```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.api import SimpleExpSmoothing, Holt
from sklearn.metrics import mean_squared_error
from sklearn.metrics import  mean_absolute_error, mean_absolute_percentage_error
```

Ex. 1: Grid search for simple exponential smoothing

```python
draw = pd.read_csv('AlgeriaExport.txt', header = None)
index = pd.date_range(start = "1960", end = "2018", freq = "Y")
T = draw.set_index(index)
T.tail()
```

	0
2013-12-31	33.209898
2014-12-31	30.219117
2015-12-31	23.171778
2016-12-31	20.860011
2017-12-31	22.638887

alpha = 0.1

```python
SES = np.array([39.043173, ])
a = 0.1
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
77.36791352652219
```

alpha = 0.2

```python
SES = np.array([39.043173, ])
a = 0.2
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
59.42247580064113
```

alpha = 0.6

```python
SES = np.array([39.043173, ])
a = 0.6
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
36.22027900901019
```

alpha = 0.8

```python
SES = np.array([39.043173, ])
a = 0.8
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
34.449856061498686
```

alpha = 0.9

```python
SES = np.array([39.043173, ])
a = 0.9
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
34.50677286670212
```

alpha = 0.85

```python
SES = np.array([39.043173, ])
a = 0.85
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
34.40885290732566
```

alpha = 0.86

```python
SES = np.array([39.043173, ])
a = 0.86
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
34.41744299430257
```

alpha = 0.84

```python
SES = np.array([39.043173, ])
a = 0.84
for i in range(0, 57):
    test = T.iloc[i][0] * a + (1 - a) * SES[i]
    SES = np.append(SES, test)

#convert numpy array to pandas dataframe
RES = pd.DataFrame(SES, columns = ['Exports'])
RES = RES.set_index(index)

#mean squared error
mean_squared_error(T, RES)
```

```
34.40580621709138
```

Statsmodel simple exponential smoothing

```python
fit = SimpleExpSmoothing(T, initialization_method = "estimated").fit()
a = fit.model.params["smoothing_level"]
fcast = fit.forecast(3).rename(r"$\alpha = %s $" % a)

#mean squared error
mean_squared_error(T, fit.fittedvalues)
```

```
34.401466385836244
```

```python
plt.figure(figsize = (12, 8))

#original data
plt.plot(T, marker = "o", color = "black")

#fit 1
plt.plot(fit.fittedvalues, marker = "o", color = "blue")
(line1, ) = plt.plot(fcast, marker = "o", color = "blue")

#my predictions
plt.plot(RES, marker = "o", color = "red")
```

```
[<matplotlib.lines.Line2D at 0x22502710130>]
```

Ex. 2: Time series forecasting workflow

```python
df = pd.read_pickle('AlgerianExport.pkl')
df.head()
```

	0
1960-12-31	39.043173
1961-12-31	46.244557
1962-12-31	19.793873
1963-12-31	24.684682
1964-12-31	25.084059

```python
df.size
```

```
58
```

