3', 'Temp3_ave', 'Temp3_sd',
                              'Temp_Ambient', 'Temp_Am_ave', 'Temp_Am_sd']]

# Show data frame
df.head(5)
```

```
Out[4]:                   Date Device_ID      Temp1  Temp1_ave  Temp1_sd      Temp2  \
        0 2018-07-22 00:00:00         4  26.809323   6.702331  0.000000  39.490255
        1 2018-07-22 00:00:01         7  47.118053  11.754296  5.051965  61.829858
        2 2018-07-22 00:00:02         6  42.906642  15.613316  6.840978  57.197306
        3 2018-07-22 00:00:03         4  41.089176  18.652690  7.925441  55.198093
        4 2018-07-22 00:00:04         8  58.213078  21.998428  9.748124  74.034385

           Temp2_ave   Temp2_sd      Temp3  Temp3_ave  Temp3_sd  Temp_Ambient  \
        0   9.872564   0.000000  13.404661   3.351165  0.000000     21.938834
        1  16.367226   6.494662  23.559027   5.877148  2.525983     22.103256
        2  21.393398   8.868215  21.453321   7.806658  3.420489     22.052069
        3  25.391006  10.340529  20.544588   9.326345  3.962720     21.742404
        4  29.622098  12.535941  29.106539  10.999214  4.874062     22.011406

           Temp_Am_ave  Temp_Am_sd
        0     5.484709    0.000000
        1     5.505261    0.020553
        2     5.507847    0.017175
        3     5.489785    0.034639
        4     5.492398    0.031420
```

Writing to datebase - csv file

```
In [5]: with open("sensor_data.csv","a") as f:
            df.to_csv(f,header=True,index=False)
```

```
In [6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 14 columns):
Date            2000 non-null datetime64[ns]
Device_ID       2000 non-null object
Temp1           2000 non-null float64
Temp1_ave       2000 non-null float64
Temp1_sd        2000 non-null float64
Temp2           2000 non-null float64
Temp2_ave       2000 non-null float64
Temp2_sd        2000 non-null float64
Temp3           2000 non-null float64
```

```
Temp3_ave       2000 non-null float64
Temp3_sd        2000 non-null float64
Temp_Ambient    2000 non-null float64
Temp_Am_ave     2000 non-null float64
Temp_Am_sd      2000 non-null float64
dtypes: datetime64[ns](1), float64(12), object(1)
memory usage: 218.8+ KB
```

1.3 Analyzing the stored data

You now have a nice big database. Load it into spark for analysis.

You are told that during the time the data was being collected, devices 3 and 10 had malfunctioning sensors - their temperature3 readings are all 200+. Verify this. Since the engineers knew about the faulty sensors, no harm has been done, but seeing those false readings in the historical data makes you unhappy. You decide to go the extra mile and replace these readings with slightly more believable (but still false) data, to practise your new machine learning skills.

Using the other devices for training, build a model to predict temperature3 given readings from the other sensors. Use the model to replace the erroneous values with the predicted ones.

Do you think this is a reasonable step to take? Explain.

```
In [69]: import findspark
         findspark.init()

         #from pyspark.sql.session import SparkSession
         from pyspark.sql import SparkSession

         spark = SparkSession.builder.master("local[*]").getOrCreate()
```

```
ERROR:py4j.java_gateway:An error occurred while trying to connect to the Java server (127.0.0.1:
Traceback (most recent call last):
  File "/usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py", line 852, in _get
    connection = self.deque.pop()
IndexError: pop from an empty deque

During handling of the above exception, another exception occurred:

Traceback (most recent call last):
  File "/usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py", line 990, in star
    self.socket.connect((self.address, self.port))
ConnectionRefusedError: [Errno 111] Connection refused
```

```
        IndexErrorTraceback (most recent call last)

        /usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in _get_connection(
```

```
    851         try:
--> 852             connection = self.deque.pop()
    853         except IndexError:


    IndexError: pop from an empty deque


During handling of the above exception, another exception occurred:


    ConnectionRefusedErrorTraceback (most recent call last)

    /usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in start(self)
    989         try:
--> 990             self.socket.connect((self.address, self.port))
    991             self.is_connected = True


    ConnectionRefusedError: [Errno 111] Connection refused


During handling of the above exception, another exception occurred:


    Py4JNetworkErrorTraceback (most recent call last)

    <ipython-input-69-1c9b50703cc7> in <module>()
      5 from pyspark.sql import SparkSession
      6
----> 7 spark = SparkSession.builder.master("local[*]").getOrCreate()


    /usr/local/spark/python/pyspark/sql/session.py in getOrCreate(self)
    181                     session = SparkSession(sc)
    182                 for key, value in self._options.items():
--> 183                     session._jsparkSession.sessionState().conf().setConfString(key,
    184                 for key, value in self._options.items():
    185                     session.sparkContext._conf.set(key, value)


    /usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in __call__(self, *
   1156             proto.END_COMMAND_PART
   1157
-> 1158         answer = self.gateway_client.send_command(command)
   1159         return_value = get_return_value(
   1160             answer, self.gateway_client, self.target_id, self.name)
```

```
/usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in send_command(sel
904          if `binary` is `True`.
905         """
--> 906         connection = self._get_connection()
907         try:
908             response = connection.send_command(command)


/usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in _get_connection(
852             connection = self.deque.pop()
853         except IndexError:
--> 854             connection = self._create_connection()
855         return connection
856


/usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in _create_connecti
858         connection = GatewayConnection(
859             self.gateway_parameters, self.gateway_property)
--> 860         connection.start()
861         return connection
862


/usr/local/spark/python/lib/py4j-0.10.6-src.zip/py4j/java_gateway.py in start(self)
995                 "server ({0}:{1})".format(self.address, self.port)
996             logger.exception(msg)
--> 997             raise Py4JNetworkError(msg, e)
998
999     def close(self, reset=False):


Py4JNetworkError: An error occurred while trying to connect to the Java server (127.0.0.
```

In [ ]:
```
# read csv file
data = spark.read.csv('sensor_data.csv',header=True)
```

In [ ]:
```
from pyspark.sql.types import DoubleType, IntegerType

#convert all columns
for col_name in data.columns:
    data = data.withColumn(col_name, data[col_name].cast(DoubleType()))
```

In [ ]:
```
# inspect the first 10 rows
data.show(10)
```

```
# the printSchema() method tells you the data type of each column
data.printSchema()
```

1.3.1 Prepare data for model

```
In [ ]: # Split the data into training and test sets (30% held out for testing)
        (trainingData, testData) = data.randomSplit([0.7, 0.3])
```

```
In [ ]: from pyspark.ml import Pipeline
        from pyspark.ml.feature import OneHotEncoder, VectorAssembler
        from pyspark.ml.regression import DecisionTreeRegressor
        from pyspark.ml.evaluation import RegressionEvaluator
```

```
In [ ]: # assemble variables to one feature column
        assembler = VectorAssembler(
            inputCols = ['Device_ID', 'Temp1', 'Temp2','Temp3','Temp_Ambient'],
            outputCol = "features")

        #    inputCols = ['Date', 'Device_ID', 'Temp1', 'Temp1_ave', 'Temp1_sd',
        #                                              'Temp2', 'Temp2_ave', 'Temp2_sd',
        #                                              'Temp3', 'Temp3_ave', 'Temp3_sd',
        #                                              'Temp_Ambient', 'Temp_Am_ave', 'Temp_Am
        #    outputCol = "features")

        #define the estimator - decision tree
        dt = DecisionTreeRegressor(labelCol="Device_ID", featuresCol="features")

        # Chain indexers and tree in a Pipeline
        pipeline = Pipeline(stages=[assembler, dt])
```

1.3.2 Fit pipeline and transform data

```
In [ ]: #fit the pipeline
        PipelineModel = pipeline.fit(trainingData)

        # transform using the pipeline
        predictions = PipelineModel.transform(testData)

        # evaluate model fit
        predictions.select("prediction", "Device_ID")
        evaluator = RegressionEvaluator(
            labelCol="Device_ID", predictionCol="prediction", metricName="rmse")
        rmse = evaluator.evaluate(predictions)
```

```
In [ ]: predictions.show()
```

```
In [ ]: ##Root mean square error
        print(rmse)
```

1.3.3 Kmeans clustering

```
In [ ]: from pyspark.ml.clustering import KMeans

        # Trains a k-means model with 4 clusters.
        kmeans = KMeans(featuresCol='features', predictionCol='prediction',k=4)

        #transform data using pipeline
        pipeline = Pipeline(stages=[assembler, kmeans])

        #fir pipeline
        PipelineModel = pipeline.fit(data)

        # transform using the pipeline
        predictions = PipelineModel.transform(data)
```

```
In [ ]: #view result
        predictions.show()
```

1.3.4 END

```
In [ ]: spark.stop()
```

1.4 Step 4: Visualization

Time to get creative. Your final task is to build up a set of visualizations that could let an engineer get a quick overview of the current status of the system. Include the current sensor readings for each device and any metrics you think would be important to display. Choose one device and show more detail - a downsampled graph showing the readings over time, perhaps.

You don't need to have your visualizations update in real time - merely show them as they would be presented at a given instant (i.e. feel free to use all the data you stored in the first section).

