Cookbook Data Science

June 17, 2019

1 Plotting

1.1 A simple plot

```
In [1]: # Simple plot
       %pylab inline
        import matplotlib.pyplot as plt
        import numpy as np
                                              # define once, and reuse often
       num_points = 100
       x_{min}, x_{max} = -np.pi, 2*np.pi
                                                 # define once, and reuse often
       x_values = np.linspace(x_min, x_max, num_points)
        y_values = np.sin(x_values)
       p_values = np.cos(x_values)
        # checking if the two arrays have the same length
        assert len(x_values) == len(y_values) , \
            "lenght-mismatch: {:d} versus {:d}".format(len(x_values),len(y_values))
       plt.plot(x_values, y_values, 'g') # label="Population A") #adds a label to the line
        #plt.legend()
                        #plot the label
       plt.plot(x_values, p_values)
        # default color is blue, 'r' is red, 'k' is black, 'g' is green
        # default solid line, ':' is dottet, '--' is dashed
        # '.' adds dot points, 'o' adds open circle points
        # plt.xlim(2,3)
                              \# optional argument to set \min and \max x- values
        # plt.ylim(5,20)
                              # optional argument to set min and max y- values
        # plt.axis('tight')
                              # optional argument to make the axis just fit the range of data
```

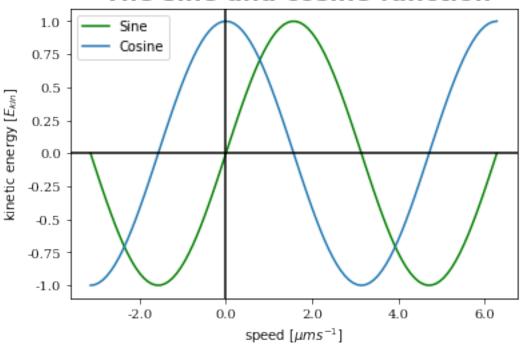
option argument to make both axis the same scale

plt.axis ('equal')

```
# optional graph modifications
                        # get current axis - returns the objext that controls as many
ax = plt.gca()
# Title of plot
ax.set title( 'The sine and cosine function', size=18, weight='bold')
# plt.title( ' My first plot', size=24, weight='bold') #alternative title on plot
# Axis lable of plot
ax.set_xlabel('speed [$\\mu m s^{-1}$]')
ax.set_ylabel('kinetic energy [$E_{kin}$]')
# Alternative axis lable of plot:
# plt.xlabel('speed')
# plt.ylabel('kinetic energy')
# Font
ax.set_xticklabels(ax.get_xticks(), family='serif', fontsize=10)
ax.set_yticklabels(ax.get_yticks(), family='serif', fontsize=10)
# Line style
# (changing after initial plot command)
lines = ax.get lines()
                          # Lines is a list of line objects.
# Make the first line thick, dashed, and red
#plt.setp(lines[0], linestyle='--', linewidth=3, color='r')
# Legend
# adding a descriptive label for each line
#plt.plot(x_values, y_values, label="Population 1")
#plt.plot(x_values, y_values**3, label="Population 2")
# use line objects to set lables after plotting.
lines[0].set_label('Sine')
lines[1].set_label('Cosine')
#lines[1].set_label('Cured Poupulation')
ax.legend()
plt.axhline(0, color='black')
plt.axvline(0, color='black')
plt.show()
```

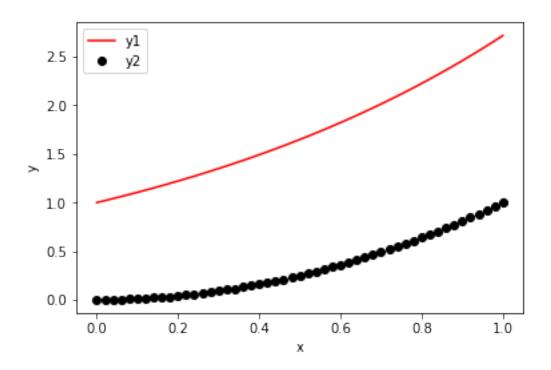
Populating the interactive namespace from numpy and matplotlib

The sine and cosine function



1.2 Plotting multiple equations in same graph

```
In [2]: import matplotlib.pyplot as plt
        import numpy as np
       x = np.linspace(0,1,51)
                                 # Define plotting range
       y1 = np.exp(x) # Define function y1
       y2 = x**2
                          # Define function y2
       plt.plot(x,y1, 'r', x, y2, 'ko')
       plt.xlabel('x')
       plt.ylabel('y')
       ax = plt.gca()
       lines = ax.get_lines()
       lines[0].set_label('y1')
       lines[1].set_label('y2')
        ax.legend()
       plt.show()
```



1.3 Linear equation plotting in 3D

plt.show()

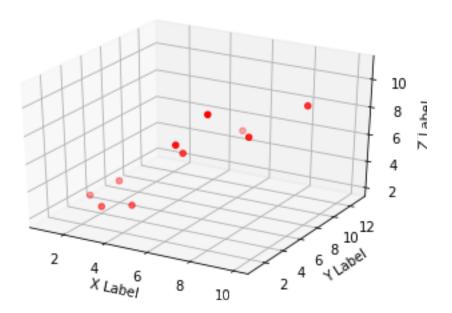
```
In [3]: from mpl_toolkits.mplot3d import Axes3D
    import matplotlib.pyplot as plt

fig = plt.figure()
    ax = fig.add_subplot(111, projection='3d')

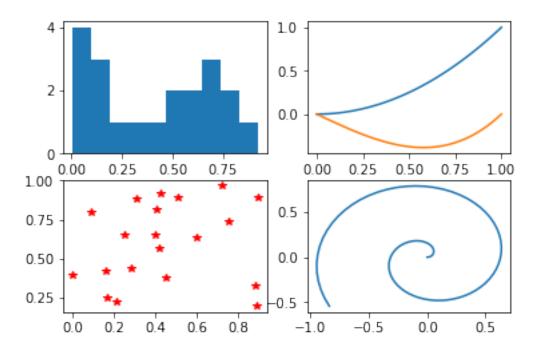
x = [1,2,3,4,5,6,7,8,9,10]
    y = [5,6,2,3,13,4,1,2,4,8]
    z = [2,3,3,3,5,7,9,11,9,10]

ax.scatter(x, y, z, c='r', marker='o')

ax.set_xlabel('X Label')
    ax.set_ylabel('Y Label')
    ax.set_zlabel('Z Label')
```



Subplots



1.4 3D color surface plot

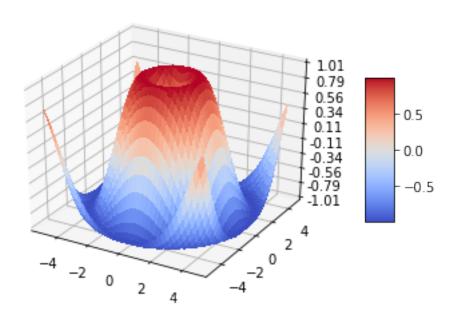
Demonstrates plotting a 3D surface colored with the coolwarm color map. The surface is made opaque by using antialiased=False.

Also demonstrates using the LinearLocator and custom formatting for the z axis tick labels.

