Case Study 1:Time Series Analysis of Power Consumption in India (2019-2020)

Importing the Libraries

```
import pandas as pd
from prophet import Prophet
from matplotlib import pyplot
from matplotlib.pyplot import figure
from sklearn.metrics import mean_absolute_error
import plotly.express as px
import plotly.graph_objects as go
```

Loading the Dataset

```
df=pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Datasets/long_data_.csv')
```

```
df.head()
```

	States	Regions	latitude	longitude	Dates	Usage
0	Punjab	NR	31.519974	75.980003	02/01/2019 00:00:00	119.9
1	Haryana	NR	28.450006	77.019991	02/01/2019 00:00:00	130.3
2	Rajasthan	NR	26.449999	74.639981	02/01/2019 00:00:00	234.1
3	Delhi	NR	28.669993	77.230004	02/01/2019 00:00:00	85.8
4	UP	NR	27.599981	78.050006	02/01/2019 00:00:00	313.9

```
df.shape
```

```
(16599, 6)
```

```
df.dtypes
```

```
States        object
Regions       object
latitude     float64
longitude    float64
Dates         object
Usage        float64
dtype: object
```

Formating Date Column into DateTime Format

```
df['Dates'] = pd.to_datetime(df['Dates'])
```

Group by Dates

```
df=df.groupby('Dates',as_index=False).mean()
print(df.head())
```

```
       Dates  latitude  longitude       Usage
0 2019-01-07  23.17822  81.794533  103.736364
1 2019-01-08  23.17822  81.794533  113.951515
2 2019-01-09  23.17822  81.794533  107.836364
3 2019-01-10  23.17822  81.794533   98.045455
4 2019-01-11  23.17822  81.794533   84.463636
<ipython-input-9-7cc86dfc4f3e>:1: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is dep
  df=df.groupby('Dates',as_index=False).mean()
```

```
df.shape
```

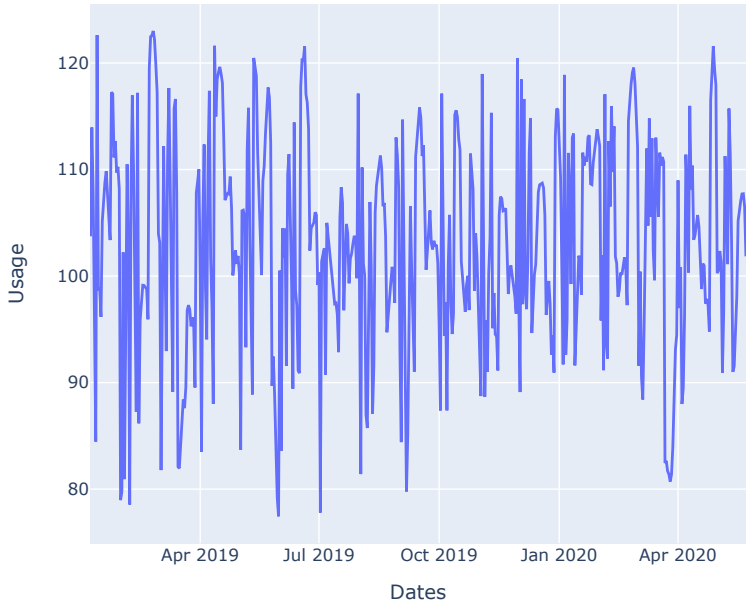
```
(498, 4)
```

Selecting DateTime Column and Target Column

```
df=df[['Dates','Usage']]
```

Ploting the Data

```
fig = px.line(df, x='Dates', y='Usage')
fig.show()
```




```
df.columns = ['ds','y']
```

```
df.head()
```

	ds	y
0	2019-01-07	103.736364
1	2019-01-08	113.951515
2	2019-01-09	107.836364
3	2019-01-10	98.045455
4	2019-01-11	84.463636

Initialize the model

```
model=Prophet()
```

Fit the model to the Dataframe

```
model.fit(df)
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpx3emyk9j/34epwzgz.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpx3emyk9j/ekecypw6.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bin', 'ra
08:18:31 - cmdstanpy - INFO - Chain [1] start processing
```

```
INFO:cmdstanpy:Chain [1] start processing
08:18:31 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7f97c3cedb10>
```

```
model.component_modes
```

```
{'additive': ['weekly',
  'additive_terms',
  'extra_regressors_additive',
  'holidays'],
 'multiplicative': ['multiplicative_terms', 'extra_regressors_multiplicative']}
```

Make Future Dataframe

```
future_dates = model.make_future_dataframe(periods=365,freq='d',include_history=True)
future_dates.shape
```

```
(863, 1)
```

```
future_dates.head()
```

	ds
0	2019-01-07
1	2019-01-08
2	2019-01-09
3	2019-01-10
4	2019-01-11

Prediction of the Model

```
prediction=model.predict(future_dates)
```

```
prediction.head()
```

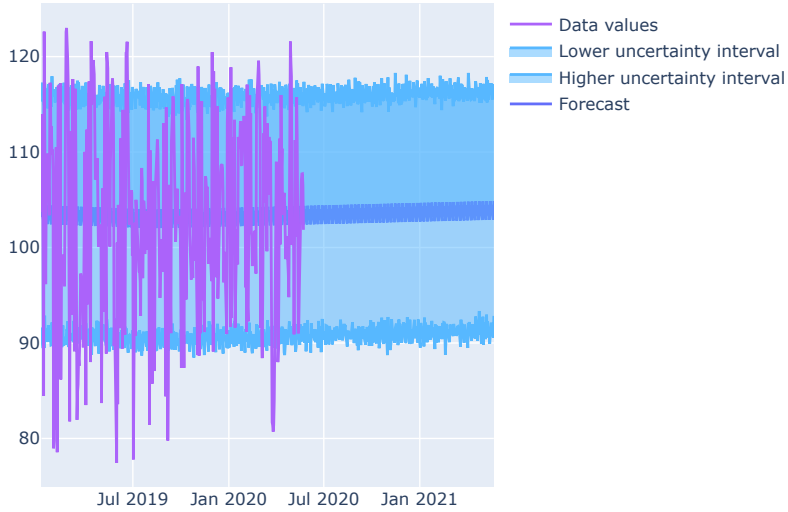
	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	additive_terms_lower	additive
0	2019-01-07	103.380111	90.463652	116.117738	103.380111	103.380111	-0.184879	-0.184879	
1	2019-01-08	103.377977	91.599491	117.265136	103.377977	103.377977	0.650401	0.650401	
2	2019-01-09	103.375844	89.890820	115.375077	103.375844	103.375844	0.151418	0.151418	
3	2019-01-10	103.373710	89.455529	115.300017	103.373710	103.373710	-0.293238	-0.293238	
4	2019-01-11	103.371576	91.292043	115.863443	103.371576	103.371576	-0.470827	-0.470827	

Ploting the Prediction

```
trace_open = go.Scatter(
    x = prediction["ds"],
    y = prediction["yhat"],
    mode = 'lines',
    name="Forecast"
)
trace_high = go.Scatter(
    x = prediction["ds"],
    y = prediction["yhat_upper"],
    mode = 'lines',
    fill = "tonexty",
```

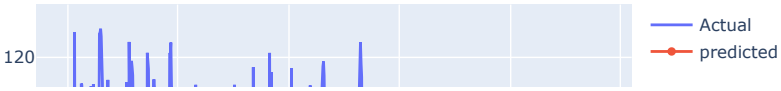
```
    line = {"color": "#57b8ff"},
    name="Higher uncertainty interval"
)
trace_low = go.Scatter(
    x = prediction["ds"],
    y = prediction["yhat_lower"],
    mode = 'lines',
    fill = "tonexty",
    line = {"color": "#57b8ff"},
    name="Lower uncertainty interval"
)
trace_close = go.Scatter(
    x = df["ds"],
    y = df["y"],
    name="Data values"
)

data = [trace_open,trace_high,trace_low,trace_close]
layout = go.Layout(title="Power consumption forecasting")
fig = go.Figure(data=data)
fig.show()
```