```
In [8]: import plotly.graph_objs as go
        import plotly.plotly as py
```

```
In [9]: import plotly
        plotly.tools.set_credentials_file(username='dgebert18', api_key='wWcelh2OcxQaebCFxNBF')
```

1.4.1 Temperature 1's info - Plotly grapf and Autocorelation Plots

```
In [10]: trace1 = go.Scatter(
             y = df['Temp1'],
             mode='lines',
             name = 'Temp 1 actual',
             marker=dict(
                 size='16',
                 color = np.random.randn(500),
                 showscale=True
             )
```

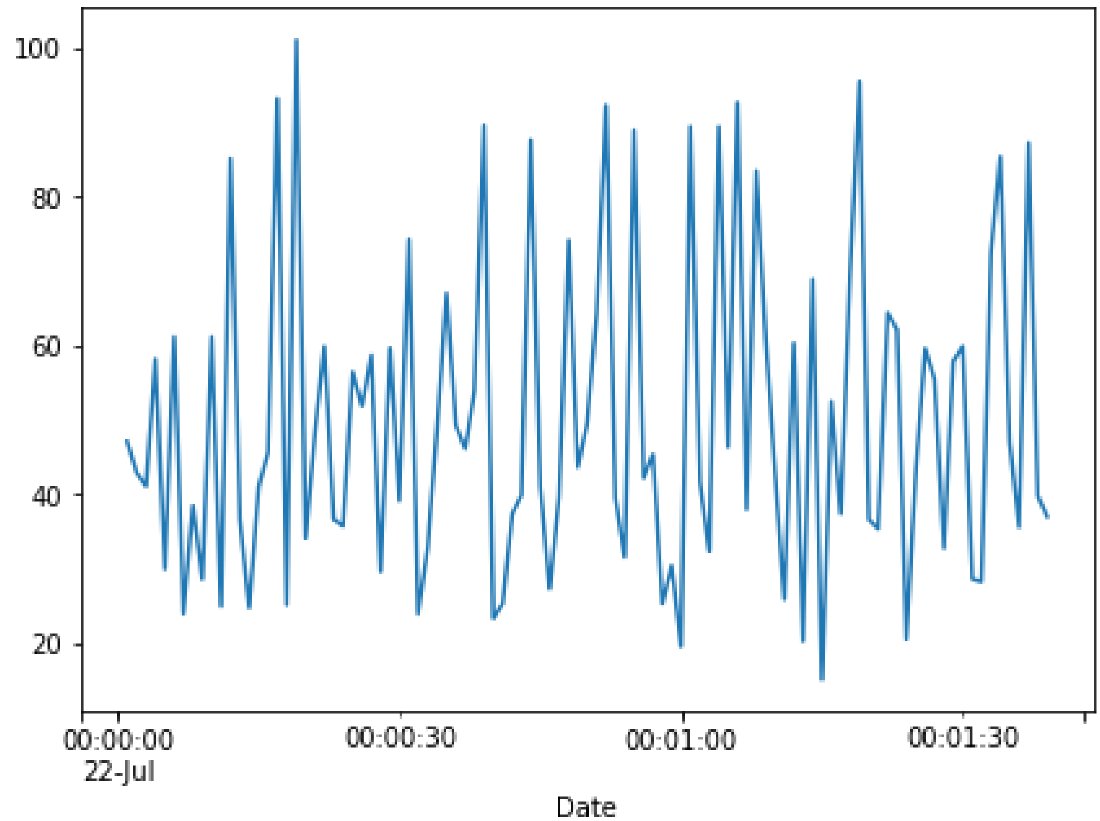
```
)
trace2 = go.Scatter(
    y = df['Temp1_ave'],
    mode='lines',
    name = 'Temp 1 average',
    marker=dict(
        size='16',
        color = np.random.randn(500),
        showscale=True
    )
)
trace3 = go.Scatter(
    y = df['Temp1_sd'],
    mode='lines',
    name = 'Temp 1 standard deviation',
    marker=dict(
        size='16',
        color = np.random.randn(500),
        showscale=True
    )
)
data = [trace1, trace2, trace3]

layout = dict(
    title='Temperature 1 High and Low values',
    xaxis=dict(
        rangeselector=dict(),
        rangeslider=dict(),
        type='date'
    )
)

#layout = dict(title = 'Temperature 1 High and Low values',
#              xaxis = dict(title = 'Time'),
#              yaxis = dict(title = 'Temperature (degrees C)'),
#              )


fig = dict(data=data, layout=layout)
py.iplot(fig, filename='styled-line')

#url_1 = py.plot(data, filename='temp1_info', auto_open=False)
#py.iplot(data, filename='temp1_info')
```

Out[10]: <plotly.tools.PlotlyDisplay object>

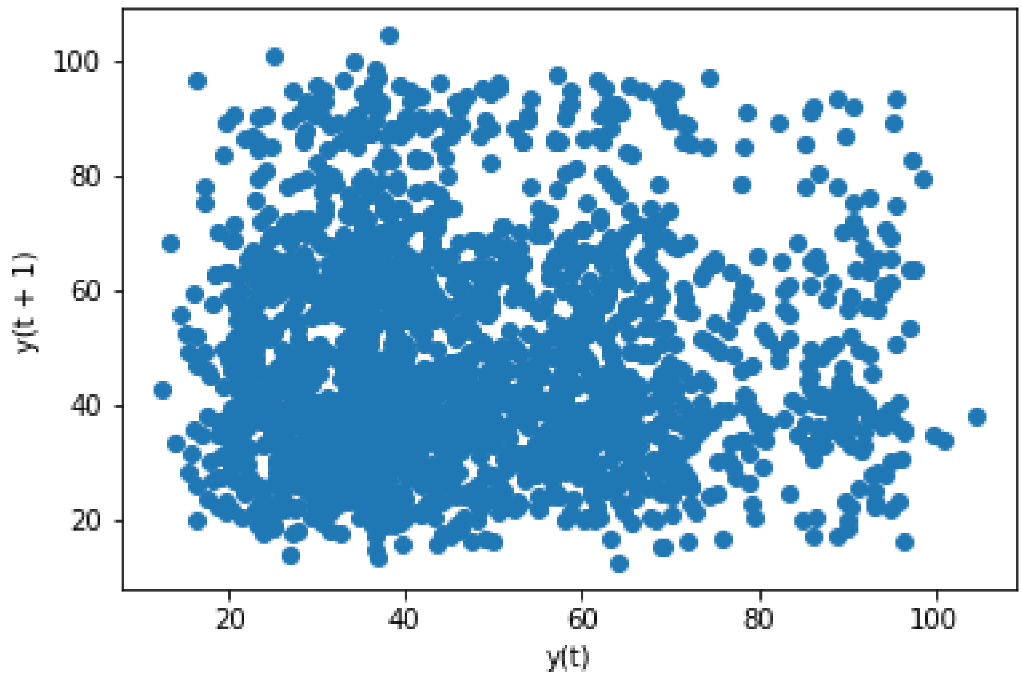
Please use the sliding scale to narrow the search / use magnification on a area of interest (down sampling did not work out for this type of plot)

In [14]:
```
import matplotlib.pyplot as pyplot
from pandas import Series
```

In [42]:
```
# The code will create the dataset for Temperature 1 Series.
tst1 = Series(df['Temp1'].values, index=df.Date)
plt = tst1[1:100].plot(figsize=(7,5))
pyplot.show(plt)
```

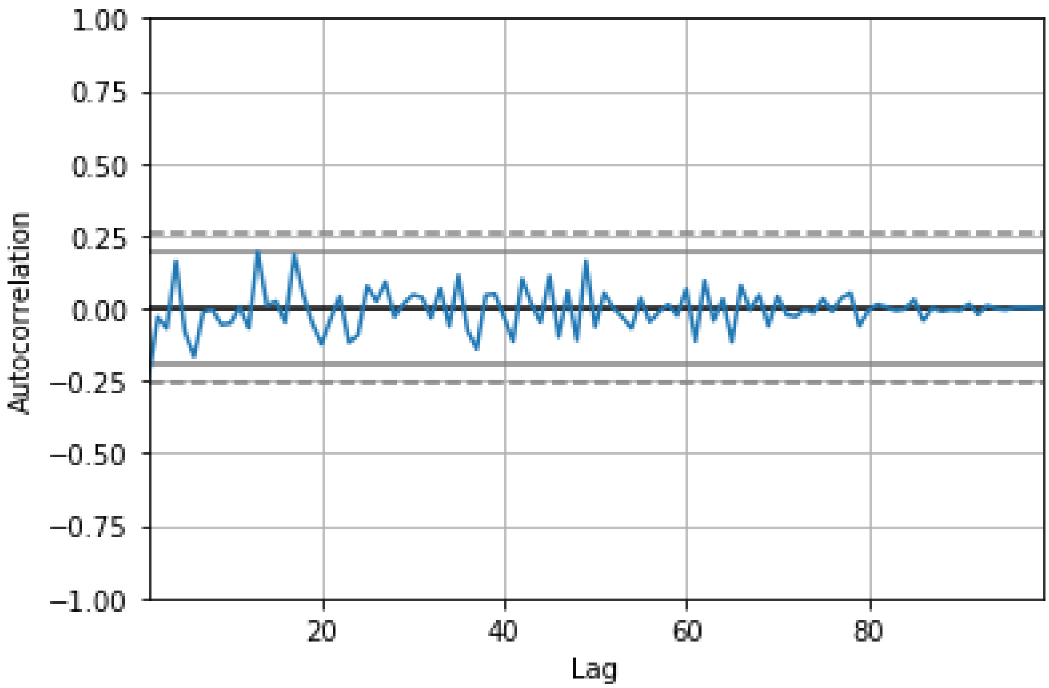


In [39]:
```
from pandas.plotting import lag_plot
lag_plot(tst1)
pyplot.show()
```



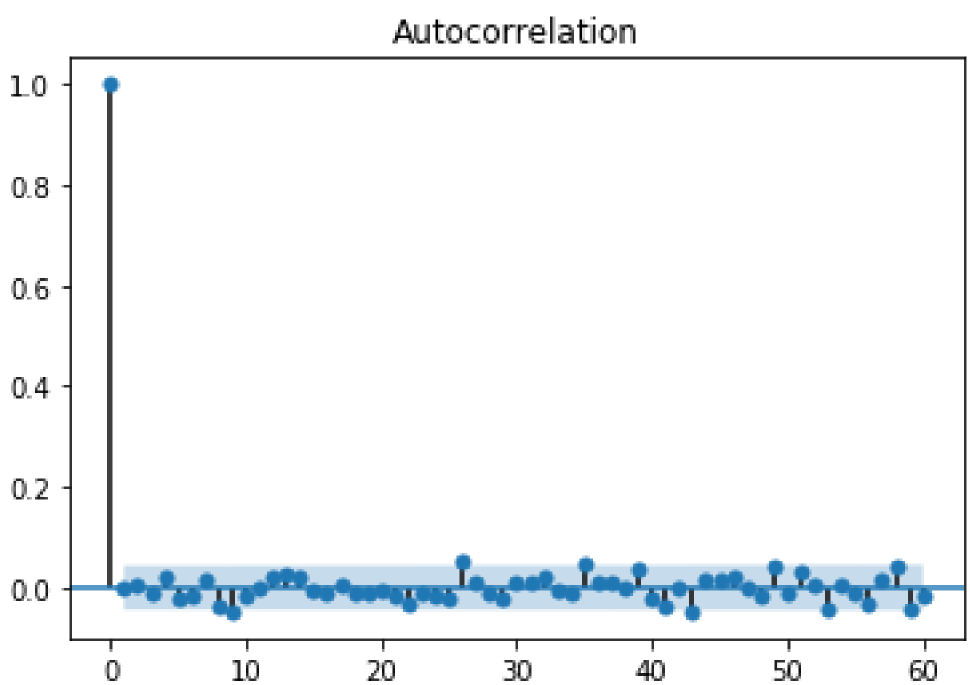
From the scatter plot I can see Temperature 1's data is spread across the diagonal line of the plot - witch again indicates a week correlation

