```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model
import matplotlib.pyplot as plt
import seaborn as sns
import fbprophet
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn import metrics
from scipy.cluster.hierarchy import linkage, fcluster, dendrogram
from sklearn.cluster import KMeans, DBSCAN
from sklearn import metrics
import plotly.figure_factory as ff
```

```
data_m = pd.read_csv('xab.csv')
data_m.head()
```

| | Trip ID | Trip Start Timestamp | Trip End Timestamp | Trip Seconds | Trip Miles | Pickup Census Tract | Dropof Censu Trac |
|---|---|---|---|---|---|---|---|
| 0 | 9c620428487cada88130ab08e2ed063c4824852d | 9/12/19 12:45 | 9/12/19 12:45 | 24 | 0.0 | 1.703184e+10 | 1.703184e+1 |
| 1 | 9c62bd8cad97bd27430e2e3ffc07628a7fa00d5d | 8/18/19 19:00 | 8/18/19 19:00 | 242 | 0.0 | 1.703108e+10 | 1.703108e+1 |
| 2 | 9c62fa73e82e32a54c9f2aca47e11f370b9bb80c | 7/8/19 17:15 | 7/8/19 17:15 | 6 | 0.0 | NaN | NaN |
| 3 | 9c69c7bba2eb3f2846988fed0916b1dc245b0b14 | 9/27/19 6:30 | 9/27/19 6:30 | 10 | 0.0 | NaN | NaN |
| 4 | 9c7214acfd1aded46abeebe484939233d618c02a | 9/28/19 22:45 | 9/28/19 22:45 | 21 | 0.0 | 1.703107e+10 | 1.703107e+1 |

5 rows × 21 columns

```
x_train, x_val, y_train, y_val = train_test_split(data_m[["Trip Seconds","Trip Miles","Additional Charges"]],data_m["Trip Total"],train_size = 0.75, test_size = 0.25, random_state = 0)
```

```
scaler = StandardScaler()
x_train.fillna(x_train.mean(), inplace=True)
x_val.fillna(x_val.mean(), inplace=True)
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_test_scaled = scaler.transform(x_val)
```

```python
#Checking first for a model with 1 predictors.
pred_variable = ['Trip Seconds']
model = linear_model.LinearRegression().fit(X = x_train_scaled[:,[0]], y = y_train)

score_train = model.score(X = x_train_scaled[:,[0]], y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled[:,[0]], y = y_val) # R squared (Validation)

print([score_train, score_val])
```

```
[0.6303826877883139, 0.6381225798264011]
```

```python
pred_variable = ['Trip Miles']
model = linear_model.LinearRegression().fit(X = x_train_scaled[:,[1]], y = y_train)

score_train = model.score(X = x_train_scaled[:,[1]], y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled[:,[1]], y = y_val) # R squared (Validation)

print([score_train, score_val])
```

```
[0.791631450720499, 0.7801969515610844]
```

```python
pred_variable = ['Additional Charges']
model = linear_model.LinearRegression().fit(X = x_train_scaled[:,[1]], y = y_train)

score_train = model.score(X = x_train_scaled[:,[2]], y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled[:,[2]], y = y_val) # R squared (Validation)

print([score_train, score_val])
```

```
[0.3191401410618644, 0.32731097885973587]
```

```python
pred_variable = ['Trip Seconds', 'Trip Miles']
model = linear_model.LinearRegression().fit(X = x_train_scaled[:,[0,1]], y = y_train)

score_train = model.score(X = x_train_scaled[:,[0,1]], y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled[:,[0,1]], y = y_val) # R squared (Validation)

print([score_train, score_val])
```

```
[0.8052335202761105, 0.7963859365267957]
```

```python
pred_variable = ['Trip Seconds', 'Additional Charges']
model = linear_model.LinearRegression().fit(X = x_train_scaled[:,[0,2]], y = y_train)

score_train = model.score(X = x_train_scaled[:,[0,2]], y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled[:,[0,2]], y = y_val) # R squared (Validation)

print([score_train, score_val])
```

```
[0.762346024707321, 0.7643372401543252]
```

```python
pred_variable = ['Trip Miles', 'Additional Charges']
model = linear_model.LinearRegression().fit(X = x_train_scaled[:,[1,2]], y = y_train)

score_train = model.score(X = x_train_scaled[:,[1,2]], y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled[:,[1,2]], y = y_val) # R squared (Validation)

print([score_train, score_val])
```

```
[0.8388472989736899, 0.8309795982200868]
```

```python
model = linear_model.LinearRegression().fit(X = x_train_scaled, y = y_train)

score_train = model.score(X = x_train_scaled, y = y_train) # R squared (training)
score_val = model.score(X = x_test_scaled, y = y_val) # R squared (validation)
print([score_train, score_val])
```

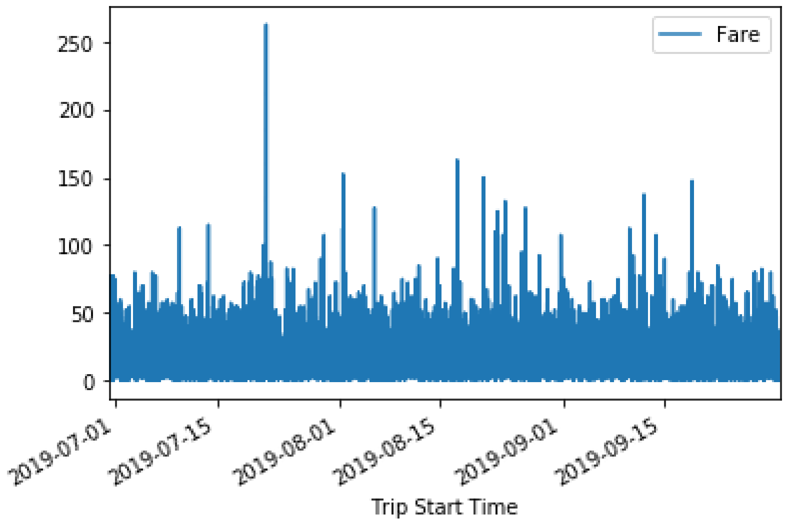
```
[0.8568569676498858, 0.8507027156783711]
```

```python
data_m['Trip Start Time']=pd.to_datetime(data_m['Trip Start Timestamp'])
data_m['Trip End Time']=pd.to_datetime(data_m['Trip End Timestamp'])
data = data_m.loc[:,['Fare']]
data = data.set_index(data_m['Trip Start Time'])
data['Fare'] = pd.to_numeric(data['Fare'], downcast = 'float', errors = 'coerce')
data.head()
```

