

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
data = pd.read_excel('gee.xlsx', header=[1])
```

```
df = pd.DataFrame(data)
df
```

	Name	Ticker \
0	Reliance Industries Ltd	RELIANCE
1	Tata Consultancy Services Ltd	TCS
2	HDFC Bank Ltd	HDFCBANK
3	Infosys Ltd	INFY
4	ICICI Bank Ltd	ICICIBANK
...
1995	Galaxy Bearings Ltd	GALXBRG
1996	Signet Industries Ltd	SIGIND
1997	Suraj Ltd	SURAJLTD
1998	Polson Ltd	POLSON
1999	LKP Finance Ltd	LKPFIN

	Sub-Sector	Market Cap	Close Price	PE
Ratio \				
0	Oil & Gas - Refining & Marketing	1.679534e+06	2467.40	
34.186904				
1	IT Services & Consulting	1.358569e+06	3626.70	
41.892356				
2	Private Banks	8.206363e+05	1486.50	
25.779258				
3	IT Services & Consulting	7.775010e+05	1853.05	
40.178853				
4	Private Banks	5.002790e+05	710.75	
27.212283				
...	
...				
1995	Heavy Machinery	1.256577e+02	385.05	
15.986985				
1996	Plastic Products	1.255488e+02	43.00	
8.999914				
1997	Iron & Steel	1.255056e+02	64.95	
91.609935				
1998	Commodity Chemicals	1.253262e+02	10440.00	
14.692403				
1999	Investment Banking & Brokerage	1.249950e+02	100.70	
2.061602				

	Return on Equity	Return on Assets	Net Profit Margin \
0	7.793277	3.957021	9.725370
1	37.74068	25.932382	19.383065

2	16.4352	1.883433	20.420916
3	27.135305	19.417895	18.847214
4	12.382897	1.243333	11.395012
...
1995	18.97634	14.784163	12.419024
1996	7.11771	2.017514	1.679812
1997	1.54881	0.76798	0.712132
1998	8.487562	4.80009	9.212658
1999	30.499522	24.118384	62.350884

	5Y Avg EBITDA Margin	...	Earnings Per Share	EBITDA \
0	17.720494	...	74.653049	103222.00
1	29.072528	...	87.043624	48462.00
2	28.206116	...	57.899268	44181.15
3	28.656802	...	45.607423	30090.00
4	11.900543	...	27.461218	27368.40
...
1995	16.395699	...	24.716981	12.27
1996	7.751415	...	4.738934	65.98
1997	9.181438	...	0.711167	17.65
1998	21.724728	...	710.833333	19.62
1999	13.740886	...	48.239175	69.56

	Long Term Investments Equivalent \	Reserves & Surplus	Cash and
0	212382.00	579376.00	169843.00
1	213.00	86063.00	38489.00
2	438823.11	148746.23	121272.52
3	11863.00	73627.00	27056.00
4	536578.62	107231.52	147570.54
...
1995	0.00	42.18	7.65
1996	0.14	144.17	20.66
1997	0.00	47.98	0.42
1998	0.99	103.96	6.63
1999	204.91	236.96	29.74

Book Value Free Cash Flow Operating Cash Flow Unnamed: 44 \

0	799432.00	-79652.00	26185.00	NaN
1	87108.00	35727.00	38802.00	NaN
2	210442.95	40780.31	42476.46	NaN
3	76782.00	21117.00	23224.00	NaN
4	167175.84	136327.09	138015.30	NaN
...
1995	45.36	1.31	6.76	NaN
1996	202.67	-8.33	6.96	NaN
1997	89.14	30.05	32.51	NaN
1998	104.77	13.20	22.41	NaN
