Time Series - Part 1 Basics

In this series of notebooks we provide a short introduction to mining of data series. In this first part, we examine the basic operations to work with series.

The content of this notebook is based on

- Rob J Hyndman and George Athanasopoulos. Forecasting: Principles and Practice available at https://otexts.com/fpp2/
- Siddharth Yadav Everything you can do with a time series
- Selva Prabhakaran Time Series Analysis in Python – A Comprehensive Guide with Examples

Libraries

First, we need to load the libraries we will be using throughout this notebook.

In [1]:
```
import pandas as pd
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns

# select the style from fivethityeight website
mpl.rcdefaults()
plt.style.use('fivethirtyeight')
mpl.rcParams['lines.linewidth'] = 2
mpl.rcParams.update({'font.size': 16})


np.random.seed(238746)

import warnings
warnings.filterwarnings('ignore')


%config InlineBackend.figure_format = 'retina' #set 'png' here when working on notebook
%matplotlib inline
```

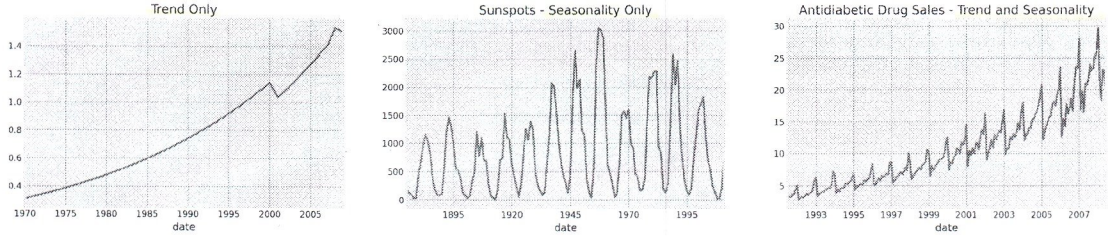
Time Series Patterns

When working with time series, we use terms like "trend", "seasonal", and "cyclic". A trend identify a long-term increase or decrease in the data. It does not have to be linear and can change direction from an increasing trend to a decreasing one or viceversa. When a time series is affected by seasonal factors (e.g., day of the week, time of the year) we say that the series has a seasonal pattern. Seasonality has usually a fixed and known frequency. When the data exhibit rises and falls that are not of a fixed frequency, we say that the series is cyclic. Fluctuations are usually due to economic conditions and their duration is usually at least 2 years. Cyclic behaviour and seasonal behaviour might look similar but in reality they are really quite different. If the fluctuations are not of a fixed frequency then they are cyclic; if the frequency is unchanging and associated with some aspect of the calendar, then the pattern is seasonal. In general, cycles are longer than seasonal patterns and cycle magnitudes tend to be more variable than the magnitudes of seasonal patterns.

Plotting Time Series

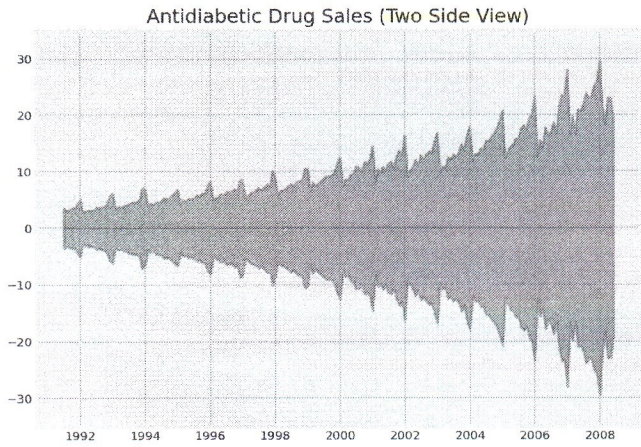
We can simply plot a time series as a function of time like in the three examples below showing a trend, a seasonal pattern of sunspots, and a combination of seasonality with a growing trend.

In [2]:
```
fig, axes = plt.subplots(1,3, figsize=(20,4), dpi=100)
guinearice = pd.read_csv('others/guinearice.csv', parse_dates=['date'], index_col='date').plot(title='Trend Only', legend=False

pd.read_csv('others/sunspotarea.csv', parse_dates=['date'], index_col='date').plot(title='Sunspots - Seasonality Only', legend=
pd.read_csv('others/a10.csv', parse_dates=['date'], index_col='date').plot(title='Antidiabetic Drug Sales - Trend and Seasonali
```