| | Fare |
|---|---|
| **Trip Start Time** | |
| **2019-09-12 12:45:00** | 10.0 |
| **2019-08-18 19:00:00** | 2.5 |
| **2019-07-08 17:15:00** | 15.0 |
| **2019-09-27 06:30:00** | 2.5 |
| **2019-09-28 22:45:00** | 2.5 |

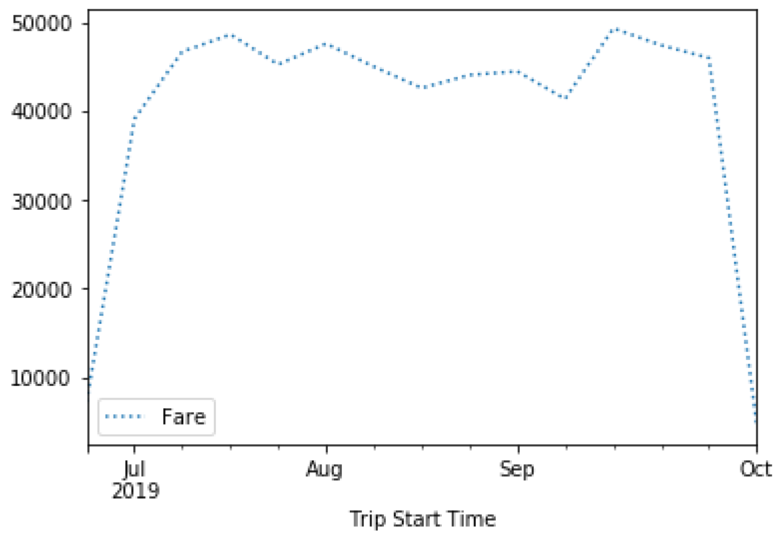
```
data.plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x21a73c791d0>
```



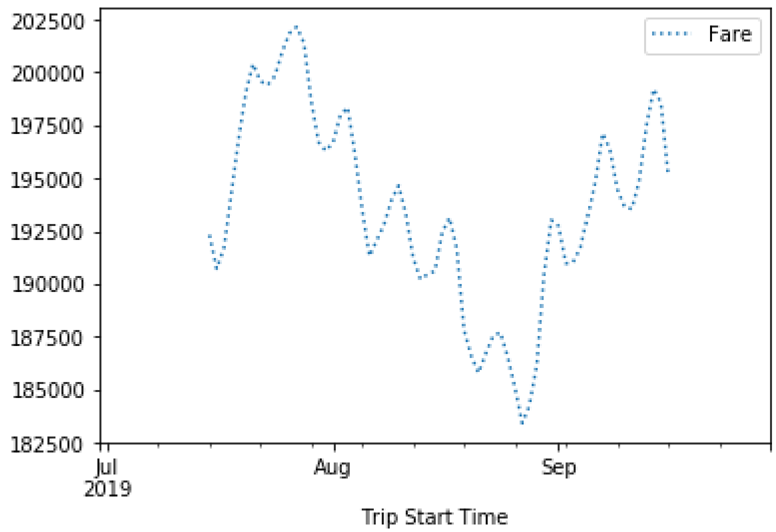
```
weekly = data.resample('W').sum()
pd.plotting.register_matplotlib_converters()
weekly.plot(style = [':','--','-'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x21a73f62668>
```



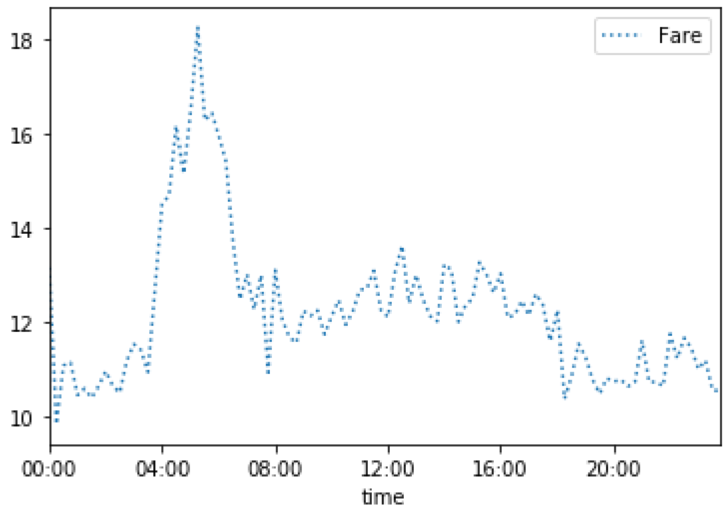
```python
daily = data.resample('D').sum()
daily.rolling(30, center=True).sum().plot(style = [':','--','-'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x21a7405eef0>
```



```
by_time = data.groupby(data.index.time).mean()
hourly_ticks = 4 * 60 * 60 * np.arange(6)
by_time.plot(xticks = hourly_ticks, style = [':','--','-'])
```