1999	253.23	-13.07	-13.03	NaN

Unnamed: 45

0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
1995	NaN
1996	NaN
1997	NaN
1998	NaN
1999	NaN

[2000 rows x 46 columns]

df.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 2000 entries, 0 to 1999

Data columns (total 46 columns):

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Name	2000 non-null	object
1	Ticker	2000 non-null	object
2	Sub-Sector	1947 non-null	object
3	Market Cap	2000 non-null	float64
4	Close Price	2000 non-null	float64
5	PE Ratio	1957 non-null	float64
6	Return on Equity	1870 non-null	object
7	Return on Assets	1952 non-null	object
8	Net Profit Margin	1953 non-null	float64
9	5Y Avg EBITDA Margin	1880 non-null	float64
10	EBITDA Margin	1953 non-null	object
11	1Y Return vs Nifty	2000 non-null	float64
12	5Y CAGR	1593 non-null	float64
13	Debt to Equity	1835 non-null	float64
14	Long Term Debt to Equity	1833 non-null	float64
15	Net Income / Liabilities	1557 non-null	float64

16	5Y Historical Revenue Growth	1871 non-null	float64
17	5Y Historical EBITDA Growth	1624 non-null	float64
18	5Y Hist Op. Cash Flow Growth	1273 non-null	float64
19	5Y Historical EPS Growth	1329 non-null	float64
20	Forward PE Ratio	531 non-null	float64
21	Enterprise Value	1999 non-null	float64
22	PB Ratio	1954 non-null	float64
23	Dividend Yield	1098 non-null	float64
24	PE Premium vs Sector	1957 non-null	float64
25	Domestic Institutional Holding	1960 non-null	float64
26	Mutual Fund Holding	1960 non-null	float64
27	Promoter Holding	1960 non-null	float64
28	Foreign Institutional Holding	1960 non-null	float64
29	Retail Investor Holding	1958 non-null	float64
30	Pledged Promoter Holdings	1960 non-null	float64
31	Insurance Firms Holding	1960 non-null	float64
32	No. of Shareholders	1950 non-null	float64
33	Total Revenue	1959 non-null	float64
34	Net Income	1959 non-null	object
35	PBT	1959 non-null	object
36	Earnings Per Share	1959 non-null	object
37	EBITDA	1959 non-null	float64
38	Long Term Investments	1954 non-null	float64
39	Reserves & Surplus	1954 non-null	float64
40	Cash and Equivalent	1954 non-null	float64
41	Book Value	1953 non-null	float64
42	Free Cash Flow	1954 non-null	float64
43	Operating Cash Flow	1954 non-null	float64
44	Unnamed: 44	0 non-null	float64
45	Unnamed: 45	1 non-null	object

dtypes: float64(36), object(10)

memory usage: 718.9+ KB

df["Sub-Sector"].unique

<bound method Series.unique of 0 Oil & Gas - Refining & Marketing

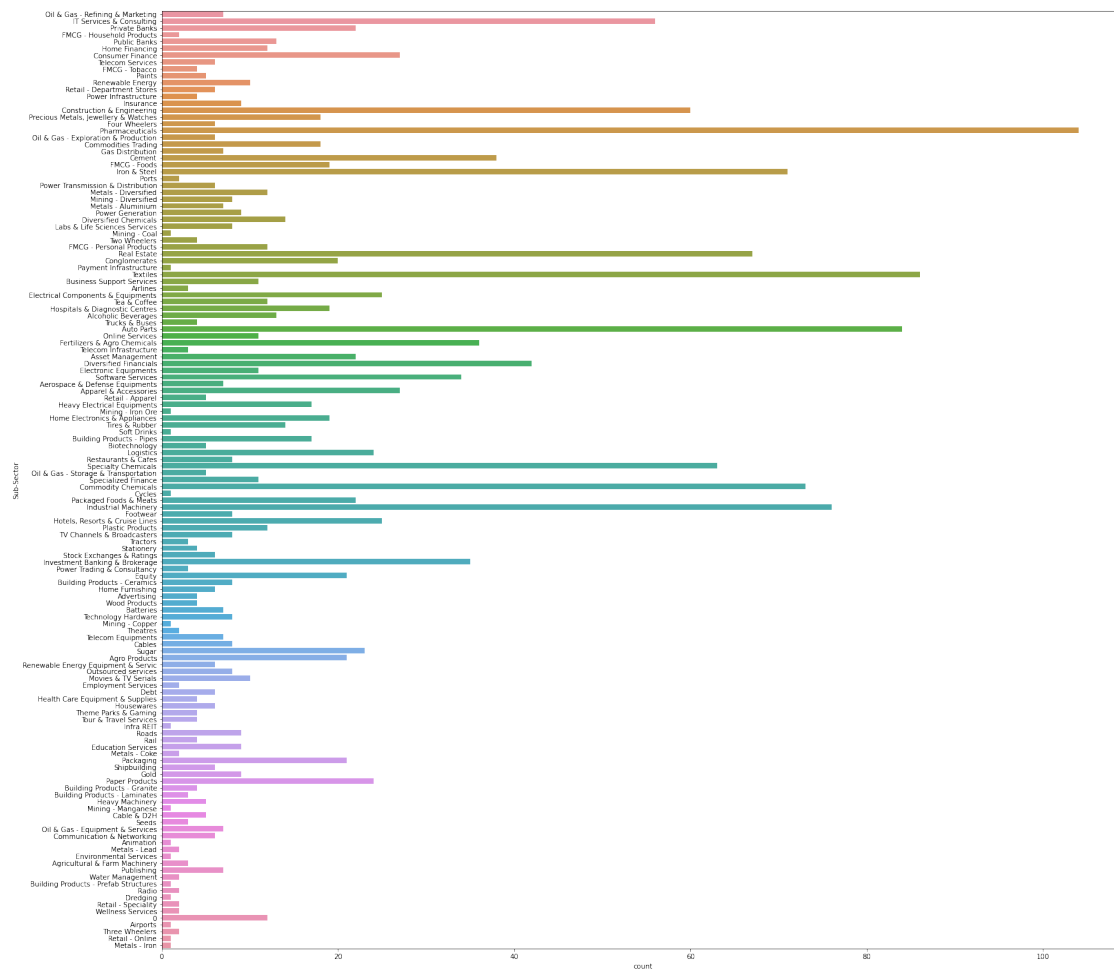
```
1      IT Services & Consulting
2      Private Banks
3      IT Services & Consulting
4      Private Banks
```