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.ticker import LinearLocator, FormatStrFormatter
import numpy as np

fig = plt.figure()
ax = fig.gca(projection='3d')
```

Make data.



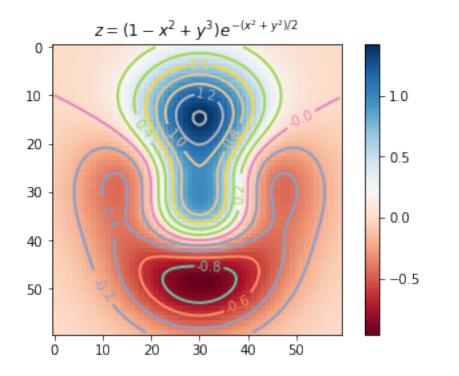
1.5 A function with two variables

the function that I'm going to plot

```
def z_func(x, y):
    return (1 - (x ** 2 + y ** 3)) * exp(-(x ** 2 + y ** 2) / 2)

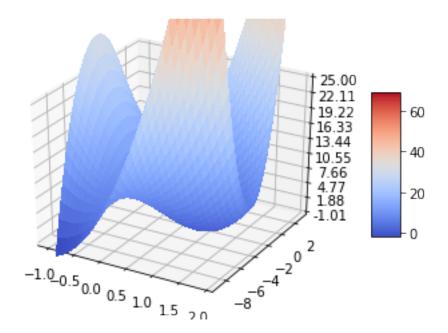
# make data
x = arange(-3.0, 3.0, 0.1)
y = arange(-3.0, 3.0, 0.1)
X, Y = meshgrid(x, y) # grid of point
Z = z_func(X, Y) # evaluation of the function on the grid

im = imshow(Z, cmap=cm.RdBu) # drawing the function
# adding the Contour lines with labels
cset = contour(Z, arange(-1, 1.5, 0.2), linewidths=2, cmap=cm.Set2)
clabel(cset, inline=True, fmt='%1.1f', fontsize=10)
colorbar(im) # adding the colobar on the right
# latex fashion title
title('$z=(1-x^2+y^3) e^{-(x^2+y^2)/2}$')
show()
```



In [7]: from mpl_toolkits.mplot3d import Axes3D
 import matplotlib.pyplot as plt
 from matplotlib import cm
 from matplotlib.ticker import LinearLocator, FormatStrFormatter
 import numpy as np

```
fig = plt.figure()
ax = fig.gca(projection='3d')
# the function that I'm going to plot
def z_func(x, y):
    return (8*x**2 + x*y**2 + 6*x*y - 7*x +8)
# make data
x = np.arange(-1.0, 2.0, 0.1)
y = np.arange(-9.0, 3.0, 0.1)
X, Y = np.meshgrid(x, y) # grid of point
Z = z_{func}(X, Y) # evaluation of the function on the grid
# Plot the surface.
surf = ax.plot_surface(X, Y, Z, cmap=cm.coolwarm,
                       linewidth=0, antialiased=False)
# Customize the z axis.
ax.set_zlim(-1.01, 25)
ax.zaxis.set_major_locator(LinearLocator(10))
ax.zaxis.set_major_formatter(FormatStrFormatter('%.02f'))
# Add a color bar which maps values to colors.
fig.colorbar(surf, shrink=0.5, aspect=5)
plt.show()
X, Y, Z = axes3d.get_test_data(0.05)
ax.plot_surface(X, Y, Z, rstride=8, cstride=8, alpha=0.3)
cset = ax.contour(X, Y, Z, zdir='z', offset=-100, cmap=cm.coolwarm)
cset = ax.contour(X, Y, Z, zdir='x', offset=-40, cmap=cm.coolwarm)
cset = ax.contour(X, Y, Z, zdir='y', offset=40, cmap=cm.coolwarm)
ax.set_xlabel('X')
ax.set xlim(-1, 1)
ax.set_ylabel('Y')
ax.set_ylim(-9, 3)
ax.set_zlabel('Z')
ax.set_zlim(-1, 50)
plt.show()
```



NameError

Traceback (most recent call last)

```
<ipython-input-7-d75ff393532f> in <module>
        32 plt.show()
        33
---> 34 X, Y, Z = axes3d.get_test_data(0.05)
        35 ax.plot_surface(X, Y, Z, rstride=8, cstride=8, alpha=0.3)
        36 cset = ax.contour(X, Y, Z, zdir='z', offset=-100, cmap=cm.coolwarm)
```

NameError: name 'axes3d' is not defined

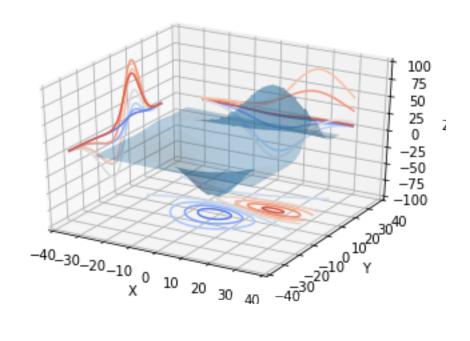
1.6 Contour plot

```
In [8]: from mpl_toolkits.mplot3d import axes3d
    import matplotlib.pyplot as plt
    from matplotlib import cm

fig = plt.figure()
    ax = fig.gca(projection='3d')
    X, Y, Z = axes3d.get_test_data(0.05)
    ax.plot_surface(X, Y, Z, rstride=8, cstride=8, alpha=0.3)
    cset = ax.contour(X, Y, Z, zdir='z', offset=-100, cmap=cm.coolwarm)
```

```
cset = ax.contour(X, Y, Z, zdir='x', offset=-40, cmap=cm.coolwarm)
cset = ax.contour(X, Y, Z, zdir='y', offset=40, cmap=cm.coolwarm)

ax.set_xlabel('X')
ax.set_xlim(-40, 40)
ax.set_ylabel('Y')
ax.set_ylim(-40, 40)
ax.set_zlabel('Z')
ax.set_zlabel('Z')
ax.set_zlim(-100, 100)
```



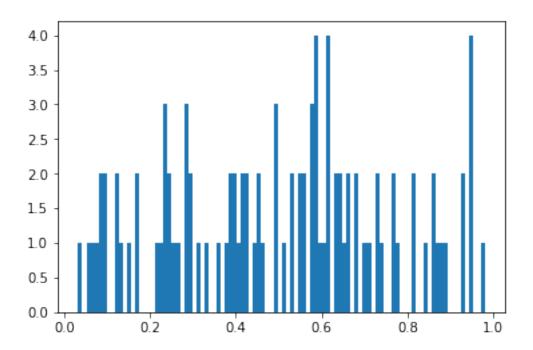
1.7 Histogram

```
In [9]: from numpy.random import random as rng
    import matplotlib.pyplot as plt

data = rng(100)

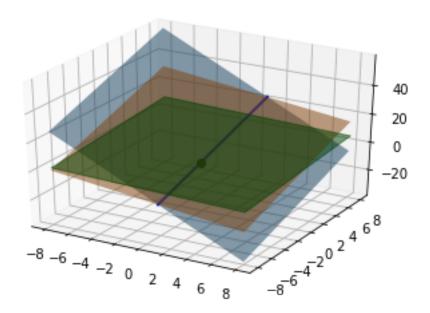
plt.hist(data, bins=100, align='mid')

plt.show()
```



1.8 3D plot of linear euquations

```
In [10]: ''' demonstration of a 3D plot of linear equations'''
         import numpy as np
         import matplotlib.pyplot as plt
         from mpl_toolkits.mplot3d import Axes3D
         fig = plt.figure()
         ax = fig.add_subplot(111, projection='3d')
         x, y = np.linspace(-8,8,100), np.linspace(-8,8,100)
         X, Y = np.meshgrid(x,y)
         Z1 = 11 - 4*X + 2*Y
         Z2 = (16 - 2*X + 4*Y) / 2
         Z3 = (17 - X + 2*Y) / 4
         ax.plot_surface(X,Y,Z1, alpha=0.5, rstride=100, cstride=100)
         ax.plot_surface(X,Y,Z2, alpha=0.5, rstride=100, cstride=100)
         ax.plot((1,1),(-8,8),(-9,23), lw=2, c='b')
         ax.plot_surface(X,Y,Z3, alpha=0.5, facecolors='g', rstride=100, cstride=100)
         ax.plot((1,),(-2,),(3,), lw=2, c='k', marker='o')
        plt.show()
```



1.9 Importing and Exporting Data