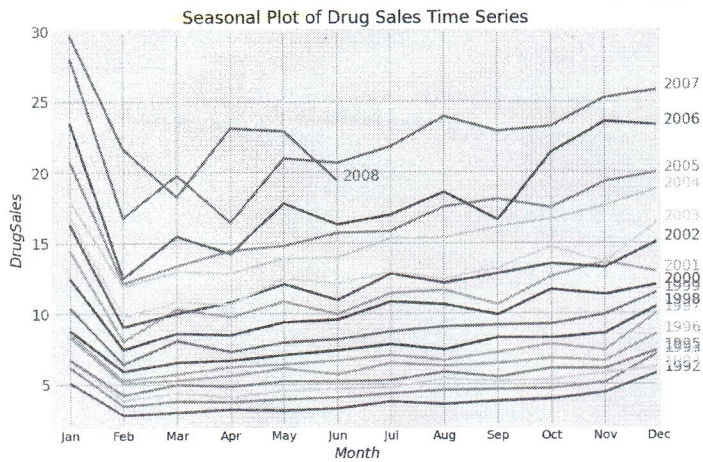
You can plot a positive time series on both sides to emphasize the trend and growth.

In [3]:
```
diabetic_drugs = pd.read_csv('others/a10.csv', parse_dates=['date'])

x = diabetic_drugs['date'].values
y = diabetic_drugs['value'].values

plt.figure(figsize=(8,6))
plt.fill_between(x, y1=y, y2=-y, alpha=0.5, linewidth=2, color='seagreen')
plt.ylim(-35, 35)
plt.title('Antidiabetic Drug Sales (Two Side View)', fontsize=16)
plt.hlines(y=0, xmin=np.min(diabetic_drugs['date'].values), xmax=np.max(diabetic_drugs['date'].values), linewidth=.5)
plt.show()
```



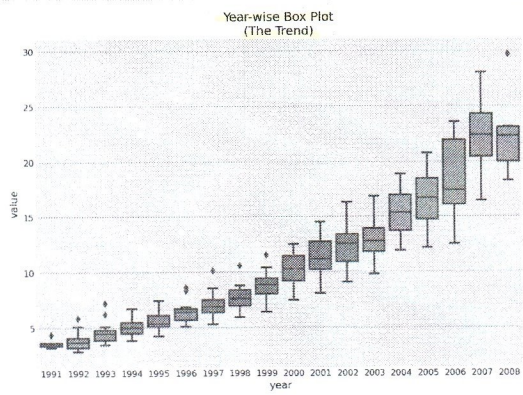
Seasonal plots report the data against the individual "seasons" in which the data were observed. For example, we can report the antidiabetic drug sales overlapping the yearly (seasonal) trends.

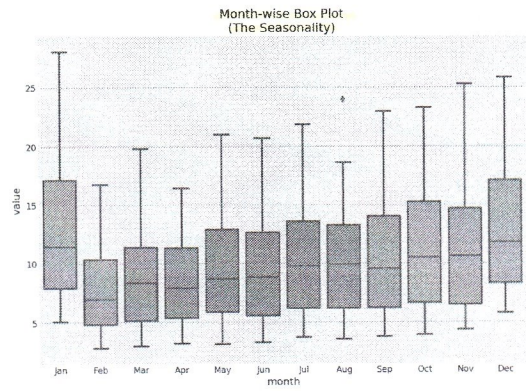
In [4]:
```
diabetic_drugs['year'] = [d.year for d in diabetic_drugs.date]
diabetic_drugs['month'] = [d.strftime('%b') for d in diabetic_drugs.date]
diabetic_drugs_years = diabetic_drugs['year'].unique()

# Prep Colors
mycolors = np.random.choice(list(mpl.colors.XKCD_COLORS.keys()), len(diabetic_drugs_years), replace=False)

# Draw Plot
plt.figure(figsize=(8,6))
for i, y in enumerate(diabetic_drugs_years):
    if i > 0:
        plt.plot('month', 'value', data=diabetic_drugs.loc[diabetic_drugs.year==y, :], color=mycolors[i], label=y)
        plt.text(diabetic_drugs.loc[diabetic_drugs.year==y, :].shape[0]-.9, diabetic_drugs.loc[diabetic_drugs.year==y, 'value']

# Decoration
plt.gca().set(xlim=(-0.3, 11), ylim=(2, 30), ylabel='$Drug Sales$', xlabel='$Month$')
plt.yticks(fontsize=12, alpha=.7)
plt.title("Seasonal Plot of Drug Sales Time Series")
plt.show()
```



You can group the data at seasonal intervals and check their distributed within a given year or month and how it compares over time.