Train test split

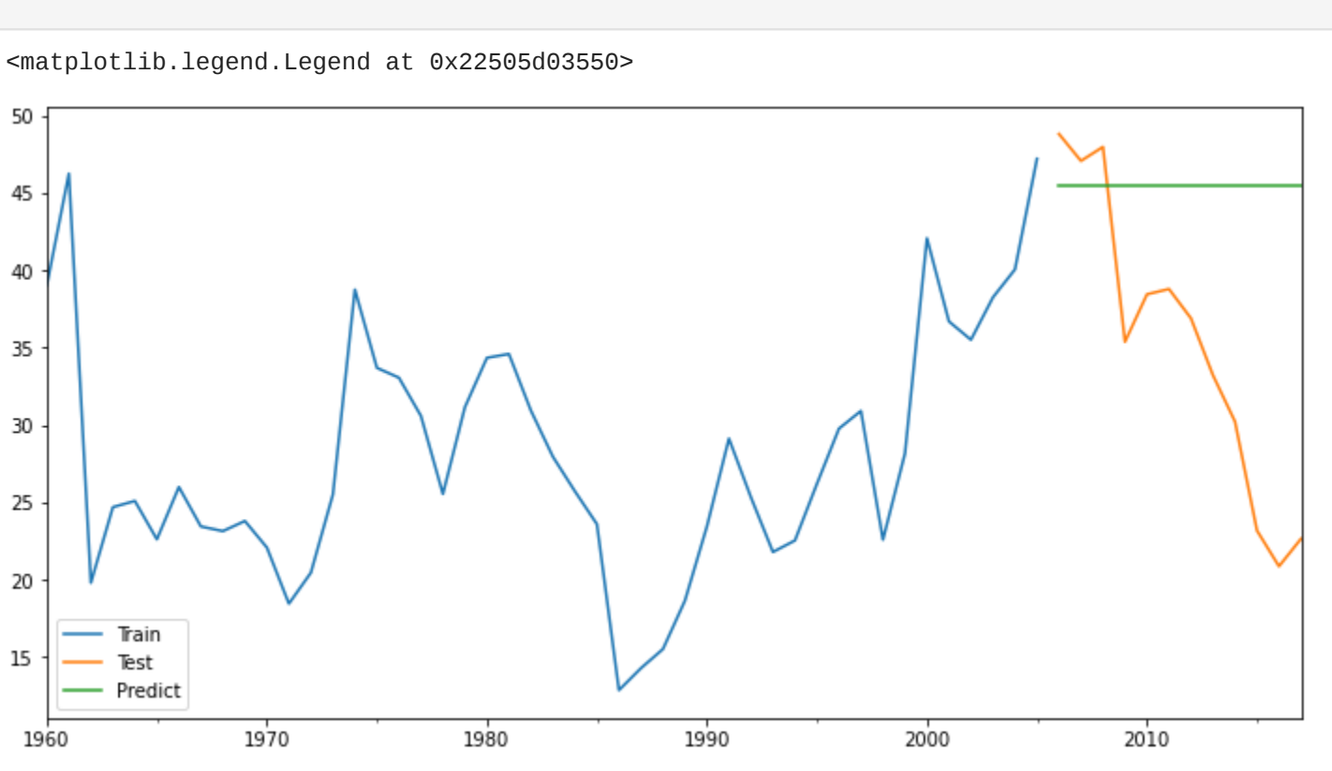
```python
ncut = int(0.8 * df.size) # 80% for training the rest is withheld for testing
ncut
```

```
46
```

```python
train_data = df.iloc[:ncut]
test_data = df.iloc[ncut:]
```

```python
ax = train_data.plot(figsize = (12, 6))
test_data.plot(ax = ax)
plt.legend(['Train', 'Test'])
```

```
<matplotlib.legend.Legend at 0x22504b2aa60>
```



Fitting the model

```python
fitted_model = SimpleExpSmoothing(train_data, initialization_method = 'estimated').fit()
test_predictions = fitted_model.forecast(test_data.size).rename('SES forecast')
```

Evaluating the model against test data

```python
ax = train_data.plot(figsize = (12, 6))
test_data.plot(ax = ax)
test_predictions.plot(ax = ax)
plt.legend(['Train', 'Test', 'Predict'])
```

```
<matplotlib.legend.Legend at 0x22505d03550>
```

```python
# MSE
mean_squared_error(test_data, test_predictions)
```

```
192.04697885954042
```

```python
# check MSE function
np.sum(np.square(np.subtract(test_data[0].values, test_predictions.values))) / test_data.size
```

```
192.04697885954042
```

```python
# MAE
mean_absolute_error(test_data, test_predictions)
```

```
11.439488124346497
```

```python
# MAPE # you must multiply by 100 to get percentage -check!
100 * mean_absolute_percentage_error(test_data, test_predictions)
```

```
42.16657213149438
```

```python
np.sum(np.divide(np.abs(np.subtract(test_data[0].values, test_predictions.values)), test_data[0].values)) / 12
```

```
0.42166572131494373
```

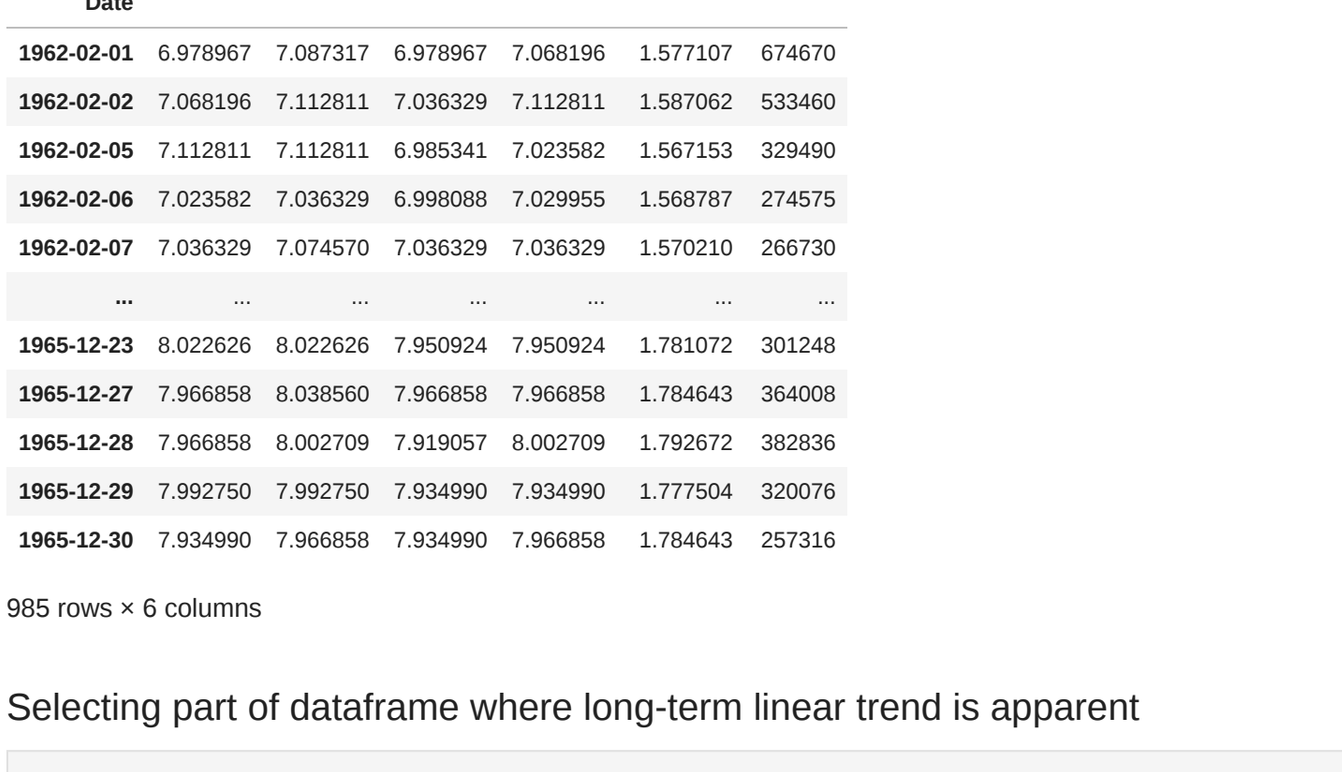
Forecasting into future

Let us assume that the model presented above turned out to be the best. We train the final model using all available data points.

```python
# we use all available data
final_model = SimpleExpSmoothing(df, initialization_method = 'estimated').fit()
forecast = final_model.forecast(test_data.size).rename('forecast')
```

```python
ax = df.plot(figsize = (12, 6))
forecast.plot(ax = ax)
plt.legend(['Past values', 'Forecast'])
```

```
<matplotlib.legend.Legend at 0x22505e4a4f0>
```



Ex. 3: Holt’s method - double exponential smoothing

Import

```python
df = pd.read_csv('IBM.csv', index_col = 'Date', parse_dates = True)
df
```

