<pre>import pandas as pd import numpy as np import matplotlib.pyplot as plt %matplotlib inline import warnings warnings.filterwarnings('ignore') from fbprophet import Prophet</pre> # !pip install fbprophet	
<pre># !pip install fbprophet # install visual c++ - visual studio # if you face errors - use conda install Loading the dataset df = pd.read_csv('Traffic data.csv') df.head()</pre>	
df . head() ID Datetime Count 0 0 25-08-2012 00:00 8 1 1 25-08-2012 01:00 2 2 2 25-08-2012 02:00 6	
3 3 25-08-2012 03:00 2 4 4 25-08-2012 04:00 2 df ID Datetime Count	
0 0 25-08-2012 00:00 8 1 1 25-08-2012 01:00 2 2 2 25-08-2012 02:00 6 3 3 25-08-2012 03:00 2	
4 4 25-08-2012 04:00 2 18283 18283 25-09-2014 19:00 868 18284 18284 25-09-2014 20:00 732 18285 18285 25-09-2014 21:00 702	
18285 16265 25-09-2014 21:00 702 18286 18286 25-09-2014 22:00 580 18287 18287 25-09-2014 23:00 534 18288 rows × 3 columns	
<pre>Preprocessing the dataset # check null values df.isnull().sum() ID 0 Datetime 0 Count 0</pre>	
<pre>dtype: int64 df.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 18288 entries, 0 to 18287 Data columns (total 3 columns): # Column Non-Null Count Dtype</class></pre>	
<pre>1 Datetime 18288 non-null object 2 Count 18288 non-null int64 dtypes: int64(2), object(1) memory usage: 428.8+ KB # convert object to datetime datatype df['Datetime'] = pd.to_datetime(df['Datetime'], format='%d-%m-%Y %H:%M') df.info() <class 'pandas.core.frame.dataframe'=""></class></pre>	
RangeIndex: 18288 entries, 0 to 18287 Data columns (total 3 columns): # Column Non-Null Count Dtype	
<pre># EDA plt.figure(figsize=(10,7)) plt.plot(df['Datetime'], df['Count']) plt.show()</pre>	
1000 - 800 - 600 -	
Z012-10 Z013-01 Z013-04 Z013-07 Z013-10 Z014-01 Z014-07 Z014-10 Format data for the model df.index = df['Datetime'] df['y'] = df['Count'] df.drop(columns=['ID', 'Datetime', 'Count'], axis=1, inplace=True)	
df = df.resample('D').sum() df.head() y Datetime 2012-08-25 76	
2012-08-26 88 2012-08-27 62 2012-08-28 58 2012-08-29 60	
df['ds'] = df.index df.head() y	
2012-08-26 88 2012-08-26 2012-08-27 62 2012-08-27 2012-08-28 58 2012-08-28 2012-08-29 60 2012-08-29	
<pre>Input Split size = 60 from sklearn.model_selection import train_test_split train, test = train_test_split(df, test_size=size/len(df), shuffle=False) train.tail()</pre>	
Datetime 2014-07-23 10130 2014-07-23 2014-07-24 8156 2014-07-25 7192 2014-07-25	
2014-07-26 6562 2014-07-26 2014-07-27 6094 2014-07-27 test.head() y ds	
Datetime 2014-07-28 8546 2014-07-28 2014-07-29 8218 2014-07-29 2014-07-30 8498 2014-07-30 2014-07-31 8740 2014-07-31	
2014-08-01 9186 2014-08-01 test.tail() y ds Datetime	
2014-09-21 9102 2014-09-21 2014-09-22 14116 2014-09-22 2014-09-23 13304 2014-09-23 2014-09-24 16856 2014-09-24	
<pre>Model Training model = Prophet(yearly_seasonality=True, seasonality_prior_scale=0.9) model.fit(train)</pre>	
<pre>INFO:numexpr.utils:NumExpr defaulting to 4 threads. INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this. <fbprophet.forecaster.prophet 0x1a0a1773a90="" at=""> future = model.make_future_dataframe(periods=60) future ds</fbprophet.forecaster.prophet></pre>	
 0 2012-08-25 1 2012-08-26 2 2012-08-27 3 2012-08-28 4 2012-08-29 	
 1 2012-08-26 2 2012-08-27 3 2012-08-28 	
1 2012-08-26 2 2012-08-27 3 2012-08-28 4 2012-08-29 757 2014-09-21 758 2014-09-22 759 2014-09-23 760 2014-09-24 761 2014-09-25 762 rows × 1 columns	upper multiplicative terms multiplicative terms lower multiplic
1 2012-08-26 2 2012-08-27 3 2012-08-28 4 2012-08-29	
1 2012-08-26 2 2012-08-27 3 2012-08-28 4 2012-08-29	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2012-08-26 2 2012-08-27 3 2012-08-28 4 2012-08-29	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 0012-08-08 2 012-08-29 3 2012-08-29 4 7072-08-19 5 2014-08-22 709 2014-08-22 70	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2012-0-2-0-5 2 2012-0-2-0-5 3 2012-0-2-0-5 3 2012-0-2-0-5 4 2012-0-2-0-5 787 2014-0-3-1 788 2014-0-3-0 788 2014-0-3-0 789 2014-0-3-0 780 20	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2012-05-07 2012-09-02 2012-09-0	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2012-05-05 2 212-05-05 4 012-05-05 2 212-05 2 212-05 2	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2010-02-5 2 201	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2010-02-5 2 201	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
3 - 20-20-207	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
2 9 19 19 19 19 19 19 19 19 19 19 19 19 1	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 37 19/10/27 2 57 19/10/27 2	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 172-1738 1 172-1738	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 SINCE 1 SINC	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
1 - 2 - 2 - 2 - 2 - 2 - 2 - 2 - 2 - 2 -	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
	175040 0.0 0.0 912400 0.0 0.0 204990 0.0 0.0 170355 0.0 0.0
	172040 0.0 0.0 0.0 1224500 0.0 0.0 0.0 1224500 0.0 0.0 0.0 1224500 0.0 0.0 0.0 1224500 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
	172040 0.0 0.0 0.0 1224500 0.0 0.0 0.0 1224500 0.0 0.0 0.0 1224500 0.0 0.0 0.0 1224500 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0