In [5]:
```
fig, axes = plt.subplots(1, 2, figsize=(20,7), dpi= 80)
sns.boxplot(x='year', y='value', data=diabetic_drugs, ax=axes[0])
sns.boxplot(x='month', y='value', data=diabetic_drugs.loc[~diabetic_drugs.year.isin([1991, 2008]), :])

axes[0].set_title('Year-wise Box Plot\n(The Trend)');
axes[1].set_title('Month-wise Box Plot\n(The Seasonality)')
plt.show()
```



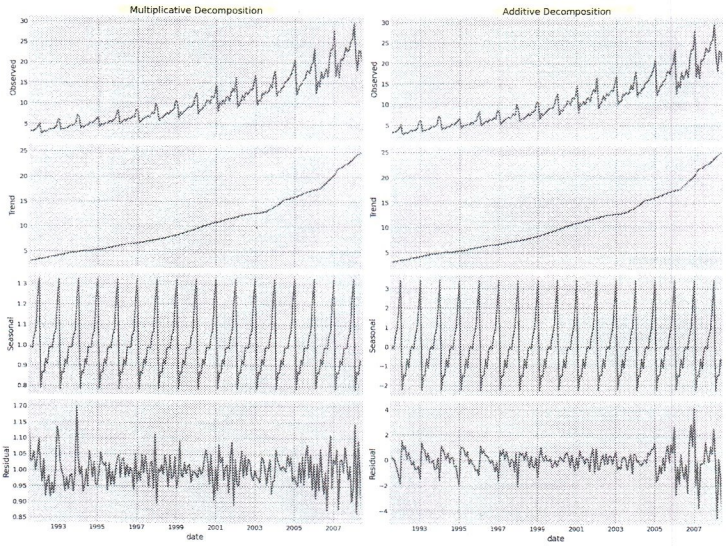


Additive and Multiplicative Time Series

Depending on the nature of the trend and seasonality, a time series can be modeled as an additive time serie or as a multiplicative one depending on whether observations can be expressed as a sum (additive) or a product (multiplicative) of the components. Values of additive time series are the sum of a base level, a trend, a seasonality, and an error. Values of multiplicative time series are the product of a base level, a trend, a seasonality, and an error.

We can decompose a time series using an additive or a multiplicative model in its its different components: (1) base level, (2) trend, (3) seasonal index, and (3) the residual. The function *seasonal_decompose* from the *statsmodels* library performs seasonal decomposition using moving averages.

In [6]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

diabetic_drugs_series = pd.read_csv('others/a10.csv', parse_dates=['date'], index_col='date')

decomposition_multiplicative = seasonal_decompose(diabetic_drugs_series['value'], model='multiplicative', extrapolate_trend='fr
decomposition_additive = seasonal_decompose(diabetic_drugs_series['value'], model='additive', extrapolate_trend='freq')

# We define a function to be able to customize the single plots if we want.
# Alternatively, we can just call decomposition_multiplicative.plot()

def plotseasonal(decomposition, axes, title=""):
    decomposition.observed.plot(ax=axes[0], legend=False)
    axes[0].set_title(title)
    axes[0].set_ylabel('Observed')
    decomposition.trend.plot(ax=axes[1], legend=False)
    axes[1].set_ylabel('Trend')
    decomposition.seasonal.plot(ax=axes[2], legend=False)
    axes[2].set_ylabel('Seasonal')
    decomposition.resid.plot(ax=axes[3], legend=False)
    axes[3].set_ylabel('Residual')