	Open	High	Low	Close	Adj Close	Volume
Date						
1962-02-01	6.978967	7.087317	6.978967	7.068196	1.577107	674670
1962-02-02	7.068196	7.112811	7.036329	7.112811	1.587062	533460
1962-02-05	7.112811	7.112811	6.985341	7.023582	1.567153	329490
1962-02-06	7.023582	7.036329	6.998088	7.029955	1.568787	274575
1962-02-07	7.036329	7.074570	7.036329	7.036329	1.570210	266730
...	...	...	...	...	...	...
1965-12-23	8.022626	8.022626	7.950924	7.950924	1.781072	301248
1965-12-27	7.966858	8.038560	7.966858	7.966858	1.784643	364008
1965-12-28	7.966858	8.002709	7.919057	8.002709	1.792672	382836
1965-12-29	7.992750	7.992750	7.934990	7.934990	1.777504	320076
1965-12-30	7.934990	7.966858	7.934990	7.966858	1.784643	257316

985 rows × 6 columns

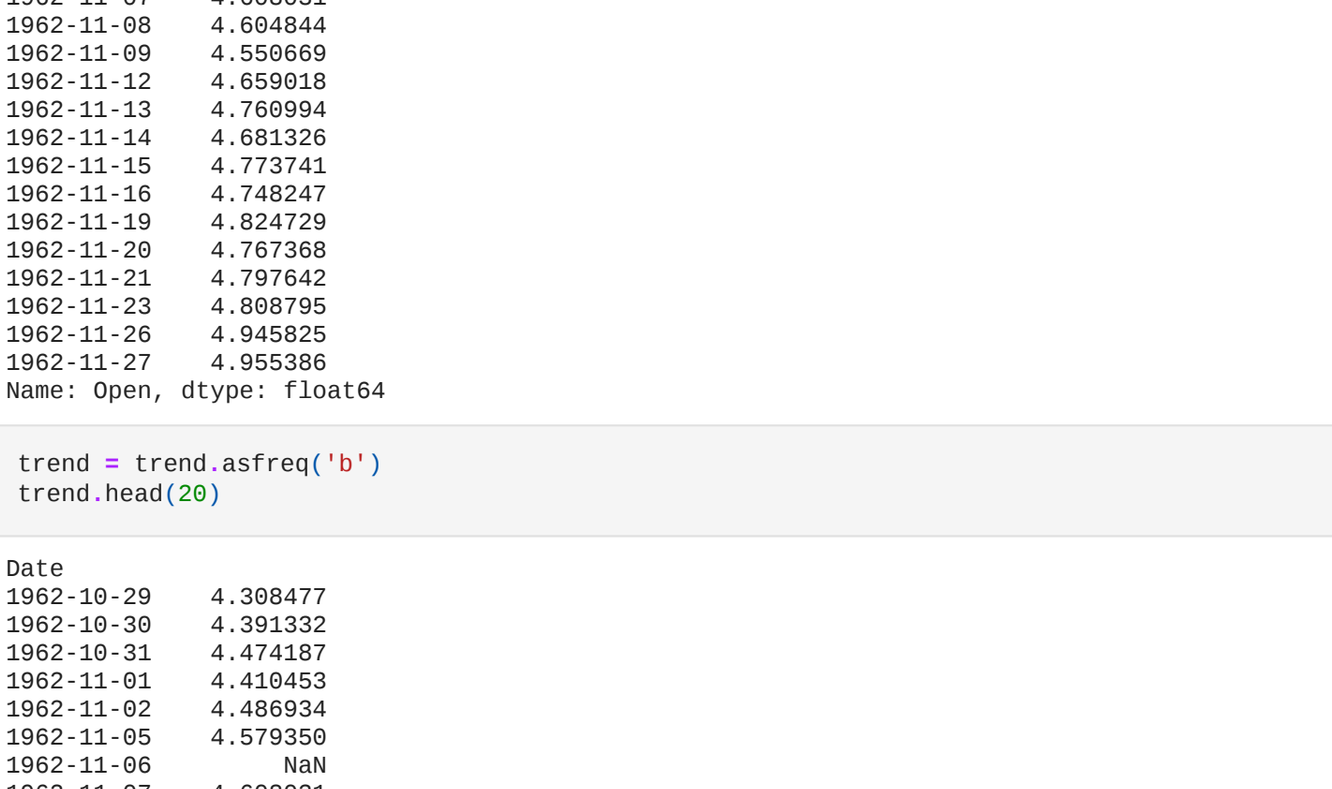
Selecting part of dataframe where long-term linear trend is apparent

```python
cut_l = int(0.19 * len(df))
cut_r = int(0.97 * len(df))
cut_l
```

```
187
```

```python
trend = df['Open'].iloc[cut_l:cut_r]
trend.plot(figsize = (12, 6))
```

```
<AxesSubplot:xlabel='Date'>
```



Set the frequency of the time series to business days

```python
trend.head(20)
```

```
Date
1962-10-29    4.308477
1962-10-30    4.391332
1962-10-31    4.474187
1962-11-01    4.410453
1962-11-02    4.486934
1962-11-05    4.579350
1962-11-07    4.608031
1962-11-08    4.604844
1962-11-09    4.550669
1962-11-12    4.659018
1962-11-13    4.760994
1962-11-14    4.681326
1962-11-15    4.773741
1962-11-16    4.748247
1962-11-19    4.824729
1962-11-20    4.767368
1962-11-21    4.797642
1962-11-23    4.808795
1962-11-26    4.945825
1962-11-27    4.955386
Name: Open, dtype: float64
```

```python
trend = trend.asfreq('b')
trend.head(20)
```

```
Date
1962-10-29    4.308477
1962-10-30    4.391332
1962-10-31    4.474187
1962-11-01    4.410453
1962-11-02    4.486934
1962-11-05    4.579350
1962-11-06         NaN
1962-11-07    4.608031
1962-11-08    4.604844
1962-11-09    4.550669
1962-11-12    4.659018
1962-11-13    4.760994
1962-11-14    4.681326
1962-11-15    4.773741
1962-11-16    4.748247
1962-11-19    4.824729
1962-11-20    4.767368
1962-11-21    4.797642
1962-11-22         NaN
1962-11-23    4.808795
Freq: B, Name: Open, dtype: float64
```

We find NaN's because the original data is missing some of those days (for example 1962-11-06)

Use forward fill to remove nans

```python
trend = trend.ffill(axis = 0)
trend.head(20)
```

```
Date
1962-10-29    4.308477
1962-10-30    4.391332
1962-10-31    4.474187
1962-11-01    4.410453
1962-11-02    4.486934
1962-11-05    4.579350
1962-11-06    4.579350
1962-11-07    4.608031
1962-11-08    4.604844
1962-11-09    4.550669
1962-11-12    4.659018
1962-11-13    4.760994
1962-11-14    4.681326
1962-11-15    4.773741
1962-11-16    4.748247
1962-11-19    4.824729
1962-11-20    4.767368
1962-11-21    4.797642
1962-11-22    4.797642
1962-11-23    4.808795
Freq: B, Name: Open, dtype: float64
```

Splitting data into train and test parts

```python
ncut = int(0.8 * len(trend))
ncut
```

```
637
```

```python
train_data = trend.iloc[:ncut]
test_data = trend.iloc[ncut:]
```

```python
ax = train_data.plot(figsize = (12, 6))
test_data.plot(ax = ax)
plt.legend(['Train', 'Test'])
```

```
<matplotlib.legend.Legend at 0x22505d6b640>
```

Simple Exponential Smoothing

```python
fit_Simple = SimpleExpSmoothing(train_data).fit()
fcast_Simple = fit_Simple.forecast(len(test_data)).rename("SimpleExpSmoothing")
```

Holt's model

```python
fit_Holt = Holt(train_data, exponential = False).fit()
fcast_Holt = fit_Holt.forecast(len(test_data)).rename("Holt's model")
```

Plotting both predictions

```python
ax = train_data.plot(figsize = (12, 6))
test_data.plot(ax = ax)
fcast_Simple.plot(ax = ax)
fcast_Holt.plot(ax = ax)
plt.legend(["Train", "Test", "SimpleExpSmoothing", "Holt's model"])
```

```
<matplotlib.legend.Legend at 0x2250491ed30>
```


Comparing mean square error

```python
#Simple exponential smoothing
print(mean_squared_error(test_data, fcast_Simple))

#Holt's method
print(mean_squared_error(test_data, fcast_Holt))
```

```
0.3981700493887258
0.07441559337618535
```