

# Stock\_Basic\_Statistics

September 29, 2021

## 1 Basic Statistics in Python

### 1.1 Statistical Analysis

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from scipy.stats import norm
import math

import warnings
warnings.filterwarnings("ignore")

# fix_yahoo_finance is used to fetch data
import fix_yahoo_finance as yf
yf.pdr_override()
```

```
[2]: # input
symbol = 'AAPL'
market = '^GSPC'
start = '2017-01-01'
end = '2019-01-01'

# Read data
df = yf.download(symbol,start,end)
dfm = yf.download(market,start,end)

# View Columns
df.head()
```

```
[*****100%*****] 1 of 1 downloaded
```

```
[*****100%*****] 1 of 1 downloaded
```

```
[2]:
```

	Open	High	Low	Close	Adj Close	\
Date						
2017-01-03	115.800003	116.330002	114.760002	116.150002	111.709831	

2017-01-04	115.849998	116.510002	115.750000	116.019997	111.584778
2017-01-05	115.919998	116.860001	115.809998	116.610001	112.152229
2017-01-06	116.779999	118.160004	116.470001	117.910004	113.402542
2017-01-09	117.949997	119.430000	117.940002	118.989998	114.441246

Date	Volume
2017-01-03	28781900
2017-01-04	21118100
2017-01-05	22193600
2017-01-06	31751900
2017-01-09	33561900

```
[3]: df.shape
```

```
[3]: (502, 6)
```

```
[4]: new_df = pd.DataFrame({symbol : df['Adj Close'], market : dfm['Adj Close']},
    ↪ index=df.index)

# compute returns
new_df[['stock_returns', 'market_returns']] = new_df[['symbol', market]] /
    ↪ new_df[['symbol', market]].shift(1) - 1
new_df = new_df.dropna()
covmat = np.cov(new_df["stock_returns"], new_df["market_returns"])

# calculate measures now
beta = covmat[0,1]/covmat[1,1]
alpha= np.mean(new_df["stock_returns"])-beta*np.mean(new_df["market_returns"])
```

```
[5]: print('Beta:', beta)
    print('Alpha:', alpha)
```

```
Beta: 1.27474949119
Alpha: 0.000476775370087
```

```
[6]: close = df['Adj Close']
```

## 1.2 Mean is the average

```
[7]: mean = np.mean(close)
    mean
```

```
[7]: 166.18815917729088
```

### 1.3 Median is the value of middlemost value

```
[8]: median = np.median(close)
     median
```

```
[8]: 165.22975150000002
```

### 1.4 Mode is the most frequent value

```
[9]: mode = stats.mode(close)
     print("The modal value is {} with a count of {}".format(mode.mode[0], mode.
     ↪count[0]))
```

The modal value is 115.41264299999999 with a count of 2

### 1.5 Range is a measure of how spread apart the values are

```
[10]: range_of_stock = np.ptp(close)
     range_of_stock
```

```
[10]: 117.807312
```

### 1.6 Variance is a measure of how variable the data is

```
[11]: variance = np.var(close)
     variance
```

```
[11]: 726.388795436073
```

### 1.7 Standard deviation is the square root of the variance and is measure how the data is spread out

```
[12]: standard_deviation = np.std(close)
     standard_deviation
```

```
[12]: 26.951600980944953
```

### 1.8 Standard error is the mean (SE of the mean) estimates the variability between sample means that you would obtain if you took multiple samples from the same population

```
[13]: standard_error = stats.sem(close)
     standard_error
```

```
[13]: 1.2041087306392817
```

## 1.9 Z-Scores measure how many standard deviations an element is from the mean

```
[14]: z = np.abs(stats.zscore(close))  
print(z)
```

```
[ 2.02133922  2.02597913  2.00492469  1.95853364  1.91999404  1.91571192  
 1.89287324  1.91071589  1.9182098  1.88395176  1.88430926  1.89180261  
 1.88395176  1.8810972  1.88502235  1.8168635  1.81472229  1.81436562  
 1.82578524  1.83577704  1.57170668  1.57955727  1.55993038  1.51675168  
 1.4725024  1.45430337  1.42025564  1.4310072  1.38907493  1.3270713  
 1.30950975  1.31524432  1.30198326  1.26686015  1.25216558  1.27295251  
 1.26829364  1.25861693  1.25646666  1.15611622  1.18586143  1.15647346  
 1.17224313  1.16579179  1.18442849  1.19589768  1.17941065  1.17726098  
 1.18478688  1.13210218  1.12385896  1.14894585  1.09626227  1.1543232  
 1.0976958  1.11561629  1.12565139  1.11704979  1.01239656  1.00092741  
 1.00773769  1.01741497  1.01598147  0.97763351  1.00451172  1.01741497  
 1.0288836  1.03497596  1.09016875  1.08407635  1.11095627  1.08300235  
 1.10558008  1.1242179  1.06113856  1.06723212  1.01813118  0.9862334  
 1.01669764  1.01275554  1.01777335  0.91276174  0.87943051  0.89555857  
 0.91455421  0.82746254  0.68231168  0.64718854  0.67335229  0.62584787  
 0.54847314  0.56286935  0.57114712  0.75900249  0.6765918  0.65787755  
 0.62440815  0.63124562  0.64780112  0.62872737  0.63808422  0.6359249  
 0.66867357  0.65355947  0.5718667  0.62656917  0.60785436  0.57474501  
 0.58842108  0.80470764  0.93282459  0.89071963  0.94218088  0.97349097  
 1.04618528  0.89971528  0.94757915  0.91662971  0.92526586  0.90187404  
 0.91842842  0.99364384  0.91806948  0.99544362  0.98320731  1.00192045  
 0.98068791  1.0296309  0.97744951  0.94577937  0.92886546  0.92130732  
 0.84825347  0.80254832  0.78383463  0.76512094  0.73129148  0.7557652  
 0.75828234  0.69278497  0.66939315  0.64348137  0.74784642  0.78599339  
 0.81370499  0.76620002  0.5110469  0.56754807  0.53803777  0.45094784  
 0.40524324  0.36997517  0.55459441  0.47655559  0.3909297  0.32770321  
 0.3511879  0.46282632  0.47583263  0.48630989  0.39345815  0.38623291  
 0.41188481  0.39056849  0.33240004  0.28037433  0.26447725  0.24099426  
 0.2391871  0.31036131  0.3165041  0.33998764  0.43500715  0.33131639  
 0.35443873  0.39815554  0.44765282  0.38984609  0.43356178  0.43139453  
 0.52749654  0.62432381  0.67851732  0.72693037  0.63335622  0.59397563  
 0.62829819  0.59794946  0.60914972  0.58494374  0.62107235  0.55206654  
 0.55531685  0.53580769  0.53363988  0.51015464  0.53002611  0.49425814  
 0.38984609  0.36852921  0.39418115  0.53074966  0.52099481  0.52388558  
 0.49028428  0.51521382  0.47908461  0.27531686  0.14272218  0.05890289  
 0.13658054  0.09250308  0.06610416  0.12932956  0.14956224  0.2012273  
 0.18821987  0.16719006  0.14180875  0.04644725  0.03549805  0.03774603  
 0.00329943  0.00286485  0.11171362  0.17770469  0.1780676  0.14615907  
 0.10917611  0.02099427  0.06493959  0.03593263  0.00939151  0.01519287  
 0.03803611  0.02679511  0.02498283  0.09467237  0.05950054  0.08016859  
 0.07835578  0.14180875  0.23064358  0.16247624  0.15558726  0.17951809  
 0.17951809  0.01852847  0.0196166  0.03702021  0.030059  0.07980568]
```

0.0787181	0.10772506	0.17915518	0.15558726	0.15486259	0.15341151
0.1893086	0.25493676	0.22230412	0.32781733	0.33361873	0.30461232
0.25167399	0.25312392	0.15087344	0.03810723	0.05261212	0.0761078
0.1120043	0.09532536	0.08263499	0.34659975	0.49199861	0.25486505
0.38140926	0.54058548	0.47177669	0.24241306	0.18307091	0.07275843
0.13184838	0.11146057	0.09034468	0.06194745	0.1140094	0.22322977
0.34956168	0.32844575	0.31861561	0.20502562	0.24907874	0.27128673
0.26582617	0.20611888	0.27565519	0.38633174	0.44968	0.38596883
0.33026538	0.33791075	0.31497523	0.21594846	0.21376425	0.06922879
0.01887629	0.16122583	0.12383954	0.03744335	0.10516003	0.05783175
0.09787872	0.0356226	0.0816072	0.12493109	0.03598663	0.02481221
0.14131505	0.11182459	0.17371669	0.1951966	0.2348807	0.32298463
0.30842141	0.12493109	0.13282974	0.15030355	0.23404017	0.20819179
0.18743937	0.25661222	0.14957661	0.00977423	0.26218523	0.27383556
0.52649874	0.57491975	0.60732195	0.65501485	0.7525849	0.72627113
0.71019005	0.64769502	0.71128672	0.66779524	0.64294328	0.69118535
0.67400823	0.71786488	0.71019005	0.72590596	0.70105345	0.68643476
0.66340979	0.7865746	0.84468421	0.8987741	0.92325973	0.90425618
0.83993303	0.82275587	0.86113043	0.80338544	0.80704055	0.73540773
0.73175322	0.62028404	0.64988717	0.61187778	0.59214274	0.49163773
0.57423356	0.56436662	0.61333959	0.59908607	0.67473913	0.55559574
0.60968563	0.70361192	0.79899999	0.79059429	0.70032255	0.81544625
0.82641042	0.81106023	0.83079643	0.79242127	0.84651175	0.83043066
0.83664309	0.88744475	0.95396065	0.93166713	0.81361927	0.7745138
0.78840102	1.19809583	1.41335937	1.43528712	1.47475832	1.40312555
1.40824186	1.46781443	1.44507537	1.49422047	1.52649529	1.54446617
1.65742658	1.81366335	1.73591156	1.72050818	1.72087446	1.73701217
1.76158444	1.82686664	1.89141513	2.01171065	2.08689494	2.18225191
2.20902424	2.1543778	2.01611195	1.95009658	1.84117058	2.04361863
1.94166142	2.13750752	2.04325119	1.82466659	1.83786933	1.84263747
1.90351786	1.81659772	1.93139079	1.98273712	1.9178212	2.08396113
2.11293525	2.16868174	2.24276598	2.34509003	2.19545465	2.05975518
2.04068422	2.1543778	1.76891955	1.69886972	1.97980331	1.80559451
1.98126964	1.94606216	1.75644997	1.87711178	1.92625632	2.00254122
1.72234139	1.8950827	1.76671946	1.61781724	1.65669286	1.86060779
1.98383773	1.4432416	1.22722394	1.30717637	1.5338298	1.50696405
1.3590141	0.97993981	0.90854083	0.70869938	0.87836251	0.95638548
0.67410392	0.34728912	0.33992908	0.17468197	0.26043354	0.2464484
0.49303104	0.44187441	0.4061749	0.63582842	0.33661651	0.26411469
0.0348292	0.07568125	0.03998177	0.05727952	0.12536535	0.0759487
0.13262593	0.05423497	0.24487641	0.39429833	0.61879868	0.76233205
0.38178516	0.41932467	0.41638065	0.36080685]		

## 1.10 Contingency Table shows correlations between two variables

```
[15]: data_crosstab = pd.crosstab(df['High'],
                                   df['Low'],
                                   margins = False)
print(data_crosstab)
```

Low	114.760002	115.750000	115.809998	116.470001	117.940002	\
High						
116.330002	1	0	0	0	0	
116.510002	0	1	0	0	0	
116.860001	0	0	1	0	0	
118.160004	0	0	0	1	0	
119.300003	0	0	0	0	0	
119.379997	0	0	0	0	0	
119.430000	0	0	0	0	1	
119.620003	0	0	0	0	0	
119.930000	0	0	0	0	0	
120.089996	0	0	0	0	0	
120.099998	0	0	0	0	0	
120.239998	0	0	0	0	0	
120.449997	0	0	0	0	0	
120.500000	0	0	0	0	0	
120.809998	0	0	0	0	0	
121.389999	0	0	0	0	0	
121.629997	0	0	0	0	0	
122.099998	0	0	0	0	0	
122.349998	0	0	0	0	0	
122.440002	0	0	0	0	0	
129.190002	0	0	0	0	0	
129.389999	0	0	0	0	0	
130.490005	0	0	0	0	0	
130.500000	0	0	0	0	0	
132.089996	0	0	0	0	0	
132.220001	0	0	0	0	0	
132.449997	0	0	0	0	0	
132.940002	0	0	0	0	0	
133.820007	0	0	0	0	0	
135.089996	0	0	0	0	0	
...	...	...	...	...	...	
222.639999	0	0	0	0	0	
222.820007	0	0	0	0	0	
222.880005	0	0	0	0	0	
222.949997	0	0	0	0	0	
222.990005	0	0	0	0	0	
223.250000	0	0	0	0	0	
223.360001	0	0	0	0	0	
223.490005	0	0	0	0	0	

223.750000	0	0	0	0	0
224.229996	0	0	0	0	0
224.300003	0	0	0	0	0
224.800003	0	0	0	0	0
225.000000	0	0	0	0	0
225.369995	0	0	0	0	0
225.839996	0	0	0	0	0
226.350006	0	0	0	0	0
226.440002	0	0	0	0	0
226.839996	0	0	0	0	0
227.270004	0	0	0	0	0
227.350006	0	0	0	0	0
228.259995	0	0	0	0	0
228.350006	0	0	0	0	0
228.410004	0	0	0	0	0
228.869995	0	0	0	0	0
229.179993	0	0	0	0	0
229.419998	0	0	0	0	0
229.669998	0	0	0	0	0
230.000000	0	0	0	0	0
232.350006	0	0	0	0	0
233.470001	0	0	0	0	0

Low	118.209999	118.220001	118.300003	118.599998	118.809998	...	\
High						...	
116.330002	0	0	0	0	0	...	
116.510002	0	0	0	0	0	...	
116.860001	0	0	0	0	0	...	
118.160004	0	0	0	0	0	...	
119.300003	1	0	0	0	0	...	
119.379997	0	0	1	0	0	...	
119.430000	0	0	0	0	0	...	
119.620003	0	0	0	0	1	...	
119.930000	0	0	0	1	0	...	
120.089996	0	0	0	0	0	...	
120.099998	0	0	0	0	0	...	
120.239998	0	1	0	0	0	...	
120.449997	0	0	0	0	0	...	
120.500000	0	0	0	0	0	...	
120.809998	0	0	0	0	0	...	
121.389999	0	0	0	0	0	...	
121.629997	0	0	0	0	0	...	
122.099998	0	0	0	0	0	...	
122.349998	0	0	0	0	0	...	
122.440002	0	0	0	0	0	...	
129.190002	0	0	0	0	0	...	
129.389999	0	0	0	0	0	...	
130.490005	0	0	0	0	0	...	

130.500000	0	0	0	0	0	...
132.089996	0	0	0	0	0	...
132.220001	0	0	0	0	0	...
132.449997	0	0	0	0	0	...
132.940002	0	0	0	0	0	...
133.820007	0	0	0	0	0	...
135.089996	0	0	0	0	0	...
...	...	...	...	...	...	...
222.639999	0	0	0	0	0	...
222.820007	0	0	0	0	0	...
222.880005	0	0	0	0	0	...
222.949997	0	0	0	0	0	...
222.990005	0	0	0	0	0	...
223.250000	0	0	0	0	0	...
223.360001	0	0	0	0	0	...
223.490005	0	0	0	0	0	...
223.750000	0	0	0	0	0	...
224.229996	0	0	0	0	0	...
224.300003	0	0	0	0	0	...
224.800003	0	0	0	0	0	...
225.000000	0	0	0	0	0	...
225.369995	0	0	0	0	0	...
225.839996	0	0	0	0	0	...
226.350006	0	0	0	0	0	...
226.440002	0	0	0	0	0	...
226.839996	0	0	0	0	0	...
227.270004	0	0	0	0	0	...
227.350006	0	0	0	0	0	...
228.259995	0	0	0	0	0	...
228.350006	0	0	0	0	0	...
228.410004	0	0	0	0	0	...
228.869995	0	0	0	0	0	...
229.179993	0	0	0	0	0	...
229.419998	0	0	0	0	0	...
229.669998	0	0	0	0	0	...
230.000000	0	0	0	0	0	...
232.350006	0	0	0	0	0	...
233.470001	0	0	0	0	0	...
Low	222.520004	222.570007	223.539993	224.020004	225.100006	\
High						
116.330002	0	0	0	0	0	
116.510002	0	0	0	0	0	
116.860001	0	0	0	0	0	
118.160004	0	0	0	0	0	
119.300003	0	0	0	0	0	
119.379997	0	0	0	0	0	
119.430000	0	0	0	0	0	



119.620003	0	0	0	0	0
119.930000	0	0	0	0	0
120.089996	0	0	0	0	0
120.099998	0	0	0	0	0
120.239998	0	0	0	0	0
120.449997	0	0	0	0	0
120.500000	0	0	0	0	0
120.809998	0	0	0	0	0
121.389999	0	0	0	0	0
121.629997	0	0	0	0	0
122.099998	0	0	0	0	0
122.349998	0	0	0	0	0
122.440002	0	0	0	0	0
129.190002	0	0	0	0	0
129.389999	0	0	0	0	0
130.490005	0	0	0	0	0
130.500000	0	0	0	0	0
132.089996	0	0	0	0	0
132.220001	0	0	0	0	0
132.449997	0	0	0	0	0
132.940002	0	0	0	0	0
133.820007	0	0	0	0	0
135.089996	0	0	0	0	0
...	...	...	...	...	...
222.639999	0	0	0	0	0
222.820007	0	0	0	0	0
222.880005	0	0	0	0	0
222.949997	0	0	0	0	0
222.990005	0	0	0	0	0
223.250000	0	0	0	0	0
223.360001	0	0	0	0	0
223.490005	0	0	0	0	0
223.750000	0	0	0	0	0
224.229996	0	0	0	0	0
224.300003	0	0	0	0	0
224.800003	0	0	0	0	0
225.000000	0	0	0	0	0
225.369995	0	0	0	0	0
225.839996	0	0	0	1	0
226.350006	0	0	0	0	0
226.440002	0	0	1	0	0
226.839996	1	0	0	0	0
227.270004	0	0	0	0	0
227.350006	0	0	0	0	0
228.259995	0	0	0	0	0
228.350006	0	1	0	0	0
228.410004	0	0	0	0	0
228.869995	0	0	0	0	0

229.179993	0	0	0	0	0
229.419998	0	0	0	0	0
229.669998	0	0	0	0	1
230.000000	0	0	0	0	0
232.350006	0	0	0	0	0
233.470001	0	0	0	0	0

Low	226.000000	226.350006	226.630005	226.729996	229.779999
High					

116.330002	0	0	0	0	0
116.510002	0	0	0	0	0
116.860001	0	0	0	0	0
118.160004	0	0	0	0	0
119.300003	0	0	0	0	0
119.379997	0	0	0	0	0
119.430000	0	0	0	0	0
119.620003	0	0	0	0	0
119.930000	0	0	0	0	0
120.089996	0	0	0	0	0
120.099998	0	0	0	0	0
120.239998	0	0	0	0	0
120.449997	0	0	0	0	0
120.500000	0	0	0	0	0
120.809998	0	0	0	0	0
121.389999	0	0	0	0	0
121.629997	0	0	0	0	0
122.099998	0	0	0	0	0
122.349998	0	0	0	0	0
122.440002	0	0	0	0	0
129.190002	0	0	0	0	0
129.389999	0	0	0	0	0
130.490005	0	0	0	0	0
130.500000	0	0	0	0	0
132.089996	0	0	0	0	0
132.220001	0	0	0	0	0
132.449997	0	0	0	0	0
132.940002	0	0	0	0	0
133.820007	0	0	0	0	0
135.089996	0	0	0	0	0

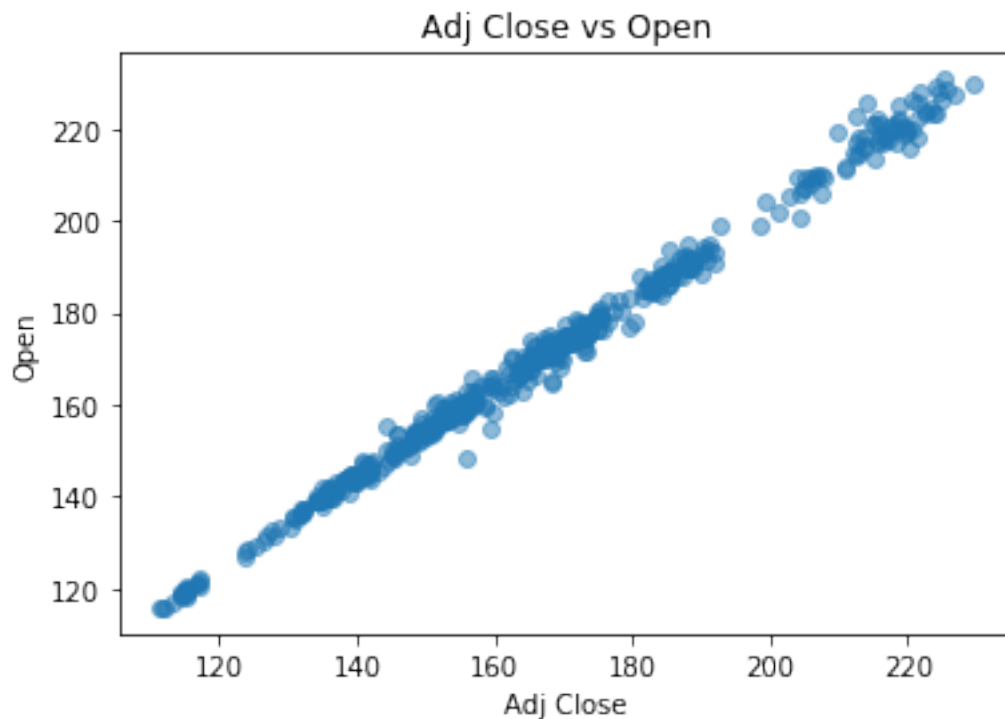
...	...	...	...	...	...
222.639999	0	0	0	0	0
222.820007	0	0	0	0	0
222.880005	0	0	0	0	0
222.949997	0	0	0	0	0
222.990005	0	0	0	0	0
223.250000	0	0	0	0	0
223.360001	0	0	0	0	0
223.490005	0	0	0	0	0

223.750000	0	0	0	0	0
224.229996	0	0	0	0	0
224.300003	0	0	0	0	0
224.800003	0	0	0	0	0
225.000000	0	0	0	0	0
225.369995	0	0	0	0	0
225.839996	0	0	0	0	0
226.350006	0	0	0	0	0
226.440002	0	0	0	0	0
226.839996	0	0	0	0	0
227.270004	0	0	0	0	0
227.350006	0	0	0	0	0
228.259995	0	0	0	0	0
228.350006	0	0	0	0	0
228.410004	0	0	0	0	0
228.869995	1	0	0	0	0
229.179993	0	0	1	0	0
229.419998	0	1	0	0	0
229.669998	0	0	0	0	0
230.000000	0	0	1	0	0
232.350006	0	0	0	1	0
233.470001	0	0	0	0	1

[482 rows x 484 columns]

### 1.11 Scatter plot shows two variables that plot along two axes and it shows correlation or not

```
[16]: plt.scatter(df['Adj Close'], df['Open'], alpha=0.5)
plt.title('Adj Close vs Open')
plt.xlabel('Adj Close')
plt.ylabel('Open')
plt.show()
```



**1.12** Regression is a measure of the relation between the mean value of one variable (e.g. output) and corresponding values of other variables

```
[17]: from sklearn.linear_model import LinearRegression
```

```
X = np.array(df['Open']).reshape(502,-1)
y = np.array(df['Adj Close'])
LR = LinearRegression().fit(X, y)
LR.score(X, y)
```

```
[17]: 0.99395097797644405
```

```
[18]: LR.coef_
```

```
[18]: array([ 1.02181913])
```

```
[19]: LR.intercept_
```

```
[19]: -7.2944207057100527
```

```
[20]: LR.predict(X)
```

```
[20]: array([ 111.03223793,  111.08332378,  111.15485112,  112.03361659,
 113.22914293,  114.06703462,  114.03638107,  114.19987622,
 114.41445722,  113.62765137,  115.32387522,  114.71078579,
 115.78369077,  115.32387522,  114.86405968,  115.75303721,
 117.03031113,  117.51056714,  116.27416701,  116.49896927,
 122.5072627 ,  123.47799497,  123.81519017,  124.65308901,
 126.09384173,  126.92152851,  127.22806199,  128.05574877,
 128.68927152,  129.08777996,  131.18251225,  131.33577899,
 130.75335026,  131.90799566,  132.11235642,  133.08309686,
 131.58102171,  132.83785413,  132.77654805,  133.60421848,
 135.76025788,  134.51363751,  135.11650671,  134.79974585,
 134.68734472,  134.47277088,  134.99389353,  134.585172  ,
 135.04498755,  135.15738868,  136.49596867,  136.78207701,
 136.1689794 ,  137.91629727,  135.60699114,  137.04774487,
 137.29298658,  135.13694718,  136.69011737,  139.52054513,
 140.04168209,  139.56142607,  139.55121401,  139.08117006,
 140.07233564,  140.1438548 ,  139.57163915,  139.43881288,
 138.76440817,  137.39517462,  137.71193651,  137.27254611,
 137.20102694,  137.68128295,  137.00687824,  138.2534986 ,
 139.33662484,  139.75557477,  140.32779042,  139.76578683,
 139.93949404,  140.97154158,  143.46476698,  141.47222274,
 142.42252271,  142.6677501 ,  144.98728362,  149.93288414,
 149.68765776,  148.48190301,  150.78099606,  152.11957708,
 152.0480569 ,  149.65700421,  147.27616359,  149.43220298,
 150.06572573,  150.98535682,  149.90223059,  149.78983048,
 150.06572573,  149.47306859,  150.03507218,  149.21761381,
 149.63656374,  150.41314015,  149.96353769,  151.10798534,
 151.34299965,  151.28169255,  141.62550481,  143.07648695,
 143.42390137,  139.15270455,  139.62273318,  139.50011999,
 142.78015021,  141.40070358,  141.65615836,  141.00219514,
 143.08669901,  140.87956662,  140.34823089,  140.57303314,
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 138.72352723,  139.95993553,  140.59345829,  141.75833108,
 141.38026311,  143.90415739,  144.77270978,  145.16099083,
 146.4689183 ,  147.5111779 ,  145.96823612,  146.57110634,
 147.81772671,  149.40154943,  149.81027095,  145.86604808,
 145.87626116,  145.05881811,  155.46092973,  153.18227715,
 152.18089849,  153.19249024,  154.76609988,  155.44048926,
 156.09445249,  152.72246161,  155.50181067,  156.87104525,
 158.17897169,  156.72799057,  154.00994861,  153.6420927 ,
 154.38801658,  155.24635589,  156.6360156 ,  155.8389977 ,
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 154.05081422,  151.90500324,  147.55204351,  145.96823612,
 147.79728624,  149.86136497,  149.95332461,  149.25849577,
```

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 152.4056844 , 153.0392235 , 153.36619745, 155.47114179,  
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 166.91552834, 165.59737349, 168.61173686, 168.96937969,  
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 163.52308167, 162.32755533, 155.27700944, 150.91383766,  
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 162.98151855, 164.00333768, 161.18312301, 169.05112726,  
 167.40599744, 166.29221867, 169.48028926, 168.69348444,  
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217.7510302 , 218.3028064 , 214.2564108 , 217.25033371,
218.52760763, 221.40914473, 222.40029499, 225.62924753,
224.91397721, 227.77507384, 228.52099772, 225.63947594,
219.76401593, 221.22520912, 223.08492811, 211.90622373,
217.93495049, 218.69110278, 216.41243487, 219.85597556,
215.31909657, 215.52345733, 217.29119932, 213.24480475,
220.16252437, 215.16582983, 213.31632392, 216.67811704,
208.46268304, 214.31771791, 216.53506338, 206.82778162,
201.46323118, 199.03129653, 203.16966708, 207.2671567 ,
202.74050509, 196.04758671, 188.51678481, 190.836303 ,
185.20608469, 187.36212408, 186.85121451, 174.96745289,
176.35712793, 171.46262042, 170.74735009, 167.95777364,
173.29167053, 179.35106617, 176.92934358, 181.19034367,
177.6037483 , 168.21322842, 169.98098574, 161.30573619,
168.11105571, 166.82355338, 166.91552834, 165.39301273,
161.76555174, 161.69403257, 162.32755533, 156.60536205,
152.98812948, 144.08807768, 144.24135974, 151.94586885,
153.6420927 , 154.69456538])

```

### 1.13 Elementary Probability Theory the outcome that could happen

1.13.1 Monte Carlo method is an experimental of computational algorithms that rely on repeated random samples.

```

[21]: df['Returns'] = df['Adj Close'].pct_change()
df['Returns'] = df['Returns'].dropna()

```

```

[22]: values = []
S = df['Returns'][-1] #Starting stock price
T = 252 #Number of trading days
mu = df['Returns'].mean() #Mean
sigma = df['Returns'].std()*math.sqrt(252) #Volatility

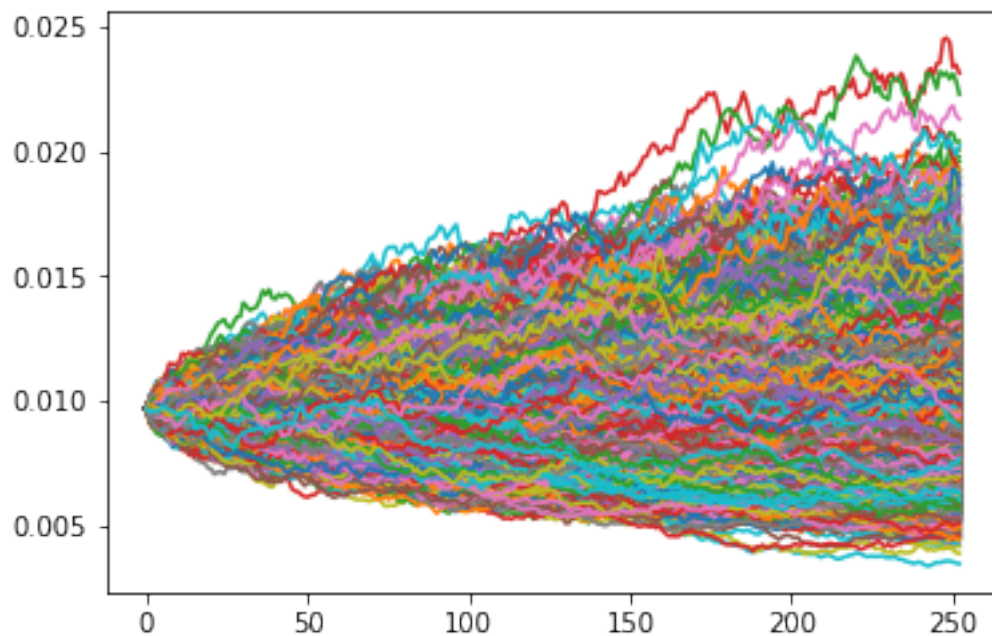
```

```
[23]: for i in range(10000):
        # Create list of daily returns using random normal distribution
        daily_returns=np.random.normal(mu/T,sigma/math.sqrt(T),T)+1

        # Set starting price and create price series generated by above random
        ↪daily returns
        price_list = [S]

        for x in daily_returns:
            price_list.append(price_list[-1]*x)

        # Plot the data
        plt.plot(price_list)
    plt.show()
```



## 1.14 Random variables and probability distributions

<https://www.investopedia.com/articles/06/probabilitydistribution.asp>

### 1.14.1 Cumulative Distribution

```
[24]: data = df['Adj Close']
        values, base = np.histogram(data, bins=40)
        #evaluate the cumulative
        cumulative = np.cumsum(values)
```

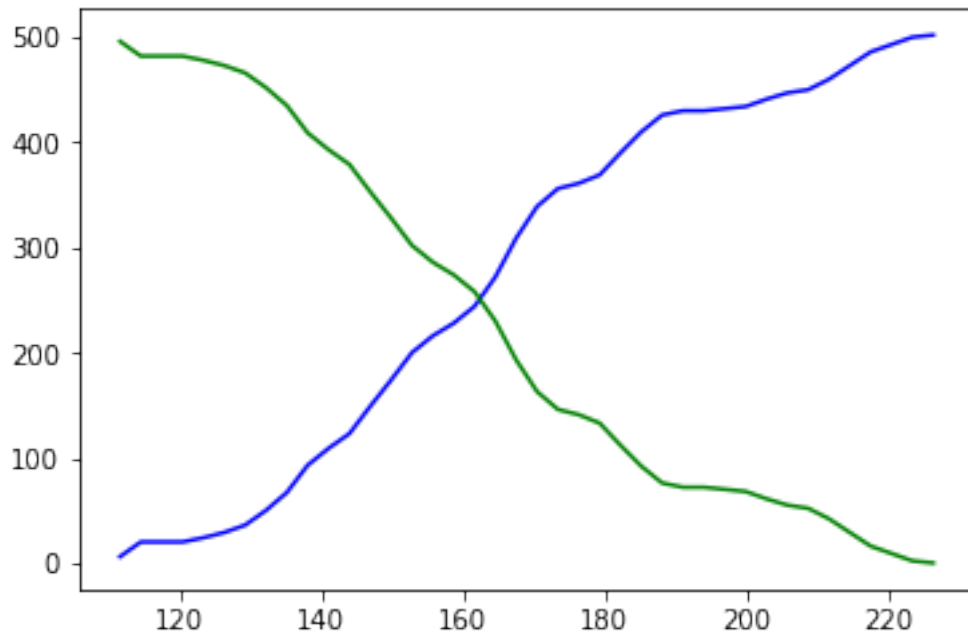


```

# plot the cumulative function
plt.plot(base[:-1], cumulative, c='blue')
#plot the survival function
plt.plot(base[:-1], len(data)-cumulative, c='green')

plt.show()

```



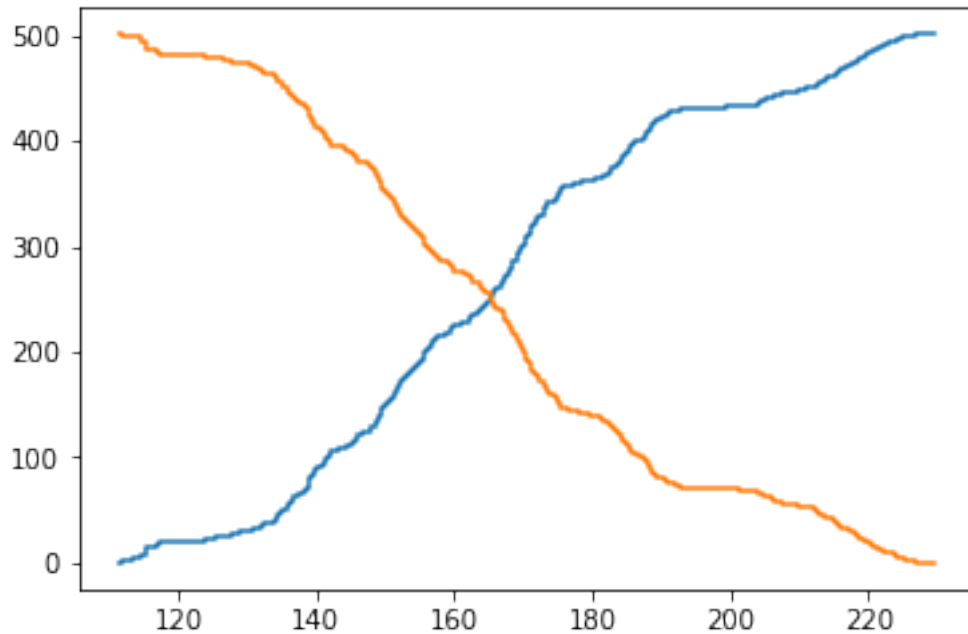
```

[25]: sorted_data = np.sort(data) # Or data.sort(), if data can be modified

# Cumulative counts:
plt.step(sorted_data, np.arange(sorted_data.size)) # From 0 to the number of
↳ data points-1
plt.step(sorted_data[:-1], np.arange(sorted_data.size)) # From the number of
↳ data points-1 to 0

plt.show()

```



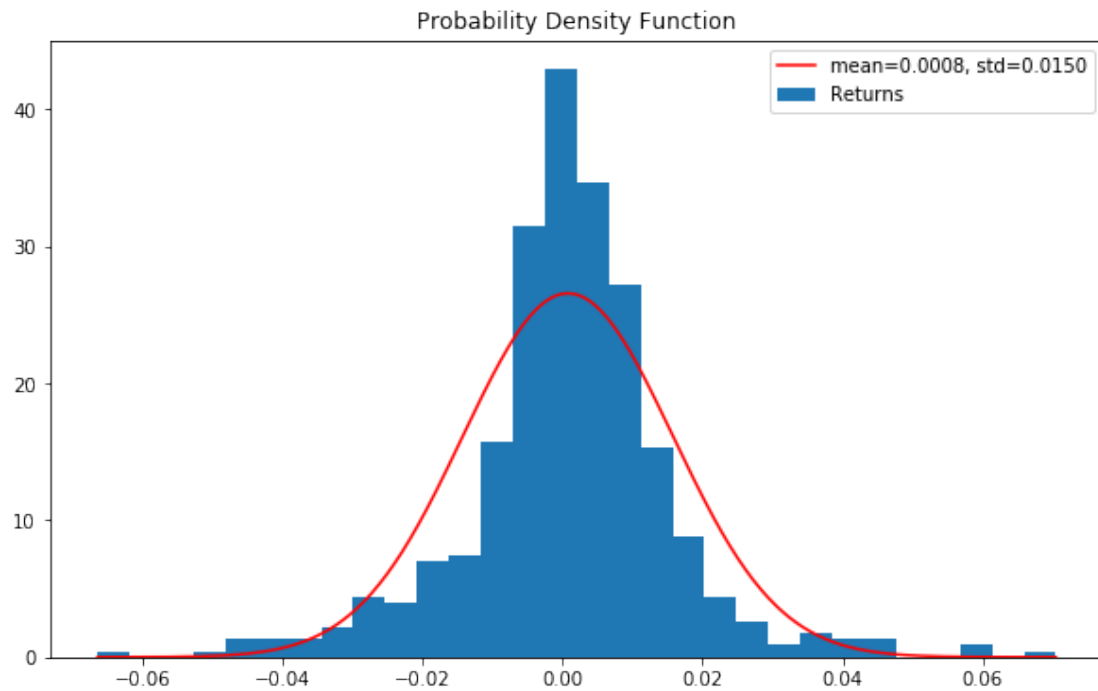
### 1.14.2 Probability Density Function

Probability Density Function (PDF) is continuous random variable and have value that is given sample in the sample space can be interpreted as providing a relative likelihood that the value of the random variable would equal that sample. (Wikipedia)

```
[26]: values = df['Returns'][1:]
x = np.linspace(values.min(), values.max(), len(values))
loc, scale = stats.norm.fit(values)
param_density = stats.norm.pdf(x, loc=loc, scale=scale)
label = 'mean=%.4f, std=%.4f' % (loc, scale)

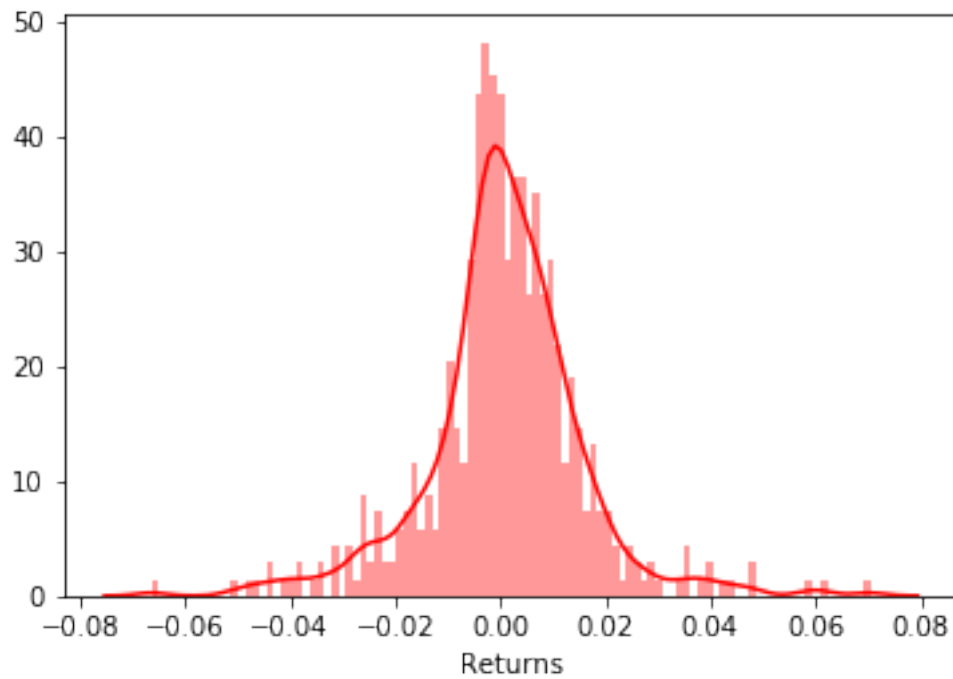
fig, ax = plt.subplots(figsize=(10, 6))
ax.hist(values, bins=30, normed=True)
ax.plot(x, param_density, 'r-', label=label)
ax.legend(loc='best')
ax.set_title("Probability Density Function")
```

```
[26]: Text(0.5,1,'Probability Density Function')
```



```
[27]: sns.distplot(df['Returns'].dropna(), bins=100, color='red')
```

```
[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1bac62f0c88>
```

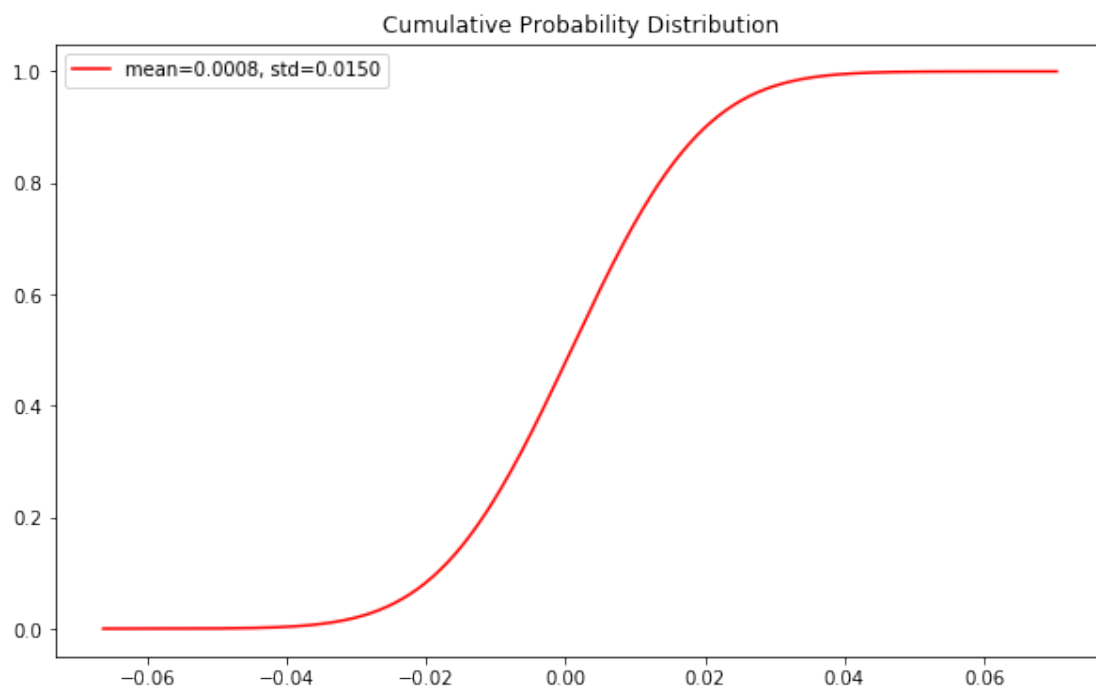


## 1.15 Cumulative Probability Distribution

```
[28]: values = df['Returns'][1:]
x = np.linspace(values.min(), values.max(), len(values))
loc, scale = stats.norm.fit(values)
param_density = stats.norm.cdf(x, loc=loc, scale=scale)
label = 'mean=%.4f, std=%.4f' % (loc, scale)

fig, ax = plt.subplots(figsize=(10, 6))
#ax.hist(values, bins=30, normed=True)
ax.plot(x, param_density, 'r-', label=label)
ax.legend(loc='best')
ax.set_title("Cumulative Probability Distribution")
```

```
[28]: Text(0.5,1,'Cumulative Probability Distribution')
```



## 1.16 Binomial Distribution

```
[29]: from scipy.stats import binom

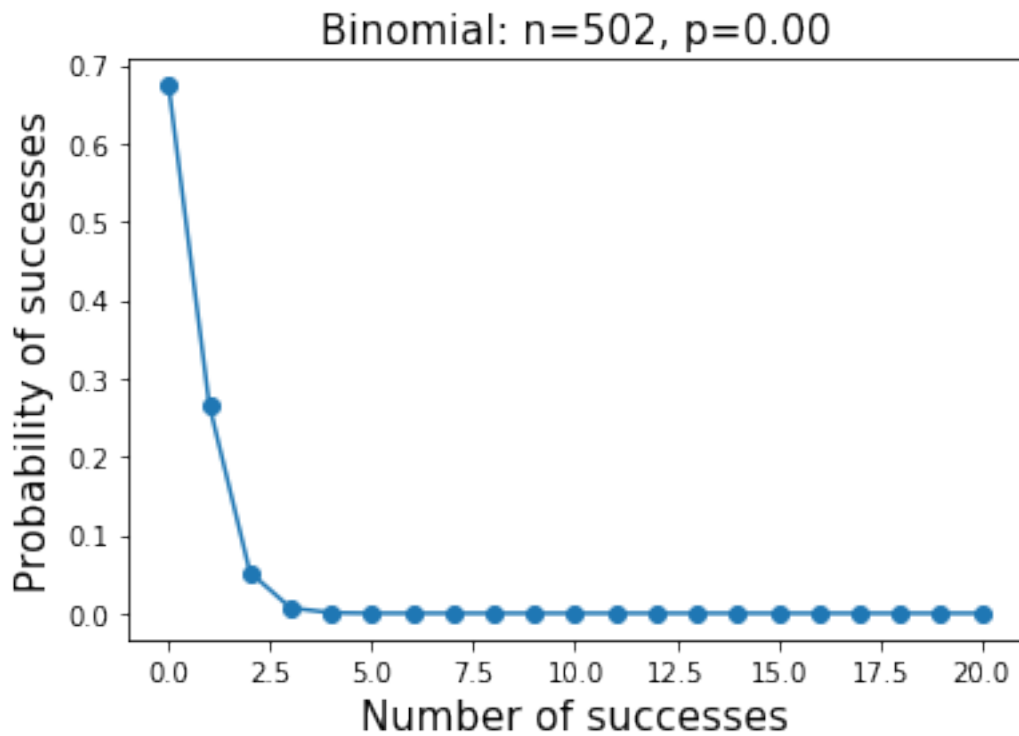
n = len(df['Returns'])
p = df['Returns'].mean()
k = np.arange(0,21)
```

```

binomial = binom.pmf(k,n,p)

plt.plot(k, binomial, 'o-')
plt.title("Binomial: n=%i, p=%.2f" % (n,p), fontsize=15)
plt.xlabel("Number of successes", fontsize=15)
plt.ylabel("Probability of successes", fontsize=15)
plt.show()

```

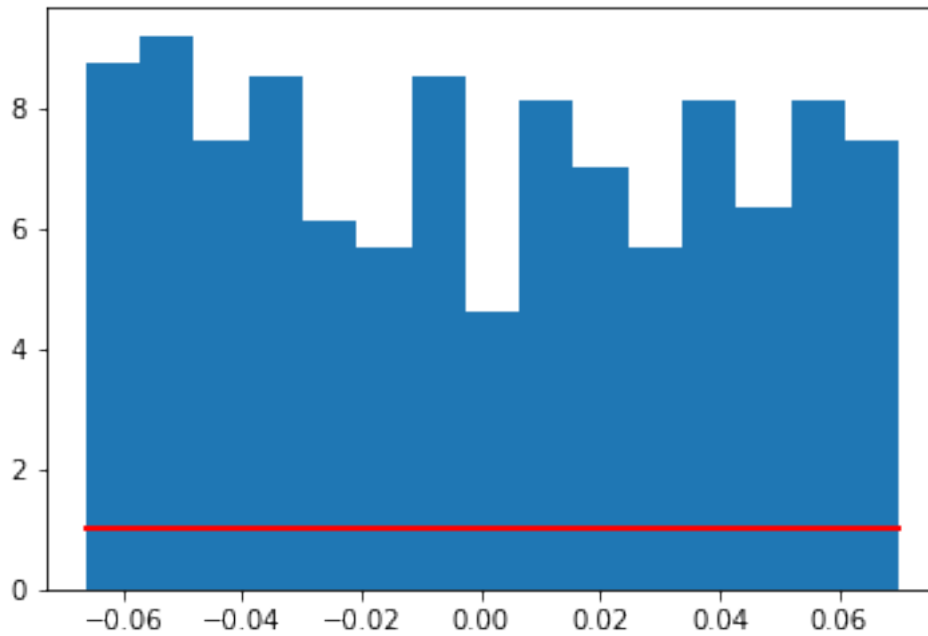


```

[30]: s = np.random.uniform(values.min(), values.max(), len(values))

import matplotlib.pyplot as plt
count, bins, ignored = plt.hist(s, 15, density=True)
plt.plot(bins, np.ones_like(bins), linewidth=2, color='r')
plt.show()

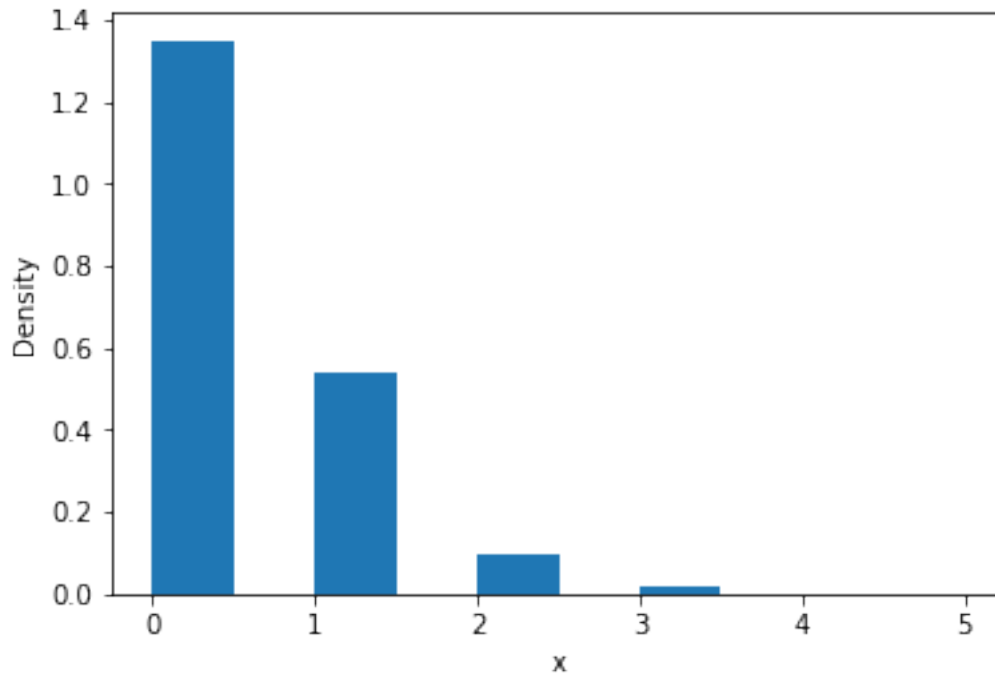
```



```
[31]: binom_sim = binom.rvs(n = n, p = p, size=10000)
print("Mean: %f" % np.mean(binom_sim))
print("SD: %f" % np.std(binom_sim, ddof=1))
plt.hist(binom_sim, bins = 10, normed = True)
plt.xlabel("x")
plt.ylabel("Density")
plt.show()
```

Mean: 0.391000

SD: 0.623665

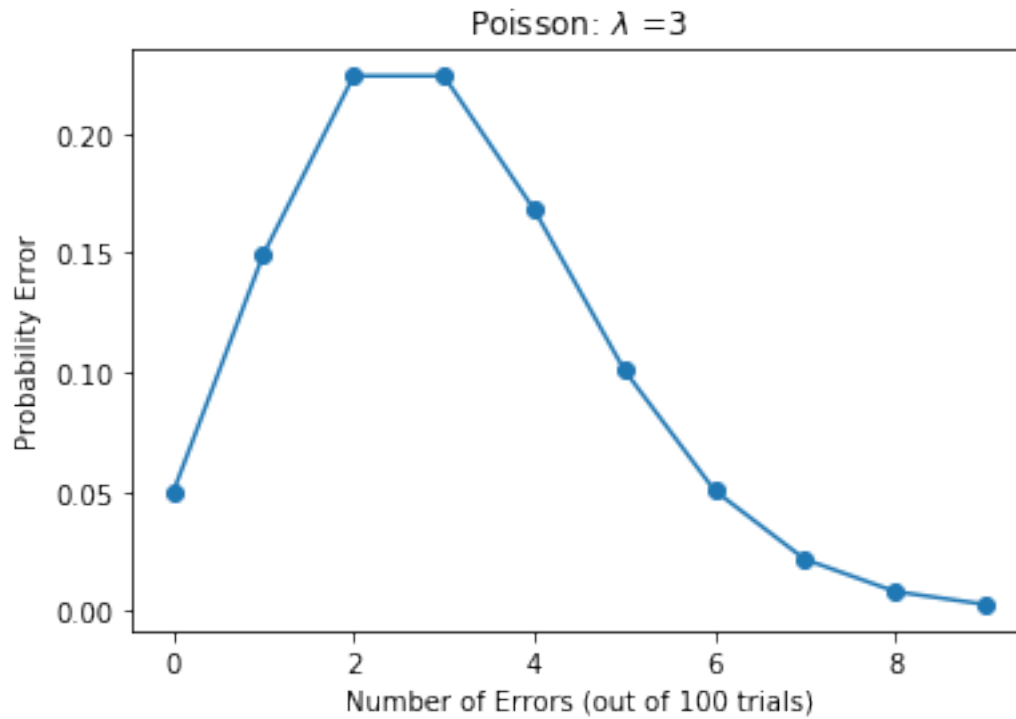


## 1.17 Poisson Distribution

```
[32]: rate = 3 # Error Rate
      n = np.arange(0,10) # Number of Trials
      y = stats.poisson.pmf(n, rate)
      y
```

```
[32]: array([ 0.04978707,  0.14936121,  0.22404181,  0.22404181,  0.16803136,
            0.10081881,  0.05040941,  0.02160403,  0.00810151,  0.0027005 ])
```

```
[33]: plt.plot(n, y, 'o-')
      plt.title('Poisson: $\lambda$ =%i' % rate)
      plt.ylabel('Probability Error')
      plt.xlabel('Number of Errors (out of 100 trials)')
      plt.show()
```



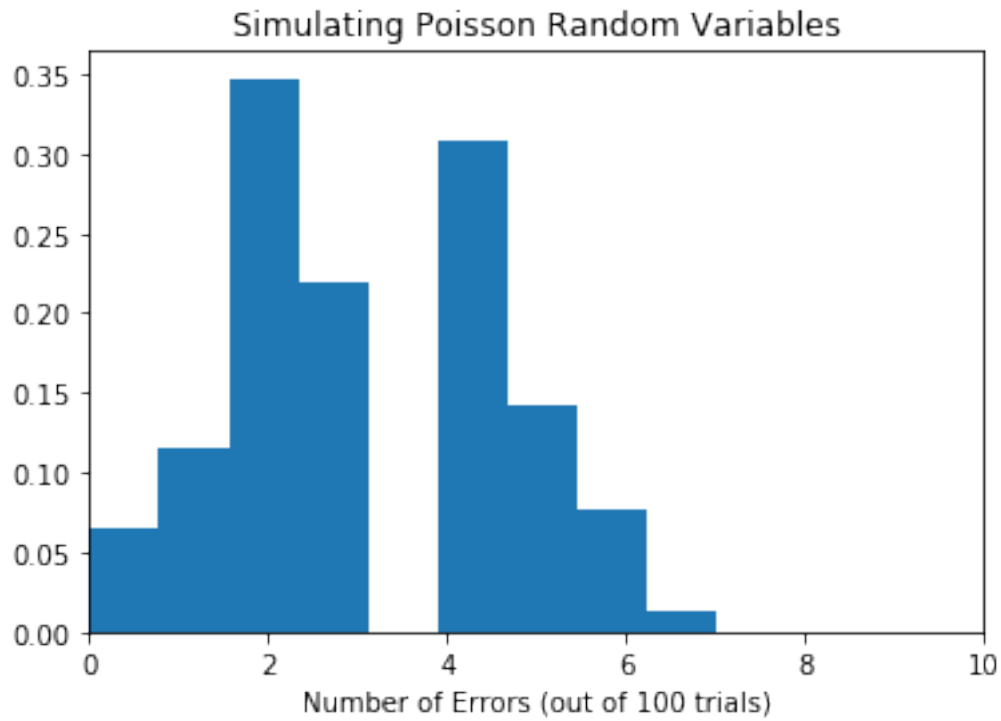
```
[34]: data = stats.poisson.rvs(mu=3, loc=0, size=100)
print("Mean: %f" % np.mean(data))
print("Standard Deviation: %f" % np.std(data, ddof=1))

plt.hist(data, bins = 9, normed = True)
plt.xlim(0,10)
plt.xlabel('Number of Errors (out of 100 trials)')
plt.title('Simulating Poisson Random Variables')
plt.show()
```

Mean: 3.080000

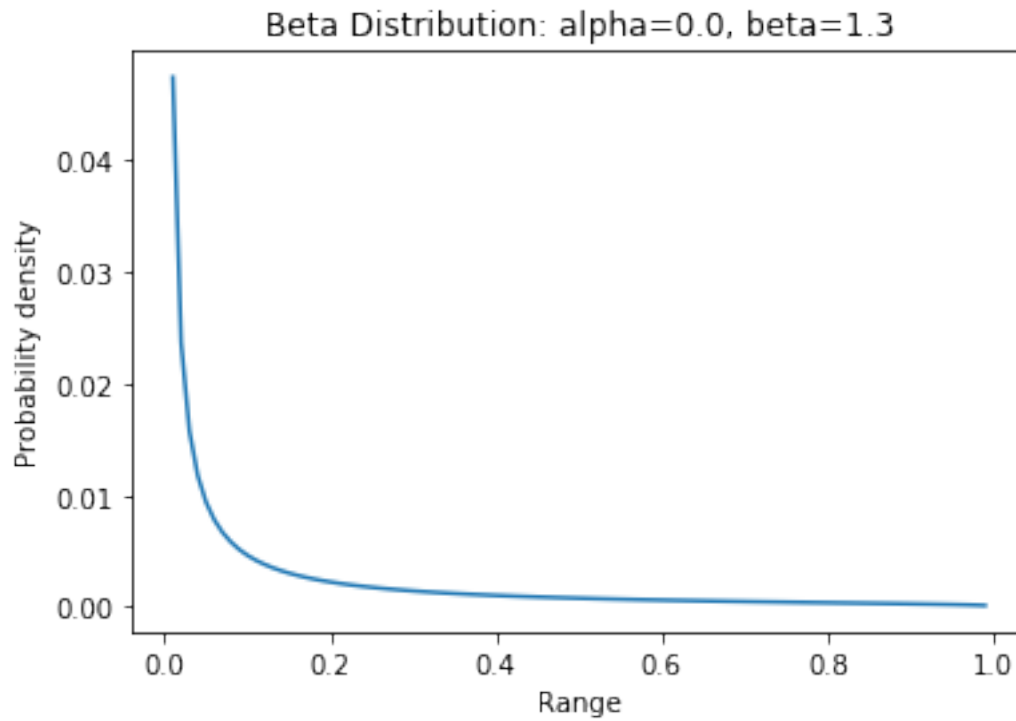
Standard Deviation: 1.574288





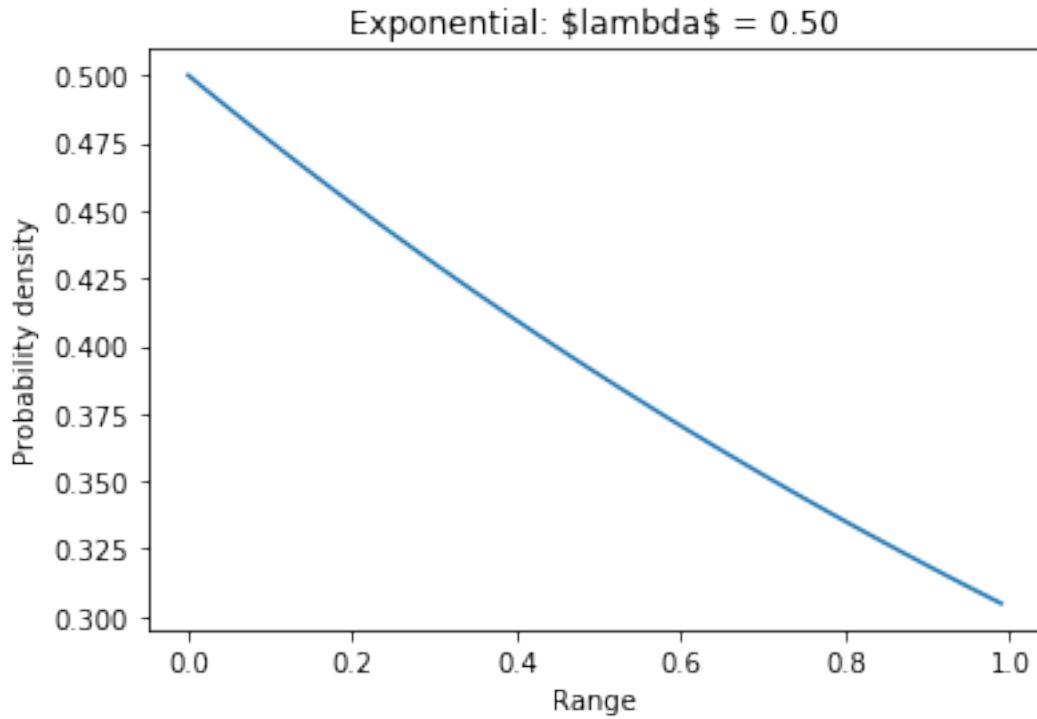
### 1.18 Beta Distribution

```
[35]: alpha = alpha
      beta = beta
      x = np.arange(0, 1, 0.01)
      y = stats.beta.pdf(x, alpha, beta)
      plt.plot(x, y)
      plt.title('Beta Distribution: alpha=%.1f, beta=%.1f' % (alpha,beta))
      plt.xlabel('Range')
      plt.ylabel('Probability density')
      plt.show()
```



### 1.19 Exponential Distribution

```
[36]: lambda = 0.5 # lambda
x = np.arange(0, 1, 0.01)
y = lambda * np.exp(-lambda * x)
plt.plot(x, y)
plt.title('Exponential:  $\lambda = %.2f$ ' % lambda)
plt.xlabel("Range")
plt.ylabel("Probability density")
plt.show()
```



## 1.20 Lognormal Distribution

```
[37]: from scipy.stats import lognorm

s = np.random.lognormal(mu, sigma, 1000)

count, bins, ignored = plt.hist(s, 100, normed=True, align='mid')
x = np.linspace(min(bins), max(bins), 10000)
pdf = (np.exp(-(np.log(x) - mu)**2 / (2 * sigma**2)) / (x * sigma * np.sqrt(2 *
↪np.pi)))

plt.plot(x, pdf, linewidth=2, color='r')
plt.xlabel('Range')
plt.ylabel('Probability')
plt.axis('tight')
plt.show()
```