```
...
1995      Heavy Machinery
1996      Plastic Products
1997      Iron & Steel
1998      Commodity Chemicals
1999      Investment Banking & Brokerage
```

Name: Sub-Sector, Length: 2000, dtype: object>

```
plt.figure(figsize=(25,25))
sns.countplot(y='Sub-Sector',data=df,orient="h" )
```

<AxesSubplot:xlabel='count', ylabel='Sub-Sector'>

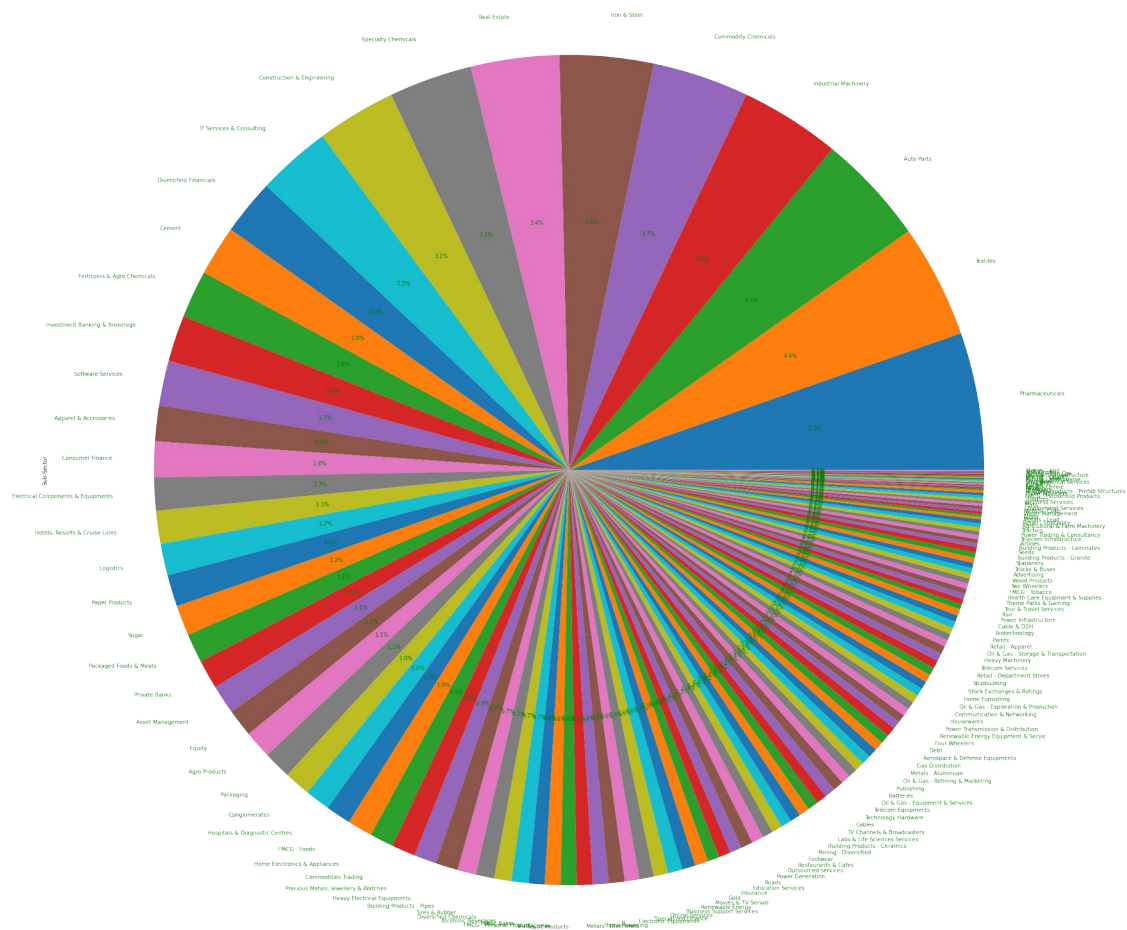


count_val= df["Sub-Sector"].value_counts()

plt.figure(figsize=(35,35))

count_val.plot(kind="pie",textprops={'color':"green"}, autopct='%1f%')

<AxesSubplot:ylabel='Sub-Sector'>



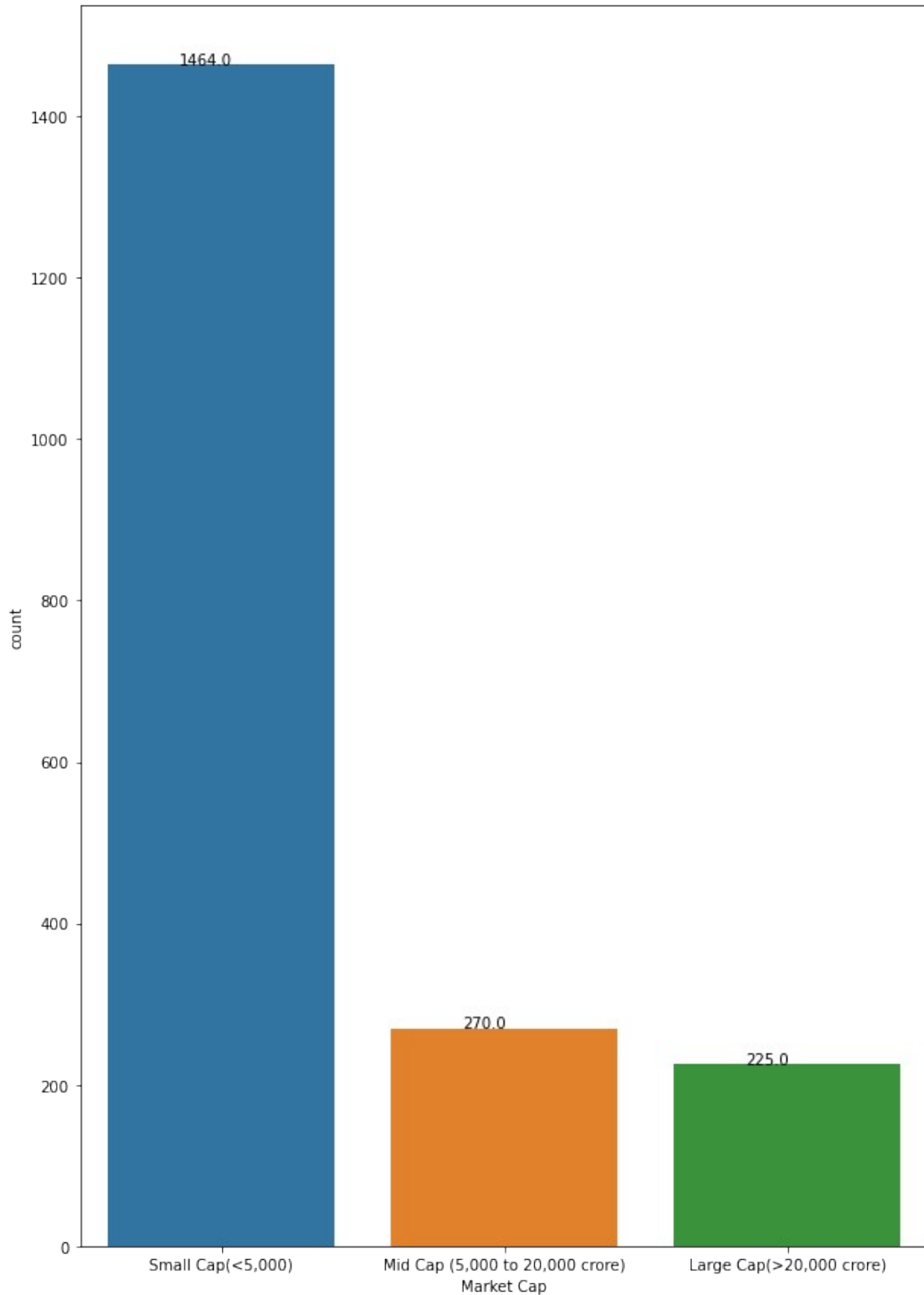
#Secondly, visualise the companies by segregating them according to Market Cap in
 #three categories: Large Cap(>20,000 crore)
 #Mid Cap (5,000 to 20,000 crore) &
 #Small Cap(<5,000)