fig, axes = plt.subplots(ncols=2, nrows=4, sharex=True, figsize=(16,12))
plotseasonal(decomposition_multiplicative, axes[:,0],"Multiplicative Decomposition")
plotseasonal(decomposition_additive, axes[:,1], "Additive Decomposition")
plt.tight_layout()
plt.show();
```



Time Series Manipulation

Most of the analysis of time series has to deal with date and time information. This is usually stored in files as plain strings, when we load the data we need to identify what information we are going to use as *time* in our data and what operations we might need to do on them.

Let's load Google stock data from 2006 until 2018. We can simply load the data as a table as we did before

In [7]:
```
google = pd.read_csv('stocks/GOOGL_2006-01-01_to_2018-01-01.csv')
google.head()
```

Out[7]:

	Date	Open	High	Low	Close	Volume	Name
0	2006-01-03	211.47	218.05	209.32	217.83	13137450	GOOGL
1	2006-01-04	222.17	224.70	220.09	222.84	15292353	GOOGL
2	2006-01-05	223.22	226.00	220.97	225.85	10815661	GOOGL
3	2006-01-06	228.66	235.49	226.85	233.06	17759521	GOOGL
4	2006-01-09	233.44	236.94	230.70	233.68	12795837	GOOGL

We can check the numerical attributes in the data,

In [8]:
```
google.describe()
```
(only for numerical variables)

Out[8]:

	Open	High	Low	Close	Volume
count	3019.000000	3019.000000	3019.000000	3019.000000	3.019000e+03
mean	428.200802	431.835618	424.130275	428.044001	3.551504e+06
std	236.320026	237.514087	234.923747	236.343238	3.038599e+06
min	131.390000	134.820000	123.770000	128.850000	5.211410e+05
25%	247.775000	250.190000	244.035000	247.605000	1.760854e+06
50%	310.480000	312.810000	307.790000	310.080000	2.517630e+06

→ same number of counts in all the values: there is no missing values

	Open	High	Low	Close	Volume
75%	572.140000	575.975000	565.900000	570.770000	4.242182e+06
max	1083.020000	1086.490000	1072.270000	1085.090000	4.118289e+07

Or just the categorical one. Obviously, the attribute 'Name' is uniteresting since it has only one value 'GOOGL'; 'Date' on the other hand is a primary key as it has as many values as the number of data points.

In [9]:
```
google.describe(include=[np.object])
```
(for categorical variables)

Out[9]:

	Date	Name
count	3019	3019
unique	3019	1
top	2010-11-16	GOOGL
freq	1	3019

We can have a coincise summary of the loaded data frame by calling the function *info()*.

In [10]:
```
google.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3019 entries, 0 to 3018
Data columns (total 7 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Date    3019 non-null   object 
 1   Open    3019 non-null   float64
 2   High    3019 non-null   float64
 3   Low     3019 non-null   float64
 4   Close   3019 non-null   float64
 5   Volume  3019 non-null   int64  
 6   Name    3019 non-null   object 
dtypes: float64(4), int64(1), object(2)
memory usage: 165.2+ KB
```

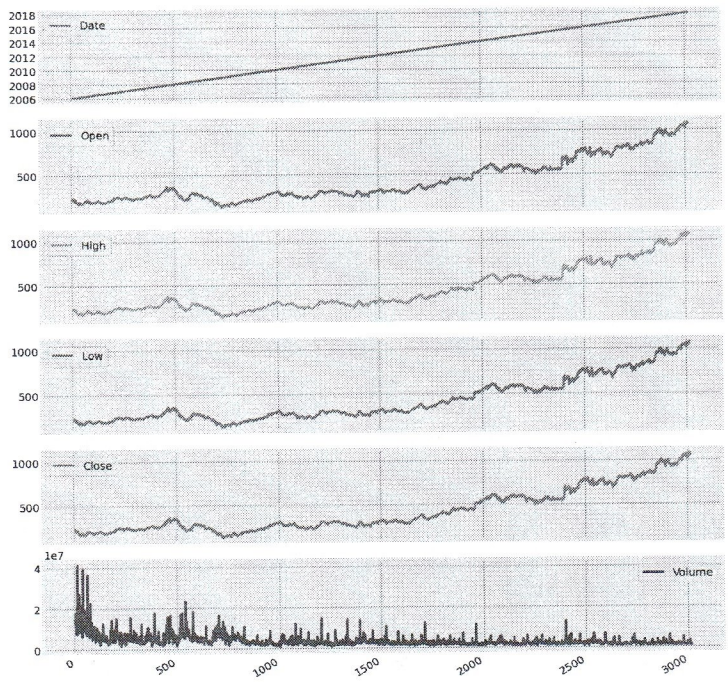
Note that the Date attribute at the moment is just a string (type *object*). We want to use it as a time indicator so we transform the attribute 'Date' into an information about time by calling the function *to_datetime*.

In [11]:
```
google.Date = pd.to_datetime(google.Date)
google.info()
```
(google.Date == google['Date'])
this allows also spaces in the name

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3019 entries, 0 to 3018
Data columns (total 7 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   Date    3019 non-null   datetime64[ns]
 1   Open    3019 non-null   float64       
 2   High    3019 non-null   float64       
 3   Low     3019 non-null   float64       
 4   Close   3019 non-null   float64       
 5   Volume  3019 non-null   int64         
 6   Name    3019 non-null   object        
dtypes: datetime64[ns](1), float64(4), int64(1), object(1)
memory usage: 165.2+ KB
```

We could now plot all the variables as time series

In [12]:
```
google.plot(subplots=True, figsize=(10,12));
```



But as you notice the plot is done according to the current dataframe index, an integer number from 0 to 3018 and the first plot is actually the index which results in straight line. The index of a panda dataframe is the one showed as bold when printing the table.

In [13]:
```
google.head()
```

Out[13]:

	Date	Open	High	Low	Close	Volume	Name

	Date	Open	High	Low	Close	Volume	Name
0	2006-01-03	211.47	218.05	209.32	217.83	13137450	GOOGL
1	2006-01-04	222.17	224.70	220.09	222.84	15292353	GOOGL
2	2006-01-05	223.22	226.00	220.97	225.85	10815661	GOOGL
3	2006-01-06	228.66	235.49	226.85	233.06	17759521	GOOGL
4	2006-01-09	233.44	236.94	230.70	233.68	12795837	GOOGL

We want to use attribute 'Date' as the main index in our analysis, so we declare it as the index of the serie.

In [14]:
```
google.set_index('Date', inplace=True)
google.head()
```

Out[14]:

Date	Open	High	Low	Close	Volume	Name
2006-01-03	211.47	218.05	209.32	217.83	13137450	GOOGL
2006-01-04	222.17	224.70	220.09	222.84	15292353	GOOGL
2006-01-05	223.22	226.00	220.97	225.85	10815661	GOOGL
2006-01-06	228.66	235.49	226.85	233.06	17759521	GOOGL
2006-01-09	233.44	236.94	230.70	233.68	12795837	GOOGL

The same result could have been be achieved just with parse_date argument of the function read_csv

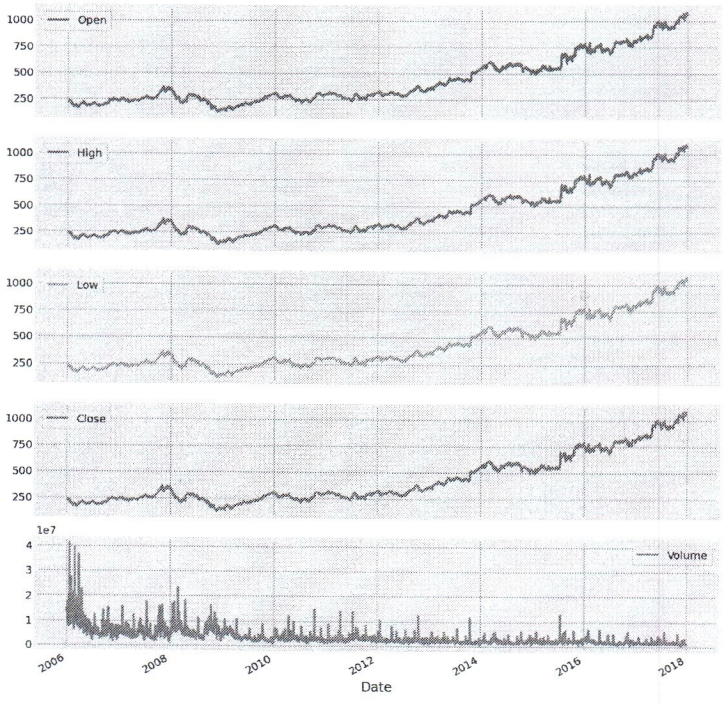
In [15]:
```
google = pd.read_csv('stocks/GOOGL_2006-01-01_to_2018-01-01.csv', index_col='Date', parse_dates=['Date'])
google.head()
```

Out[15]:

Date	Open	High	Low	Close	Volume	Name
2006-01-03	211.47	218.05	209.32	217.83	13137450	GOOGL
2006-01-04	222.17	224.70	220.09	222.84	15292353	GOOGL
2006-01-05	223.22	226.00	220.97	225.85	10815661	GOOGL
2006-01-06	228.66	235.49	226.85	233.06	17759521	GOOGL
2006-01-09	233.44	236.94	230.70	233.68	12795837	GOOGL

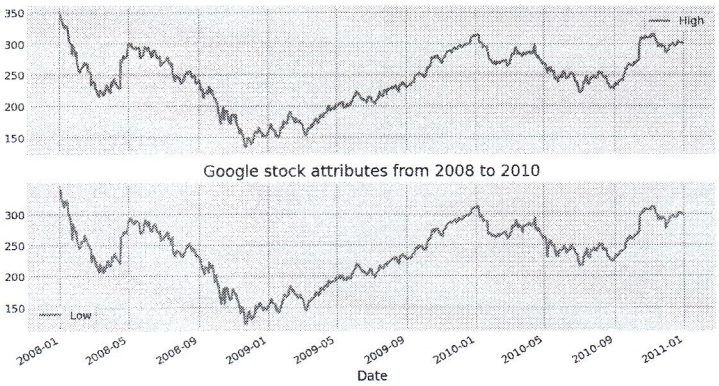
We can now plot all the data using 'Date' as the main index

In [16]:
```
google.plot(subplots=True, figsize=(10,12));
```



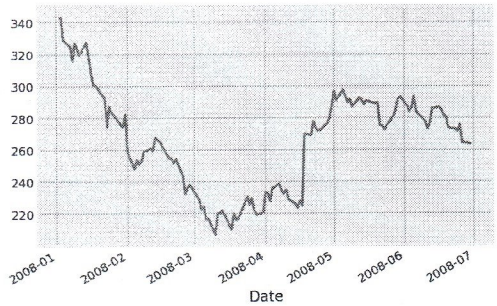
We can plot only some of them for a specific period

In [17]:
```
google[['High','Low']]['2008':'2010'].plot(subplots=True, figsize=(10,6))
plt.title('Google stock attributes from 2008 to 2010')
plt.savefig('stocks.png')
plt.show()
```

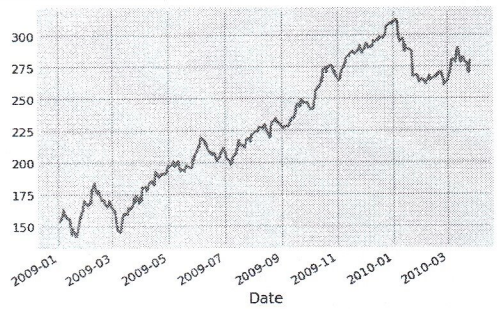


Having the index of *Datetime* type allows to select and resample data in several ways. We can select specific intervals and we can plot just one variable,

In [18]:
```
google['2008-1':'2008-6'].Close.plot();
```



In [19]:
```
google['2009-1-1':'2010-3-26'].Low.plot();
```



We can sample the data to a certain frequency. We currently have 3019 data points collected daily, we can resample them as montly data, quaterly data, weekly data, etc. The method used (*asfreq*) takes as the main argument a date offset https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.tseries.offsets.DateOffset.html

For instance, we can resample the google data monthly and keep only the last day of the month,

In [20]:
```
google_monthly = google.asfreq('M')
google_monthly.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 143 entries, 2006-01-31 to 2017-11-30
Freq: M
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Open    102 non-null    float64
 1   High    102 non-null    float64
 2   Low     102 non-null    float64
 3   Close   102 non-null    float64
 4   Volume  102 non-null    float64
 5   Name    102 non-null    object 
dtypes: float64(5), object(1)
memory usage: 7.8+ KB
```

However, we might have values that are missing since we have no data for that specific day, as for instance it happens for September 30, 2017.

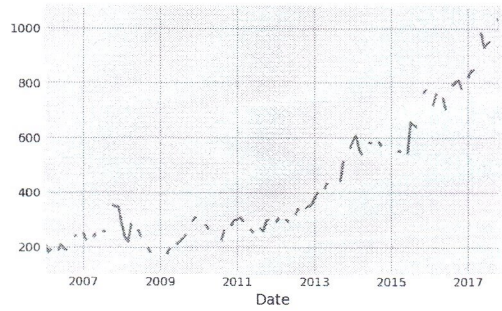
In [21]:
```
google_monthly.tail()
```

Out[21]:

Date	Open	High	Low	Close	Volume	Name
2017-07-31	960.00	961.19	941.72	945.50	2293389.0	GOOGL
2017-08-31	946.30	957.20	946.25	955.24	1693313.0	GOOGL
2017-09-30	NaN	NaN	NaN	NaN	NaN	NaN
2017-10-31	1033.00	1041.00	1026.30	1033.04	1516278.0	GOOGL
2017-11-30	1039.94	1044.14	1030.07	1036.17	2254590.0	GOOGL

there were no missing values but if we consider only the last day of each mont, for example, it may happen that it's a sunday → no values

In [22]:
```
google_monthly.Close.plot();
```



We might use the start of the month, but still face the same issue for a different month.

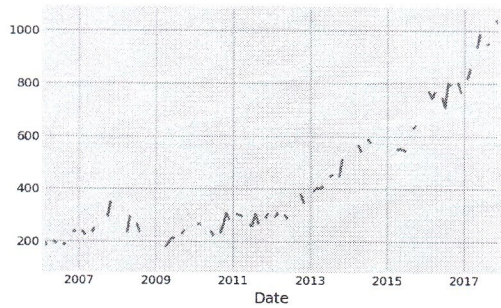
In [23]:
```
google_monthly = google.asfreq('MS')
google_monthly.tail()
```

Out[23]:

Date	Open	High	Low	Close	Volume	Name
2017-08-01	947.81	954.49	944.96	946.56	1332456.0	GOOGL
2017-09-01	957.47	958.33	950.28	951.99	1042885.0	GOOGL
2017-10-01	NaN	NaN	NaN	NaN	NaN	NaN
2017-11-01	1036.32	1047.86	1034.00	1042.60	2163073.0	GOOGL
2017-12-01	1030.41	1037.24	1016.90	1025.07	1888081.0	GOOGL

In [24]:
```
google_monthly.Close.plot()
```

Out[24]:
```
<AxesSubplot:xlabel='Date'>
```



We can fill missing data using three main strategies,

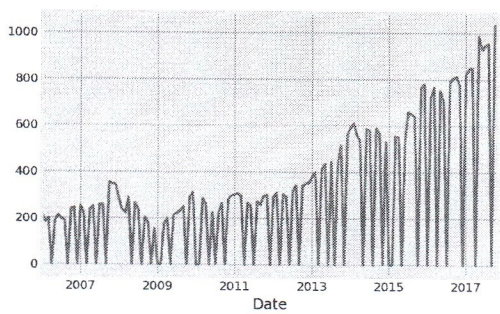
- 'pad'/'ffill' propagates the last valid observation forward to next valid
- 'backfill'/'bfill' uses the next valid observation to fill
- 'fill_value' uses a specific value

Suppose it's Sunday and we have no value → we use the value of Monday
Suppose it's Saturday and we have no value → we use the value of Friday

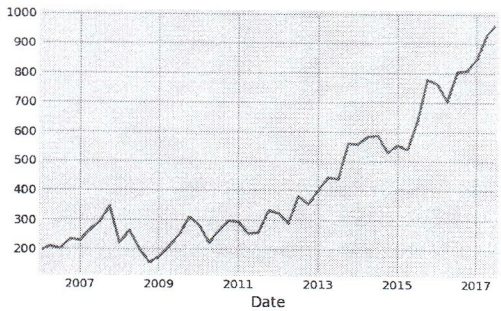
In [25]:
```
google_monthly_zero = google.asfreq('M',fill_value=0)
google_quaterly_bfill = google.asfreq('Q',method='bfill')
google_yearly_ffill = google.asfreq('Y',method='ffill')
```

In [26]:
```
google_monthly_zero.Close.plot()
```

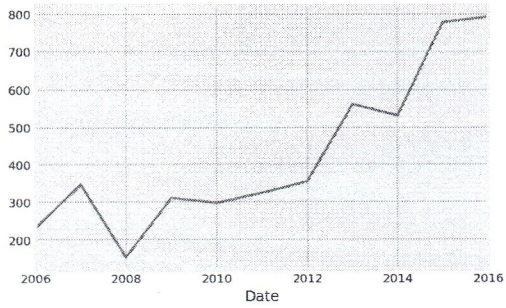
Out[26]:
```
<AxesSubplot:xlabel='Date'>
```



In [27]:
```
google_quaterly_bfill.Close.plot();
```



In [28]:
```
google_yearly_ffill.Close.plot();
```

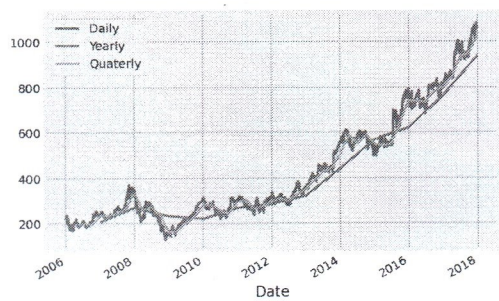


We can resample the data and compute each point as a function of the sampled period. So for instance, we can plot the average closing price of every year, or the average closing price of every quarter.

L we can resample the data and we're going to use not just one point but, for instance, the average/mean/median of a group of points

In [29]:
```
google_yearly = google.resample('Y').mean()
google_quaterly = google.resample('Q').mean()
google.Close.plot(label="Daily")
google_yearly.Close.plot(label="Yearly")
google_quaterly.Close.plot(label="Quaterly")
plt.legend();
```

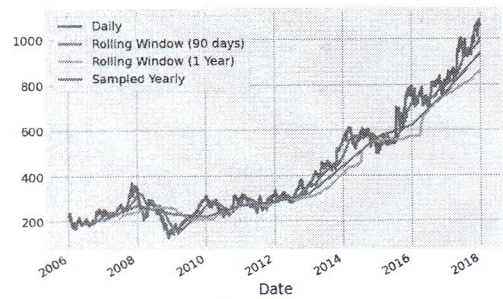
→ every point is the mean of the year



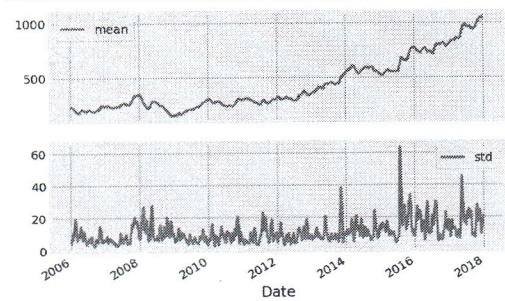
There are also several functions that work over moving (rolling) windows. For example, instead of using the raw data of the closing price, we can use, for each day, the average of the 30 previous points.

In [30]:
```
google['Close Rolling Window'] = google['Close'].rolling(window=90).mean()
```

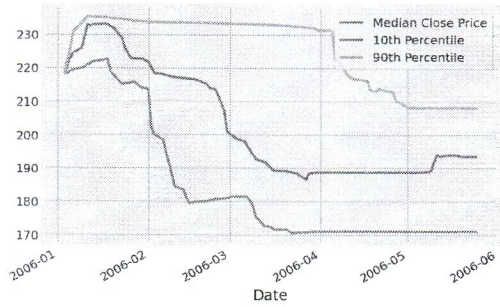
In [31]:
```
google.Close.plot(label="Daily")
google['Close Rolling Window'].plot(label="Rolling Window (90 days)")
google['Close'].rolling(window=365).median().plot(label="Rolling Window (1 Year)")
google_yearly.Close.plot(label="Sampled Yearly")
plt.legend();
```



In [32]:
```
google['Close'].rolling(window='30D').agg(['mean', 'std']).plot(subplots=True);
```



In [33]:
```
rolling_close_price = google['Close'].rolling('90D')
rolling_close_data = rolling_close_price.median().to_frame('Median Close Price')
rolling_close_data['10th Percentile'] = rolling_close_price.quantile(.1)
rolling_close_data['90th Percentile'] = rolling_close_price.quantile(.9)
rolling_close_data.head(100).plot();
```



We can shift the series forward and backward by a given amount. So for instance we can shift the data for attribute "Closed" by one day forward, two days back, or we can shift the same serie after it has been

In [34]:
```
google['Shifted'] = google.Close.shift()
google[['Close','Shifted']].head()
```

. shift() is shifting ahead of 1 value of the index

Out[34]:

Date	Close	Shifted
2006-01-03	217.83	NaN
2006-01-04	222.84	217.83
2006-01-05	225.85	222.84
2006-01-06	233.06	225.85
2006-01-09	233.68	233.06

In [35]:
```
google['Shifted'] = google.Close.shift(periods=-2)
google[['Close','Shifted']].head()
```

we can shift negatively, by 2 for example

Out[35]:

Date	Close	Shifted
2006-01-03	217.83	225.85
2006-01-04	222.84	233.06
2006-01-05	225.85	233.68
2006-01-06	233.06	235.11
2006-01-09	233.68	236.05

In [36]:
```
google['Shifted'] = google.Close.asfreq('3D').shift()
google[['Close','Shifted']].head(15)
```

we take the frequence of 3 days

Out[36]:

Date	Close	Shifted
2006-01-03	217.83	NaN
2006-01-04	222.84	NaN
2006-01-05	225.85	NaN
2006-01-06	233.06	217.83
2006-01-09	233.68	233.06
2006-01-10	235.11	NaN
2006-01-11	236.05	NaN
2006-01-12	232.05	233.68
2006-01-13	233.36	NaN
2006-01-17	233.79	NaN
2006-01-18	222.68	NaN
2006-01-19	218.44	NaN
2006-01-20	199.93	NaN
2006-01-23	213.96	NaN
2006-01-24	221.74	NaN

We can compute the difference between series like for instance x_t and x_{t-1}

In [37]:
```
google['Shifted'] = google.Close.shift()
google['Diff'] = google.Close - google.Shifted #x_t - x_{t-1}
google[['Close','Diff']].head()
```

Out[37]:

Date	Close	Diff
2006-01-03	217.83	NaN
2006-01-04	222.84	5.01
2006-01-05	225.85	3.01
2006-01-06	233.06	7.21
2006-01-09	233.68	0.62

In [38]:
```
# same result with one command
google['Diff2'] = google['Close'].diff()
google[['Close','Diff','Diff2']].head()
```

Out[38]:

Date	Close	Diff	Diff2
2006-01-03	217.83	NaN	NaN
2006-01-04	222.84	5.01	5.01
2006-01-05	225.85	3.01	3.01
2006-01-06	233.06	7.21	7.21
2006-01-09	233.68	0.62	0.62

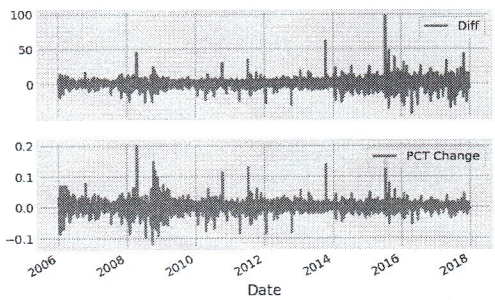
We can compute the percentage change $(x_t - x_{t-1})/x_{t-1}$ using *pct_change()* function.

In [39]:
```
google['PCT Change']=google.Close.pct_change()
google[['Close','Diff','PCT Change']].head()
```

Out[39]:

Date	Close	Diff	PCT Change
2006-01-03	217.83	NaN	NaN
2006-01-04	222.84	5.01	0.023000
2006-01-05	225.85	3.01	0.013507
2006-01-06	233.06	7.21	0.031924
2006-01-09	233.68	0.62	0.002660

In [40]:
```
google[['Diff','PCT Change']].plot(subplots=True);
```



In [ ]: