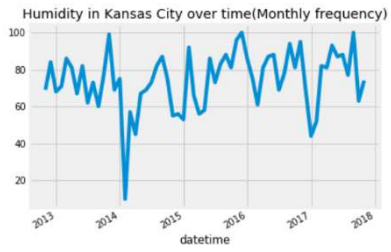
Visualization of Time Series

https://www.kaggle.com/kashnitsky/topic-9-part-1-time-series-analysis-in-python

```
import warnings                                         # `do not disturbe` mode
warnings.filterwarnings('ignore')

import numpy as np                                      # vectors and matrices
import pandas as pd                                     # tables and data manipulations
import matplotlib.pyplot as plt                         # plots
import seaborn as sns                                   # more plots

from dateutil.relativedelta import relativedelta # working with dates with style
from scipy.optimize import minimize                     # for function minimization

import statsmodels.formula.api as smf                   # statistics and econometrics
import statsmodels.tsa.api as smt
import statsmodels.api as sm
import scipy.stats as scs

from itertools import product                           # some useful functions
from tqdm import tqdm_notebook



%matplotlib inline
```

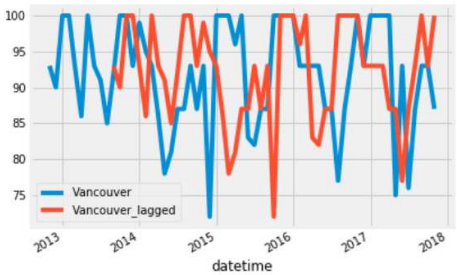
datetime	Vancouver	Portland	San Francisco	Seattle	Los Angeles	San Diego	Las Vegas	Phoenix	Albuquerque	Denver	San Antonio	Dallas	Houston	Kansas City	Minneapolis	Saint Louis	Chicago	Nashville	Indianapolis	Atlanta
2012-10-01 13:00:00	76.0	81.0	88.0	81.0	88.0	82.0	22.0	23.0	50.0	62.0	93.0	87.0	93.0	71.0	67.0	71.0	71.0	100.0	76.0	94.0
2012-10-01 14:00:00	76.0	80.0	87.0	80.0	88.0	81.0	21.0	23.0	49.0	62.0	92.0	86.0	92.0	70.0	66.0	71.0	70.0	99.0	76.0	94.0
2012-10-01 15:00:00	76.0	80.0	86.0	80.0	88.0	81.0	21.0	23.0	49.0	62.0	92.0	86.0	90.0	70.0	66.0	71.0	70.0	99.0	76.0	94.0
2012-10-01 16:00:00	77.0	80.0	85.0	79.0	88.0	81.0	21.0	23.0	49.0	62.0	92.0	86.0	89.0	70.0	65.0	71.0	70.0	99.0	76.0	94.0
2012-10-01 17:00:00	78.0	79.0	84.0	79.0	88.0	80.0	21.0	24.0	49.0	63.0	92.0	86.0	88.0	69.0	65.0	71.0	69.0	99.0	76.0	94.0



humidity["Kansas City"].asfreq('M').plot() # asfreq method is used to convert a time series to a specified frequency. Here it is monthly frequency.
plt.title('Humidity in Kansas City over time(Monthly frequency)')

google['2008':'2010'].plot(subplots=True, figsize=(10,12))
plt.title('Google stock attributes from 2008 to 2010')
#plt.savefig('stocks.png')
plt.show()

humidity["Vancouver"].asfreq('M').plot(legend=True)
shifted = humidity["Vancouver"].asfreq('M').shift(10).plot(legend=True)
shifted.legend(['Vancouver','Vancouver_lagged'])



Plot Moving Average (includes anomalies and confidence intervals)

```
def plotMovingAverage(series, window, plot_intervals=False, scale=1.96, plot_anomalies=False):

    """
```

```
        series - dataframe with timeseries
        window - rolling window size
        plot_intervals - show confidence intervals
        plot_anomalies - show anomalies

    """
    rolling_mean = series.rolling(window=window).mean()

    plt.figure(figsize=(15,5))
    plt.title("Moving average\n window size = {}".format(window))
    plt.plot(rolling_mean, "g", label="Rolling mean trend")

    # Plot confidence intervals for smoothed values
    if plot_intervals:
        mae = mean_absolute_error(series[window:], rolling_mean[window:])
        deviation = np.std(series[window:] - rolling_mean[window:])
        lower_bond = rolling_mean - (mae + scale * deviation)
        upper_bond = rolling_mean + (mae + scale * deviation)
        plt.plot(upper_bond, "r--", label="Upper Bond / Lower Bond")
        plt.plot(lower_bond, "r--")

        # Having the intervals, find abnormal values
        if plot_anomalies:
            anomalies = pd.DataFrame(index=series.index, columns=series.columns)
            anomalies[series<lower_bond] = series[series<lower_bond]
            anomalies[series>upper_bond] = series[series>upper_bond]
            plt.plot(anomalies, "ro", markersize=10)

    plt.plot(series[window:], label="Actual values")
    plt.legend(loc="upper left")
    plt.grid(True)
```

Plot Exponential Smoothing

```
def plotExponentialSmoothing(series, alphas):
    """
        Plots exponential smoothing with different alphas

        series - dataset with timestamps
        alphas - list of floats, smoothing parameters

    """
    with plt.style.context('seaborn-white'):
        plt.figure(figsize=(15, 7))
        for alpha in alphas:
            plt.plot(exponential_smoothing(series, alpha), label="Alpha {}".format(alpha))
        plt.plot(series.values, "c", label = "Actual")
        plt.legend(loc="best")
        plt.axis('tight')
        plt.title("Exponential Smoothing")
        plt.grid(True);
```

e.g. plotExponentialSmoothing(ads.Ads, [0.3, 0.05])

Plot Double Exponential Smoothing

```
def plotDoubleExponentialSmoothing(series, alphas, betas):
    """
        Plots double exponential smoothing with different alphas and betas
```

```
        series - dataset with timestamps
        alphas - list of floats, smoothing parameters for level
        betas - list of floats, smoothing parameters for trend
    """

    with plt.style.context('seaborn-white'):
        plt.figure(figsize=(20, 8))
        for alpha in alphas:
            for beta in betas:
                plt.plot(double_exponential_smoothing(series, alpha, beta), label="Alpha {}, beta
{}".format(alpha, beta))
        plt.plot(series.values, label = "Actual")
        plt.legend(loc="best")
        plt.axis('tight')
        plt.title("Double Exponential Smoothing")
        plt.grid(True)
```

e.g. plotDoubleExponentialSmoothing(ads.Ads, alphas=[0.9, 0.02], betas=[0.9, 0.02])

Plot Triple Exponential Smoothing (Holt Winters Method)

```
def plotHoltWinters(series, plot_intervals=False, plot_anomalies=False):
    """
        series - dataset with timeseries
        plot_intervals - show confidence intervals
        plot_anomalies - show anomalies
    """

    plt.figure(figsize=(20, 10))
    plt.plot(model.result, label = "Model")
    plt.plot(series.values, label = "Actual")
    error = mean_absolute_percentage_error(series.values, model.result[:len(series)])
    plt.title("Mean Absolute Percentage Error: {0:.2f}%".format(error))

    if plot_anomalies:
        anomalies = np.array([np.NaN]*len(series))
        anomalies[series.values<model.LowerBond[:len(series)]] = \
            series.values[series.values<model.LowerBond[:len(series)]]
        anomalies[series.values>model.UpperBond[:len(series)]] = \
            series.values[series.values>model.UpperBond[:len(series)]]
        plt.plot(anomalies, "o", markersize=10, label = "Anomalies")

    if plot_intervals:
        plt.plot(model.UpperBond, "r--", alpha=0.5, label = "Up/Low confidence")
        plt.plot(model.LowerBond, "r--", alpha=0.5)
        plt.fill_between(x=range(0,len(model.result)), y1=model.UpperBond,
                         y2=model.LowerBond, alpha=0.2, color = "grey")

    plt.vlines(len(series), ymin=min(model.LowerBond), ymax=max(model.UpperBond), linestyles='dashed')
    plt.axvspan(len(series)-20, len(model.result), alpha=0.3, color='lightgrey')
    plt.grid(True)
    plt.axis('tight')
    plt.legend(loc="best", fontsize=13);
```

OHLC Chart (for stock price viz)

```
plt.style.use('fivethirtyeight')
# Above is a special style template for matplotlib, highly useful for visualizing time series data
%matplotlib inline
```

```
from pylab import rcParams
from plotly import tools
import plotly.plotly as py
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.figure_factory as ff

# OHLC chart of June 2008
trace = go.Ohlc(x=google['06-2008'].index,
                open=google['06-2008'].Open,
                high=google['06-2008'].High,
                low=google['06-2008'].Low,
                close=google['06-2008'].Close)
data = [trace]
iplot(data, filename='simple_ohlc')
# OHLC chart of 2008
trace = go.Ohlc(x=google['2008'].index,
                open=google['2008'].Open,
                high=google['2008'].High,
                low=google['2008'].Low,
                close=google['2008'].Close)
data = [trace]
iplot(data, filename='simple_ohlc_2008')

# OHLC chart of 2008-2016
trace = go.Ohlc(x=google.index,
                open=google.Open,
                high=google.High,
                low=google.Low,
                close=google.Close)
data = [trace]
iplot(data, filename='simple_ohlc_yearly')
```

CandleStick charts

Candlestick Charts display multiple bits of price information such as the open price, close price, highest price and lowest price through the use of candlestick-like symbols. Each symbol represents the compressed trading activity for a single time period (a minute, hour, day, month, etc). Each Candlestick symbol is plotted along a time scale on the x-axis, to show the trading activity over time.

The main rectangle in the symbol is known as the real body, which is used to display the range between the open and close price of that time period. While the lines extending from the bottom and top of the real body is known as the lower and upper shadows (or wick). Each shadow represents the highest or lowest price traded during the time period represented. When the market is Bullish (the closing price is higher than it opened), then the body is coloured typically white or green. But when the market is Bearish (the closing price is lower than it opened), then the body is usually coloured either black or red.

Candlestick Charts are great for detecting and predicting market trends over time and are useful for interpreting the day-to-day sentiment of the market, through each candlestick symbol's colouring and shape. For example, the longer the body is, the more intense the selling or buying pressure is. While, a very short body, would indicate that there is very little price movement in that time period and represents consolidation.

Candlestick Charts help reveal the market psychology (the fear and greed experienced by sellers and buyers) through the various indicators, such as shape and colour, but also by the many identifiable patterns that can be found in Candlestick Charts. In total, there are 42 recognised patterns that are divided into simple and complex patterns. These patterns found in Candlestick Charts are useful for displaying price relationships and can be used for predicting the possible future movement of the market. You can find a list and description of each pattern here.

Please bear in mind, that Candlestick Charts don't express the events taking place between the open and close price - only the relationship between the two prices. So you can't tell how volatile trading was within that single time period.

```
plt.style.use('fivethirtyeight')
# Above is a special style template for matplotlib, highly useful for visualizing time series data
%matplotlib inline
from pylab import rcParams
from plotly import tools
import plotly.plotly as py
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.figure_factory as ff

# Candlestick chart of march 2008
trace = go.Candlestick(x=google['03-2008'].index,
                       open=google['03-2008'].Open,
                       high=google['03-2008'].High,
                       low=google['03-2008'].Low,
                       close=google['03-2008'].Close)
data = [trace]
iplot(data, filename='simple_candlestick')
```
➔ can play around with period e.g. google['2008']: year of 2008 ; google: yearly

AutoCorrelation / Partial Autocorrelation Plots

* Autocorrelation (ACF) measures how a series is correlated with itself at different lags.
* Partial Autocorrelation - The partial autocorrelation function can be interpreted as a regression of the series against its past lags. The terms can be interpreted the same way as a standard linear regression, that is the contribution of a change in that particular lag while holding others constant.