```
In [41]: from pandas.plotting import autocorrelation_plot

         autocorrelation_plot(tst1[1:100])
         pyplot.show()
```



Looking at Temperature 1 there is a very week correlation with a swing of only 0.25 to - 0.25

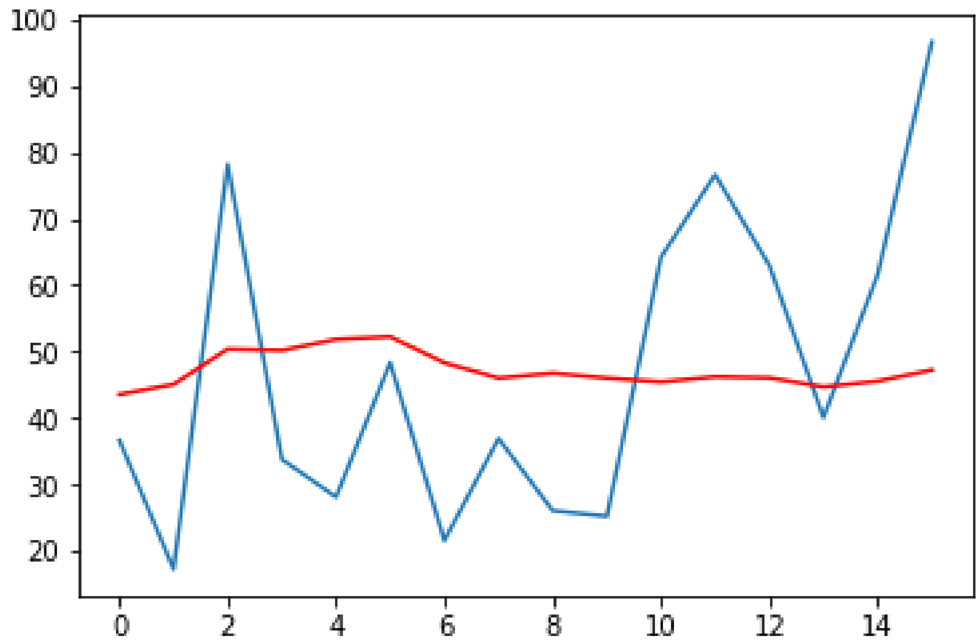
```
In [32]: from statsmodels.graphics.tsaplots import plot_acf
         plot_acf(tst1, lags=60)
         pyplot.show()
```



```
In [34]: from statsmodels.tsa.ar_model import AR
         from sklearn.metrics import mean_squared_error

         # split dataset to get only the values
         ts_values = tst1.values

         train, test = ts_values[1:len(ts_values)-16], ts_values[len(ts_values)-16:]

         # train autoregression
         model = AR(train)
         model_fit = model.fit()
         print('Lag: %s' % model_fit.k_ar)
         print('Coefficients: %s' % model_fit.params)

         predictions = model_fit.predict(start=len(train), end=len(train)+len(test)-1, dynamic=F
         for i in range(len(predictions)):
                 print('predicted=%f, expected=%f' % (predictions[i], test[i]))
         error = mean_squared_error(test, predictions)
         print('Test MSE: %.3f' % error)
         # plot results
         pyplot.plot(test)
         pyplot.plot(predictions, color='red')
         pyplot.show()
```

```
Lag: 25
Coefficients: [  5.52448459e+01   2.23449576e-03  -1.27184661e-03  -1.37110952e-02
   2.38284626e-02  -2.21058245e-02  -1.36697268e-02   1.33099454e-02
  -3.30370467e-02  -4.48351345e-02  -1.67587497e-02  -5.38333508e-04
   2.68968361e-02   2.10936620e-02   2.44511578e-02  -3.94294422e-03
  -8.99362771e-03   8.41885866e-03  -1.20510373e-02  -9.33873038e-03
  -7.74145186e-03  -1.43078687e-02  -2.96654252e-02  -1.30514898e-02
  -1.94202971e-02  -2.11975112e-02]
predicted=43.572488, expected=36.631970
predicted=45.081649, expected=17.254900
predicted=50.409032, expected=78.207766
predicted=50.213273, expected=33.785923
predicted=51.869925, expected=28.099166
predicted=52.264579, expected=48.343542
predicted=48.321485, expected=21.566449
predicted=46.038349, expected=36.915755
predicted=46.779606, expected=26.057700
predicted=46.034037, expected=25.201797
predicted=45.455520, expected=64.241779
predicted=46.232537, expected=76.657513
predicted=46.065451, expected=62.973846
```

```
predicted=44.706429, expected=40.101864
predicted=45.569028, expected=61.580303
predicted=47.248962, expected=96.633182
Test MSE: 524.303
```



Running the AR model, I can see that lag: 25 was chosen and trained. The 16-hour forecast is printed above. The forecast sort of follows the actual values

1.4.2 Temperature 2's info - Plotly grapf and Autocorelation Plots

```
In [48]: trace4 = go.Scatter(
             y = df['Temp2'],
             mode='lines',
             name = 'Temp 2 actual',
             marker=dict(
                 size='16',
                 color = np.random.randn(500),
                 showscale=True
             )
         )
         trace5 = go.Scatter(
             y = df['Temp2_ave'],
             mode='lines',
             name = 'Temp 2 average',
```

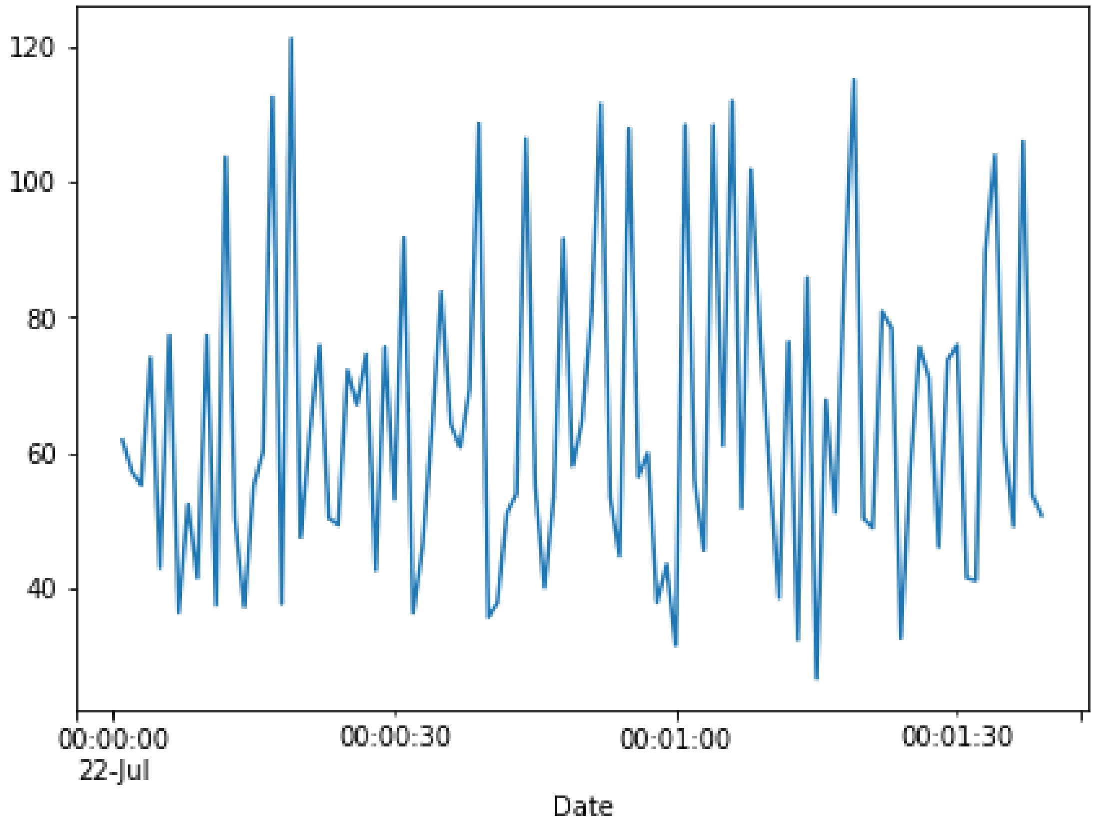
```
        marker=dict(
            size='16',
            color = np.random.randn(500),
            showscale=True
        )
    )
    trace6 = go.Scatter(
        y = df['Temp2_sd'],
        mode='lines',
        name = 'Temp 2 standard deviation',
        marker=dict(
            size='16',
            color = np.random.randn(500),
            showscale=True
        )
    )

    data = [trace4, trace5, trace6]

    layout = dict(
        title='Temperature 2 High and Low values',
        xaxis=dict(
            rangeselector=dict(),
            rangeslider=dict(),
            type='date'
        )
    )

    fig = dict(data=data, layout=layout)
    py.iplot(fig, filename='styled-line')
```

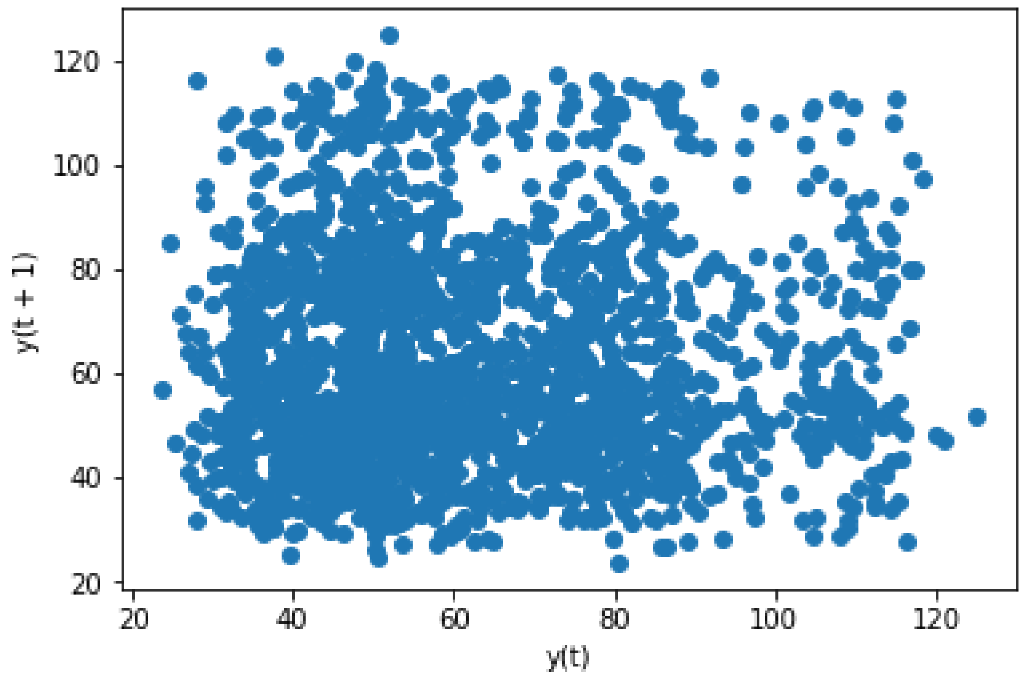
Out[48]: <plotly.tools.PlotlyDisplay object>

1.4.3 Please use the sliding scale to narrow the search / use magnification on a area of interest (down sampling did not work out for this type of plot)

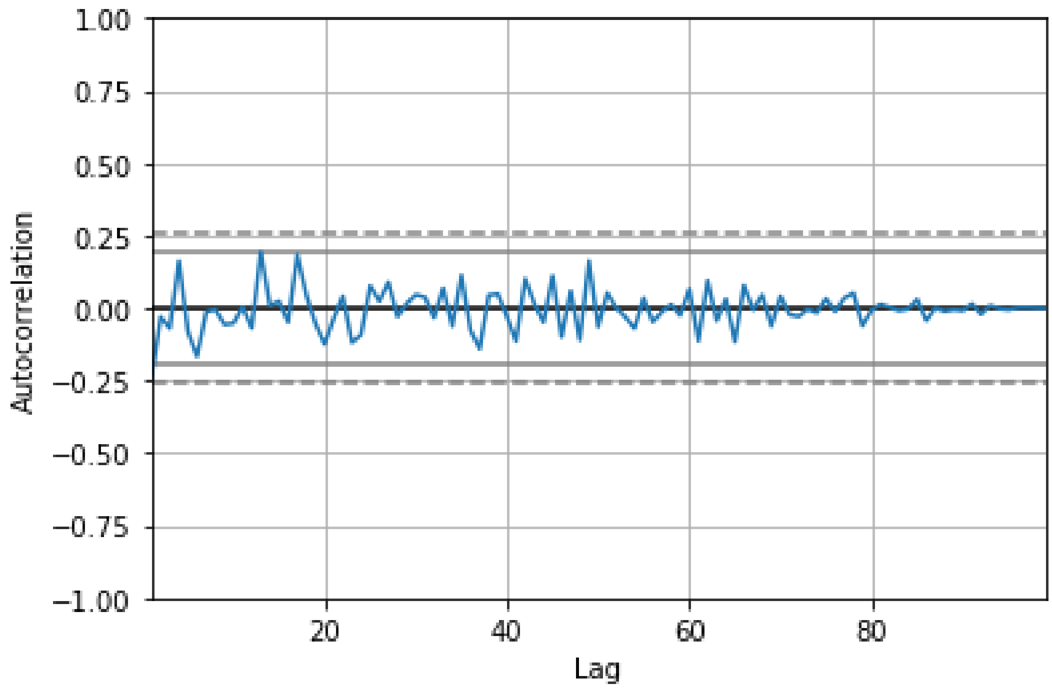
```
In [60]: # The code will create the dataset for Temperature 2 Series.
         tst2 = Series(df['Temp2'].values, index=df.Date)
         plt = tst2[1:100].plot(figsize=(7,5))
         pyplot.show(plt)

         lag_plot(tst2)
         pyplot.show()

         autocorrelation_plot(tst2[1:100])
         pyplot.show()

         plot_acf(tst2, lags=60)
```

```
pyplot.show()
```

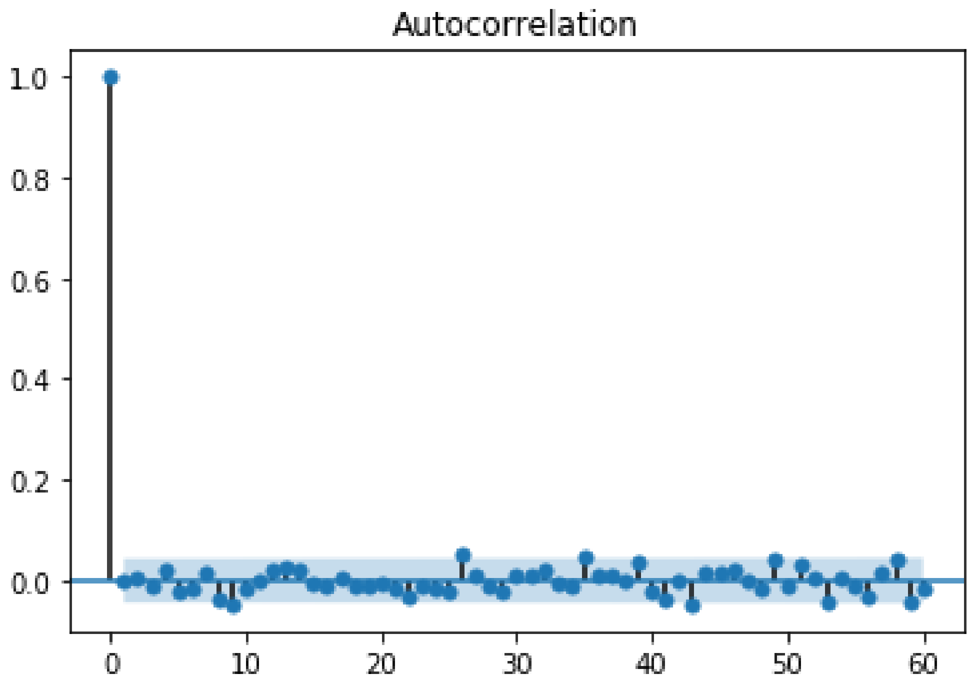




120
100
80
60
40
20
y(t + 1)
20
40
60
80
100
120
y(t)



1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Autocorrelation
20
40
60
80
Lag

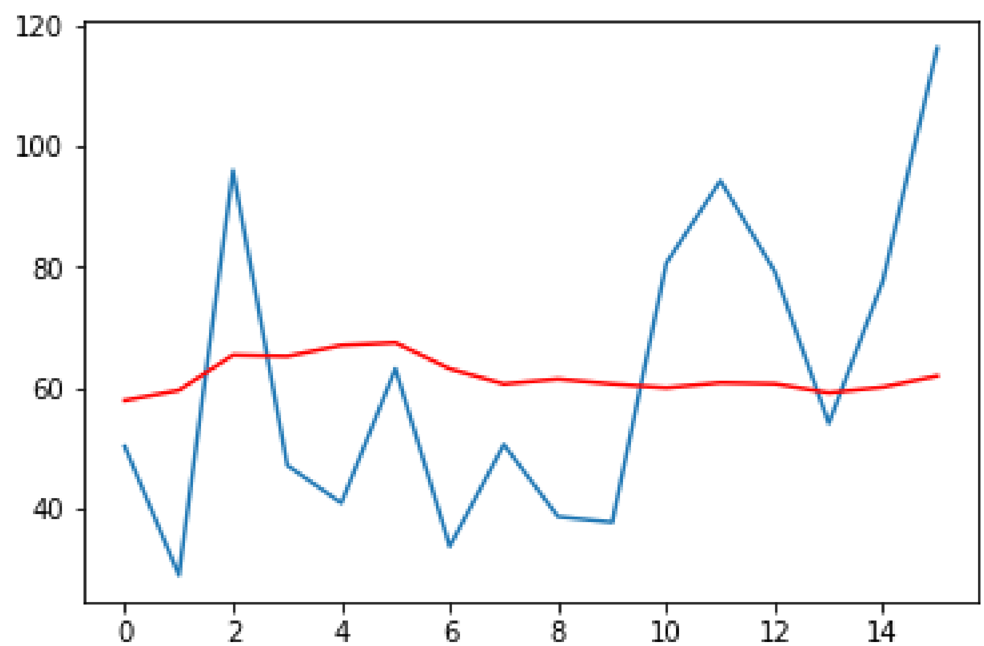


This is a similar picture / indication (Temperature sensor 1) of a week correlation of Temperature sensor 2

```
In [47]: # split dataset to get only the values
         ts_values = tst2.values

         train, test = ts_values[1:len(ts_values)-16], ts_values[len(ts_values)-16:]

         # train autoregression
         model = AR(train)
         model_fit = model.fit()
         print('Lag: %s' % model_fit.k_ar)
         print('Coefficients: %s' % model_fit.params)

         predictions = model_fit.predict(start=len(train), end=len(train)+len(test)-1, dynamic=F
         for i in range(len(predictions)):
                 print('predicted=%f, expected=%f' % (predictions[i], test[i]))
         error = mean_squared_error(test, predictions)
         print('Test MSE: %.3f' % error)
         # plot results
         pyplot.plot(test)
         pyplot.plot(predictions, color='red')
         pyplot.show()
```

```
Lag: 25
Coefficients: [  7.24233777e+01   2.23449576e-03  -1.27184661e-03  -1.37110952e-02
```

```
   2.38284626e-02  -2.21058245e-02  -1.36697268e-02   1.33099454e-02
  -3.30370467e-02  -4.48351345e-02  -1.67587497e-02  -5.38333508e-04
   2.68968361e-02   2.10936620e-02   2.44511578e-02  -3.94294422e-03
  -8.99362771e-03   8.41885866e-03  -1.20510373e-02  -9.33873038e-03
  -7.74145186e-03  -1.43078687e-02  -2.96654252e-02  -1.30514898e-02
  -1.94202971e-02  -2.11975112e-02]
predicted=57.929737, expected=50.295167
predicted=59.589814, expected=28.980390
predicted=65.449935, expected=96.028542
predicted=65.234601, expected=47.164515
predicted=67.056917, expected=40.909083
predicted=67.491037, expected=63.177896
predicted=63.153633, expected=33.723094
predicted=60.642184, expected=50.607330
predicted=61.457567, expected=38.663470
predicted=60.637441, expected=37.721976
predicted=60.001072, expected=80.665957
predicted=60.855790, expected=94.323264
predicted=60.671996, expected=79.271230
predicted=59.177072, expected=54.112051
predicted=60.125931, expected=77.738333
predicted=61.973858, expected=116.296500
Test MSE: 634.406
```



Running the AR model, I can see that lag: 25 was chosen and trained. The 16-hour forecast is printed above. The forecast sort of follows the actual values

1.4.4 Temperature 3's info

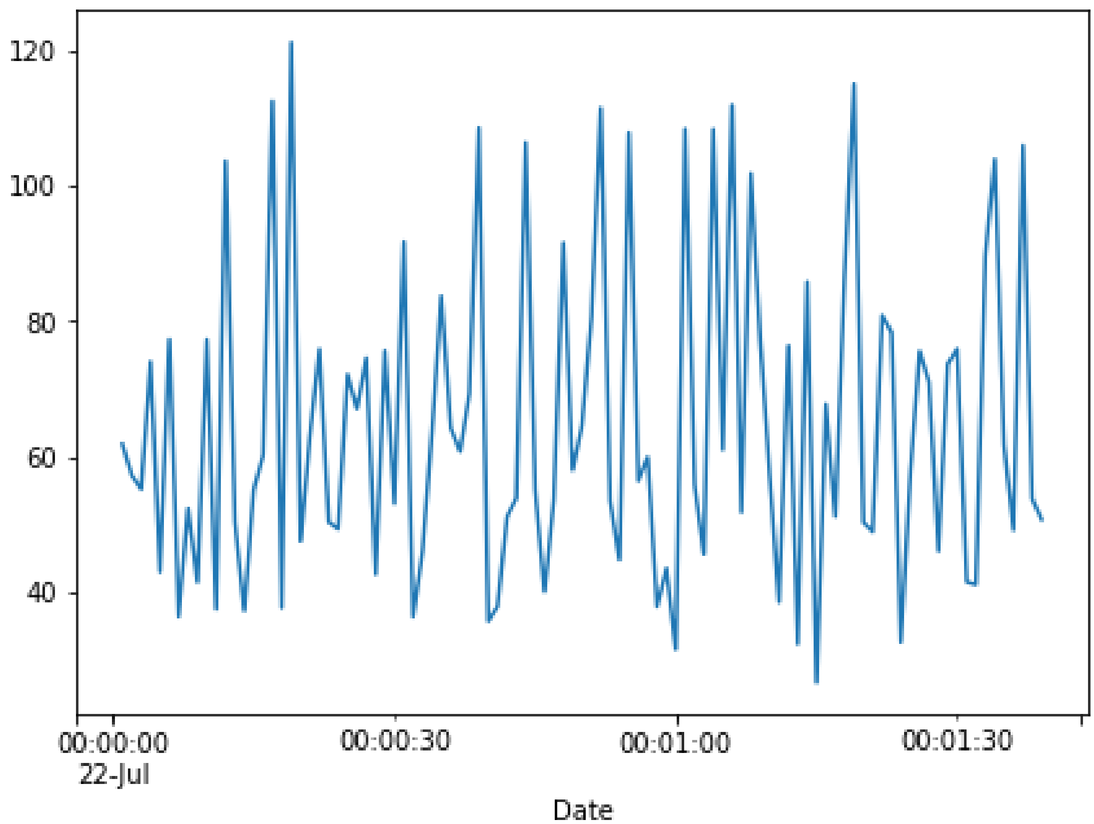
In [54]:
```
trace7 = go.Scatter(
    y = df['Temp3'],
    mode='lines',
    name = 'Temp 3 actual',
    marker=dict(
        size='16',
        color = np.random.randn(500),
        showscale=True
    )
)
trace8 = go.Scatter(
    y = df['Temp3_ave'],
    mode='lines',
    name = 'Temp 3 average',
    marker=dict(
        size='16',
        color = np.random.randn(500),
        showscale=True
    )
)
trace9 = go.Scatter(
    y = df['Temp3_sd'],
    mode='lines',
    name = 'Temp 3 standard deviation',
    marker=dict(
        size='16',
        color = np.random.randn(500),
        showscale=True
    )
)

data = [trace7, trace8, trace9]

layout = dict(
    title='Temperature 3 High and Low values',
    xaxis=dict(
        rangeselector=dict(),
        rangeslider=dict(),
        type='date'
    )
)

