

# US Stocks Fundamentals

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# Contents

## **1 Introduction**

1.1 Data Description and background .....	3
1.2 Data Select .....	4

## **2 Analysis**

2.1 Virtualization of data .....	7
2.2 Relationship and data Description .....	9
2.3 Principal component analysis .....	15
2.4 Analysis for target companies.....	21

## **3 Conclusion**

3.1 Summary .....	27
3.2 FutureAnalysis .....	28

# Introduction

## 1.1 Data Description and background

This dataset contains US stocks fundamental data, such as income statement, balance sheet and cash flows.

- 12,129 companies
- 8,526 unique indicators
- ~20 indicators comparable across most companies
- Five years of data, yearly

The data is provided by <http://usfundamentals.com>.

I picked this dataset as my final project Since I really interesting on some of companies in this dataset which I hope I can work with in the future. In this project, I will virtualize the dataset, and try to analysis the relationship between each indicators of these companies using PCA,R-value and data description by table or graphs which I learned in this course.

The main script language I will use in this project is Python.

## 1.2 Data Select

The main dataset has a large amount of indicators which not every indicators assign to every companies, So I would like to pick some indicators share by large number of companies to do the analysis here.

### Top 25 indicators share by companies:

Assets	6886.0
LiabilitiesAndStockholdersEquity	6789.0
StockholdersEquity	6095.0
CashAndCashEquivalentsAtCarryingValue	5416.0
NetCashProvidedByUsedInOperatingActivities	4738.0
NetIncomeLoss	4490.0
NetCashProvidedByUsedInFinancingActivities	4374.0
CommonStockSharesAuthorized	3939.0
CashAndCashEquivalentsPeriodIncreaseDecrease	3836.0
CommonStockValue	3579.0
CommonStockSharesIssued	3371.0
RetainedEarningsAccumulatedDeficit	3000.0
CommonStockParOrStatedValuePerShare	2749.0
NetCashProvidedByUsedInInvestingActivities	2628.0
PropertyPlantAndEquipmentNet	2378.0
AssetsCurrent	2017.0
LiabilitiesCurrent	1992.0
CommonStockSharesOutstanding	1606.0
Liabilities	1141.0
OperatingIncomeLoss	1067.0
IncomeTaxExpenseBenefit	847.0
InterestExpense	558.0
ShareBasedCompensation	481.0
PaymentsToAcquirePropertyPlantAndEquipment	400.0
AccumulatedOtherComprehensiveIncomeLossNetOfTax	286.0

## Part of Python Script to find first 25 popular indicators:

```
df=pd.read_csv('indicators_by_company.csv')
#number of indicators by company
df_ind_count = pd.concat([ df[['company_id', 'indicator_id', '2010']].dropna().groupby('company_id')['indicator_id'].count(),
df[['company_id', 'indicator_id', '2011']].dropna().groupby('company_id')['indicator_id'].count(),
df[['company_id', 'indicator_id', '2012']].dropna().groupby('company_id')['indicator_id'].count(),
df[['company_id', 'indicator_id', '2013']].dropna().groupby('company_id')['indicator_id'].count(),
df[['company_id', 'indicator_id', '2014']].dropna().groupby('company_id')['indicator_id'].count(),
df[['company_id', 'indicator_id', '2015']].dropna().groupby('company_id')['indicator_id'].count(),
df[['company_id', 'indicator_id', '2016']].dropna().groupby('company_id')['indicator_id'].count()
], axis=1)
df_ind_count.columns=['2010','2011','2012','2013','2014','2015','2016']
#df_ind_count.head()
df_comp_count = pd.concat([
df[['company_id', 'indicator_id', '2010']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False),
df[['company_id', 'indicator_id', '2011']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False),
df[['company_id', 'indicator_id', '2012']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False),
df[['company_id', 'indicator_id', '2013']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False),
df[['company_id', 'indicator_id', '2014']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False),
df[['company_id', 'indicator_id', '2015']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False),
df[['company_id', 'indicator_id', '2016']].dropna().groupby('indicator_id')['company_id'].count().sort_values(ascending=False)
], axis=1)
df_comp_count.columns=['2010','2011','2012','2013','2014','2015','2016']
```

```
: list_s_int=[]
for c in df_comp_count.columns:
    df_comp_count.sort_values(c, axis=0, ascending=False, inplace=True)
    li=df_comp_count.index
    s_int = pd.Series(np.zeros(len(li)), index=li)
    s1=df.loc[((df['indicator_id']==li[0]) & (df[c].notnull())),'company_id'].unique()
    s_int[li[0]]=len(s1)
    for i in range(1,len(li)):
        s2=df.loc[((df['indicator_id']==li[i]) & (df[c].notnull())),'company_id'].unique()
        s1=pd.Series(np.intersect1d(s1, s2))
        s_int[li[i]]=len(s1)
    list_s_int.append(s_int)

df_comp_int_count = pd.concat(list_s_int, axis=1)
df_comp_int_count.columns=['2010','2011','2012','2013','2014','2015','2016']
```

## **Selected Data indicators:**

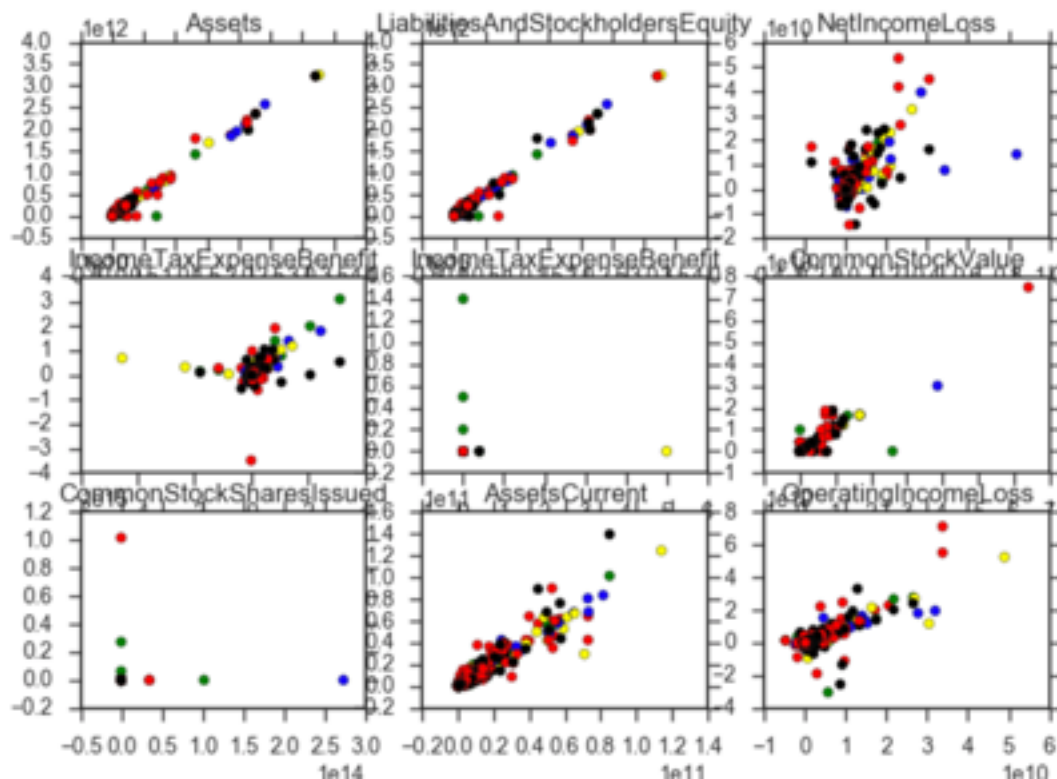
Assets  
LiabilitiesAndStockholdersEquity  
NetIncomeLoss  
IncomeTaxExpenseBenefit  
CommonStockSharesAuthorized  
CommonStockValue  
CommonStockSharesIssued  
AssetsCurrent  
OperatingIncomeLoss  
PropertyPlantAndEquipmentNet

There are 2250 companies with not null values in the data set for these 10 indicators

These are the ten data indicators I want to use in my project which all shared with 2250 companies.

## 2.1 Virtualization and mean of data

### Virtualization of dataset indicators by years:



As Graphs show above, I virtualized these nine indicators by years of 2011,2012,2013,2014, and 2015 represent by colors red, green, blue, yellow ,and black. All these indicators have a different shape of scatter graph. Assets and LiabilitiesAndStockholdersEquity both represent by a scatter graph mostly linearly distributed, and NetIncomeLoss, IncomeTaxExpenseBenefit, AssetsCurrent, and OperatingIncomeLoss are distribute by 5 different shape with some data concentrated at one or two center. IncomeTaxExpenseBenefit and CommonStockSharesIssued are shaped similar in graph with few points.

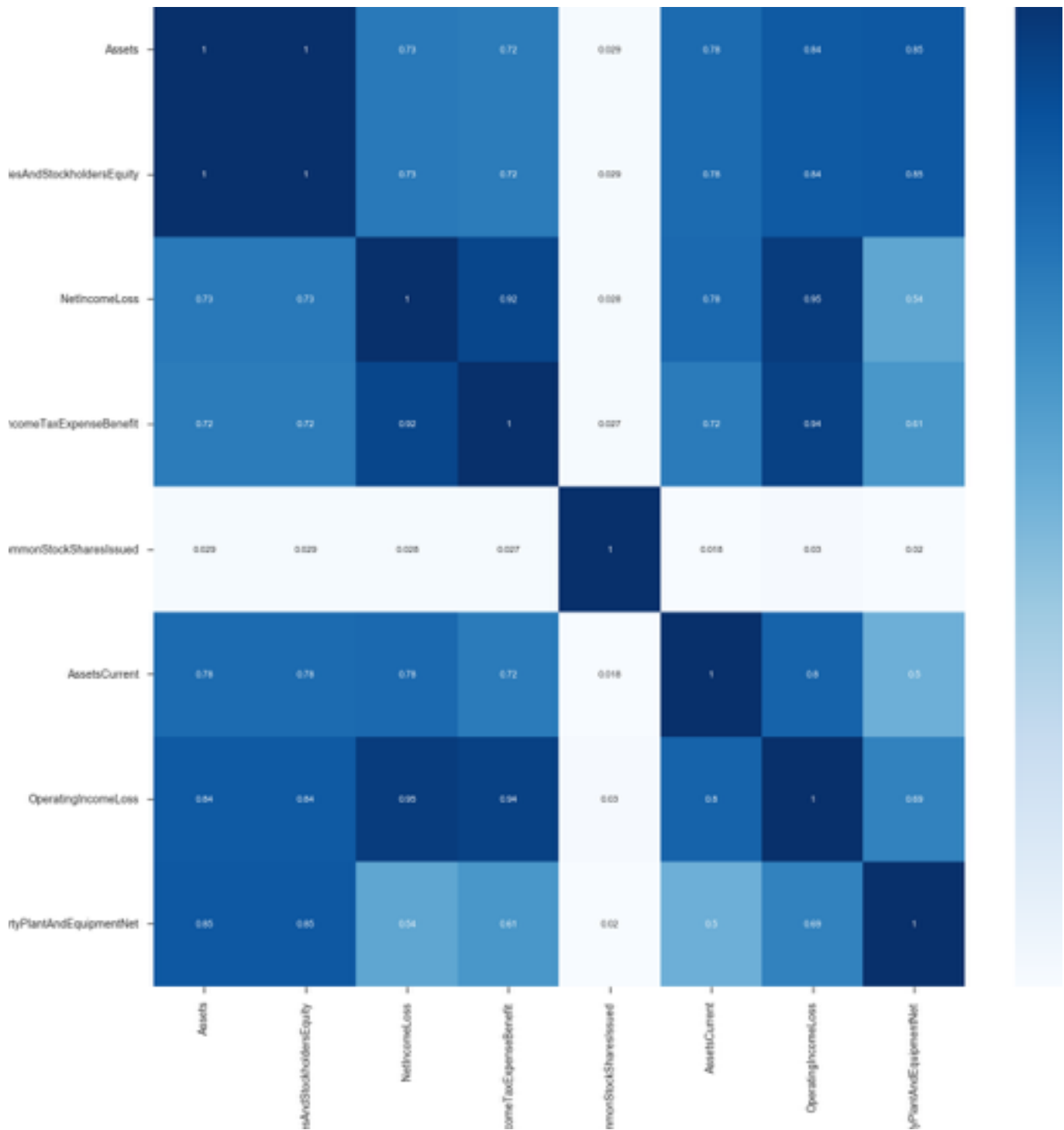
## Part of Python Script to make scatter graph:

```
companies_pd = pd.read_csv("companies.csv")
indicator_pd = pd.read_csv("indicators_by_company.csv")
balance_pd = pd.merge(companies_pd, indicator_pd, how="outer", on="company_id")
asset_col = balance_pd['indicator_id'] == "Assets"
asset_pd = balance_pd[asset_col]
plt.subplot(331)
plt.scatter(asset_pd['2011'], asset_pd['2012'], c=["red", "green"])
plt.scatter(asset_pd['2013'], asset_pd['2014'], c=["blue", "yellow"])
plt.scatter(asset_pd['2011'], asset_pd['2015'], c=["red", "black"])
plt.title('Assets')
#plt.show()
plt.subplot(332)
asset_col = balance_pd['indicator_id'] == "LiabilitiesAndStockholdersEquity"
asset_pd = balance_pd[asset_col]
plt.scatter(asset_pd['2011'], asset_pd['2012'], c=["red", "green"])
plt.scatter(asset_pd['2013'], asset_pd['2014'], c=["blue", "yellow"])
plt.scatter(asset_pd['2011'], asset_pd['2015'], c=["red", "black"])
plt.title('LiabilitiesAndStockholdersEquity')
plt.subplot(333)
asset_col = balance_pd['indicator_id'] == "NetIncomeLoss"
asset_pd = balance_pd[asset_col]
plt.scatter(asset_pd['2011'], asset_pd['2012'], c=["red", "green"])
plt.scatter(asset_pd['2013'], asset_pd['2014'], c=["blue", "yellow"])
plt.scatter(asset_pd['2011'], asset_pd['2015'], c=["red", "black"])
plt.title('NetIncomeLoss')
#plt.show()
plt.subplot(334)
asset_col = balance_pd['indicator_id'] == "IncomeTaxExpenseBenefit"
asset_pd = balance_pd[asset_col]
plt.scatter(asset_pd['2011'], asset_pd['2012'], c=["red", "green"])
plt.scatter(asset_pd['2013'], asset_pd['2014'], c=["blue", "yellow"])
plt.scatter(asset_pd['2011'], asset_pd['2015'], c=["red", "black"])
plt.title('IncomeTaxExpenseBenefit')
#plt.show()
plt.subplot(335)
asset_col = balance_pd['indicator_id'] == "CommonStockSharesAuthorized"
asset_pd = balance_pd[asset_col]
```



## 2.2 Relationship and data Description

R-Value:



## Relationship between 8 indicators by R-Value:

In statistics, the correlation coefficient  $r$  measures the strength and direction of a linear relationship between two variables on a scatterplot. The value of  $r$  is always between  $+1$  and  $-1$ . To interpret its value, see which of the following values your correlation  $r$  is closest to: Exactly  $-1$ .

As the graph show above, the diagonal of this matrix is the  $r$ -value to it-self which are all zeros represent by dark blue cell in graph. The  $r$  value from 0 to 1 in graph with color from white to light blue to dark blue which shows how strong correlation between two indicators.

The indicator CommonStockSharesIssued has almost none relationship with all other indicators, so both row and col cells contain it is almost white here.

There are some very strong relationship between two different indicators such as asset and LiabilitiesAndStockholdersEquity with  $r$ -value 1 which means these two dataset is exactly positive related to each other. NetIncomeLoss and OperatingIncomeLoss are also really close related with  $r$ -value 0.95, both NetIncomeLoss and OperatingIncomeLoss relate to asset with  $r$ -value 0.73 and 0.72 which is a litter weaker.

There are reasonable r-value between these indicators. It is really easy to understand that why NetIncomeLoss and OperatingIncomeLoss are as strong as 0.95. It is a little surprise to me that asset and LiabilitiesAndStockholdersEquity related with r-value as high as 1, so I check google with the definition of both indicators.

**Stockholders' equity represents the equity stake currently held on the books by a firm's equity investors. It is calculated either as a firm's total assets minus its total liabilities or as share capital plus retained earnings minus treasury shares.**

**Assets** are sometimes defined as resources or things of value that are owned by a **company**. Some examples of **assets** which are obvious and will be reported on a **company's** balance sheet include: cash, accounts receivable, inventory, investments, land, buildings, and equipment.

As above definition show, it is still reasonable for assets and LiabilitiesAndStockholdersEquity have the r-values 1 in darkest blue cell.

## Part of Python Script for r-value graph:

```
#heatmap visualization
def heatmap(data,title):
    fig, ax = plt.subplots(figsize=(15, 15))
    heatmap = sns.heatmap(data, cmap=plt.cm.Blues,annot=True, annot_kws={"size": 8})
    #ax.xaxis.tick_top()
    ax.set_title(title)
    # rotate
    plt.xticks(rotation=90)
    plt.yticks(rotation=0)
    plt.tight_layout()
    plt.show()

#skipy linregress
#Pearson Correlation
rvalue = DataFrame(np.nan,index=indicators,columns=indicators)
#PValue
pvalue = DataFrame(np.nan,index=indicators,columns=indicators)
#StdErr
stderr = DataFrame(np.nan,index=indicators,columns=indicators)

#
for c_X in indicators:
    for c_Y in indicators:
        R=linregress(Values[[c_X,c_Y]])
        rvalue.set_value(c_Y,c_X, R.rvalue)
        pvalue.set_value(c_Y,c_X, R.pvalue)
        stderr.set_value(c_Y,c_X, R.stderr)

heatmap(rvalue, 'R-value')
```

Above defined function can do graph with R-value,P-value, and std error.

## Data Description:

	Year	Indicator	count	mean	std	min	25%	50%	75%
0	2011	Assets	6886.0	7.202514e+09	7.278970e+10	0.000000e+00	7582307.50	229456000.0	1.6412
1	2011	LiabilitiesAndStockholdersEquity	6877.0	7.174764e+09	7.282371e+10	-1.885475e+07	6742805.00	223932000.0	1.6232
2	2011	NetIncomeLoss	6124.0	1.527939e+08	1.150205e+09	-1.685500e+10	-2494862.00	229500.0	3.4230
3	2011	IncomeTaxExpenseBenefit	4679.0	8.593623e+07	7.595561e+08	-1.803600e+10	0.00	2233000.0	3.0897
4	2011	CommonStockSharesAuthorizedCommonStockValue	0.0	NaN	NaN	NaN	NaN	NaN	NaN
5	2011	CommonStockSharesIssued	5680.0	2.436211e+10	1.425945e+12	0.000000e+00	11062962.00	33040728.0	8.8405
6	2011	AssetsCurrent	5276.0	8.834772e+08	3.685341e+09	-6.260200e+04	1484145.75	57659134.0	3.9774
7	2011	OperatingIncomeLoss	4933.0	2.531529e+08	1.212602e+09	-4.776000e+09	-1794724.00	2412240.0	9.5271
8	2011	PropertyPlantAndEquipmentNet	5320.0	1.191808e+09	6.160671e+09	0.000000e+00	1769880.50	23227214.5	2.3663
9	2012	Assets	6888.0	7.433265e+09	7.312632e+10	-1.700000e+01	7421109.25	245950000.0	1.8075
10	2012	LiabilitiesAndStockholdersEquity	6889.0	7.426497e+09	7.322370e+10	-3.436755e+06	6526836.00	243098978.0	1.7995
11	2012	NetIncomeLoss	6240.0	1.589616e+08	1.229245e+09	-4.326000e+09	-2682787.00	82204.5	3.7319
12	2012	IncomeTaxExpenseBenefit	4631.0	8.389121e+07	8.568514e+08	-3.483100e+10	0.00	2408000.0	3.2376
13	2012	CommonStockSharesAuthorizedCommonStockValue	0.0	NaN	NaN	NaN	NaN	NaN	NaN
14	2012	CommonStockSharesIssued	5680.0	2.386571e+11	1.399633e+13	-8.537050e+05	11565212.75	34742048.5	9.0243
15	2012	AssetsCurrent	5314.0	9.483120e+08	4.025543e+09	-2.840000e+02	1461378.50	61200500.0	4.3530
16	2012	OperatingIncomeLoss	5033.0	2.451229e+08	1.471333e+09	-3.036300e+10	-2105758.00	1572000.0	9.5883
17	2012	PropertyPlantAndEquipmentNet	5377.0	1.325307e+09	6.873712e+09	0.000000e+00	1662080.00	26512000.0	2.5590
18	2013	Assets	6799.0	7.828172e+09	7.417835e+10	0.000000e+00	8021700.00	276124000.0	2.6848
19	2013	LiabilitiesAndStockholdersEquity	6816.0	7.779820e+09	7.408425e+10	-2.037150e+05	7284328.75	265403500.0	2.0350
20	2013	NetIncomeLoss	6139.0	2.029816e+08	1.742652e+09	-3.573000e+09	-2994502.00	9876.0	4.2678
21	2013	IncomeTaxExpenseBenefit	4928.0	8.469089e+07	9.713848e+08	-4.541500e+10	0.00	2419000.0	3.6013

21	2013	IncomeTaxExpenseBenefit	4928.0	8.469089e+07	9.713848e+08	-4.541500e+10	0.00	2419000.0	3.6013
22	2013	CommonStockSharesAuthorizedCommonStockValue	0.0	NaN	NaN	NaN	NaN	NaN	NaN
23	2013	CommonStockSharesIssued	5634.0	6.042663e+10	3.743528e+12	-1.106000e+09	12622747.50	36478979.0	9.4785
24	2013	AssetsCurrent	5261.0	1.027348e+09	4.455280e+09	0.000000e+00	1702727.00	70404000.0	4.6717
25	2013	OperatingIncomeLoss	4986.0	2.804888e+08	1.453066e+09	-2.234600e+09	-2203175.50	1603210.0	1.0912
26	2013	PropertyPlantAndEquipmentNet	5332.0	1.423857e+09	7.337361e+09	0.000000e+00	1572885.75	27880000.0	2.8705
27	2014	Assets	6697.0	8.355857e+09	7.585223e+10	0.000000e+00	12841170.00	323073352.0	2.3535
28	2014	LiabilitiesAndStockholdersEquity	6709.0	8.313736e+09	7.578285e+10	0.000000e+00	11871222.00	315944195.0	2.3334
29	2014	NetIncomeLoss	6126.0	1.818968e+08	1.206398e+09	-7.224200e+09	-3847372.25	180935.5	5.0636
30	2014	IncomeTaxExpenseBenefit	4992.0	1.094332e+08	5.886248e+08	-2.619000e+09	0.00	2899757.5	3.8992
31	2014	CommonStockSharesAuthorizedCommonStockValue	0.0	NaN	NaN	NaN	NaN	NaN	NaN
32	2014	CommonStockSharesIssued	5559.0	1.675114e+08	1.008625e+09	-2.014000e+06	14134955.50	37847163.0	9.7832
33	2014	AssetsCurrent	5180.0	1.084693e+09	4.599384e+09	0.000000e+00	2509946.00	85633500.0	4.9499
34	2014	OperatingIncomeLoss	4970.0	2.877811e+08	1.417556e+09	-9.445300e+09	-3364695.25	1513519.5	1.1610
35	2014	PropertyPlantAndEquipmentNet	5295.0	1.518621e+09	7.692342e+09	-8.675470e+05	1737315.50	30731000.0	3.1004
36	2015	Assets	5997.0	9.114170e+09	7.567919e+10	0.000000e+00	26126768.00	463601000.0	2.8054
37	2015	LiabilitiesAndStockholdersEquity	6012.0	9.350417e+09	7.877916e+10	0.000000e+00	24327165.00	451729500.0	2.7680
38	2015	NetIncomeLoss	5492.0	1.746629e+08	1.442698e+09	-1.468500e+10	-7063904.75	18177.0	5.3891
39	2015	IncomeTaxExpenseBenefit	4614.0	9.185107e+07	6.159236e+08	-6.065000e+09	0.00	2704500.0	3.7098
40	2015	CommonStockSharesAuthorizedCommonStockValue	0.0	NaN	NaN	NaN	NaN	NaN	NaN
41	2015	CommonStockSharesIssued	4901.0	1.622055e+08	1.388616e+09	0.000000e+00	14559381.00	38359454.0	9.9107
42	2015	AssetsCurrent	4598.0	1.195995e+09	5.185320e+09	0.000000e+00	6232325.00	117133234.0	5.7027
43	2015	OperatingIncomeLoss	4522.0	2.805663e+08	1.881981e+09	-2.548100e+10	-6549250.00	1436571.0	1.2134
44	2015	PropertyPlantAndEquipmentNet	4585.0	1.757120e+09	8.475151e+09	0.000000e+00	5810817.00	58333500.0	5.7735

Above description shows the regular statistic description for all nine indicators such as count, mean, std, min, 25%, 50%, 75%, max which are all widely use in statistic description and very helpful.

We can check with this description table to get more information of our indicators statistic information.

### Part of Python Script for Description table:

```
df_rtba=df.loc[df['indicator_id'].isin(indicators),['company_id','indicator_id','2011','2012','2013','2014','2015']]

l_df=[]
for y in years:
    for c in indicators:
        d=list(df_rtba.loc[df_rtba['indicator_id']==c,y].dropna().describe())# describe dataset
        d.insert(0,y)
        d.insert(1,c)
        l_df.append(d)
df_ind_desc=DataFrame(l_df,columns=['Year','Indicator','count','mean','std','min','25%','50%','75%','max'])
df_ind_desc.head(45)
```

## 2.3 Principal component analysis

First four Principal component with python code:

```
] : scaler = StandardScaler().fit(Values[indicators])
Values_Scaled = scaler.transform(Values[indicators])

print(Values_Scaled[:,0].mean())
print(Values_Scaled[:,0].std())
var_exp=[]
cum_var_exp=[]
pca = PCA(n_components=4)
pca.fit(Values_Scaled)
var_exp=pca.explained_variance_ratio_
cum_var_exp = np.cumsum(var_exp)
with plt.style.context('seaborn-whitegrid'):
    plt.figure(figsize=(10, 8))

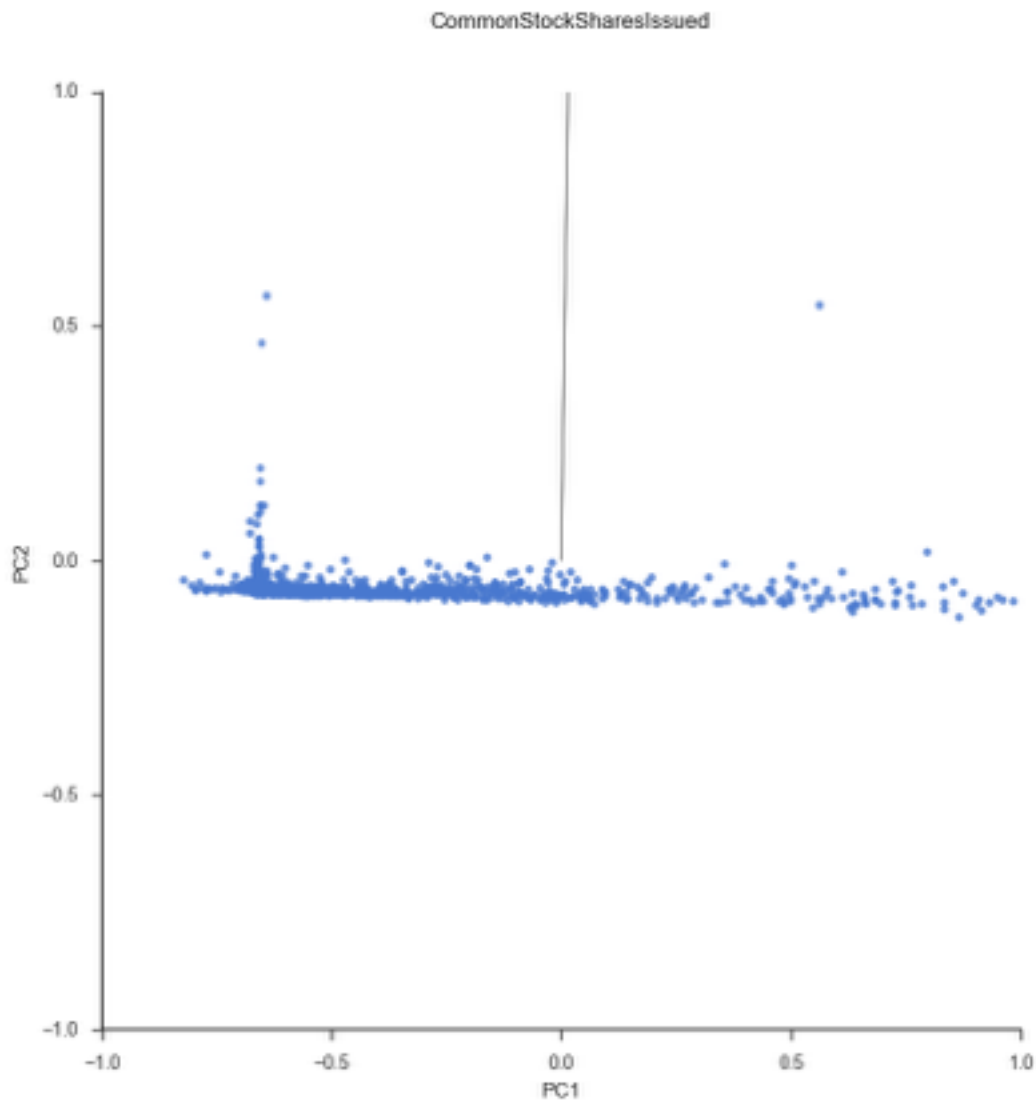
    plt.bar(range(4), var_exp, alpha=0.5, align='center',
            label='individual explained variance')
    plt.step(range(4), cum_var_exp, where='mid',
            label='cumulative explained variance')
    plt.ylabel('Explained variance ratio')
    plt.xlabel('Principal components')
    plt.legend(loc='best')
    plt.tight_layout()
pca = PCA(n_components=4)
pc_scores = pd.DataFrame(pca.fit_transform(Values_Scaled))
pc_scores.columns = ['PC'+str(i+1) for i in range(len(pc_scores.columns))]
pc_scores.head()

-6.9186244962e-18
1.0
```

```
] :
```

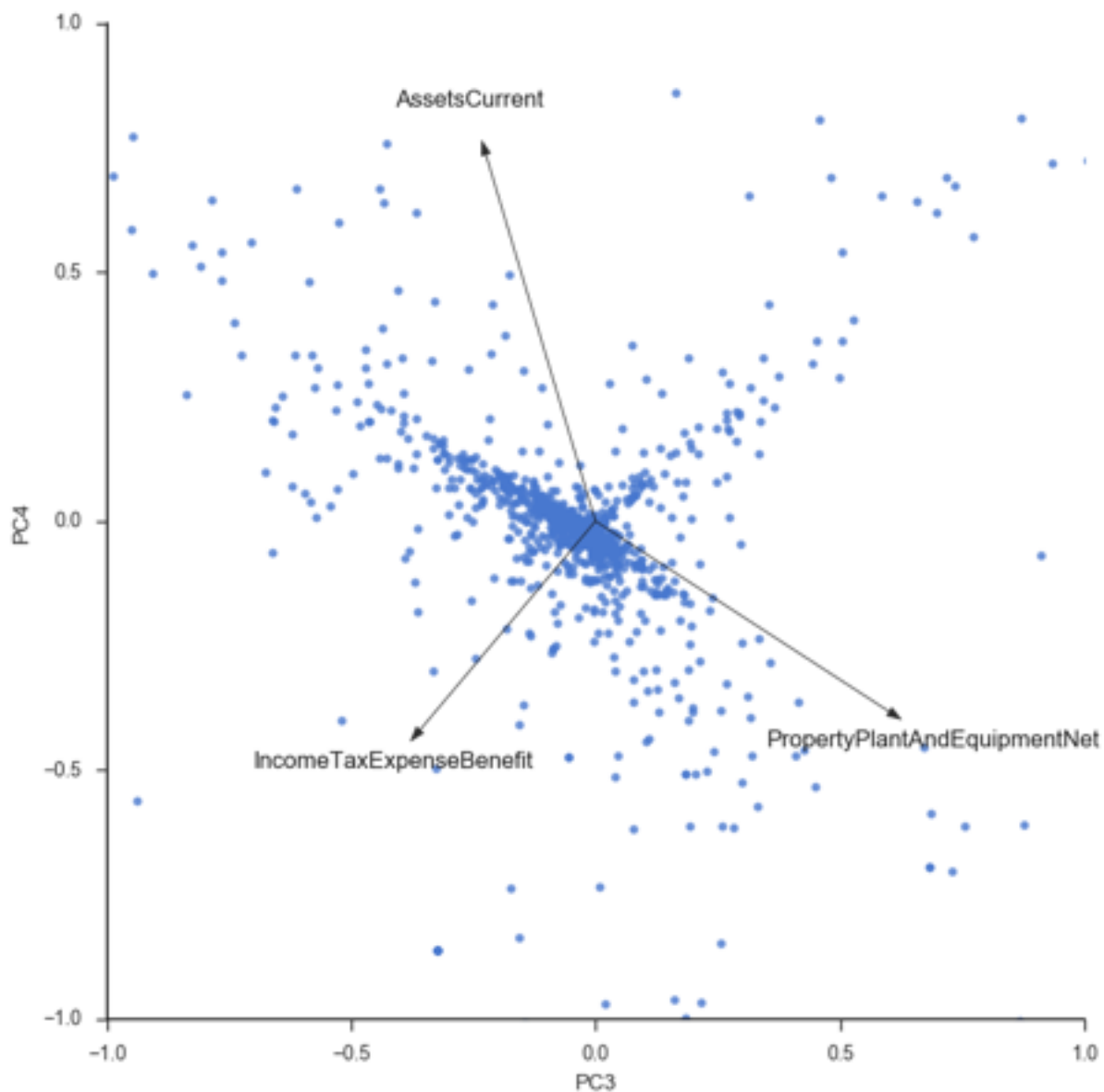
	PC1	PC2	PC3	PC4
0	-0.591511	-0.068120	-0.035582	-0.006771
1	-0.641576	-0.069308	-0.001812	-0.003370
2	-0.557480	-0.072393	-0.044514	-0.000186
3	-0.652365	-0.067850	-0.002520	-0.010621
4	-0.346659	-0.069770	-0.151481	0.068830

## 2-D Principal component analysis:



This is the plot of first two principal of our indicators dataset, which shows the arrow of CommonStockShareIssued on graph which has no relationship with other indicators.





This graph shows the plot of third and fourth principal of our indicator dataset. In the 2-D graph we can see these 3 arrow represent AssetsCurrent, income TaxExpenseBenefit, and PropertyPlantAndEquipmentNet. These three indicators shows with blue

or light blue color on our r-value graph which means middle close relationship between these indicators. AssetsCurrent to income

TaxExpenseBenefit with r-value 0.72, to

PropertyPlantAndEquipmentNet with 0.5.

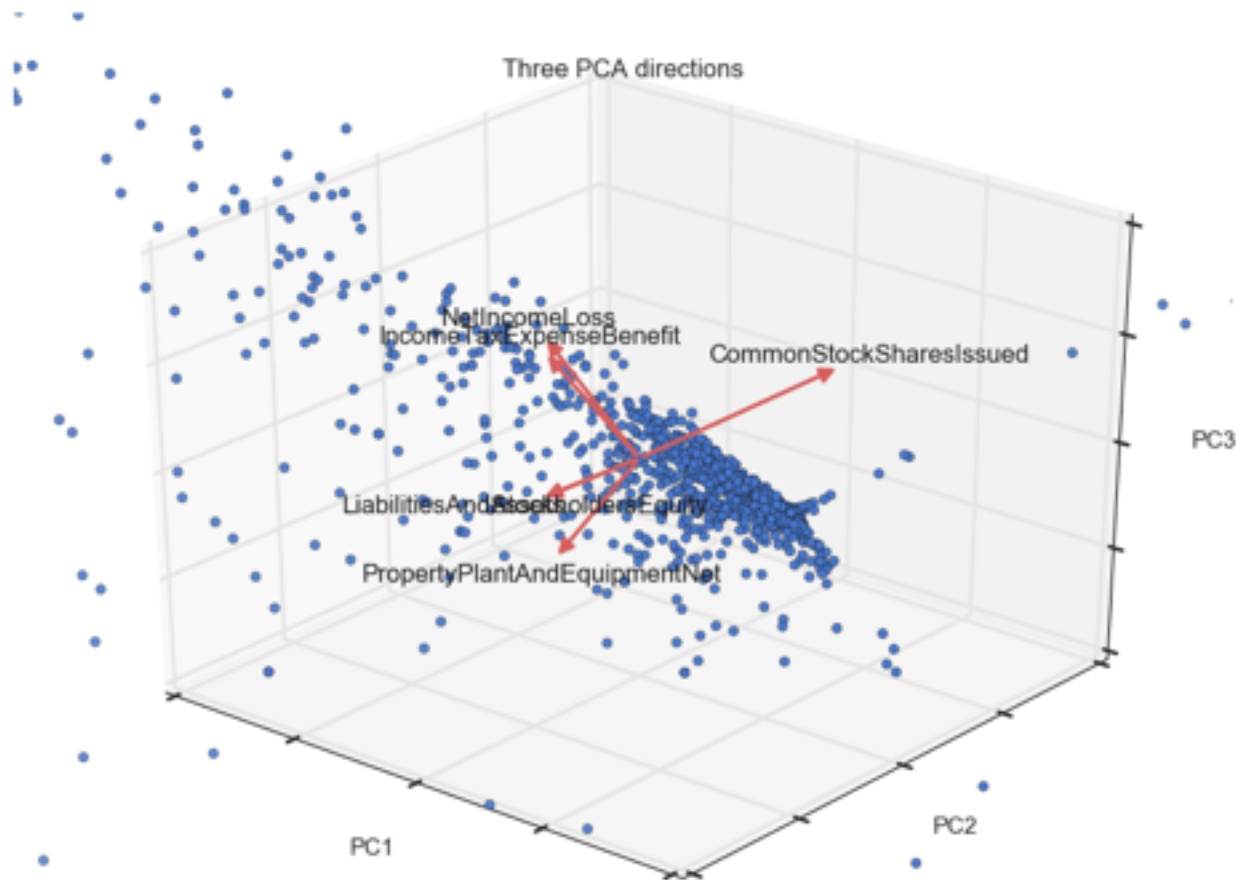
PropertyPlantAndEquipmentNet and TaxExpenseBenefit with r-value 0.61 which represent by different direction of each arrow on 2-D principal component graph.

## 2-D Principal component plot with python code:

```
def pca_biplot(x_pc=0, y_pc=1, max_arrow=0.2):
    n = pc.shape[1]
    sns.set(style="ticks", palette="muted", color_codes=True)

    g = sns.lmplot(x='PC{}'.format(x_pc + 1), y='PC{}'.format(y_pc + 1), data=pc_scores,
                  fit_reg=False, size=8)
    for i in range(n):
        # Only plot the longer ones
        length = sqrt(pc.iloc[x_pc, i] ** 2 + pc.iloc[y_pc, i] ** 2)
        if length < max_arrow:
            continue
        plt.arrow(0, 0, pc.iloc[x_pc, i], pc.iloc[y_pc, i], color='k', alpha=0.9)
        plt.text(pc.iloc[x_pc, i] * 1.15, pc.iloc[y_pc, i] * 1.15,
                pc.columns.tolist()[i], color='k', ha='center', va='center')
    g.set(ylim=(-1, 1))
    g.set(xlim=(-1, 1))
    plt.show()
```

### 3-D Principal component analysis:



3-D plot with first three principal component.

As graph show above, Assets and LiabilitiesAndStockholdersEquity shows in exactly same arrow which reflect their r-value is 1.

NetIncomeLoss and IncomeTaxExpenseBenefit differ by a small angle

in the same 2-D plane, and they have r-value equal to 0.92 which shows strong related to each other. The CommonStockSharesAuthorized is clearly shows in a different 3-D plane with other indicators since it has almost none relationship with other indicators.

## 3-D Principal component plot with python code:

```
class Arrow3D(FancyArrowPatch):
    def __init__(self, xs, ys, zs, *args, **kwargs):
        FancyArrowPatch.__init__(self, (0,0), (0,0), *args, **kwargs)
        self._verts3d = xs, ys, zs
    def draw(self, renderer):
        xs3d, ys3d, zs3d = self._verts3d
        xs, ys, zs = proj3d.proj_transform(xs3d, ys3d, zs3d, renderer.M)
        self.set_positions((xs[0],ys[0]),(xs[1],ys[1]))
        FancyArrowPatch.draw(self, renderer)

def pca_3Dplot(x_pc=0, y_pc=1, z_pc=2, max_arrow=0.2):
    fig = plt.figure(1, figsize=(8, 6))
    ax = Axes3D(fig, elev=-150, azim=50)
    sns.set(style="ticks", palette="muted", color_codes=True)

    ax.scatter(pc_scores.iloc[:, x_pc], pc_scores.iloc[:, y_pc], pc_scores.iloc[:, z_pc],
               cmap=plt.cm.Paired)
    n = pc.shape[1]
    for i in range(n):
        length = sqrt(pc.iloc[0, i] ** 2 + pc.iloc[1, i] ** 2 + pc.iloc[2, i] ** 2)
        if length < max_arrow:
            continue
        a = Arrow3D([0, pc.iloc[0, i]], [0, pc.iloc[1, i]], [
                    0, pc.iloc[2, i]], mutation_scale=20,
                    lw=2, arrowstyle="->", color="r")
        ax.add_artist(a)
        ax.text(x=pc.iloc[x_pc, i]*1.15, y=pc.iloc[y_pc, i]*1.15, z=pc.iloc[z_pc, i]*1.15,
               s=pc.columns.tolist()[i], color='k', ha='center', va='center')
    ax.set_title("Three PCA directions")
    ax.set_xlabel('PC{}'.format(x_pc + 1))
    ax.w_xaxis.set_ticklabels([])
    ax.set_ylabel('PC{}'.format(y_pc + 1))
    ax.w_yaxis.set_ticklabels([])
    ax.set_zlabel('PC{}'.format(z_pc + 1))
    ax.w_zaxis.set_ticklabels([])
    ax.set_xlim3d(-1, 1)
    ax.set_ylim3d(-1, 1)
    ax.set_zlim3d(-1, 1)
    plt.show()
```

## 2.4 Analysis for target companies

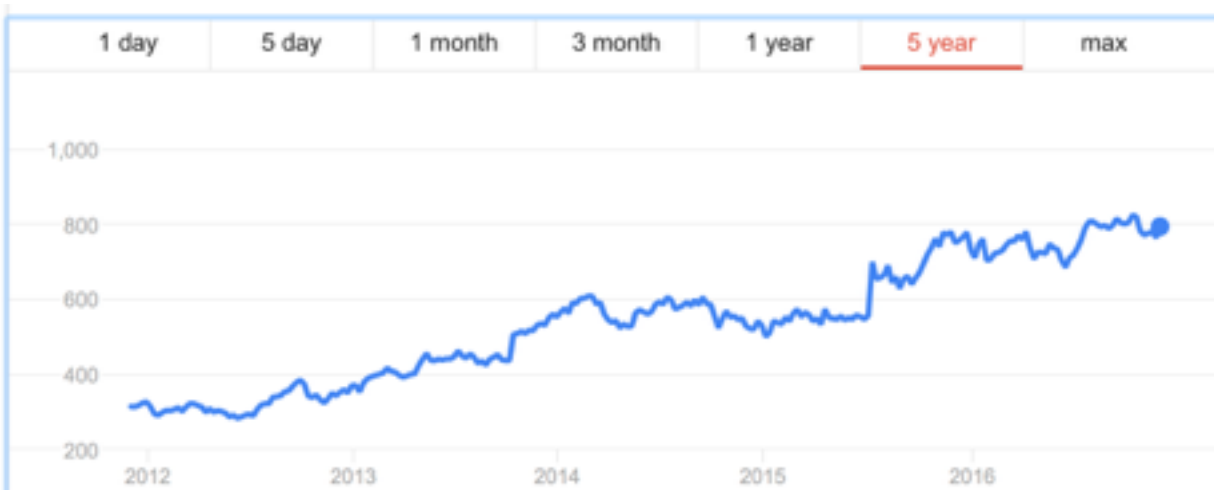
### Data and stock graph for Microsoft:

	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531221	789019	Assets	1.087040e+11	121271000000	142431000000				
			2013	2014	2015	2016			
1531221	172384000000		176223000000	193694000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531425	789019	LiabilitiesAndStockholdersEquity	1.087040e+11						
			2011	2012	2013	2014	2015	2016	
1531425	121271000000		142431000000	172384000000	176223000000	193694000000			
			2016						
1531425	NaN								
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531450	789019	NetIncomeLoss	2.315000e+10	16978000000	21863000000				
			2013	2014	2015	2016			
1531450	22074000000		12193000000	16798000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531396	789019	IncomeTaxExpenseBenefit	4.921000e+09	5289000000					
			2012	2013	2014	2015	2016		
1531396	5189000000		5746000000	6314000000	2953000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531278	789019	CommonStockSharesAuthorized	2.400000e+10	24000000000					
			2012	2013	2014	2015	2016		
1531278	24000000000		24000000000	24000000000	24000000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531222	789019	AssetsCurrent	7.491800e+10	85084000000	101466000000				
			2013	2014	2015	2016			
1531222	114246000000		124712000000	139660000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531454	789019	OperatingIncomeLoss	2.716100e+10	21763000000					
			2012	2013	2014	2015	2016		
1531454	26764000000		27759000000	18161000000	20182000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	2014	2015	2016
1531510	789019	PropertyPlantAndEquipmentNet	8.162000e+09	8269000000					
			2012	2013	2014	2015	2016		
1531510	9991000000		13011000000	14731000000	18356000000	NaN			



## Data and stock graph for Google:

	company_id	indicator_id	2010	2011	2012	2013	\	
click to scroll output; double click to hide	Assets		NaN	72574000000	93798000000	110920000000		
		2014	2015	2016				
494512	131133000000	147461000000	NaN					
	company_id		indicator_id	2010	2011		\	
494729	1288776	LiabilitiesAndStockholdersEquity		NaN	72574000000			
		2012	2013	2014	2015	2016		
494729	93798000000	110920000000	131133000000	147461000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	\	
494748	1288776	NetIncomeLoss	NaN	97370000000	107370000000	129200000000		
		2014	2015	2016				
494748	144440000000	163480000000	NaN					
	company_id		indicator_id	2010	2011	2012	\	
494700	1288776	IncomeTaxExpenseBenefit	NaN	25890000000	25980000000			
		2013	2014	2015	2016			
494700	22820000000	33310000000	33030000000	NaN				
	company_id		indicator_id	2010	2011		\	
494557	1288776	CommonStockSharesAuthorized	NaN	90000000000				
		2012	2013	2014	2015	2016		
494557	120000000000	120000000000	NaN	150000000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	2014	\
494560	1288776	CommonStockValue	NaN	325000	330000	336000	NaN	
		2015	2016					
494560	687000	NaN						
	company_id		indicator_id	2010	2011	2012		\
494558	1288776	CommonStockSharesIssued	NaN	324895000	329979000			
		2013	2014	2015	2016			
494558	335832000	NaN	687348000	NaN				
	company_id	indicator_id	2010	2011	2012		\	
494513	1288776	AssetsCurrent	NaN	527580000000	604540000000			
		2013	2014	2015	2016			
494513	728860000000	806850000000	901140000000	NaN				
	company_id	indicator_id	2010	2011	2012		\	
494755	1288776	OperatingIncomeLoss	NaN	117420000000	127600000000			
		2013	2014	2015	2016			
494755	139660000000	164960000000	193600000000	NaN				
	company_id		indicator_id	2010	2011		\	
494816	1288776	PropertyPlantAndEquipmentNet	NaN	96030000000				
		2012	2013	2014	2015	2016		
494816	118540000000	165240000000	238830000000	290160000000	NaN			



## Data and stock graph for Facebook:

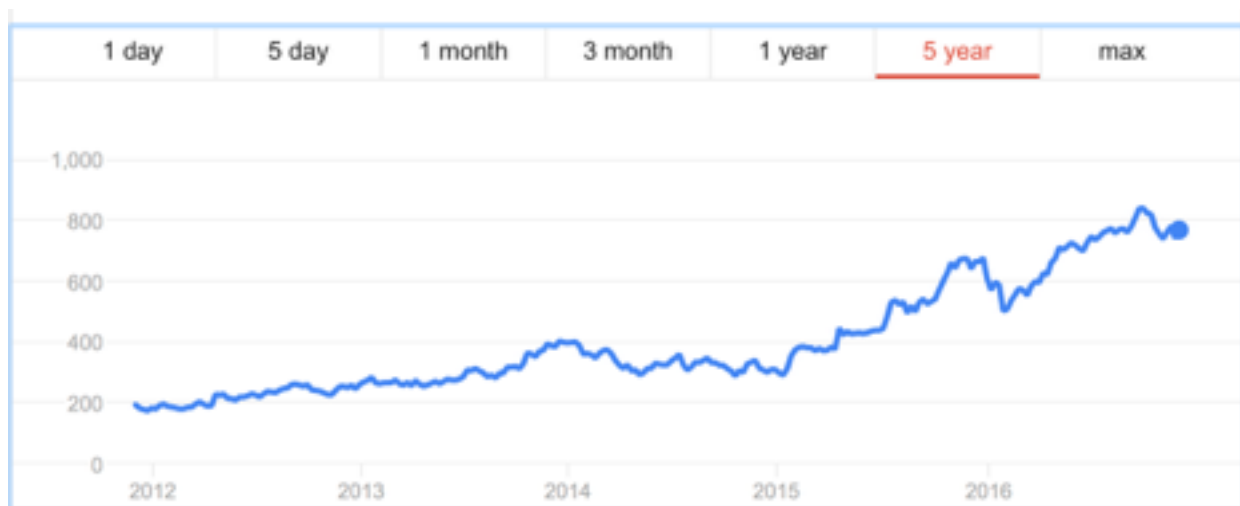
	company_id	indicator_id	2010	2011	2012	2013	\
566659	1326801	Assets	NaN	NaN	15103000000	17895000000	
			2014	2015	2016		
566659	40184000000	49407000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	\
566774	1326801	LiabilitiesAndStockholdersEquity	NaN	NaN	15103000000		
			2013	2014	2015	2016	
566774	17895000000	40184000000	49407000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	\
566783	1326801	NetIncomeLoss	NaN	NaN	53000000	1500000000	
			2014	2015	2016		
566783	29400000000	36880000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	\
566749	1326801	IncomeTaxExpenseBenefit	NaN	NaN	441000000	1254000000	
			2014	2015	2016		
566749	19700000000	25060000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	\
566660	1326801	AssetsCurrent	NaN	NaN	11267000000	13070000000	
			2014	2015	2016		
566660	13670000000	21652000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	\
566788	1326801	OperatingIncomeLoss	NaN	NaN	538000000	2804000000	
			2014	2015	2016		
566788	49940000000	62250000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	\
566825	1326801	PropertyPlantAndEquipmentNet	NaN	NaN	2391000000		
			2013	2014	2015	2016	
566825	28820000000	39670000000	56870000000	NaN			





## Data and stock graph for Amazon:

	company_id	indicator_id	2010	2011	2012	2013	%	
55410	1018724	Assets	NaN	25278000000	32555000000	40159000000		
		2014	2015	2016				
55410	54505000000	65444000000	NaN					
	company_id	indicator_id	2010	2011	2012	2013	%	
55580	1018724	LiabilitiesAndStockholdersEquity	NaN	25278000000				
		2012	2013	2014	2015	2016		
55580	32555000000	40159000000	54505000000	65444000000	NaN			
	company_id	indicator_id	2010	2011	2012	2013	%	
55403	1018724	NetIncomeLoss	NaN	431000000	-39000000	274000000		
		2014	2015	2016				
55403	-241000000	596000000	NaN					
	company_id	indicator_id	2010	2011	2012	2013	%	
55558	1018724	IncomeTaxExpenseBenefit	NaN	291000000	428000000			
		2013	2014	2015	2016			
55558	167000000	950000000	NaN					
	company_id	indicator_id	2010	2011	2012	2013	%	
55454	1018724	CommonStockSharesAuthorized	NaN	5000000000	5000000000			
		2013	2014	2015	2016			
55454	5000000000	5000000000	5000000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	2014	%
55457	1018724	CommonStockValue	NaN	5000000	5000000	5000000	5000000	
		2015	2016					
55457	5000000	NaN						
	company_id	indicator_id	2010	2011	2012	2013	%	
55455	1018724	CommonStockSharesIssued	NaN	4730000000	4780000000			
		2013	2014	2015	2016			
55455	4830000000	4880000000	4940000000	NaN				
	company_id	indicator_id	2010	2011	2012	2013	2014	%
55411	1018724	AssetsCurrent	NaN	17490000000	21294000000	24625000000		
		2014	2015	2016				
55411	31327000000	36474000000	NaN					
	company_id	indicator_id	2010	2011	2012	2013	2014	%
55405	1018724	OperatingIncomeLoss	NaN	862000000	476000000	745000000		
		2014	2015	2016				
55405	1780000000	2233000000	NaN					
	company_id	indicator_id	2010	2011	2012	2013	2014	%
55458	1018724	PropertyPlantAndEquipmentNet	NaN	4417000000	7040000000			
		2013	2014	2015	2016			
55458	10949000000	16967000000	21838000000	NaN				





## Analysis:

All these software tech companies has very high value in Assets, PropertyPlantAndEquipmentNet, NetIncomeLoss and all other indicators represent the successful of a company. Compare to the description of our dataset these target companies are way above 75%. Amazon has a huge positive NetIncomeLoss at 2015 show in our dataset, and their stock price raise 200% during 2015 to 2016 show in Stock diagram. All of four companies have raised their stock value between 200% to 300%+, and our dataset indicators also shows their huge gain in Assets, NetIncomeLoss, and PropertyPlantAndEquipmentNet. These are three most important indicators related to the stock value in our dataset. The stock value graph I simply get from google search which shows a dynamic change for these target company in detail.

## Part of Python Script to get target companies data indicators:

```
import pandas as pd
import numpy as np
df = pd.read_csv('indicators_by_company.csv',
dtype={'2011': str, '2012': str, '2013': str, '2014': str, '2015': str})

df = df[df['company_id']==1018724]
#df = df[df['year']=='2011']
#df['indicator_id'].unique()
print(df[df['indicator_id']=='Assets'])
print(df[df['indicator_id']=='LiabilitiesAndStockholdersEquity'])
print(df[df['indicator_id']=='NetIncomeLoss'])
print(df[df['indicator_id']=='IncomeTaxExpenseBenefit'])
print(df[df['indicator_id']=='CommonStockSharesAuthorized'])
print(df[df['indicator_id']=='CommonStockValue'])
print(df[df['indicator_id']=='CommonStockSharesIssued'])
print(df[df['indicator_id']=='AssetsCurrent'])
print(df[df['indicator_id']=='OperatingIncomeLoss'])
print(df[df['indicator_id']=='PropertyPlantAndEquipmentNet'])
```

**End Of Analysis**

# Conclusion

## 3.1 Summary

This dataset is very interesting and contains with large amount of information about American companies. There are huge amount of indicators I can work with, but I do chose the ten most common and important indicators to analysis. The project help me to understand the relationship between each indicators and how they related to the real stock value change. The four target I chose are all software tech companies, and I may work with them in my future. I do get the partial reason that why these companies are so successful from this dataset. The flag tech companies are always the outlier in these 12,129 US companies. They do have a huge NetIncomeLoss and Assets.

## 3.2 Future Analysis

In this project, I focus on analysis with these indicators in US stocks fundamental data with yearly dataset. However I would like to try to find some weekly or daily dataset with these target tech companies to do more deep analysis to get know in more detail why they are so successfully and how their stock value raise that much in these five years. It will be great if we can try to predicate the stock value from data analysis!



THE END