Plot the Actual Vs Predicted without Optimization

```
fig = go.Figure([go.Scatter(x=df['ds'], y=df['y'],mode='lines', name='Actual')])
fig.add_trace(go.Scatter(x=prediction['ds'], y=prediction['yhat'],mode='lines+markers',name='predicted'))
fig.show()
```



Mean Absolute Error

```
y_true = df['y'].values
y_pred = prediction['yhat'][:498].values
mae = mean_absolute_error(y_true, y_pred)
print('MAE: %.3f' % mae)
```

```
MAE: 7.910
```

Optimizing the Model for better Forecasting

```
model1=Prophet(daily_seasonality=True).add_seasonality(name='yearly',period=365,fourier_order=70)
```

Fiting Model for Hyper Parameter Tuning

```
model1.fit(df)
```

```
INFO:prophet:Found custom seasonality named 'yearly', disabling built-in 'yearly' seasonality.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpx3emyk9j/hb3bro3_.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpx3emyk9j/5jue_v7f.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bin', 'ra
08:27:21 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
08:27:21 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7f97c3c2f700>
```

```
model1.component_modes
```

```
{'additive': ['yearly',
  'weekly',
  'daily',
  'additive_terms',
  'extra_regressors_additive',
  'holidays'],
 'multiplicative': ['multiplicative_terms', 'extra_regressors_multiplicative']}
```

Make future dataframe for next 1 year

```
future_dates1=model1.make_future_dataframe(periods=365)
```

Predict the Datapoint for next year

```
prediction1=model1.predict(future_dates1)
```

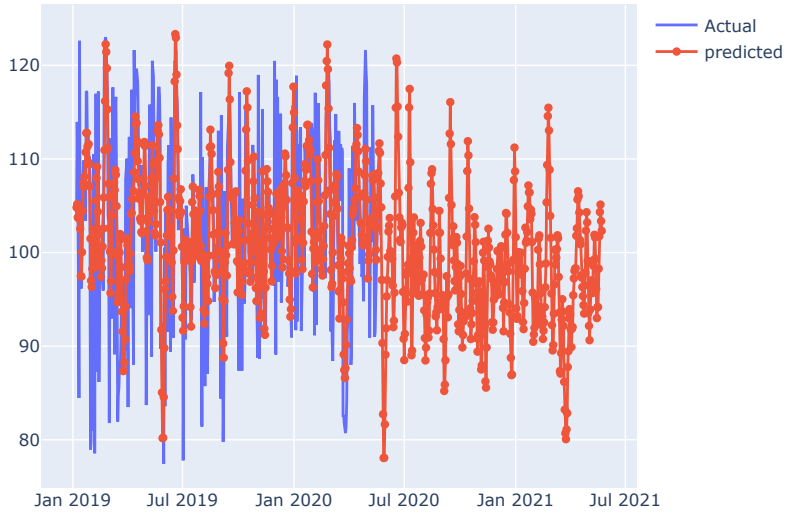
Mean Square Value

```
from sklearn.metrics import mean_absolute_error
y_true = df['y'].values
y_pred = prediction1['yhat'][:498].values
mae = mean_absolute_error(y_true, y_pred)
print('MAE: %.3f' % mae)
```

```
MAE: 5.600
```

Plot the Actual Vs Predicted after Optimization

```
import plotly.graph_objects as go
fig = go.Figure([go.Scatter(x=df['ds'], y=df['y'],mode='lines',name='Actual')])
fig.add_trace(go.Scatter(x=prediction1['ds'], y=prediction1['yhat'],mode='lines+markers',name='predicted'))
fig.show()
```



Case Study 2: Time Series Analysis of Application Count (2016)

Loading the Dataset

```
df=pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Datasets/energydata_complete.csv')
```

```
df.head()
```

	date	Appliances	lights	T1	RH_1	T2	RH_2	T3	RH_3	T4	...	T9	RH_9	T_out
0	2016-01-11 17:00:00	60	30	19.89	47.596667	19.2	44.790000	19.79	44.730000	19.000000	...	17.033333	45.53	6.600000
1	2016-01-11 17:10:00	60	30	19.89	46.693333	19.2	44.722500	19.79	44.790000	19.000000	...	17.066667	45.56	6.483333
2	2016-01-11 17:20:00	50	30	19.89	46.300000	19.2	44.626667	19.79	44.933333	18.926667	...	17.000000	45.50	6.366667
3	2016-01-11 17:30:00	50	40	19.89	46.066667	19.2	44.590000	19.79	45.000000	18.890000	...	17.000000	45.40	6.250000
4	2016-01-11 17:40:00	60	40	19.89	46.333333	19.2	44.530000	19.79	45.000000	18.890000	...	17.000000	45.40	6.133333

5 rows × 29 columns

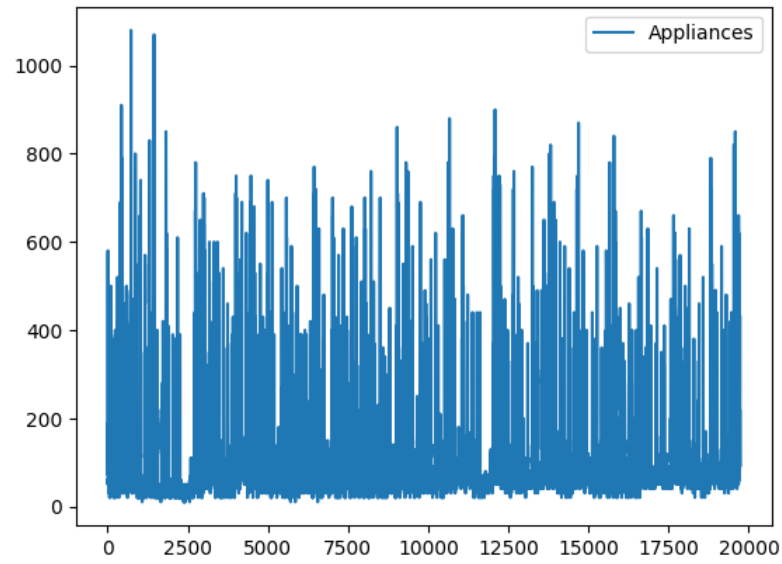
Selecting the Date and Target Column

```
df=df[['date','Appliances']]
```

Ploting the Dataframe

```
df.plot()
```

```
<Axes: >
```



3. Rename column to ds and y

```
ds - datestamp column
y - target column
```

```
df.columns = ['ds','y']
df.head()
```

	ds	y
0	2016-01-11 17:00:00	60
1	2016-01-11 17:10:00	60
2	2016-01-11 17:20:00	50
3	2016-01-11 17:30:00	50
4	2016-01-11 17:40:00	60

Initializing Model

```
model = Prophet()
```

Fiting The Model

```
model.fit(df)
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpx3emyk9j/atreo6n9.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpx3emyk9j/qd_4ckiu.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bin', 'ra
08:48:34 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
08:48:42 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7f97c46bdb70>
```

```
model.component_modes
```

```
{'additive': ['weekly',
  'daily',
  'additive_terms',
  'extra_regressors_additive',
  'holidays'],
 'multiplicative': ['multiplicative_terms', 'extra_regressors_multiplicative']}
```

Create future dates of 150 days

```
future_dates=model.make_future_dataframe(periods=150)
```

Predict the target for the next 150 days

```
prediction=model.predict(future_dates)
```

Finding the Mean Absolute Error

```
y_true = df['y'].values
y_pred = prediction['yhat'][:19735].values
mae = mean_absolute_error(y_true, y_pred)
print('MAE: %.3f' % mae)
```

```
MAE: 52.743
```