```
df = df.dropna(subset=["Market Cap", "Earnings Per Share"])

plt.figure(figsize=(10,15))
cat= pd.cut(df["Market Cap"],bins=[0,5000,20000,np.inf],labels=["Small Cap(<5,000)", "Mid Cap (5,000 to 20,000 crore)", "Large Cap(>20,000 crore)"])
ax=sns.countplot(cat)
for p in ax.patches:
    ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()+0.01))

plt.show()
```

```
C:\Users\gargi\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  warnings.warn(
```



V : Intrinsic Value EPS : The Company's last 12 month earnings per share 8.5 : The constant represents the appropriate P-E ratio for a no-growth company as proposed by Graham. g : The company's long-term (five years) earnings growth estimate 6 : The average Return of

FDs (6%) Y : The current yield on AAA corporate bonds. The current yield is equal to the annual interest earned divided by the current price of the bond. =7.232% in India

```
df_rand = df.sample(10)
df_rand=df_rand.reset_index()
df_rand
```

	index	Name	Ticker \
0	1754	Add-Shop E-Retail Ltd	ASRL
1	1981	Maha Rashtra Apex Corporation Ltd	MAHAPEXLTD
2	117	Canara Bank Ltd	CANBK
3	1098	Ncl Industries Ltd	NCLIND
4	1669	T T Ltd	TTL
5	1825	Indian Acrylics Ltd	INDIANACRY
6	259	Gillette India Ltd	GILLETTE
7	1844	U. P. Hotels Ltd	UPHOT
8	1224	Aarti Surfactants Ltd	AARTISURF
9	299	Brigade Enterprises Ltd	BRIGADE

	Sub-Sector	Market Cap	Close Price	PE
Ratio \				
0	FMCG - Personal Products	196.514634	99.85	
25.554569				
1	Consumer Finance	130.068237	91.35	
3.857302				
2	Public Banks	41008.414346	224.95	
14.186866				
3	Cement	813.737892	174.60	
5.594623				
4	Textiles	228.416781	110.10	-
30.015346				
5	Textiles	172.671079	12.90	
27.451682				
6	FMCG - Personal Products	15871.330000	4901.50	
51.135157				
7	Hotels, Resorts & Cruise Lines	167.400000	325.50	-
21.796875				
8	Specialty Chemicals	581.729386	777.90	
26.882134				
9	Real Estate	12184.347754	521.85	-
263.047231				

	Return on Equity	Return on Assets	Net Profit Margin	...	\
0	46.71932	19.707842	9.787451	...	
1	25.541585	13.797901	93.953748	...	
2	5.498606	0.299895	3.086267	...	
3	24.381249	11.863107	8.277703	...	
4	-10.679203	-2.023425	-1.927168	...	
5	4.334941	1.054652	1.178543	...	
6	36.509066	22.597249	15.206134	...	

7	-8.221378	-6.448092	-21.682665	...
8	15.362772	6.698031	4.645472	...
9	-1.886608	-0.355428	-2.301089	...

	Earnings Per Share	EBITDA	Long Term Investments	Reserves & Surplus \
0	3.992194	11.480000	0.00	
8.97				
1	23.884741	32.170000	235.99	
124.79				
2	21.595971	4719.570000	286191.25	
30606.49				
3	32.155876	290.780000	0.00	
407.24				
4	-3.539856	14.310000	0.00	
30.62				
5	0.464817	66.199999	0.00	
12.77				
6	95.251782	492.230000	0.00	
723.52				
7	-14.222222	-4.069999	0.00	
84.43				
8	28.531961	45.570000	0.00	
125.07				
9	-2.231214	458.640000	37.71	
847.91				

	Cash and Equivalent	Book Value	Free Cash Flow	Operating Cash
Flow \				
0	0.52	20.30	-0.84	
0.58				
1	7.66	148.90	0.86	
0.87				
2	178866.37	63202.97	58194.95	
59117.67				
3	70.94	664.70	95.11	
240.56				
4	2.54	68.14	39.73	
40.14				
5	10.91	148.48	4.44	
11.23				
6	166.32	789.01	352.99	
443.16				
7	34.38	89.83	-2.13	-
0.54				
8	6.73	152.07	-25.66	
35.83				
9	610.71	2463.31	307.52	
802.88				

	Unnamed: 44	Unnamed: 45
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
5	NaN	NaN
6	NaN	NaN
7	NaN	NaN
8	NaN	NaN
9	NaN	NaN

[10 rows x 47 columns]

```
def good(EPS,Y):
    g = 15
    return (EPS * (8.5 + 2*g) * 6) / Y
```

```
def bad(EPS,Y):
    g=-5
    return (EPS * (8.5 + 2*g) * 6) / Y
```

```
def best(EPS,Y):
    g= 25
    return (EPS * (8.5 + 2*g) * 6) / Y
```

```
V_good=[]
V_Bad=[]
V_best=[]
for i in range(10):
    V_good.append(good( df_rand.loc[i,"Earnings Per Share"],7.232))
    V_Bad.append(bad( df_rand.loc[i, "Earnings Per Share"],7.232))
    V_best.append(best(df_rand.loc[i, "Earnings Per Share"],7.232))
```

```
data_plot = {'Name':df_rand["Name"],'V_Good': V_good ,
'V_Bad':V_Bad,'V_Best': V_best,'Earnings Per Share':df_rand["Earnings
Per Share"]}
df_plot = pd.DataFrame(data=data_plot)
df_plot
```

V_Best \	Name	V_Good	V_Bad
0	Add-Shop E-Retail Ltd	127.516150	-4.968162
193.758306			
1	Maha Rashtra Apex Corporation Ltd	762.911398	-29.723821
1159.229007			
2	Canara Bank Ltd	689.804932	-26.875517
1048.145156			

3	Ncl Industries Ltd	1027.102797	-40.016992	
1560.662691				
4	T T Ltd	-113.067854	4.405241	-
171.804402				
5	Indian Acrylics Ltd	14.846883	-0.578450	
22.559549				
6	Gillette India Ltd	3042.472586	-118.537893	
4622.977825				
7	U. P. Hotels Ltd	-454.277286	17.699115	-
690.265487				
8	Aarti Surfactants Ltd	911.349963	-35.507141	
1384.778515				
9	Brigade Enterprises Ltd	-71.268032	2.776677	-
108.290386				

	Earnings Per Share
0	3.992194
1	23.884741
2	21.595971
3	32.155876
4	-3.539856
5	0.464817
6	95.251782
7	-14.222222
8	28.531961
9	-2.231214

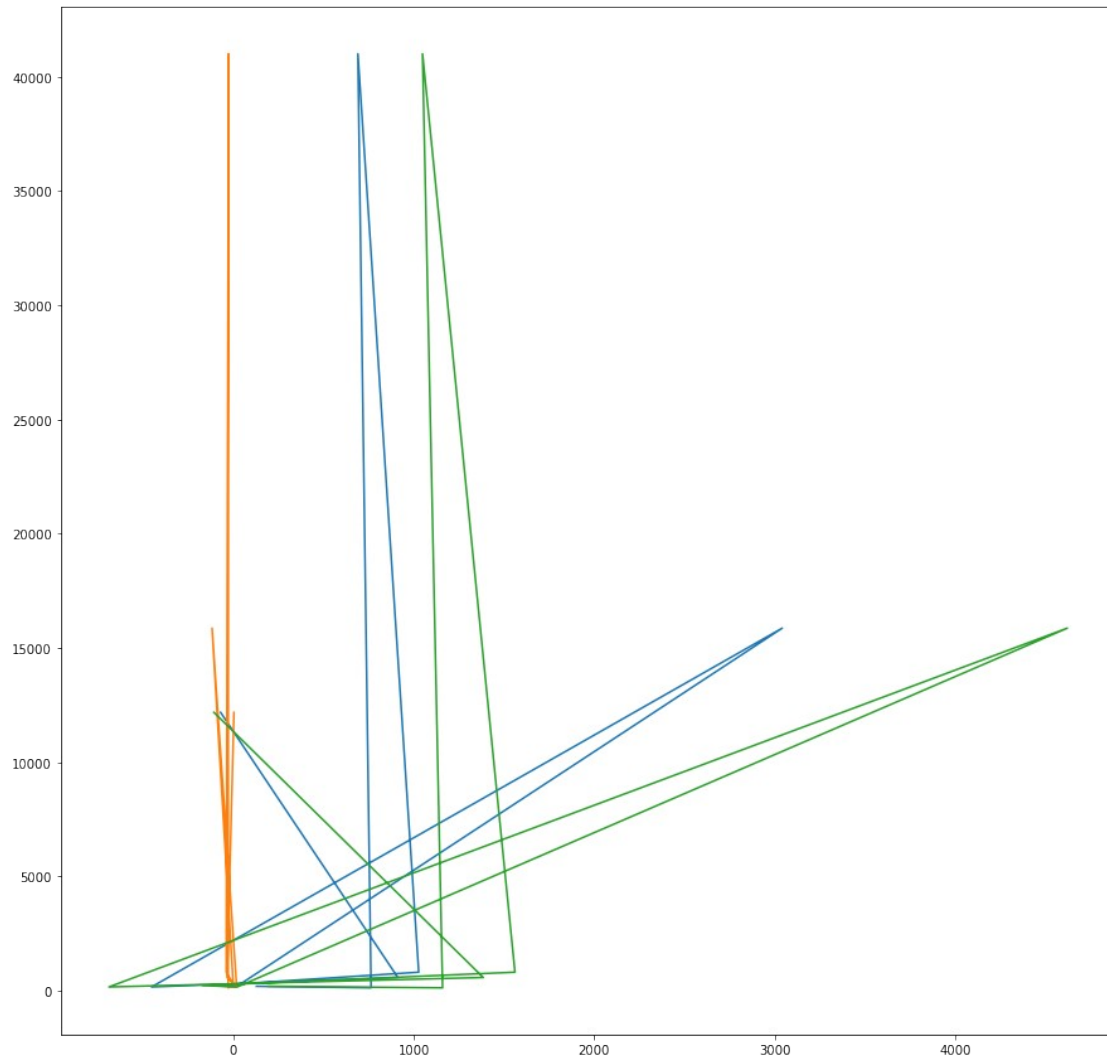
df_plot.sort_values(by=["Earnings Per Share"])

V_Best \	Name	V_Good	V_Bad	
7	U. P. Hotels Ltd	-454.277286	17.699115	-
690.265487				
4	T T Ltd	-113.067854	4.405241	-
171.804402				
9	Brigade Enterprises Ltd	-71.268032	2.776677	-
108.290386				
5	Indian Acrylics Ltd	14.846883	-0.578450	
22.559549				
0	Add-Shop E-Retail Ltd	127.516150	-4.968162	
193.758306				
2	Canara Bank Ltd	689.804932	-26.875517	
1048.145156				
1 Maha Rashtra Apex Corporation Ltd	762.911398	-29.723821		
1159.229007				
8	Aarti Surfactants Ltd	911.349963	-35.507141	
1384.778515				
3	Ncl Industries Ltd	1027.102797	-40.016992	
1560.662691				
6	Gillette India Ltd	3042.472586	-118.537893	

4622.977825

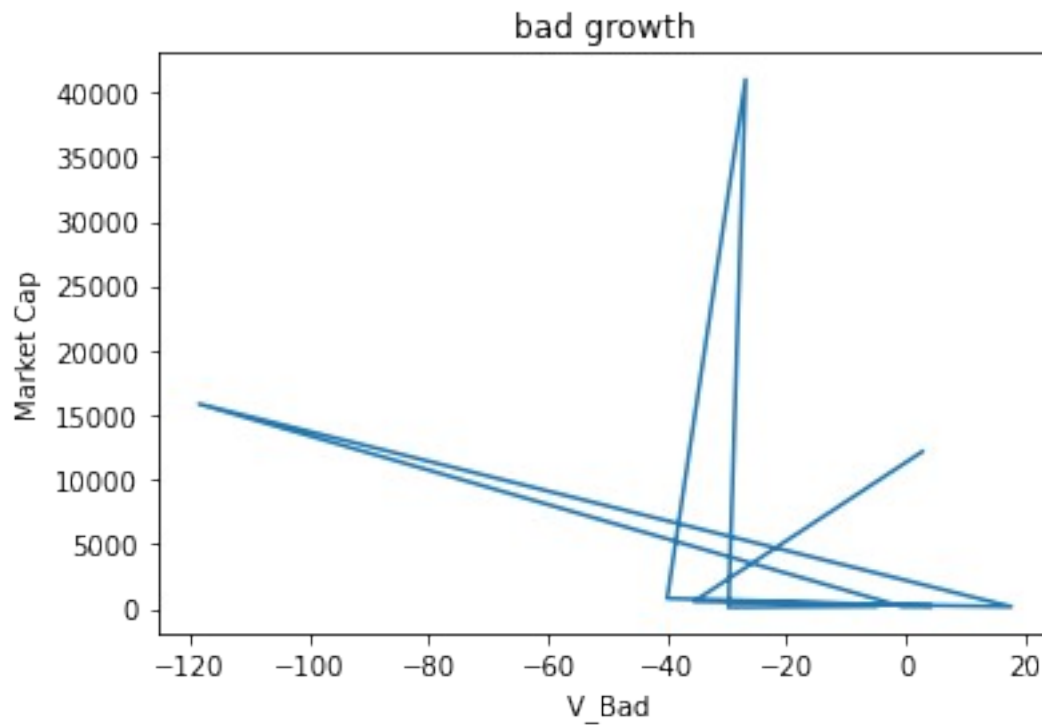
	Earnings Per Share
7	-14.222222
4	-3.539856
9	-2.231214
5	0.464817
0	3.992194
2	21.595971
1	23.884741
8	28.531961
3	32.155876
6	95.251782

```
plt.figure(figsize=(15,15))
plt.plot( V_good,df_rand["Market Cap"])
plt.plot( V_Bad, df_rand["Market Cap"])
plt.plot( V_best, df_rand["Market Cap"])# Plot the chart
plt.show()
```

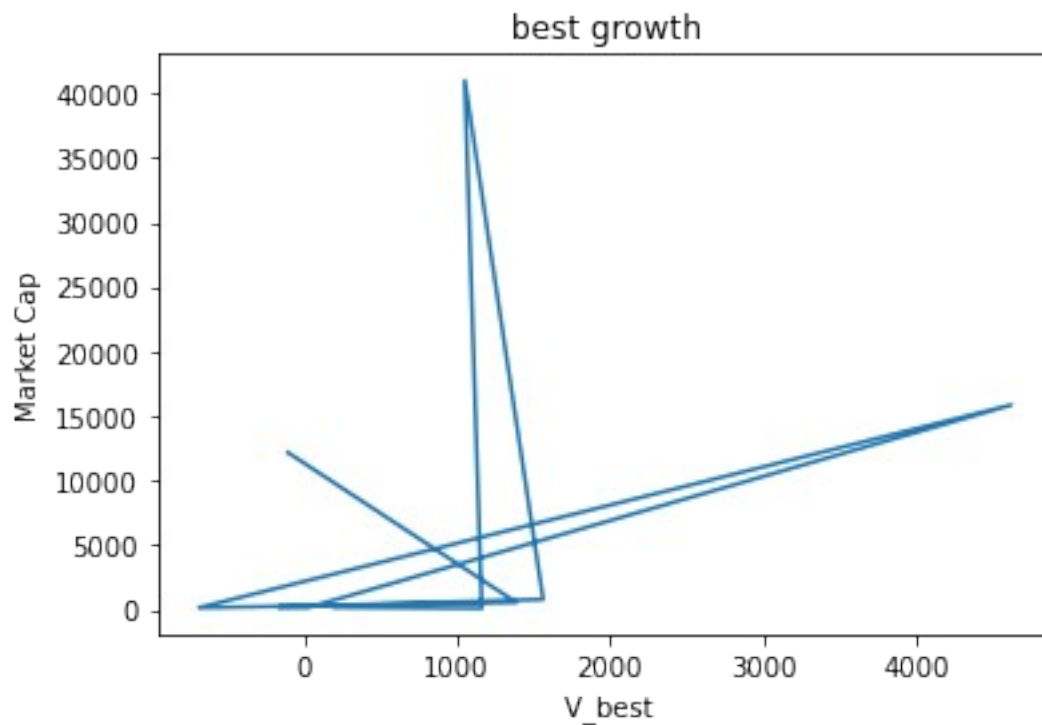


```
plt.plot( V_Bad, df_rand["Market Cap"]) # Plot the chart
```

```
plt.xlabel(" V_Bad") # add X-axis label  
plt.ylabel("Market Cap") # add Y-axis label  
plt.title("bad growth") # add title  
plt.show()
```



```
plt.plot( V_best, df_rand["Market Cap"])  
plt.xlabel(" V_best") # add X-axis label  
plt.ylabel("Market Cap") # add Y-axis label  
plt.title("best growth") # add title  
plt.show()
```



```
plt.plot( V_good, df_rand["Market Cap"])  
plt.xlabel(" V_good") # add X-axis label  
plt.ylabel("Market Cap") # add Y-axis label  
plt.title("good growth") # add title  
plt.show()
```