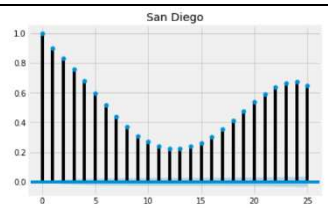
If all lags are either close to 1 or at least greater than the confidence interval, they are statistically significant.

Purpose: For checking randomness! & Used in the model identification stage for Box-Jenkins autoregressive, moving average time series models

Each spike that rises above or falls below the dashed lines is considered to be statistically significant. This means the spike has a value that is significantly different from zero. If a spike is significantly different from zero, that is evidence of autocorrelation.

If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero. But data that does not show significant autocorrelation can still exhibit non-randomness in other ways

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Autocorrelation of humidity of San Diego
plot_acf(humidity["San Diego"], lags=25, title="San Diego")
```



As all lags are either close to 1 or at least greater than the confidence interval, they are statistically significant.

```
# Another way creating autocorrelation_plot

pd.plotting.autocorrelation_plot(df)
```

```
# Partial Autocorrelation of humidity of San Diego
plot_pacf(humidity["San Diego"],lags=25)
plt.show()
```

Trends, Seasonality and Noise

Trend - Consistent upwards or downwards slope of a time series

Seasonality - Clear periodic pattern of a time series (like sine function)

Noise - Outliers or missing values

```
# Now, for decomposition... shows observed, trend, seasonal and residual
```

```
rcParams['figure.figsize'] = 11, 9
decomposed_google_volume = sm.tsa.seasonal_decompose(google["High"],freq=360) # The frequncy is annual
figure = decomposed_google_volume.plot()
plt.show( )
```

White Noise

Noise that has White noise has constant mean and variance and zero auto-correlation at all lags

```
# Now, for decomposition...
rcParams['figure.figsize'] = 11, 9
decomposed_google_volume = sm.tsa.seasonal_decompose(google["High"],freq=360) # The frequncy is annual
figure = decomposed_google_volume.plot()
plt.show()
```

Stationarity

A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time.

* Strong stationarity: is a stochastic process whose unconditional joint probability distribution does not change when shifted in time. Consequently, parameters such as mean and variance also do not change over time.
* Weak stationarity: is a process where mean, variance, autocorrelation are constant throughout the time

Stationarity is important as non-stationary series that depend on time have too many parameters to account for when modelling the time series. diff() method can easily convert a non-stationary series to a stationary series.

```
# The original non-stationary plot
decomposed_google_volume.trend.plot()

# The new stationary plot
decomposed_google_volume.trend.diff().plot()
```

Comprehensive Plot (Times Series Line plot with Dickey Fuller p value, autocorrelation plot, partial autocorrelation plot)

```
def tsplot(y, lags=None, figsize=(12, 7), style='bmh'):
    """
        Plot time series, its ACF and PACF, calculate Dickey-Fuller test

        y - timeseries
        lags - how many lags to include in ACF, PACF calculation
    """
    if not isinstance(y, pd.Series):
        y = pd.Series(y)

    with plt.style.context(style):
        fig = plt.figure(figsize=figsize)
        layout = (2, 2)
        ts_ax = plt.subplot2grid(layout, (0, 0), colspan=2)
        acf_ax = plt.subplot2grid(layout, (1, 0))
        pacf_ax = plt.subplot2grid(layout, (1, 1))

        y.plot(ax=ts_ax)
        p_value = sm.tsa.stattools.adfuller(y)[1]
        ts_ax.set_title('Time Series Analysis Plots\n Dickey-Fuller:
p={0:.5f}'.format(p_value))
        smt.graphics.plot_acf(y, lags=lags, ax=acf_ax)
        smt.graphics.plot_pacf(y, lags=lags, ax=pacf_ax)
        plt.tight_layout()
```