```
In [11]: """
         Created: 2018
         Author: Stephan Goldberg (Python 3.4)
         Description:
         Importing and Exporting Data
         11 11 11
         import numpy as np
         # 1. import method:
         # import data from local directory, specifying that it is a csv file
         data_set = np.loadtxt("HIVseries.csv", delimiter=',')
         # 2. import method:
         # specifiying the complete path of a file on local computer
         data_file = '/Users/stephangoldberg/Google Drive/Python Projects/MathProblems/PMLSdate
         data_set02 = np.loadtxt(data_file, delimiter=',')
         # 3. import method:
         # specifying home directory, data directory once, to safe work later:
         home_dir = '/Users/stephangoldberg/Google Drive/Python Projects/MathProblems/'
         data_dir = home_dir + 'PMLSdata/01HIVseries/'
         data_set03 = np.loadtxt(data_dir+ 'HIVseries.csv', delimiter=',')
```

```
# 4. importing other kinds of text
# to be used when line by line is to be imported
my_file = open('HIVseries.csv')
temp_data = []
                            # creates an object that can read the data file
for line in my_file:
    print(line)
    x, y = line.split(',') # uses split line method to break the line into numbers u
    temp_data += [(float(x), float(y))] #converts text into numbers
my_file.close()
data_set04 = np.array(temp_data)
# 5. direct web import
import urllib.request
web_file = urllib.request.urlopen( " http://www.physics.upenn.edu/biophys/PMLS/Datase
data_set05 = np.loadtxt(web_file, delimiter = ',')
# saving data
x = np.linspace(0,1,1001)
y = 3* np.sin(x)**3 - np.sin(x)
np.save('x_values', x)
np.save('y_values', y)
np.savetxt('x_values.dat',x)
np.savetxt('y_values.dat', y)
np.savez ('xy_values', x_vals=x, y_vals=y)
# recovering data
x2 = np.load('x_values.npy')
y2 = np.loadtxt('y_values.dat')
w = np.load('xy_values.npz')
print(w.keys())
x2 == x
y2 == y
w['x\_vals'] == x
w['y\_vals'] == y
# Writing information directly into a file:
my_file = open('power.txt', 'w')
                                        # opens file and prepares it with 'w' writing
print('N \t\t2**N\t\t3**N')
                                        # print labels for columns, also '\t' inserts
print('---\t\t----')
                                        # print separator.
my_file.write('N \t\t2**N\t\t3**N') # write lables to file
my_file.write('---\t\t----\t\t----') # write separators to file
```

2 Statistics Basics

Importing the python libraries:

```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    %pylab inline
```

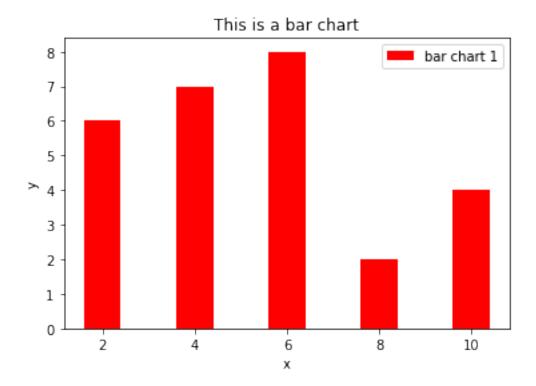
Populating the interactive namespace from numpy and matplotlib

Terminology: (cited from page 10, unit 1) - Observations _ (or cases, or sampling units) refer to objects (people, countries, . . .) on which characteristics are recorded. - Variables are the characteristics recorded, and the pattern of variation of a variable is its distribution. - Variables are linked if they are each recorded for the same observations. - A variable is **continuous** if its values are numerical and all values in an interval are possible. - A variable is **discrete** if its values are numerical but only particular values (typically, integers) are possible. - A variable is **categorical** if its values indicate to which group an observation belongs. - A categorical variable is **ordinal** if its values correspond to labels which have a natural ordering. - A categorical variable is __nominal__if its values correspond to labels but the labels do not have a natural ordering.

2.1 A bar chart

A bar chart is usually used for categorical data or with numerical data that are discrete.

```
plt.xlabel('x')
plt.ylabel('y')
plt.title('This is a bar chart')
plt.legend()
plt.show()
```

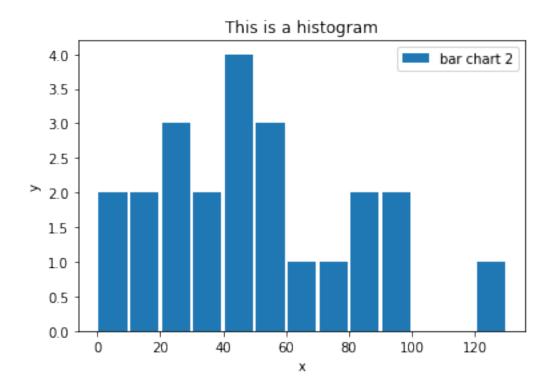


2.2 A histogram chart

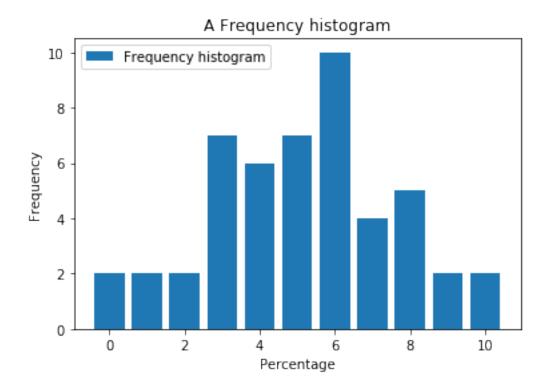
- A histogram chart is generally used with continuous data.
- Histograms need a reasonably large dataset and are sensitive to the choice of cutpoints.

```
In [41]: population_ages = [12,34,65,87,23,123,3,7,45,92,54,74,41,21,98,34,43,10,20,50,40,85,5]
    bins = [0,10,20,30,40,50,60,70,80,90,100,110,120,130]

    plt.hist(population_ages, bins, histtype = 'bar', rwidth = 0.9, label = 'bar chart 2',
        plt.xlabel('x')
        plt.ylabel('y')
        plt.title('This is a histogram')
        plt.legend()
        plt.show()
```



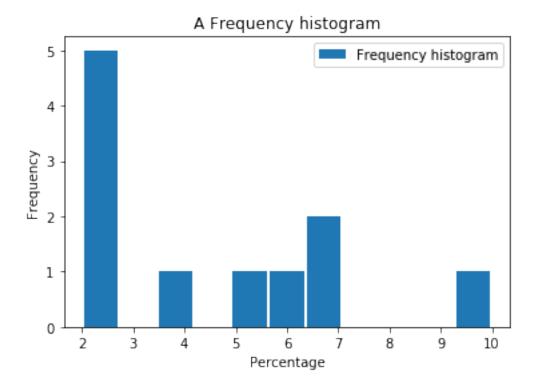
2.3 A frequency histogram (according to M248)



Frequency histogram according to https://www.mathsisfun.com/definitions/frequency-histogram.html

note: the occurances of values of same magnitude are stacked!!!