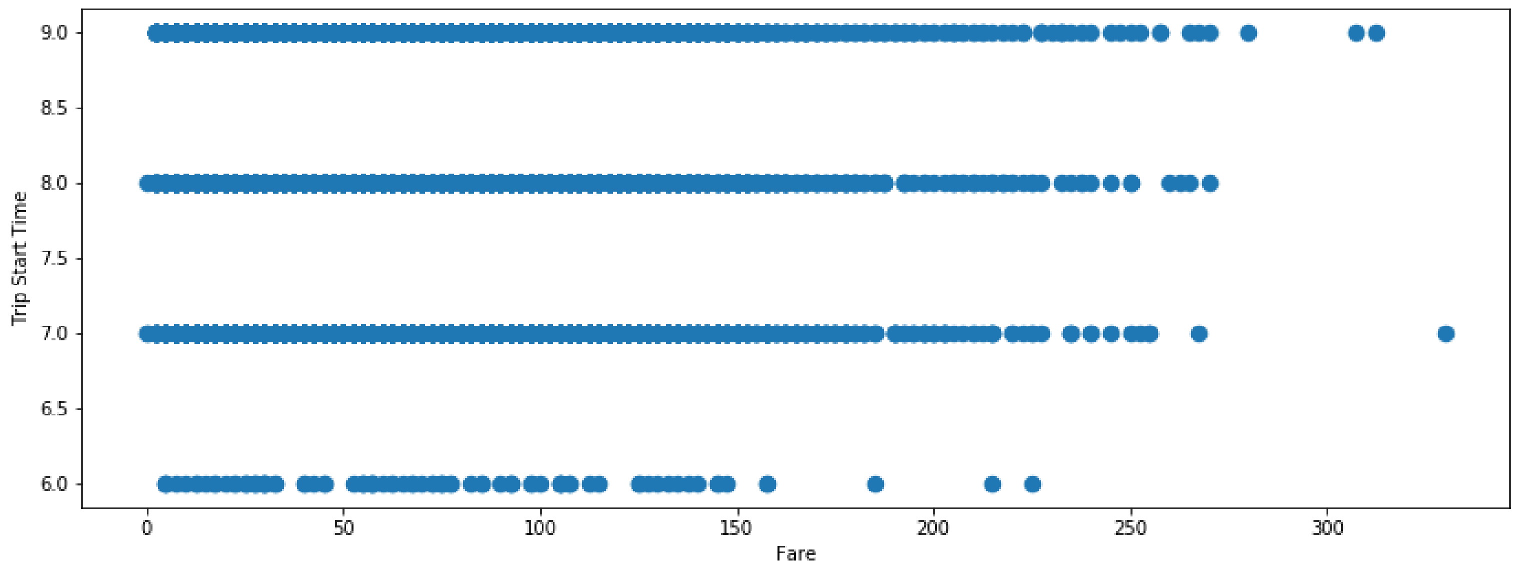
```
<matplotlib.axes._subplots.AxesSubplot at 0x21a740f7198>
```



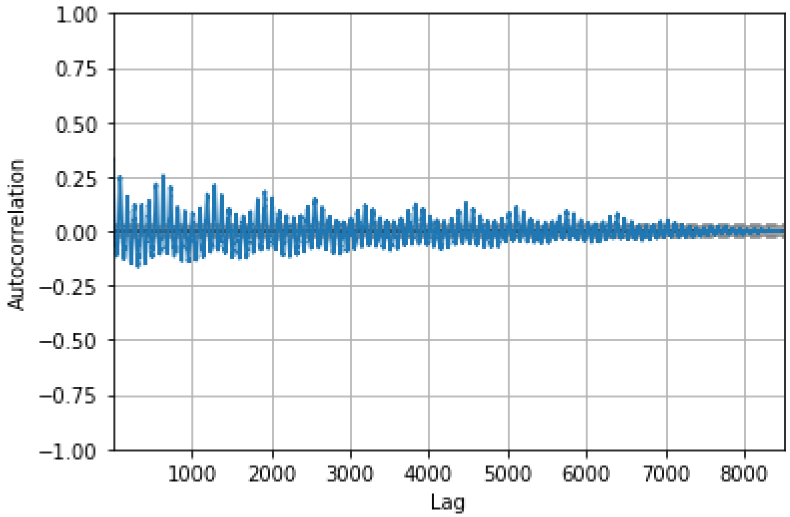

```
df = data_m.loc[:,['Trip Start Time', 'Fare']]
df['Fare'] = pd.to_numeric(df['Fare'], errors = 'coerce')
df = df.groupby(['Trip Start Time']).sum().reset_index()
df.head()
```

| | Trip Start Time | Fare |
|---|---|---|
| 0 | 2019-06-30 00:00:00 | 25.0 |
| 1 | 2019-06-30 00:15:00 | 102.5 |
| 2 | 2019-06-30 00:30:00 | 112.5 |
| 3 | 2019-06-30 00:45:00 | 35.0 |
| 4 | 2019-06-30 01:00:00 | 167.5 |

```
mon = data_m['Trip Start Time']
temp = pd.DatetimeIndex(mon)
month = pd.Series(temp.month)
to_be_plotted = df.drop(['Trip Start Time'], axis = 1)
to_be_plotted = to_be_plotted.join(month)
to_be_plotted.plot.scatter(x = 'Fare', y = 'Trip Start Time', figsize = (14,5), linewidth
= 5, fontsize = 10)
plt.show()
```



```
pd.plotting.autocorrelation_plot(df['Fare'])
plt.show()
```



```
df2 = data_m
df2.reset_index(inplace=True)
df2 = df2.rename(columns={'Trip Start Timestamp':'ds','Trip Total':'y'})
df2.head()
```

| | index | Trip ID | ds | Trip End Timestamp | Trip Seconds | Trip Miles | Pickup Census Tract | Drop Cens Tr |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 9c620428487cada88130ab08e2ed063c4824852d | 9/12/19 12:45 | 9/12/19 12:45 | 24 | 0.0 | 1.703184e+10 | 1.703184e |
| 1 | 1 | 9c62bd8cad97bd27430e2e3ffc07628a7fa00d5d | 8/18/19 19:00 | 8/18/19 19:00 | 242 | 0.0 | 1.703108e+10 | 1.703108e |
| 2 | 2 | 9c62fa73e82e32a54c9f2aca47e11f370b9bb80c | 7/8/19 17:15 | 7/8/19 17:15 | 6 | 0.0 | NaN | NaN |
| 3 | 3 | 9c69c7bba2eb3f2846988fed0916b1dc245b0b14 | 9/27/19 6:30 | 9/27/19 6:30 | 10 | 0.0 | NaN | NaN |
| 4 | 4 | 9c7214acfd1aded46abeebe484939233d618c02a | 9/28/19 22:45 | 9/28/19 22:45 | 21 | 0.0 | 1.703107e+10 | 1.703107e |

5 rows × 24 columns

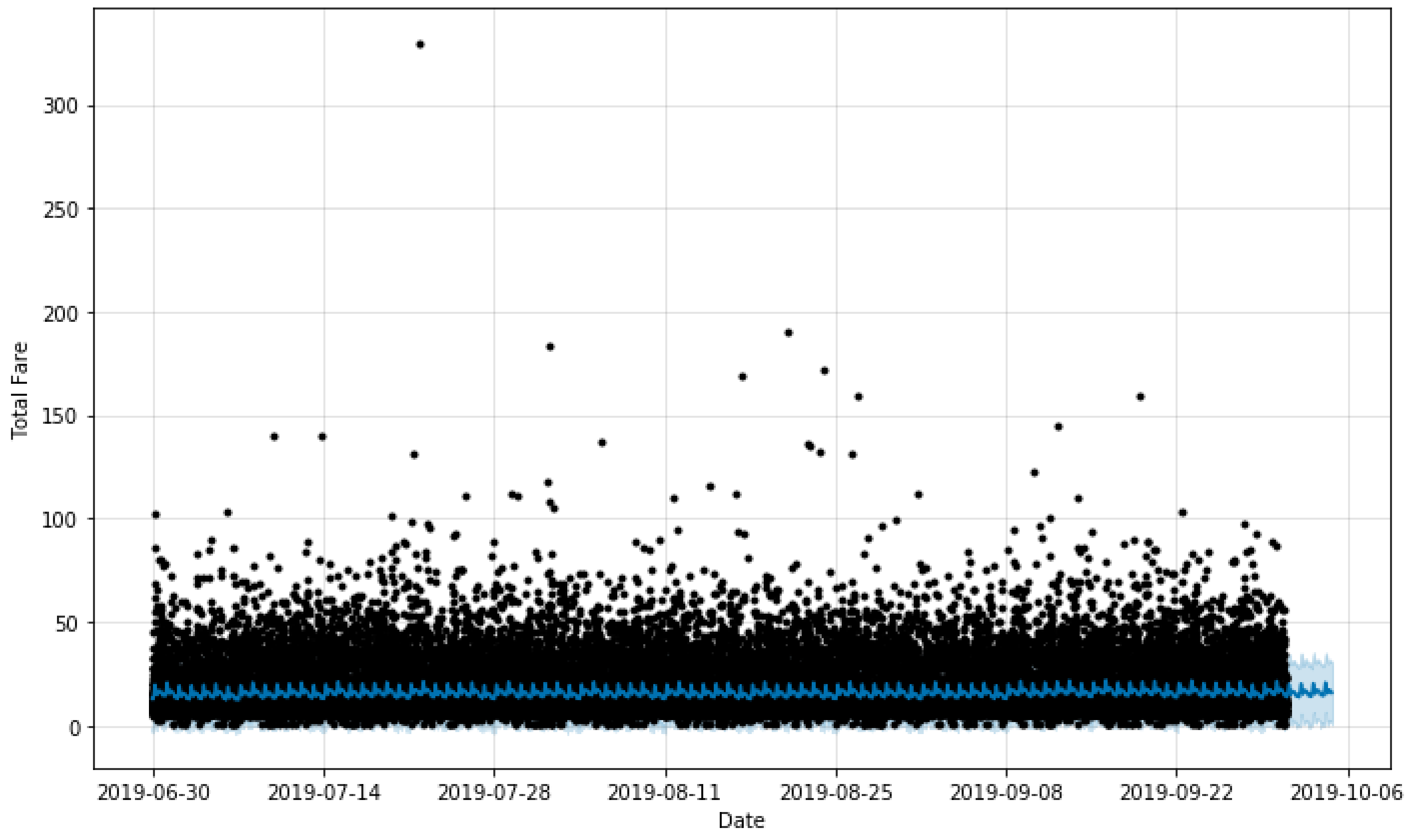
```
df2_prophet = fbprophet.Prophet(changepoint_prior_scale=0.10)
df2_prophet.fit(df2)
```

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
```

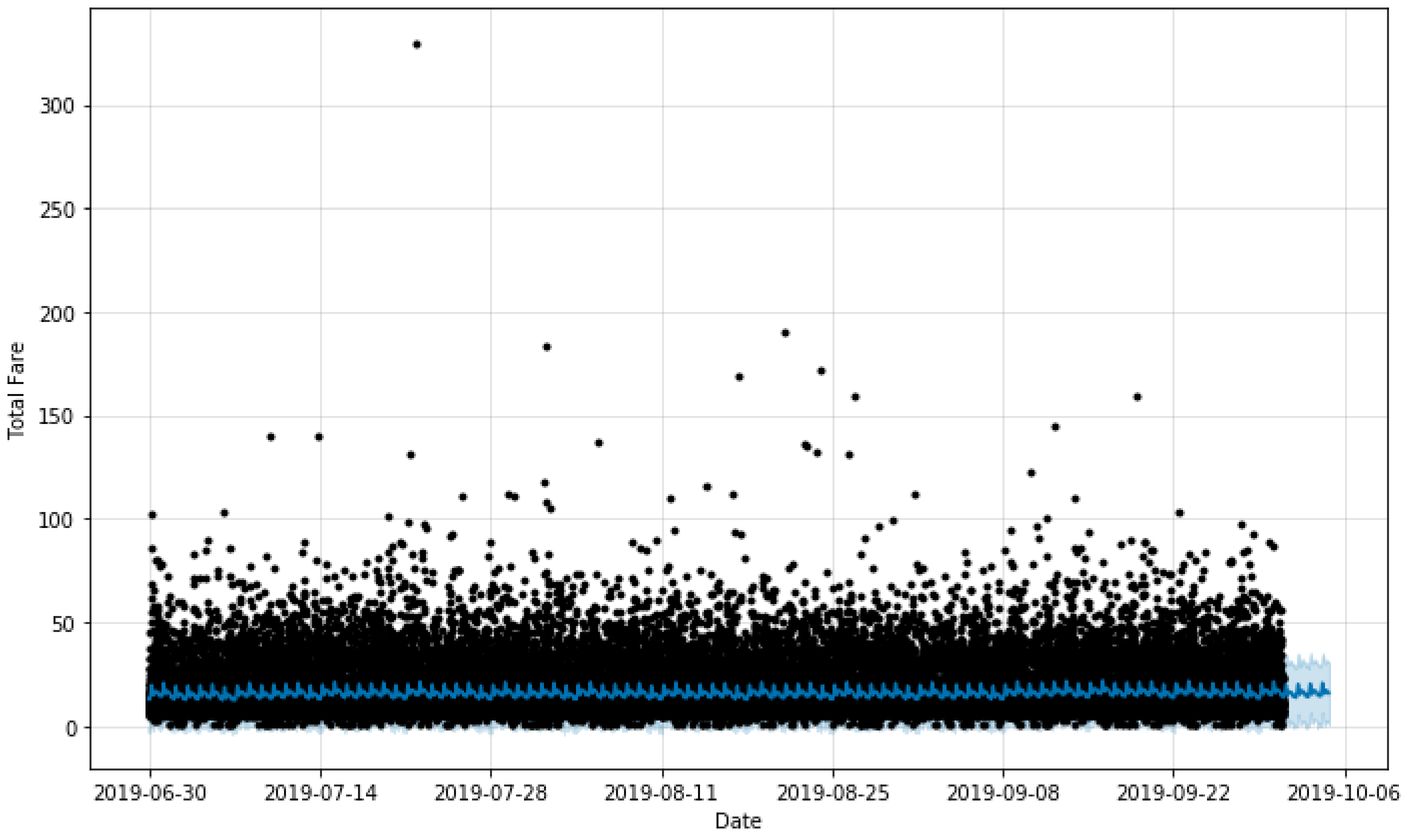
```
<fbprophet.forecaster.Prophet at 0x21a74206278>
```

```
df2_forecast = df2_prophet.make_future_dataframe(periods= 30*3, freq = 'H')
df2_forecast = df2_prophet.predict(df2_forecast)
```

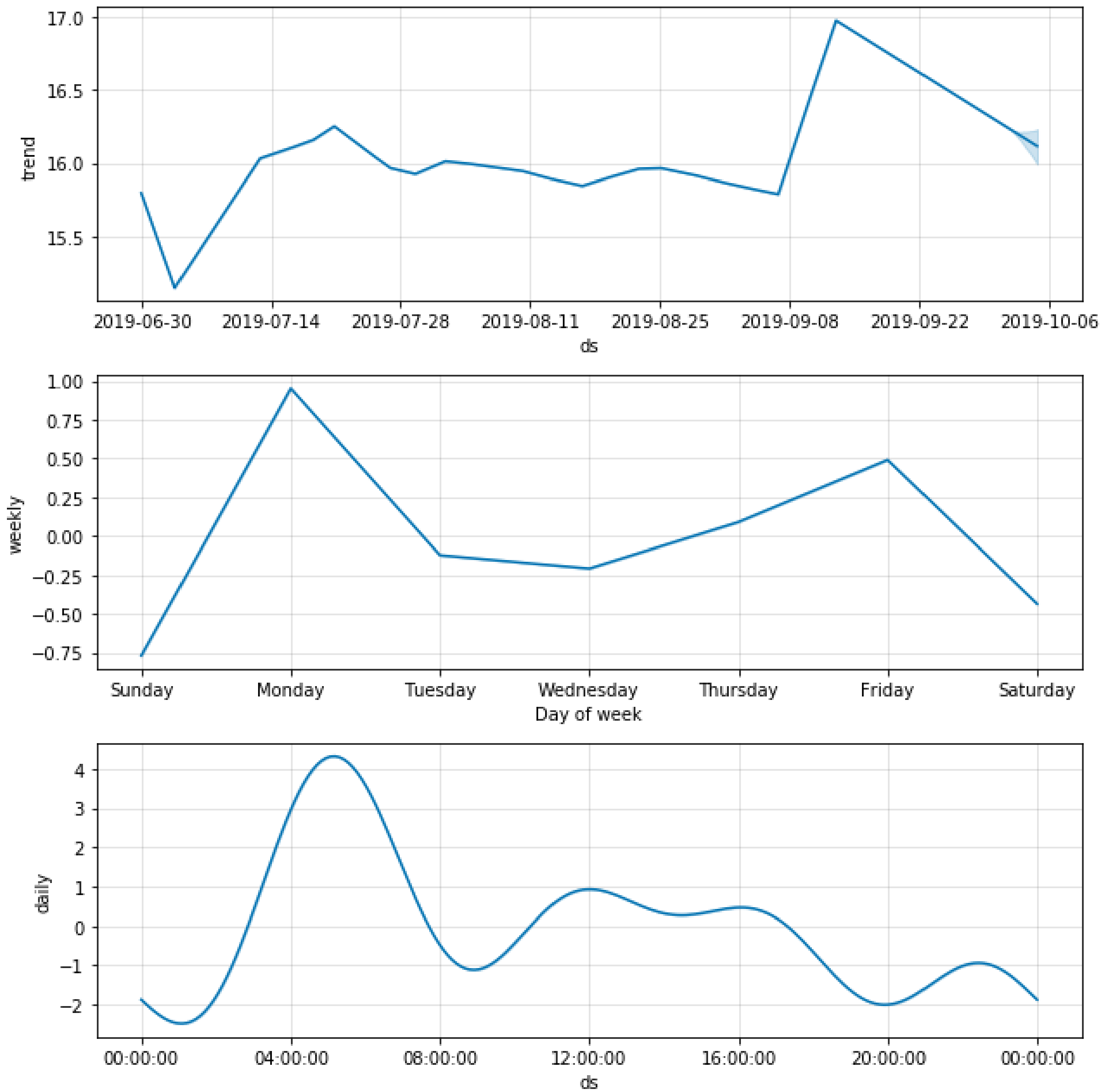
```
df2_prophet.plot(df2_forecast, xlabel = 'Date', ylabel = 'Total Fare')
```

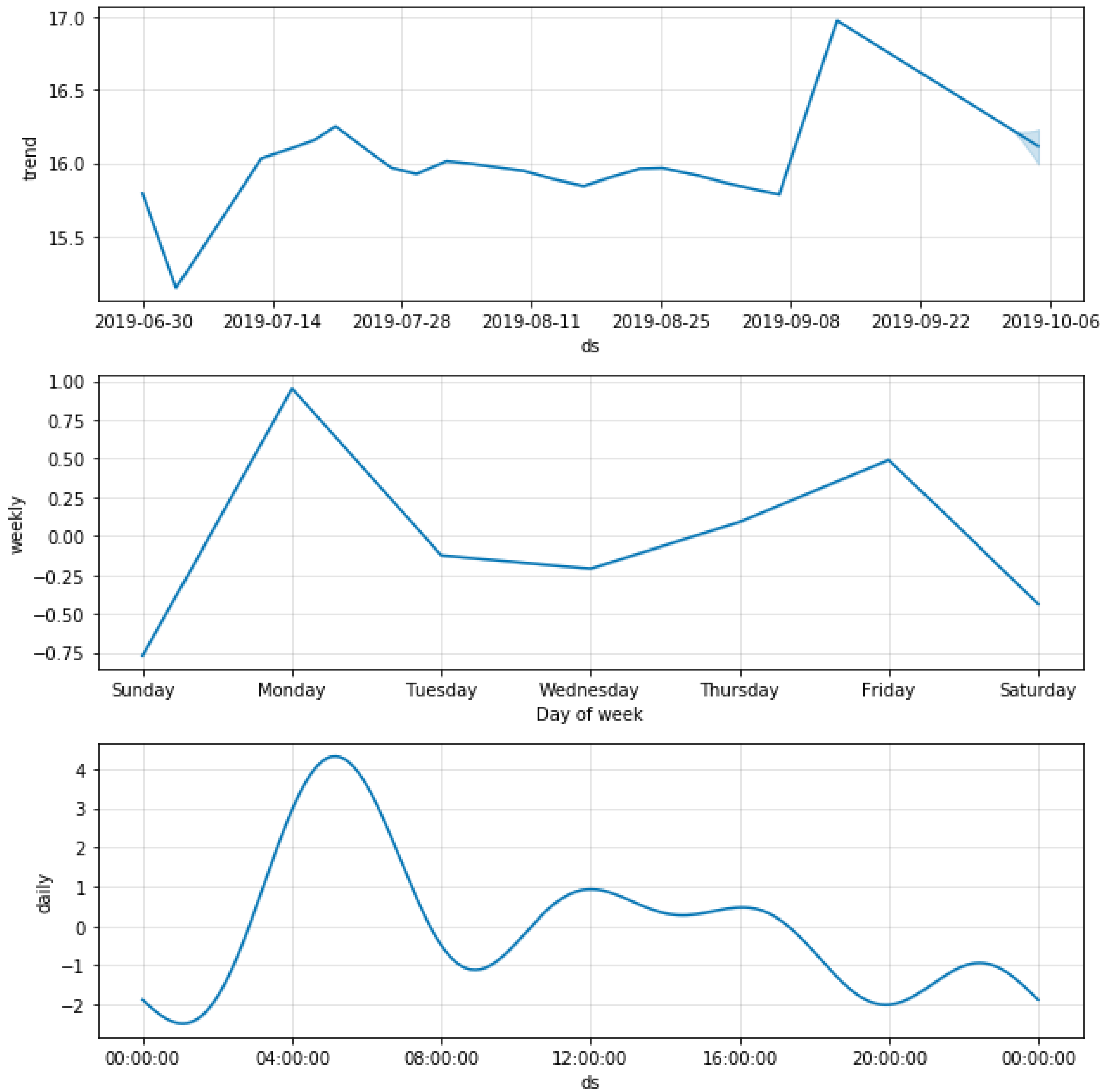


Total Fare
300
250
200
150
100
50
0
2019-06-30
2019-07-14
2019-07-28
2019-08-11
2019-08-25
2019-09-08
2019-09-22
2019-10-06
Date


300
250
200
150
100
50
0
Total Fare
2019-06-30
2019-07-14
2019-07-28
2019-08-11
2019-08-25
2019-09-08
2019-09-22
2019-10-06
Date

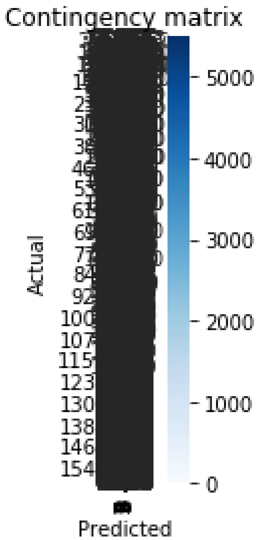
```
df2_prophet.plot_components(df2_forecast)
```


17.0
16.5
16.0
15.5
trend
2019-06-30
2019-07-14
2019-07-28
2019-08-11
2019-08-25
2019-09-08
2019-09-22
2019-10-06
ds
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
weekly
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week
4
3
2
1
0
−1
−2
daily
00:00:00
04:00:00
08:00:00
12:00:00
16:00:00
20:00:00
00:00:00
ds


17.0
16.5
16.0
15.5
trend
2019-06-30
2019-07-14
2019-07-28
2019-08-11
2019-08-25
2019-09-08
2019-09-22
2019-10-06
ds
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
weekly
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week
4
3
2
1
0
−1
−2
daily
00:00:00
04:00:00
08:00:00
12:00:00
16:00:00
20:00:00
00:00:00
ds

```python
# K-Means with 5 clusters, 10 iterations
# "Trip Seconds","Trip Miles","Additional Charges"
# Variables used: 'Trip Seconds'[0] , 'Trip Miles'[1], 'Additional Charges'[2]

# pick certain variables from x_train_scaled
X = []
for i in x_train_scaled:
    X.append([i[1]])


# cluster observations
clustering = KMeans(n_clusters = 10, init='random', max_iter = 25, random_state=0).fit(X,
y_train)
clusters = clustering.labels_

# build and display contingency matrix
cont_matrix = metrics.cluster.contingency_matrix(y_train, clusters)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap = plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()

# determine adjusted rand index and silhouette coefficient
adjusted_rand_index = metrics.adjusted_rand_score(y_train, clusters)
silhouette_coefficient = metrics.silhouette_score(X, clusters)
print([adjusted_rand_index, silhouette_coefficient])
```

```
[0.21679215799007667, 0.556602484739871]
```



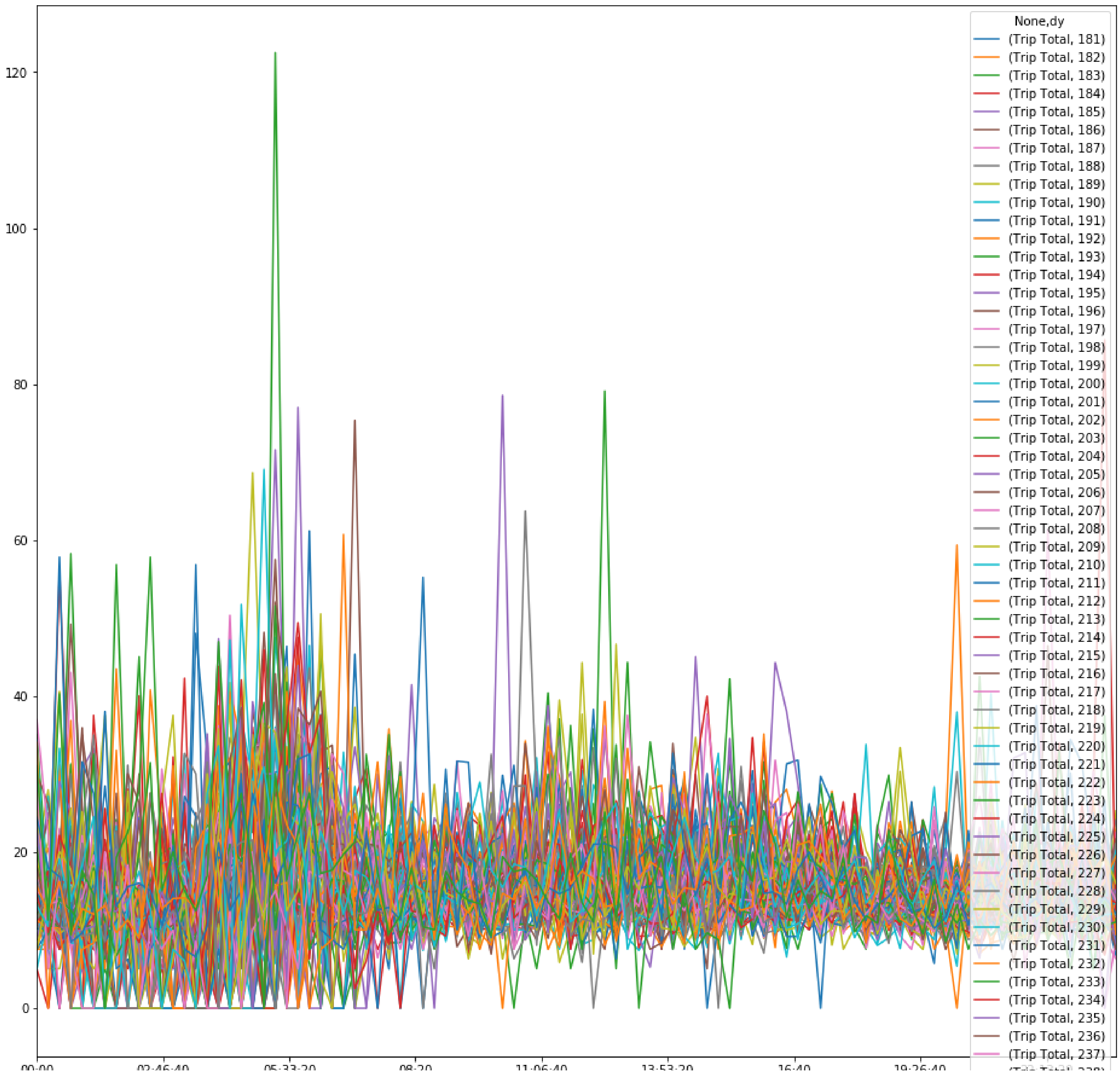
```
data_m['Trip Date'] = pd.to_datetime(data_m['Trip Start Timestamp'])
data_m['dy'] = data_m['Trip Date'].dt.dayofyear
data_m['Hours'] = data_m['Trip Date'].dt.time
data = data_m.loc[:,['Hours','dy','Trip Total']]
temp = data_m.loc[:,['dy','Trip Total']]
data['Trip Total'] = pd.to_numeric(data['Trip Total'],errors = 'coerce')
temp = temp.set_index(data['Hours'])
temp = data.pivot_table(index=['Hours'],columns = ['dy'], values = ['Trip Total'], fill_va
lue = 0)
temp.head()
```

| | Trip Total | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| dy | 181 | 182 | 183 | 184 | 185 | 186 | 187 | 188 | 189 | 190 | ... | 264 |
| Hours | | | | | | | | | | | | |
| 00:00:00 | 10.883333 | 18.14 | 19.233333 | 27.575 | 10.810000 | 26.830000 | 14.540000 | 18.771429 | 14.4875 | 8.8000 | ... | 14.4250 |
| 00:15:00 | 14.211111 | 13.80 | 9.550000 | 11.850 | 12.975000 | 10.327778 | 11.328571 | 8.958333 | 13.8000 | 16.3000 | ... | 9.67500 |
| 00:30:00 | 13.855556 | 22.15 | 16.050000 | 13.660 | 9.488889 | 10.110000 | 10.875000 | 8.981250 | 14.7300 | 10.5500 | ... | 22.1500 |
| 00:45:00 | 7.958333 | 20.42 | 0.000000 | 8.800 | 15.162500 | 12.520000 | 8.216667 | 10.933333 | 15.5500 | 21.1625 | ... | 18.1585 |
| 01:00:00 | 12.984375 | 6.94 | 0.000000 | 10.050 | 11.050000 | 16.583333 | 9.425000 | 13.133333 | 8.2200 | 0.0000 | ... | 10.0500 |

5 rows × 93 columns

```
temp.plot(figsize=(16,16))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x21a3dc59400>
```



None,dy
(Trip Total, 181)
(Trip Total, 182)
(Trip Total, 183)
(Trip Total, 184)
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(Trip Total, 186)
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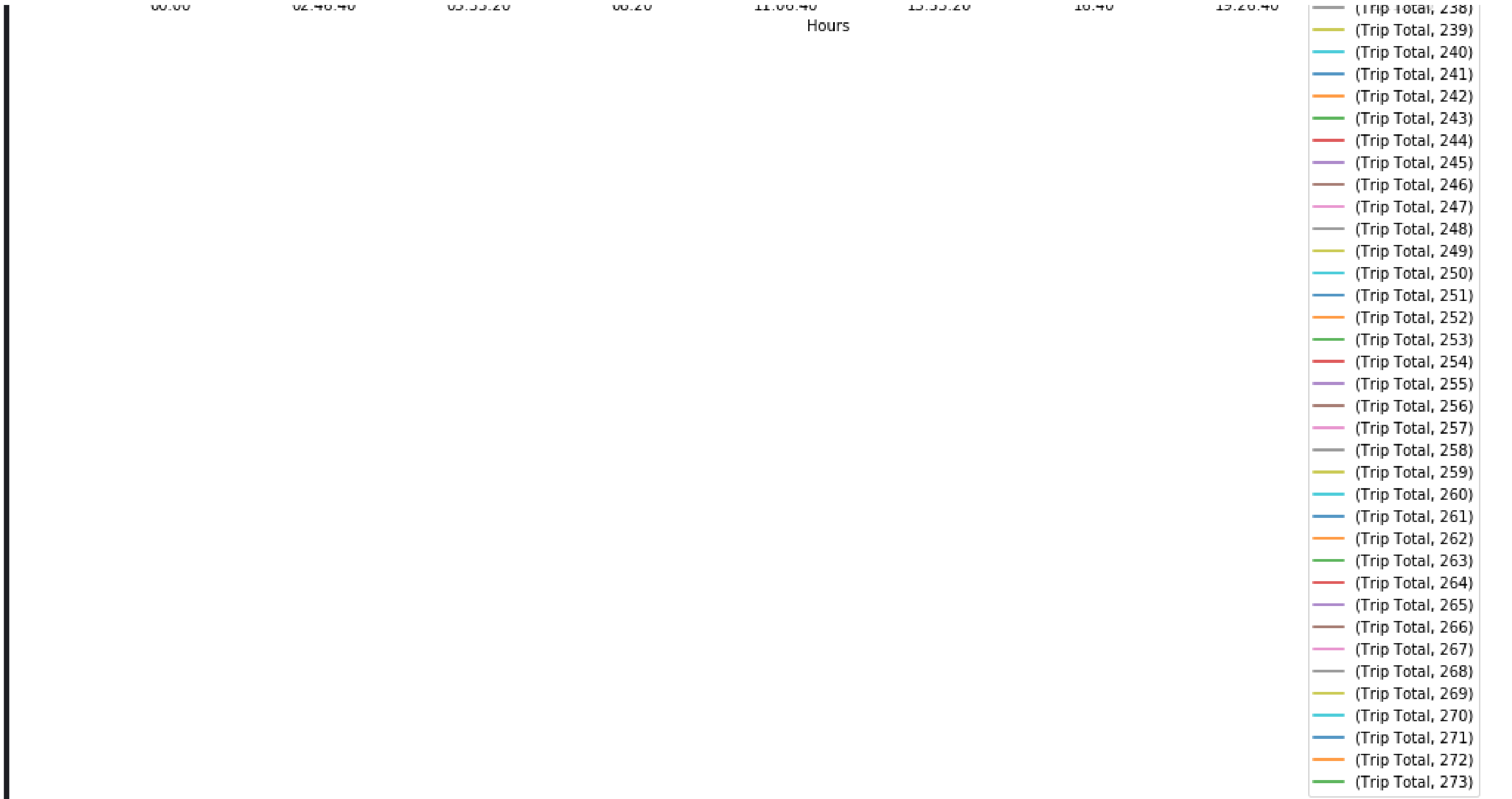
(Trip Total, 231)
(Trip Total, 232)
(Trip Total, 233)
(Trip Total, 234)
(Trip Total, 235)
(Trip Total, 236)
(Trip Total, 237)
120
100
80
60
40
20
0




```
z = linkage(temp.iloc[:,:], 'ward')
```

```
plt.figure(figsize=(25,10))
plt.title('Hierarchical Clustering Technique')
plt.xlabel('s')
plt.ylabel('f')
dendrogram(
           z,
           leaf_rotation = 90,
           leaf_font_size = 8,
)
plt.show()
```