fig = dict(data=data, layout=layout)
```

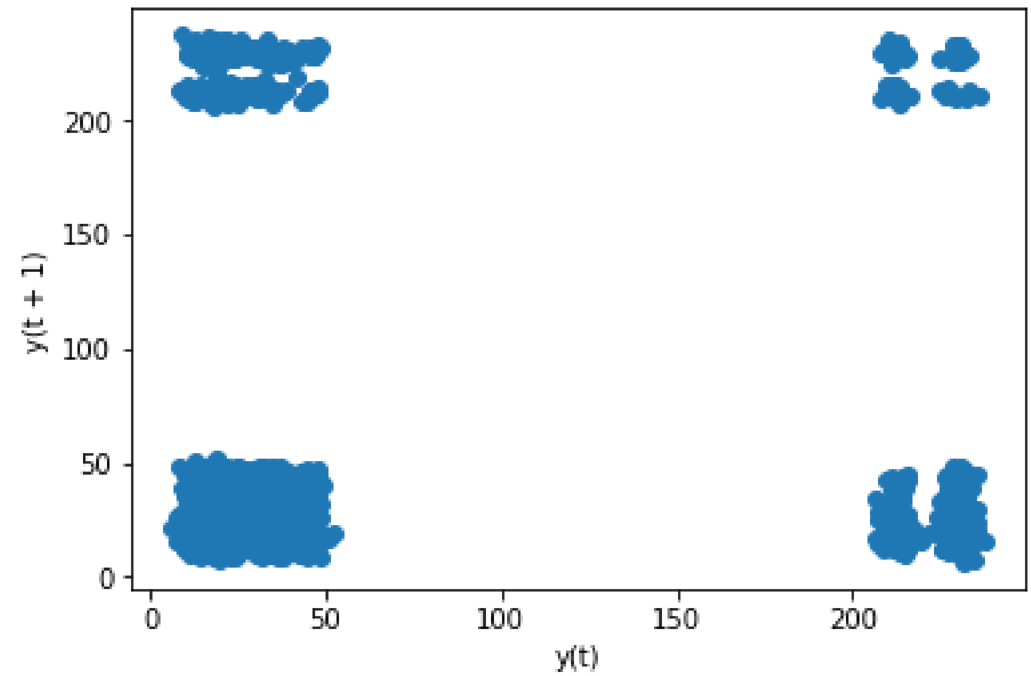
```
py.iplot(fig, filename='styled-line')
```

Out[54]: <plotly.tools.PlotlyDisplay object>

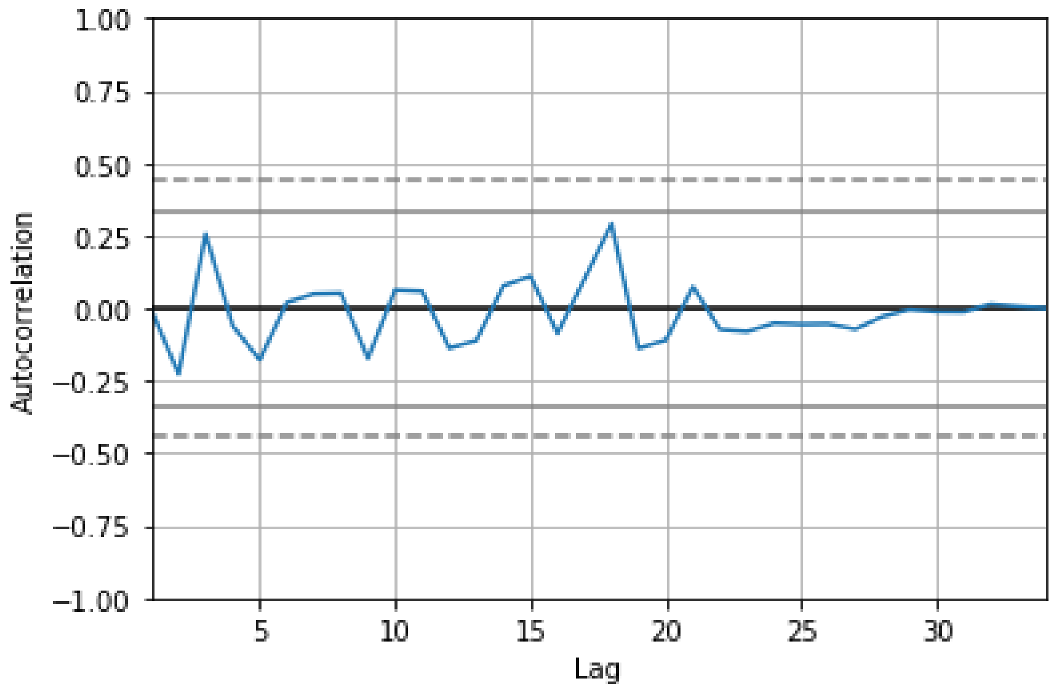
1.4.5 Please use the sliding scale to narrow the search / use magnification on a area of interest (down sampling did not work out for this type of plot)

```
In [62]: # The code will create the dataset for Temperature 3 Series.
         tst3 = Series(df['Temp3'].values, index=df.Date)
         plt = tst2[1:100].plot(figsize=(7,5))
         pyplot.show(plt)

         lag_plot(tst3)
         pyplot.show()

         autocorrelation_plot(tst3[1:100])
         pyplot.show()

         plot_acf(tst3, lags=60)
         pyplot.show()
```

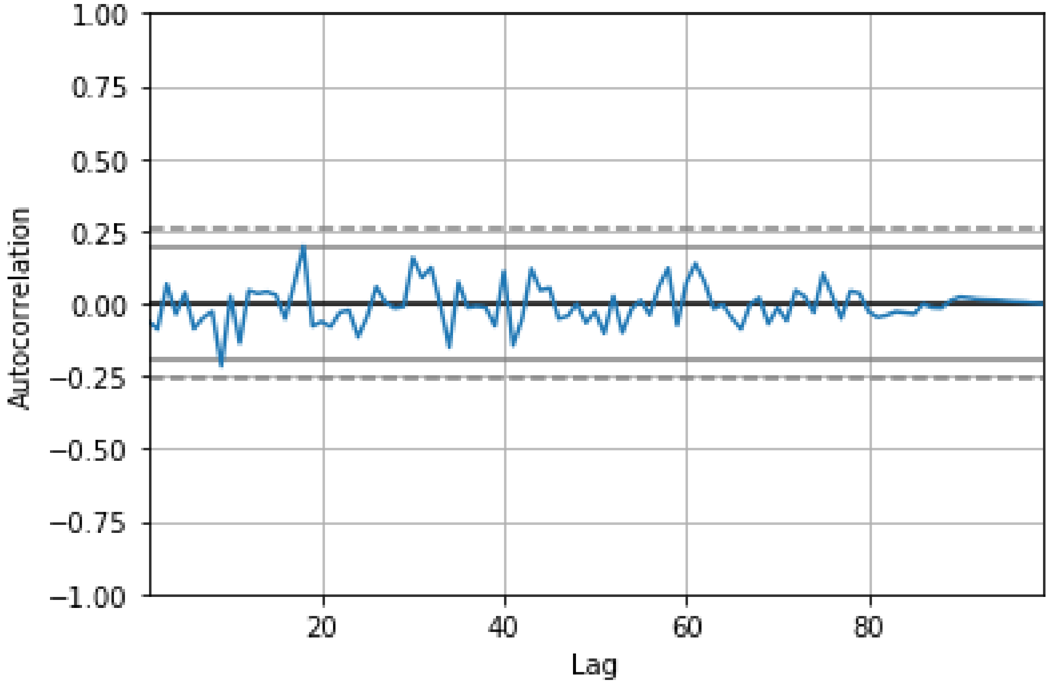


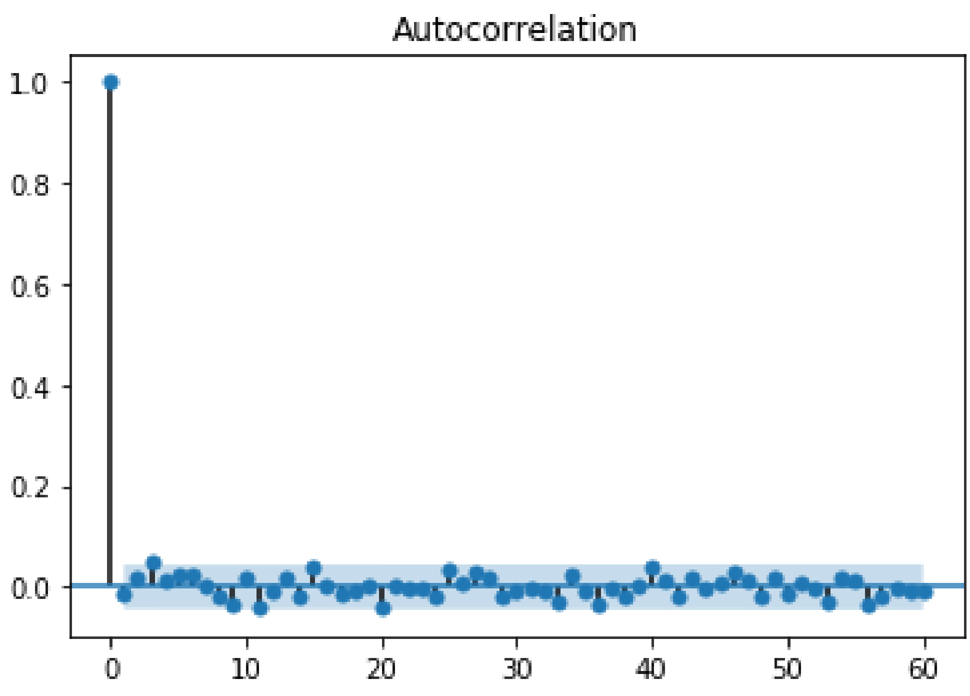


200
150
100
50
0
y(t + 1)
0
50
100
150
200
y(t)



1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Autocorrelation
5
10
15
20
25
30
Lag


1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Autocorrelation
20
40
60
80
Lag

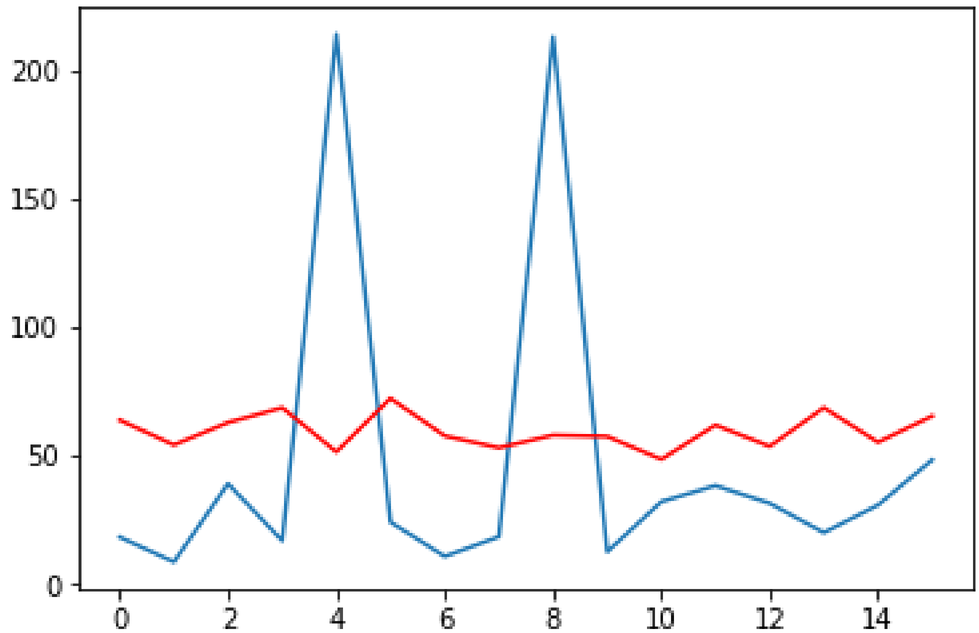

Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
0
10
20
30
40
50
60

This picture is slightly different but still a very week correlation. The data from Temperature sensor 3 is grouped in the corners across the diagonal line of the plot

```
In [61]: # split dataset to get only the values
         ts_values = tst3.values

         train, test = ts_values[1:len(ts_values)-16], ts_values[len(ts_values)-16:]

         # train autoregression
         model = AR(train)
         model_fit = model.fit()
         print('Lag: %s' % model_fit.k_ar)
         print('Coefficients: %s' % model_fit.params)

         predictions = model_fit.predict(start=len(train), end=len(train)+len(test)-1, dynamic=F
         for i in range(len(predictions)):
                 print('predicted=%f, expected=%f' % (predictions[i], test[i]))
         error = mean_squared_error(test, predictions)
         print('Test MSE: %.3f' % error)
         # plot results
         pyplot.plot(test)
         pyplot.plot(predictions, color='red')
         pyplot.show()
```

```
Lag: 25
Coefficients: [  5.59978137e+01  -1.04120543e-02   2.00623249e-02   4.62024193e-02
   1.73631752e-02   2.89807545e-02   1.95073802e-02   3.82435078e-03
  -2.55587717e-02  -3.74439006e-02   1.38307500e-02  -3.67027446e-02
  -6.31804168e-03   2.01473526e-02  -1.16677391e-02   4.49016735e-02
   3.68074183e-03  -9.88835703e-03  -1.42628190e-02  -4.71354738e-04
  -4.88825260e-02   5.74478786e-03  -8.82449307e-04   1.84671549e-04
  -1.30737253e-02   3.28170546e-02]
predicted=63.837555, expected=18.315985
predicted=54.176626, expected=8.627450
predicted=62.896705, expected=39.103883
predicted=68.673615, expected=16.892961
predicted=51.456087, expected=214.049583
predicted=72.322973, expected=24.171771
predicted=57.674683, expected=10.783225
predicted=53.076903, expected=18.457877
predicted=57.968395, expected=213.028850
predicted=57.481478, expected=12.600898
predicted=48.548418, expected=32.120889
predicted=61.918293, expected=38.328756
predicted=53.618871, expected=31.486923
predicted=68.689367, expected=20.050932
predicted=55.217424, expected=30.790151
predicted=65.431021, expected=48.316591
```

```
Test MSE: 4386.013
```



Running the AR model, I can see that lag: 25 was chosen again and model was trained on this. The 16-hour forecast is printed above. The forecast deviates quite a bit from the actual values peaking at 4 and 8

1.4.6 Ambient Temperature info - Plotly grapf and Autocorelation Plots

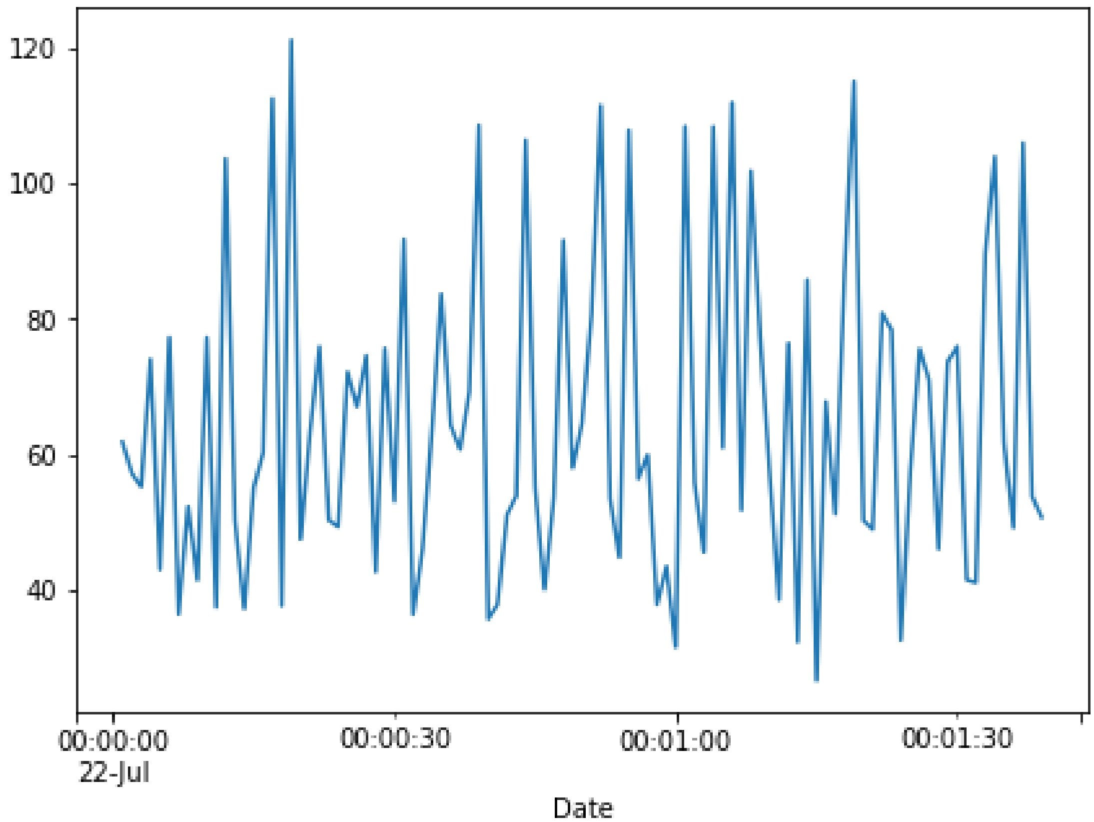
```
In [66]: trace10 = go.Scatter(
             y = df['Temp_Ambient'],
             mode='lines',
             name = 'Ambient Temp actual',
             marker=dict(
                 size='16',
                 color = np.random.randn(500),
                 showscale=True
             )
         )
         trace11 = go.Scatter(
             y = df['Temp_Am_ave'],
             mode='lines',
             name = 'Ambient Temp average',
             marker=dict(
                 size='16',
```

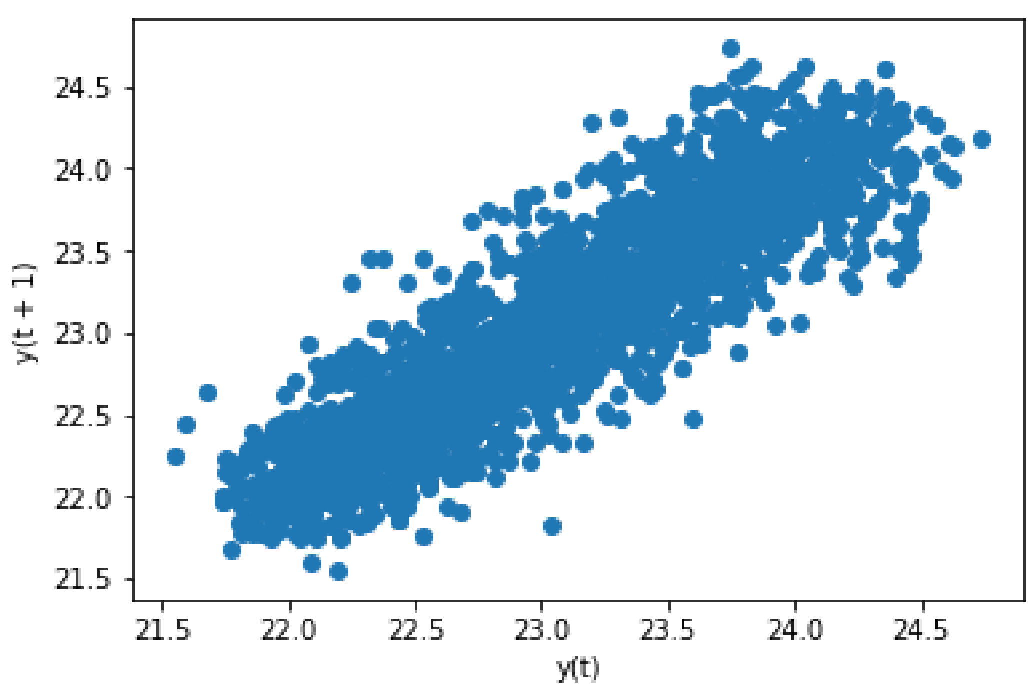
```
            color = np.random.randn(500),
            showscale=True
        )
    )
    trace12 = go.Scatter(
        y = df['Temp_Am_sd'],
        mode='lines',
        name = 'Ambient Temp standard deviation',
        marker=dict(
            size='16',
            color = np.random.randn(500),
            showscale=True
        )
    )

    data = [trace10, trace11, trace12]

    layout = dict(
        title='Temperature 3 High and Low values',
        xaxis=dict(
            rangeselector=dict(),
            rangeslider=dict(),
            type='date'
        )
    )

    fig = dict(data=data, layout=layout)
    py.iplot(fig, filename='styled-line')
```

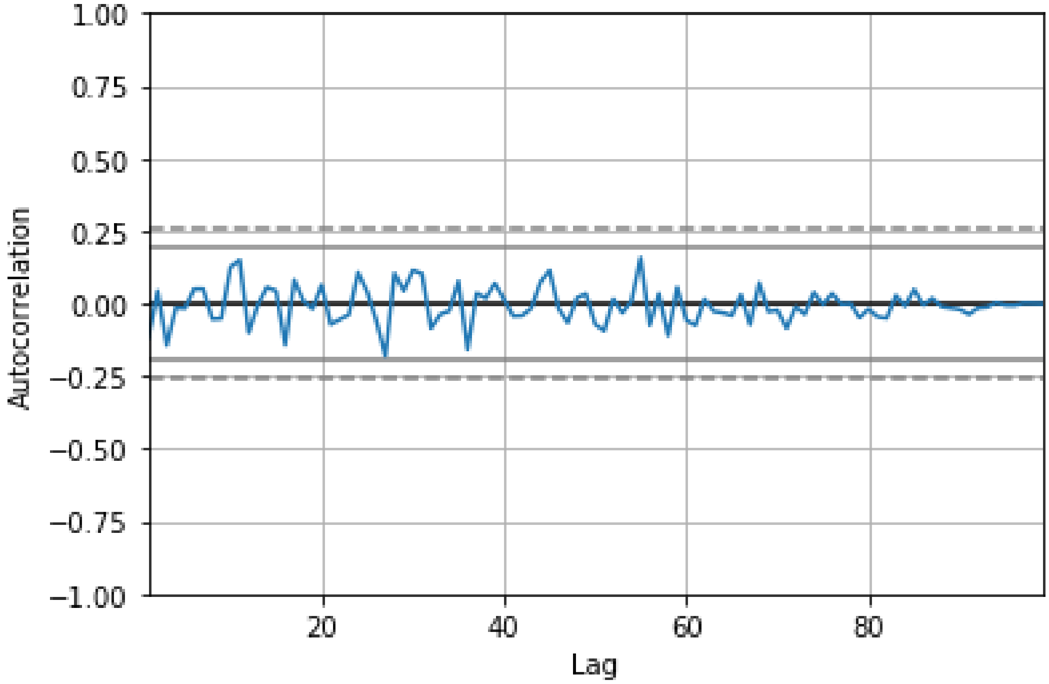
Out[66]: <plotly.tools.PlotlyDisplay object>

1.4.7 Please use the sliding scale to narrow the search / use magnification on a area of interest (down sampling did not work out for this type of plot)

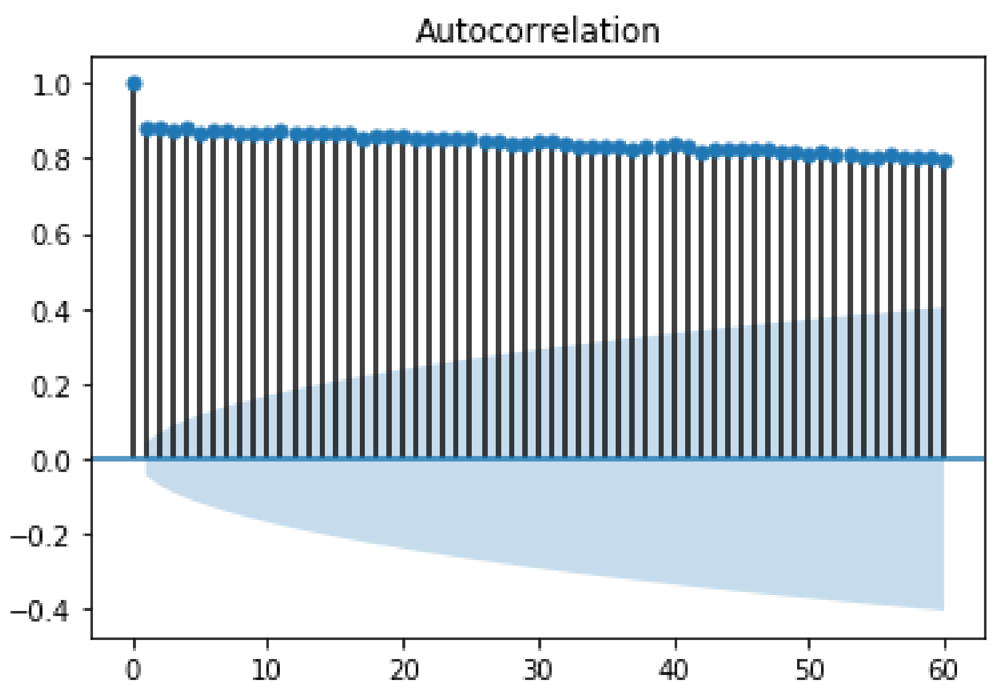
In [67]:
```
# The code will create the dataset for Temperature 3 Series.
tstA = Series(df['Temp_Ambient'].values, index=df.Date)
plt = tst2[1:100].plot(figsize=(7,5))
pyplot.show(plt)

lag_plot(tstA)
pyplot.show()

autocorrelation_plot(tstA[1:100])
pyplot.show()

plot_acf(tstA, lags=60)
pyplot.show()
```


120
100
80
60
40
00:00:00
22-Jul
00:00:30
00:01:00
00:01:30
Date


24.5
24.0
23.5
23.0
22.5
22.0
21.5
y(t + 1)
21.5
22.0
22.5
23.0
23.5
24.0
24.5
y(t)



1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Autocorrelation
20
40
60
80
Lag

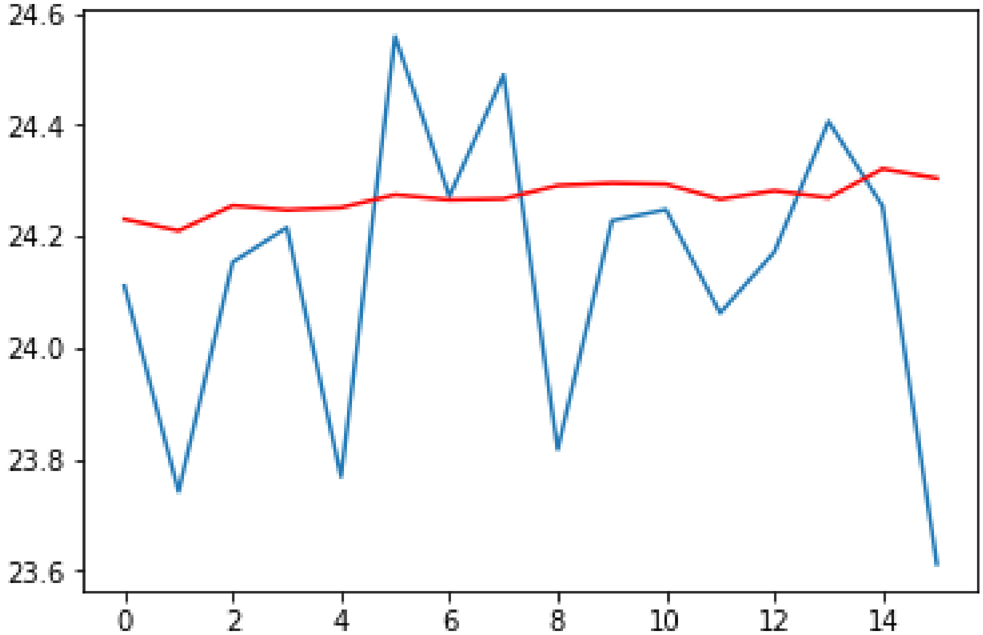


Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0
10
20
30
40
50
60

These pictures from the Ambient Temperature sensor indicate a high correlation but the correlation coefficient is still only between 0.25 and -0.25 which says this is a week correlation. The data spread across the diagonal line of the plot indicating a linear trend.

```
In [68]: # split dataset to get only the values
         ts_values = tstA.values

         train, test = ts_values[1:len(ts_values)-16], ts_values[len(ts_values)-16:]

         # train autoregression
         model = AR(train)
         model_fit = model.fit()
         print('Lag: %s' % model_fit.k_ar)
         print('Coefficients: %s' % model_fit.params)

         predictions = model_fit.predict(start=len(train), end=len(train)+len(test)-1, dynamic=F
         for i in range(len(predictions)):
                 print('predicted=%f, expected=%f' % (predictions[i], test[i]))
         error = mean_squared_error(test, predictions)
         print('Test MSE: %.3f' % error)
         # plot results
         pyplot.plot(test)
         pyplot.plot(predictions, color='red')
         pyplot.show()
```

```
Lag: 25
Coefficients: [ 0.10670338  0.04401479  0.05021367  0.00963759  0.05193998 -0.01580651
  0.04833818  0.06457539 -0.00534046 -0.00145579  0.02052801  0.07627349
  0.03171924  0.03096298  0.03677596  0.08002705  0.10041067 -0.0189653
  0.0385952   0.04453086  0.08712103  0.0145506   0.02567537  0.03542656
  0.07829053  0.06807416]
predicted=24.230786, expected=24.110918
predicted=24.210119, expected=23.741410
predicted=24.255270, expected=24.153455
predicted=24.247411, expected=24.215799
predicted=24.251645, expected=23.768086
predicted=24.274848, expected=24.558904
predicted=24.265577, expected=24.271811
predicted=24.267449, expected=24.489534
predicted=24.291308, expected=23.817173
predicted=24.295784, expected=24.228087
predicted=24.293777, expected=24.248050
predicted=24.266753, expected=24.062023
predicted=24.282027, expected=24.171938
predicted=24.269308, expected=24.406753
predicted=24.321363, expected=24.254122
predicted=24.304326, expected=23.611311
Test MSE: 0.087
```



Running the AR model, I can see that lag: 25 was chosen again and model was trained on this. The 16-hour forecast is printed above. The upward trend of the forecast is appropriate to the data.

1.5 Final thoughts:

This was a very challenging Summative assessment but I learnt allot in terms of managing Time series data. This is a great park of my daily work and discussions I have with my customers.

I did not manage to get data to SQL so I instead followed the advice of the moderators to create and use a csv file as my database.

Spark failed me on many occasions (I have two lines of code that i used - the greyed out one keeps requesting a java file link)

Visualizing the data was great: Plotly took some time to get going and autocorrelation porting was informative to myself.