```
In [47]: plt.hist(frequency, bins=11, histtype = 'bar', rwidth = 0.9, label = 'Frequency histogram')
    plt.xlabel('Percentage')
    plt.ylabel('Frequency')
    plt.title('A Frequency histogram')
    plt.legend()
    plt.show()
```



Defining a new data set:

2.4 Sample Size

The sample size is the number of observations a dataset contains:

In [5]: len(data)

Out[5]: 19

2.5 Sorting the data:

Out[6]: array([7, 23, 23, 23, 56, 56, 78, 85, 234, 234, 324, 345, 432, 456, 456, 756, 1223]) 234,

2.6 The sample mean:

If the *n* values in a dataset are denoted x_1 , x_2 , x_3 ,... x_n , then the **sample mean**, which is denoted \bar{x} is given by

$$\bar{x} = \frac{x_1 + x_2 + x_3 + n_n}{n} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

it is also called the 'average'.

In [7]: x_bar = sum(data) /len(data)
 x_bar

Out[7]: 265.6842105263158

Mean in numpy:

In [8]: mean = np.mean(data)
 mean

Out[8]: 265.6842105263158

2.7 The population mean:

The population mean (or mean or expected value or expectation) of a random variable is given: - if X is discrete with p.m.f p(x), by

$$\mu = E(X) = \sum_{x} x p(x)$$

- if X is continuous with p.d.f. f(x), by

$$\mu = E(X) = \int x f(x)$$

where the integral is taken over all values x in the range of X.

2.8 The sample median:

The sample median is defined as 'the middle value' of the dataset.

$$m = x_{\left(\frac{1}{2}(n+1)\right)}$$

- if *n* is even, then the sample median lies exactly half way between the two centre values.
- the median, just like the interquartile range are more resistant to unusual values in the data than are the mean and the standard deviation.

Median in numpy:

In [9]: np.median(data)

Out [9]: 234.0

2.9 The sample quartiles:

Let a dataset x_1 , x_2 , x_n , n = 3, 4, ... be recorded as $x_{(1)}$, $x_{(2)}$, $x_{(n)}$. Then the **sample lower quartile**, q_L , is given by

$$q_L = x_{\left(\frac{1}{4}(n+1)\right)}$$

and the **sample upper quartile**, q_U , is given by

$$q_U = x_{\left(\frac{3}{4}(n+1)\right)}$$

!!! Note: numpy and pandas define quartiles different than M248 or Minitab !!! (see page 37, unit 1)!!!

Upper and lower quartiles in numpy:

Upper and lower quartiles in pandas:

Upper and lower quartiles in M248 (and Minitab):

First, ensure that the data is sorted in ascending order.

```
In [17]: data1 = [66,72,79,84,102,110,123,144,162,169,414]
```

Lower quartile for data-set with n+1 divisable by 4:

Upper quartile for data-set with n+1 divisable by 4:

162

79

Lower quartile for data-set with n+1 NOT divisible by 4:

removing the outlier in the data-set (to make it undividable by 4):

finding the position of the integer value x_n and the corresponding $\frac{3}{4}$ -fraction of the lower quartile in the new data set and then finding the lower quartile:

Upper quartile for n+1 NOT divisable by 4):

finding the position of the integer value x_n and the corresponding $\frac{1}{4}$ -fraction of the upper quartile in the new data set, and then findin the upper quartile:

2.10 The sample interquartile range

The_ sample interquartile range _ is defined as $q_U - q_L$, where q_U is the sample upper quartile and q_L is the sample lower quartile.

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2.11 The standard deviation

If *n* values in a dataset are denoted $x_1, x_2, ..., x_n$ and their sample mean is $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$, then the

```
sample standard deviation, s is defined by: s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}
```

2.12 The sample variance

The square of the standard deviation is the sample variance. Hence it is given by: $s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$

Out[36]: 8.732000000000005

2.13 Unit-area histogram

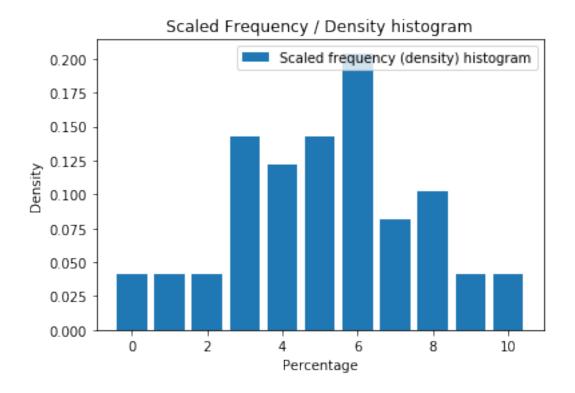
A **unit-area histogram** is a frequency histogram in which the frequencies are scaled so that the total area of the bars in the histogram is 1

```
In [53]: frequency = [2, 2, 2, 7, 6, 7, 10, 4, 5, 2, 2]
    y_pos = np.arange(len(frequency))

scaled_frequency = frequency/np.sum(frequency)

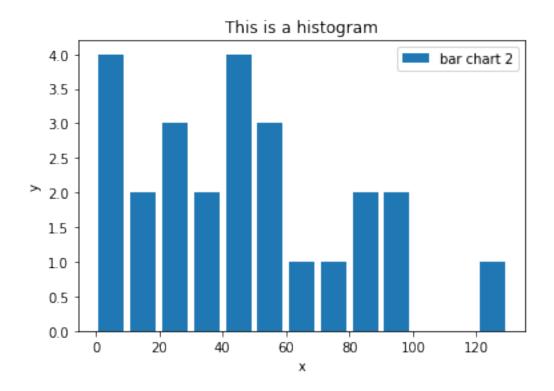
plt.bar(y_pos, scaled_frequency, label = 'Scaled frequency (density) histogram')

plt.xlabel('Percentage')
    plt.ylabel('Density')
    plt.title('Scaled Frequency / Density histogram')
    plt.legend()
    plt.show()
```



A non-scaled histogram:

```
In [71]: population_ages = [2,5,12,34,65,87,23,123,3,7,45,92,54,74,41,21,98,34,43,10,20,50,40,50]
    bins = [0,10,20,30,40,50,60,70,80,90,100,110,120,130]
    plt.hist(population_ages, bins, histtype = 'bar', rwidth = 0.8, label = 'bar chart 2'.plt.xlabel('x')
    plt.ylabel('y')
    plt.title('This is a histogram')
    plt.legend()
    plt.show()
```

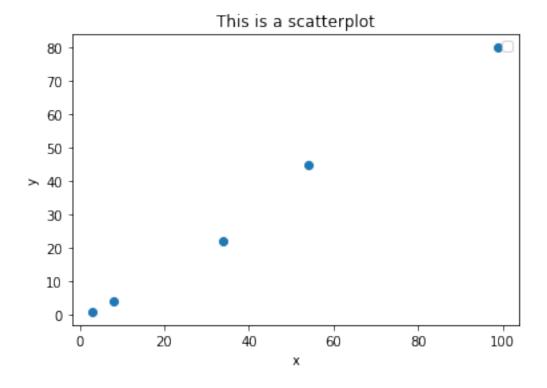


2.14 A Scatterplot

A scatterplots are used to investigate the relationship between two numercial variables.

```
In [73]: x = [3,8,34,54,99]
    y = [1,4,22,45,80]
    plt.xlabel('x')
    plt.ylabel('y')
    plt.title('This is a scatterplot')
    plt.legend()
    plt.scatter(x, y,label = 'scatterplot')
    plt.show()
```

No handles with labels found to put in legend.

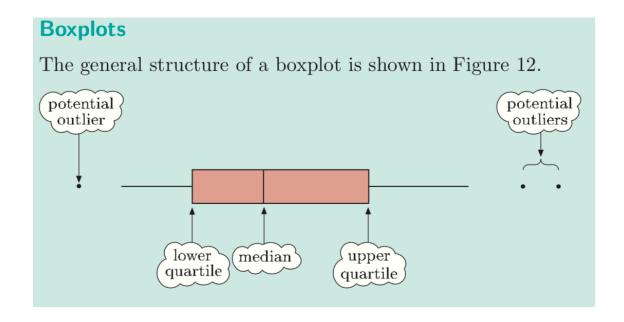


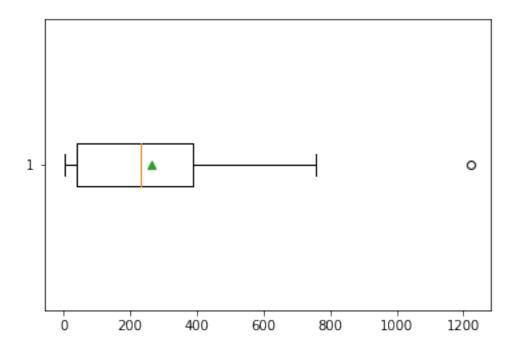
Scatterplot Interpretation checklist

- 1. Is the relationship positive, negative or neither?
- 2. Is the relationship linear or non-linear?
- 3. Is the relationship strong or weak?
- 4. Are there any outliers?

2.15 A boxplot

- A boxplot, just like the histogram is also used with continuous data.
- Boxplots cannot show how many modes a distribution has.
- Comperative boxplots allow more than one continuous variable to be displayed.





3 P.D.F. and C.D.F

3.1 P.d.f. Probability distribution functions (Excercise 8)

Out[65]: [<matplotlib.lines.Line2D at 0x119fc1ac8>]

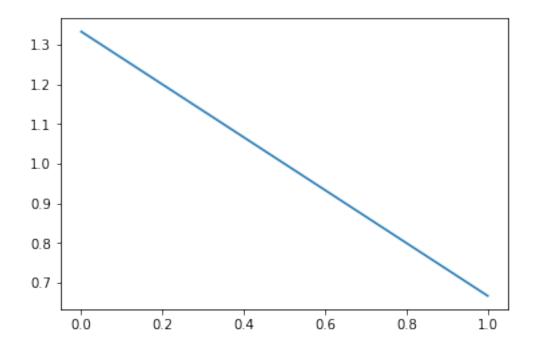
```
In [65]: from scipy.integrate import quad
    num_points = 100
    x_min, x_max = 0 , 1

    x = np.linspace(x_min, x_max, num_points)

def integrand(x):
    return 2/3 * (2-x) # insert function here

ans, err = quad(integrand, x_min, x_max)
    print ("The integral over the interval over the range (" + str(x_min) + ", " + str(x_min))

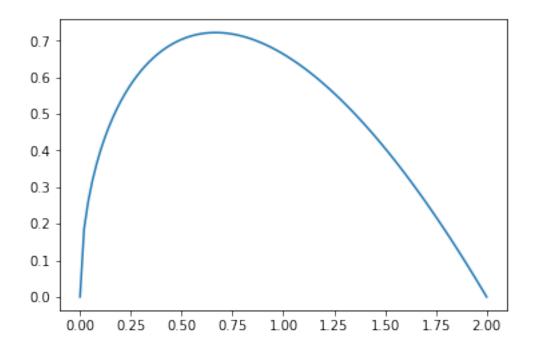
plt.plot(x, integrand(x))
The integral over the interval over the range (0, 1) evaluates to 1.0
```



3.2 C.d.f. Comulative distribution function (Activity 24)

```
a)
In [70]: def F(x):
             return x**3
         a = F(3/4)-F(1/2)
         Fraction (a)
Out[70]: Fraction(19, 64)
In [72]: def F(x):
             return x**3
         a = 1 - F(0.6)
         а
Out[72]: 0.784
In [75]: def F(x):
             return x**3
         a = F(0.6)-F(0.1)
         round(a,3)
Out[75]: 0.215
  b
  i)
```

```
In [77]: def F(x):
             return x/5 - x**2/500 -16/5
         a = 1-F(22)
         round(a,3)
Out[77]: 0.768
   ii)
In [78]: def F(x):
             return x/5 - x**2/500 -16/5
         a = F(29)-F(21)
         round(a,3)
Out[78]: 0.8
3.3 P.d.f. and c.d.f.(Activity 25)
a)
   As seen from the graph, f(x)>0 for all x. We test if the integral of f(x) with respect to x is 1:
In [8]: from scipy.integrate import quad
        import numpy as np
        import matplotlib.pyplot as plt
        %pylab inline
        num_points = 100
        x_min, x_max = 0, 2
        x = np.linspace(x_min, x_max, num_points)
        def integrand(x):
            return 15/(16*np.sqrt(2)) * np.sqrt(x) * (2-x) # insert function here
        ans, err = quad(integrand, x_min, x_max)
        print ("The integral over the interval over the range (" + str(x_min) + ", " + str(x_m
        plt.plot(x, integrand(x))
Populating the interactive namespace from numpy and matplotlib
The integral over the interval over the range (0, 2) evaluates to 1.0
Out[8]: [<matplotlib.lines.Line2D at 0x113cb5358>]
```



c)

Out[9]: 0.381281566461771

the probability is 38% that the bulldozers return time is greater than a minute. **d)**

In [10]: F(1)-F(0.5)

Out[10]: 0.353093433538229

the probabilit is 35.3% (to three s.f.) that the bulldozer returns between 30 seconds and one minute

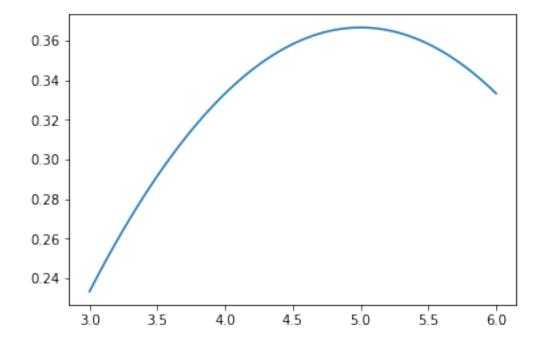
3.4 P.d.f. and c.d.f. (Exercise 10)

a)

```
In [11]: from scipy.integrate import quad
   import numpy as np
   import matplotlib.pyplot as plt
   %pylab inline
```

Populating the interactive namespace from numpy and matplotlib The integral over the interval over the range (3, 6) evaluates to 1.0

Out[11]: [<matplotlib.lines.Line2D at 0x113d1d4e0>]



The integral over the interval is 1 and the function is non-negative over the interval, so yes, f is a valid p.f.d..

Out[12]: 0.28888888888888903

c)

```
In [13]: F(5) - F(4)
```

Out[13]: 0.355555555555555

3.4.1 TMA 01, Question 2 b) ii)

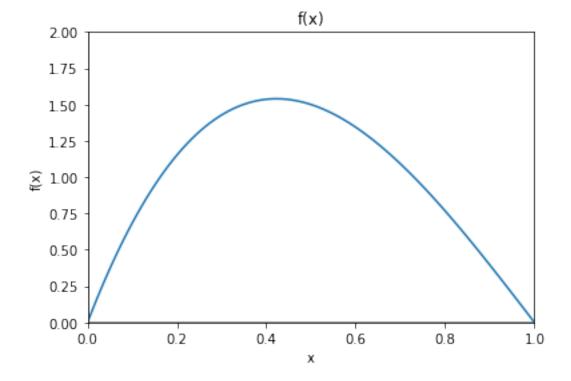
We plot f(x) in for the range $\{0,6\}$:

```
In [28]: # defining the plotting limits:
    xmin, xmax, ymin, ymax, number_of_dots = 0, 1, 0, 2, 100 #fill limits in here

# defining f(x) and x:
    def f(x):
        return 4*x*(1-x)*(2-x) #fill function in here
    x = np.linspace(xmin , xmax , number_of_dots)

# plotting:
    plt.xlim(xmin, xmax),plt.ylim(ymin, ymax),plt.axhline(0, color="grey"),plt.axvline(0, plt.ylabel('f(x)'), plt.xlabel('x'),plt.title('f(x)'),
        plt.plot(x, f(x))
```

Out[28]: [<matplotlib.lines.Line2D at 0x151dab03c8>]



In []:

4 Discrete Probability Distributions

The mean of a discrete distribution with p.m.f. p(x):

$$\mu = E(X) = \sum x p(x)$$

The variance of a discrete random variable with p.m.f. p(x):

$$\sigma^2 = V(X) = E[(X - \mu)^2] = \sum (x - \mu)^2 p(x)$$

also:

$$\sigma^2 = V(X) = E(X^2) - \mu^2$$

("the variance equals the mean of the squares minus the square of the mean")

The standard variation:

$$\sigma = S(X) = \sqrt{V(X)}$$

Mean and variance of linear functions:

If Y is a linear function of X, so that Y = aX + b, where a and b are constants, then:

$$E(Y) = aE(X) + b$$

and

$$V(Y) = a^1 v(X)$$

4.1 Bernoulli distribution, Bernoulli (p)

A single bernoulli trial with probability p.

Examples: - the probability of obtaining heads on a fair coin toss. - whether it rains in the Atacama desert in a certain year, or not

The mean:

$$\mu = E(X) = p$$

The variance:

$$\sigma^2 = V(X) = p(1-p)$$

The p.m.f. $X \sim Bernoulli(p)$:

$$p(1) = 1$$
, $p(0) = 0$

or

$$p(x) = p^{x}(1-p)^{1-x}$$
 $x = 0, 1.$

4.2 Binomial distribution, B(n, p)

A binomial distribution is a number of events (bernoulli trials) with probability p happening in a given sample size n.

Examples: - the number of defective items coming from a production line in a sample of 100. - the number of arrows from an archer that hit the centre of the target - the number of matches a tennis player wins against his friend in a series of matches.

The mean:

$$\mu = E(X) = np$$

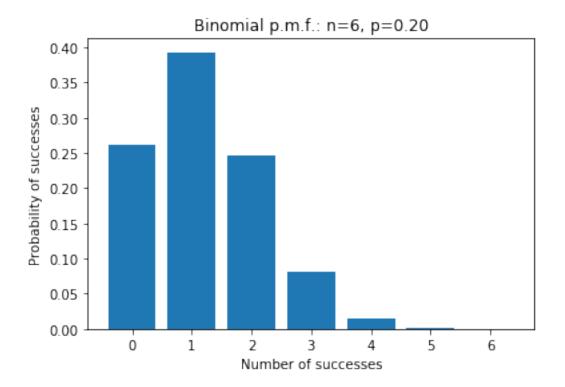
The variance:

$$\sigma^2 = V(X) = np(1-p)$$

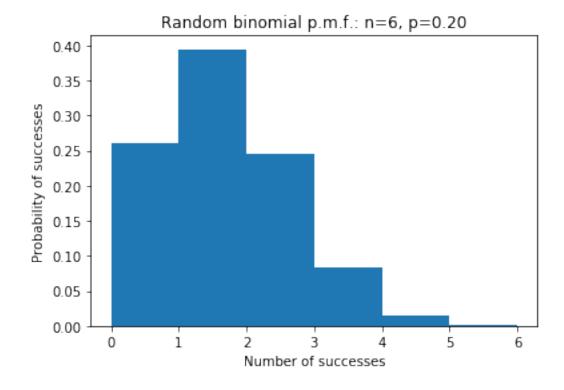
The p.m.f. $X \sim B(n, p)$:

$$p(x) = {n \choose x} p^x (1-p)^{n-x}$$
 $x = 0, 1, 3, ..., n$

```
In [5]: # p.m.f. of binomial distribution
        def factorial(n):
            if n == 0:
                return 1
            else:
                return n * factorial(n-1)
        \# n = total number of Bernoulli trials
        # p = probability of positive outcome
        # X = number of trials with a positive outcome
        def B(n,p,X):
            return factorial(n) / factorial(X) / factorial (n-X) * p**X * (1-p)**(n-X)
In [4]: # graph of p.m.f. of binomial distribution
        import scipy, scipy.stats
        import matplotlib.pyplot as plt
                                            # number of trials
        n = 6
        p = 0.2
                                           # probability of each successfull outcome
        x = scipy.linspace(0,n,n+1)
        binomial = scipy.stats.binom.pmf(x,n,p)
        plt.bar(x, binomial)
        plt.xlabel('Number of successes')
        plt.ylabel('Probability of successes')
        plt.title('Binomial p.m.f.: n=%i, p=%.2f' % (n,p))
        plt.show()
```



In [34]: # alternative graph of p.m.f. of binomial distribution import scipy, scipy.stats import numpy as np import matplotlib.pyplot as plt n = 6# number of trials # probability of each successfull outcome p = 0.2# number of simulation runs number_of_runs = 10000 binom_sim = scipy.stats.binom.rvs(n,p,size=number_of_runs) plt.hist(binom_sim, bins = n, normed = True) plt.xlabel('Number of successes') plt.ylabel('Probability of successes') plt.title('Random binomial p.m.f.: n=%i, p=%.2f' % (n,p)) plt.show()



4.3 Geometric distribution, G(p)

A geometric distribution is a series n of bernoulli trials until the outcome with probability p is positive.

Examples: - the number of times a fair coin needs to be tossed to obtain 'heads' - the number of times a die needs to be rolled to obtain a 6. - the number of times a tennis player needs to play against his friend, until he wins.

The mean:

$$\mu = E(X) = \frac{1}{p}$$

The variance:

$$\sigma^2 = V(X) = \frac{1 - p}{p^2}$$

Dispersion: A geometric distribution is: - under-dispersed when $\frac{(1-p)}{p} < 1$ - equi-dispersed when $\frac{(1-p)}{p} = 1$ - over-dispersed when $\frac{(1-p)}{p} > 1$

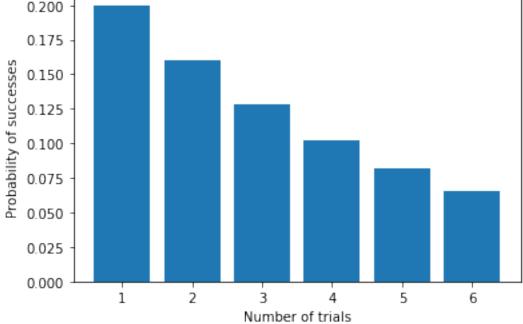
The p.m.f. $X \sim G(p)$:

$$p(x) = P(X = x) = (1 - p)^{x-1}p, \quad x = 1, 2, 3,$$

The c.d.f.:

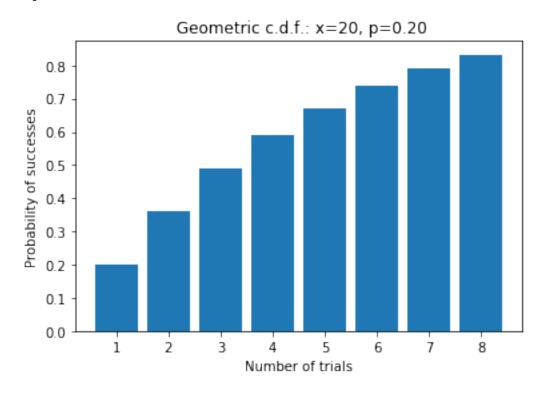
$$F(x) = P(X \le x) = 1 - (1 - p)^x, \quad x = 1, 2, 3, ...$$

```
In [5]: # geometric p.m.f.
       def G(p,x):
            return (1-p)**(x-1)*p
In [121]: # graph of geometric p.m.f.
          import scipy, scipy.stats
          import matplotlib.pyplot as plt
          X = 6
                                             # number of trials
          p = 0.2
                                             # probability of each successfull outcome
          x = scipy.linspace(1,X,X)
          geometrical = scipy.stats.geom.pmf(x,p)
          plt.bar(x, geometrical)
          plt.xlabel('Number of trials')
          plt.ylabel('Probability of successes')
          plt.title(' geometric p.m.f.: x=%i, p=%.2f' % (n,p))
          plt.show()
                            geometric p.m.f.: x=10, p=0.20
         0.200
         0.175
         0.150
```



In [53]: # geometric c.d.f.

```
def F(p,x):
             return 1 - (1-p)**(x)
In [90]: # graph of geometric c.d.f.
         import scipy, scipy.stats
         import matplotlib.pyplot as plt
         X = 8
                                            # number of trials
         p = 0.2
                                             # probability of each successfull outcome
         x = scipy.linspace(1,X,X)
         geometrical = scipy.stats.geom.cdf(x,p)
         plt.bar(x, geometrical)
         plt.xlabel('Number of trials')
         plt.ylabel('Probability of successes')
         plt.title(' Geometric c.d.f.: x=%i, p=%.2f' % (n,p))
         plt.show()
```



4.4 Poisson distribution, (λ)

Examples: - the number of claims on a motor insurance policy over a certain period - the number of yeast cells found in a randomly chose small square on a microscope slide

The mean:

$$\mu = E(X) = \lambda$$

The variance:

$$\sigma^2 = V(X) = \lambda$$

Comment: whenever it is suggested that the poisson distribution model is to be used to model a data-set, calculate the mean and the variance of the sample data. If they are close to each other, a possion is likely to be a good model to be used.

The p.m.f $X \sim Poisson(\lambda)$:

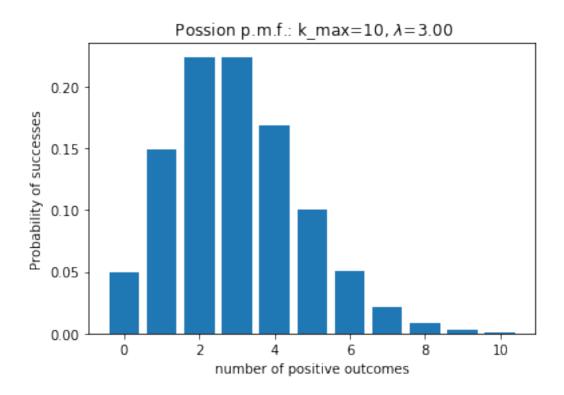
$$p(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$
 $x = 0, 1, 2, ...$

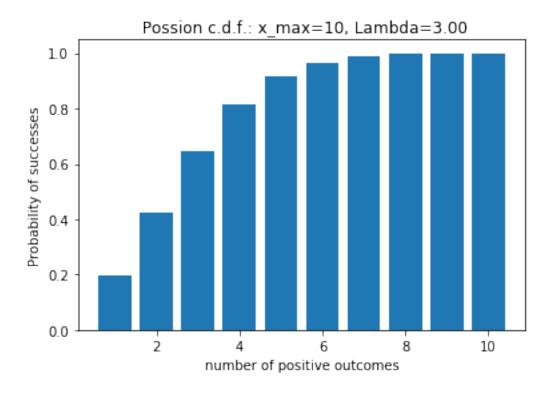
, where

$$\lambda = \frac{n}{t}$$

, where n is the number of observed occurances per unit of time/space, and t is the unit of time/space.

```
In [6]: # The Poisson p.m.f.
        import numpy as np
        def factorial(k):
            if k == 0:
                return 1
            else:
                return k * factorial(k-1)
        def P(x, Lambda):
            return (np.exp(-Lambda) * Lambda**x ) / factorial(x) # poisson p.m.f.
In [4]: # graph of poisson p.m.f.:
        import scipy, scipy.stats
        import numpy as np
        import matplotlib.pyplot as plt
        k = 10
                                                  # maximum number of occurances
        Lambda = 3
                                                  # parameter lambda
        x = np.arange (0,k+1)
        y = scipy.stats.poisson.pmf(x,Lambda)
        plt.bar(x, y)
        plt.xlabel('number of positive outcomes')
        plt.ylabel('Probability of successes')
        plt.title(' Possion p.m.f.: k_max=%i, $\lambda$=%.2f' % (k,Lambda))
        plt.show()
```





4.5 Discrete uniform distribution on m, m + 1, ..., n

The mean:

$$\mu = E(X) = \frac{m+n}{2}$$

The variance:

$$\sigma^2 = V(X) = \frac{1}{12}(n-m)(n-m+2)$$

The p.m.f.:

$$p(x) = \frac{1}{n-m+1}$$
 $x = m, m+1, m+1, ..., n.$

, where m is the mimimum and n is the maximum attainable value.

The c.d.f.:

$$F(x) = P(X \le x) = \frac{x - m + 1}{n - m + 1}$$
 $x = m, m + 1, m + 2, ..., n.$

In [1]: # p.m.f. of discrete uniform distribution

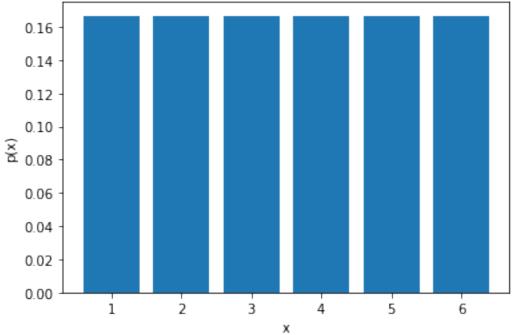
def p(m,n,x):
 return 1 / n-m+1

In [173]: # graph for p.m.f. of discrete uniform distribution

import numpy as np

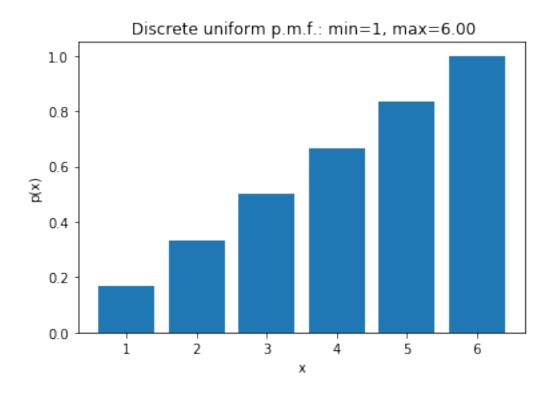
import matplotlib.pyplot as plt





In [2]: # c.d.f. of discrete uniform distribution:
 def F(m,n,x):
 return (x-m+1) / (n-m+1)

```
In [176]: # graph of c.d.f. of discrete uniform distribution
          import numpy as np
          import matplotlib.pyplot as plt
          def F(m,n):
              return (x-m+1) / (n-m+1)
          m = 1
                                                    # minimum attainable value
          n = 6
                                                    # maximum attainable value
          x = np.arange (m,n+1)
          y = F(m,n)
          plt.bar(x, y)
          plt.xlabel('x')
          plt.ylabel('p(x)')
          plt.title(' Discrete uniform p.m.f.: min=%i, max=%.2f' % (m,n))
          plt.show()
```



5 Continuous Probability Distributions

The mean of a continuous distribution with p.d.f. f(x):

$$\mu = E(X) = \int x f(x) dx$$

The variance of a continuous random variable with p.d.f. f(x):

$$\sigma^2 = V(X) = E[(X - \mu)^2] = \int (x - \mu)^2 f(x) dx$$

also:

$$\sigma^2 = V(X) = E(X^2) - \mu^2$$

("the variance equals the mean of the squares minus the square of the mean")

5.1 Continuous uniform distribution, U(a, b)

The mean:

$$\mu = E(X) = \frac{a+b}{2}$$

The variance:

$$\sigma^2 = V(X) = \frac{1}{12}(b - a)^2$$

The p.d.f. $X \sim U(a,b)$:

$$f(x) = \frac{1}{b - a}, \quad a < x < b$$

The c.d.f. of $X \sim U(a, b)$:

$$F(x) = P(X \le x) = \frac{x - a}{b - a}, \quad a < x < b$$

5.2 Standard uniform distribution

The p.d.f. of the the standard uniform distribution $V \sim U(0,1)$:

$$f(v) = 1, \quad 0 < v < 1$$

The C.d.f. of the the standard uniform distribution $V \sim U(0,1)$:

$$F(v) = v$$
, $0 < v < 1$

In []:

5.3 Exponential distribution, $M(\lambda)$

A random variable *X* has an **exponential distribution** with parameter λ , where $\lambda > 0$, if it has:

Examples: -

The mean:

$$\mu = E(X) = \frac{1}{\lambda}$$

The variance:

$$\sigma^2 = V(X) = \frac{1}{\lambda^2}$$

The standard deviation:

$$\sigma = \sqrt{V(X)} = \frac{1}{\lambda}$$

The p.d.f. $X \sim M(\lambda)$:

$$f(x) = \lambda e^{-\lambda x}, \qquad x > 0$$

The c.d.f.:

$$F(x) = 1 - e^{\lambda x}, \quad x > 0$$

```
In [19]: import numpy as np
    import matplotlib.pyplot as plt

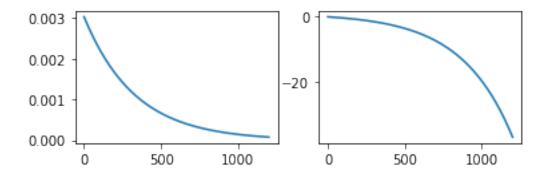
Lambda = 67/22120
    x = np.linspace(0, 1200, 1000)

# p.d.f. of eponential distribution
    def exponential_pdf(Lambda,x):
        return Lambda * np.exp(-Lambda * x)

# c.d.f. of exponential distribution
    def exponential_cdf(Lambda,x):
        return 1 - np.exp(Lambda * x)

plt.figure()
    plt.subplot(2,2,1); plt.plot(x, exponential_pdf(Lambda, x))
    plt.subplot (2,2,2); plt.plot(x, exponential_cdf(Lambda, x))
    plt.show()
```

Upper r



6 Linear regression

```
In [20]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    data = pd.read_csv("cholesterol.csv", header = [0])

# the data
    N = data['Age'].count()
    response = data[["Cholesterol"]]
    predictor = data[["Age"]]

# Create data points
#N = 10
#x = np.random.rand(N)
#y = np.random.rand(N)
```

```
# desired probability for confidence interval
probability = 0.95
# Regression function
xbar = np.mean(predictor)
ybar = np.mean(response)
Sxx = np.sum((predictor - xbar) ** 2)
Sxy = np.sum((predictor - xbar) * (response - ybar))
beta_hat = Sxy / Sxx
alpha_hat = ybar - beta_hat * xbar
# Least square line
x_values = np.linspace(min(x_values), max(x_values), 100)
y_values = alpha_hat + beta_hat * x_values
print(' ')
print('The least square line is given by:')
print('y = '+ str(alpha_hat) +' + ' + str(beta_hat) +' x')
# students t-value for two sided confidence interval
from scipy.stats import t
p = 0.5 + (probability / 2) # probability converted to lookup t-value
df = N - 2
                            # degrees of freedom
t_value = t.ppf(p, df)
# Fitted values:
y_hat = alpha_hat + beta_hat * predictor
# Residuals:
w = response - y_hat
# unbiased estimator of variance:
variance = (np.sum(y - y_hat)) / (N - 2)
# confidence interval for slope of beta hat:
beta_lower = beta_hat - t_value * (np.sqrt(variance))/(np.sqrt(Sxx))
beta_upper = beta_hat + t_value * (np.sqrt(variance))/(np.sqrt(Sxx))
y_values_lower = alpha_hat + beta_lower * x_values
y_values_upper = alpha_hat + beta_upper * x_values
# Linear regression Plot
plt.scatter(predictor, response)
plt.plot(x_values, y_values,'r')
# plt.plot(x_values, y_values_lower, 'y')
# plt.plot(x_values, y_values_upper, 'y')
plt.title('Linear regression model')
plt.xlabel('Predictor')
```

```
plt.ylabel('Response')
     ax = plt.gca()
     lines = ax.get_lines()
     lines[0].set_label('Least square line')
     #lines[1].set_label('Confidence interval')
     ax.legend()
     plt.show()
     # Resiual plot
     plt.scatter(y_hat, w )
     plt.title('Residual plot')
     plt.axhline(0, color='black')
     plt.xlabel('Fitted value $\hat{y}$')
     plt.ylabel('Residuals $w$')
     ax.legend()
     plt.show()
     # Normal probability plot of the residuals
     from scipy import stats
     w = stats.norm.rvs(loc=0, scale=1, size=N)
     stats.probplot(w, plot=plt, dist='norm')
     plt.show()
     # unbiased estimator of the variance:
     variance_estimate = np.sum(response - y_hat)/( N - 2)
     print('an unbiased estimator of the variacne is ' + str(variance_estimate))
    NameError
                                              Traceback (most recent call last)
    <ipython-input-20-140fd3031a5e> in <module>
     28 # Least square line
---> 29 x_values = np.linspace(min(x_values), max(x_values), 100)
     30 y_values = alpha_hat + beta_hat * x_values
     31 print(' ')
    NameError: name 'x_values' is not defined
```

In []: xbar

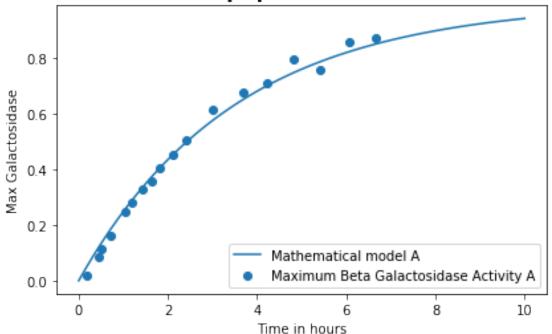
6.1 Fitting experimental data to a model

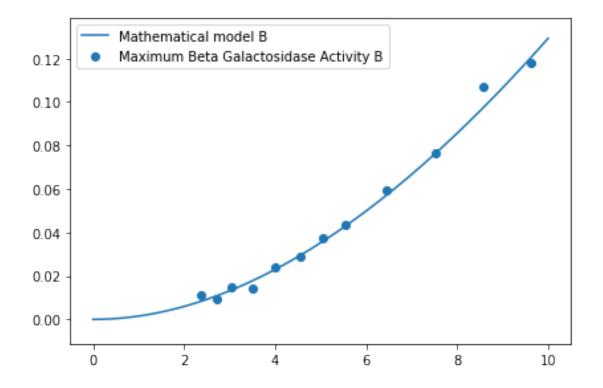
```
In [21]: #!/usr/bin/env python3
         # -*- coding: utf-8 -*-
         .....
         Created on Wed Feb 28 20:01:56 2018
         Purpose: Exercise of fitting a mathematical model onto experimental data from two fil
         Qauthor: stephangoldberg
         import numpy as np
         import matplotlib.pyplot as plt
         # importing the datasets (each set has 2 columns)
         data_set_A = np.loadtxt('g149novickA.csv', delimiter=',')
         data_set_B = np.loadtxt('g149novickB.csv', delimiter=',')
         # choosig from data_set_B only the entries where the first column is smaller than 10:
         B = data_set_B[(data_set_B[:,0:1]<10).all(1)]</pre>
         # slicing the two data sets(separating the columns):
         time_in_hours_A = data_set_A[:, 0] #first column
         max_beta_galactosidase_activity_A = data_set_A[:, 1] # second column
         time_in_hours_B = B[:, 0] #first column
         max_beta_galactosidase_activity_B = B[:, 1] #second column
         # creating a mathematical model, which represents the data
         # Define parameters:
         A = 1
         tau_A = 3.5
         tau_B = 18
         # Defining the range of x-values for both models
         time_model = np.linspace (0,10,101)
         # Defining the y-values (These are the formulas for the models)
         V_t = 1 - np.exp(- time_model / tau_A)
         W_t = A * (np.exp(-time_model/tau_B) - 1 + time_model / tau_B)
         # plotting the actual data and the model:
         plt.scatter(time_in_hours_A, max_beta_galactosidase_activity_A, label = "Maximum Beta
         plt.plot(time_model, V_t, label = "Mathematical model A")
```

```
# getting control of the axis
ax = plt.gca()
ax.set_xlabel("Time in hours")
ax.set_ylabel ("Max Galactosidase", size=10)
ax.set_title( " Bacterial population in a culture", size=16, weight="bold")
                    # showing the labels of the plotted curves
plt.tight layout() # ensures that labels of x- or y-axis are not cut off
plt.figure()
                # plotting the first figure with data_set_A
plt.scatter(time_in_hours_B, max_beta_galactosidase_activity_B, label = "Maximum Beta
plt.plot(time_model, W_t, label = "Mathematical model B")
ax.set_xlabel("Time in hours")
ax.set_ylabel ("Max Galactosidase", size=10)
ax.set_title( " Bacterial population in a culture", size=16, weight="bold")
                    # showing the labels of the plotted curves
plt.tight_layout() # ensures that labels of x- or y-axis are not cut off
plt.figure()
                #plotting the second figure with data_set_B
```

plt.show() # showing the plot







<Figure size 432x288 with 0 Axes>

In []: