

# Low-Level Documentation

Investment Analytics - FDI data.

## Document Version Control

Version	Date	Author	Comments
0.0.1	23-07-22	Sri Venkatesh	First Document prepared

Tableau Server is essentially a communication tool that shares data connections and visualizations with the end-users or clients. So, now that we have learned about the functioning of each component in a Tableau server. Let us understand how all these components work in tandem. For this, we will club the server components into layers or tiers. So, we have five layers or sections in the Tableau Server; customer data, data connectors, main components, gateway, and clients.

The customer data layer contains all sorts of data sources available for a Tableau user like data warehouses, data marts, flat files, and multi-dimensional cubes, relational databases. Next lies the data connectors layers which consist of a data engine, repository, SQL Connector, and MDX Connector. These components interact directly with the data sources. The Data engine processes the data requested by the user and assigns the data type, decides whether it is a measure or a dimension, and creates TDEs (data extracts). In the background of the data, the engine runs an SQL Connector which creates an SQL query for all the user requests and interacts with the data sources. The SQL Connector primarily deals with data marts and flat files. Similarly, the MDX Connector deals with multi-dimensional cubes.

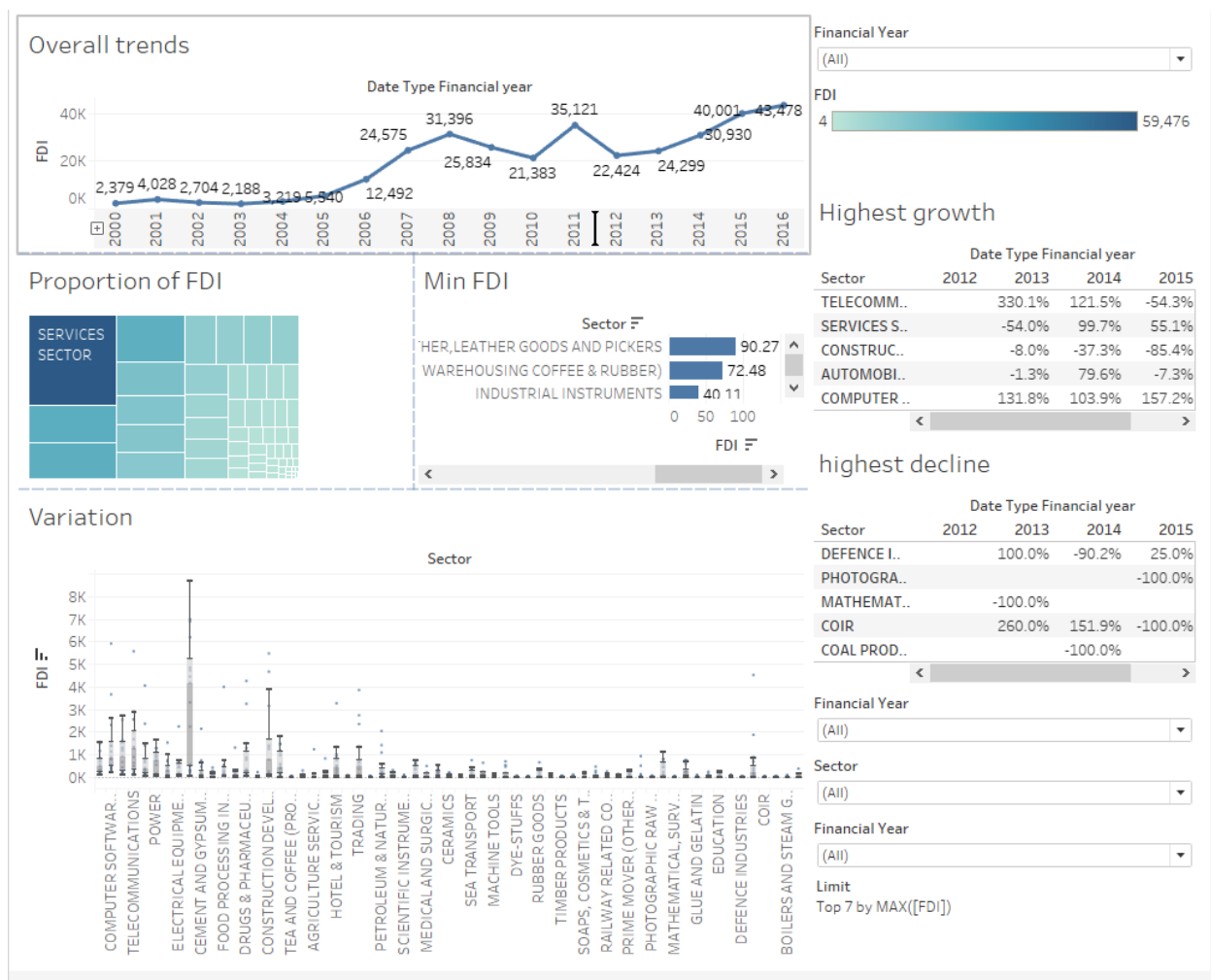
The next layer comprises all the main components, essentially the data server which regulates and monitors the functioning of the components of the data connector layer. Along with this, it includes a VizQL Server and Application Server. The application server takes all the user requests coming from Tableau Desktop, mobile, or browser for accessing the visualization. It processes the requests and detects the type of request, checks user authorization and grants access accordingly. The VizQL Server is a patented component of Tableau, where VizQL stands for Visualization Query language. It works behind the logic of Tableau visualization and creates the visualization as per your instructions on the dashboard.

The gateway acts as a gatekeeper of the Tableau Server and any request or query sent by the client first hits the gateway or load balancer. A gateway is nothing but a primary server that receives the queries and redirects them to an appropriate and available secondary server, known as a worker server.

## Data Description

The data comprises FDI data of India from the period: 2000-2001 to 2016-2017. In order to construct the dashboard, we created a pivot view of the columns under years, since having the horizontal data was not very effective for generating views on Tableau.

Here is the Tableau Dashboard:



The Colab Notebook has been attached:

<https://colab.research.google.com/drive/14gZ8AzdTCd7ZEu4Y4Sb0NtVKC2bq2k43?usp=sharing>

[INeuron\\_data\\_analytics\\_FDI\\_data.pdf](#)

## FDI\_DATA

Required libraries:

1. Pandas
2. Matplotlib

```
#import libs
```

```
import pandas as pd
import matplotlib.pyplot as plt
```

```
#import data
```

```
df = pd.read_csv('FDI_in_India.csv')
```

```
!ls
```

```
FDI_in_India.csv  sample_data
```

```
###Generate descriptive statistics.
```

```
df.describe()
```

	2000-01	2001-02	2002-03	2003-04	2004-05 \
count	63.000000	63.000000	63.000000	63.000000	63.000000
mean	37.757302	63.931587	42.925714	34.727778	51.090317
std	112.227860	157.878737	86.606439	67.653735	101.934873
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.200000	0.215000	0.715000
50%	4.030000	5.070000	11.010000	6.370000	9.090000
75%	23.510000	44.830000	36.555000	38.660000	43.205000
max	832.070000	873.230000	419.960000	368.320000	527.900000

	2005-06	2006-07	2007-08	2008-09	2009-10
\count	63.000000	63.000000	63.000000	63.000000	63.000000
mean	87.932540	198.281905	390.085714	498.348571	410.069524
std	206.436967	686.783115	1026.249935	1134.649040	926.814626
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.230000	4.160000	9.950000	11.950000	7.880000
50%	22.620000	25.820000	58.820000	84.880000	69.740000
75%	63.855000	108.325000	279.270000	383.320000	341.595000

max	1359.970000	4713.780000	6986.170000	6183.490000	5466.130000
	2010-11	2011-12	2012-13	2013-14	2014-15
\count	63.000000	63.000000	63.000000	63.000000	63.000000
mean	339.413810	557.472698	355.930000	385.703492	490.959841
std	627.141139	1031.474056	778.091368	658.429944	837.787060
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	8.430000	22.720000	15.115000	16.610000	33.800000
50%	58.070000	129.360000	95.410000	113.780000	177.220000
75%	304.280000	593.525000	288.025000	473.060000	595.390000
max	3296.090000	5215.980000	4832.980000	3982.890000	4443.260000

	2015-16	2016-17
count	63.000000	63.000000
mean	634.936349	690.131111
std	1335.307706	1411.965354
min	0.000000	0.000000
25%	30.000000	19.905000
50%	159.130000	110.860000
75%	519.070000	741.220000
max	6889.460000	8684.070000

###Output the shape and first 5 rows of the dataframe

```
print(df.shape)
df.head()
```

(63, 18)

	Sector	2000-01	2001-02	2002-03	2003-04	2004-
05 \						
0	METALLURGICAL INDUSTRIES	22.69	14.14	36.61	8.11	
200.38						
1	MINING	1.32	6.52	10.06	23.48	
9.92						
2	POWER	89.42	757.44	59.11	27.09	
43.37						
3	NON-CONVENTIONAL ENERGY	0.00	0.00	1.70	4.14	
1.27						
4	COAL PRODUCTION	0.00	0.00	0.00	0.04	

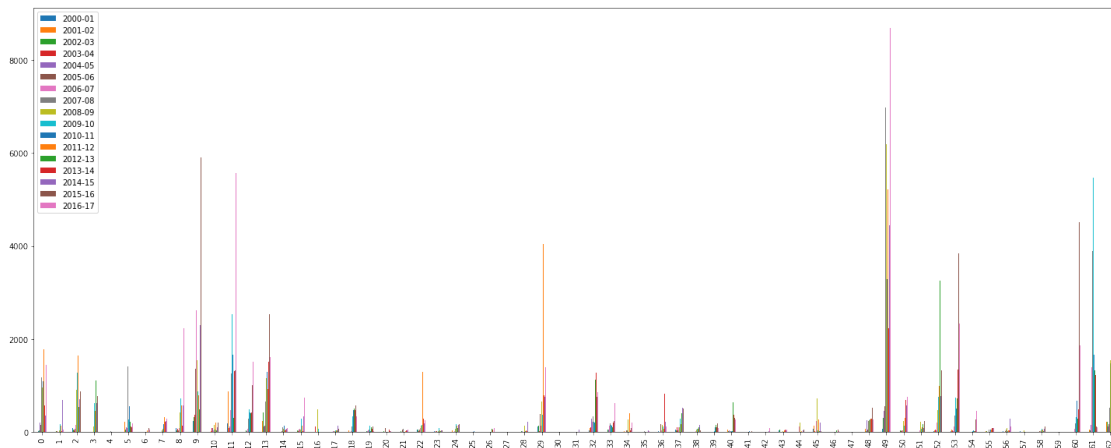
0.00

	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12
2012-13 \							
0	149.13	169.94	1175.75	959.94	419.88	1098.14	1786.14
	1466.23						
1	7.40	6.62	444.36	34.16	174.40	79.51	142.65
	57.89						
2	72.69	157.15	988.68	907.66	1271.79	1271.77	1652.38
	535.68						
3	1.35	2.44	58.82	125.88	622.52	214.40	452.17
	1106.52						
4	9.14	1.30	14.08	0.22	0.00	0.00	0.00
	0.00						

	2013-14	2014-15	2015-16	2016-17
0	567.63	359.34	456.31	1440.18
1	12.73	684.39	520.67	55.75
2	1066.08	707.04	868.80	1112.98
3	414.25	615.95	776.51	783.57
4	2.96	0.00	0.00	0.00

```
df.plot(figsize=(25,10), kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7dd4d4f610>
```



### Setting the index

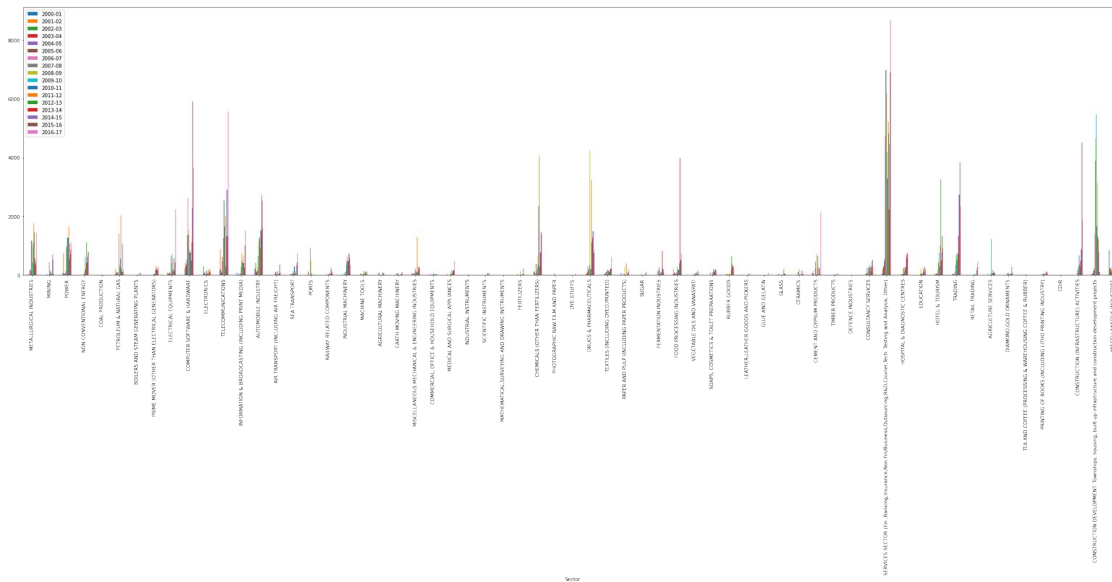
```
df.set_index('Sector', inplace=True)
```

### Plotting the data after setting the index

```
df.plot(kind='bar', figsize = (40,10))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7dd4100b90>
```

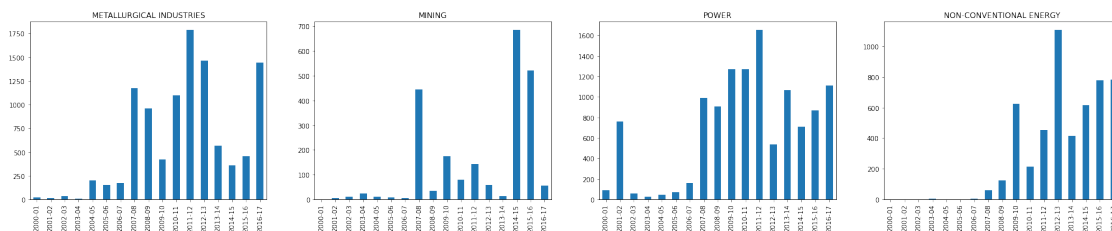




## Plotting the first 4 rows

```
fig, axes = plt.subplots(nrows=1, ncols=4)
```

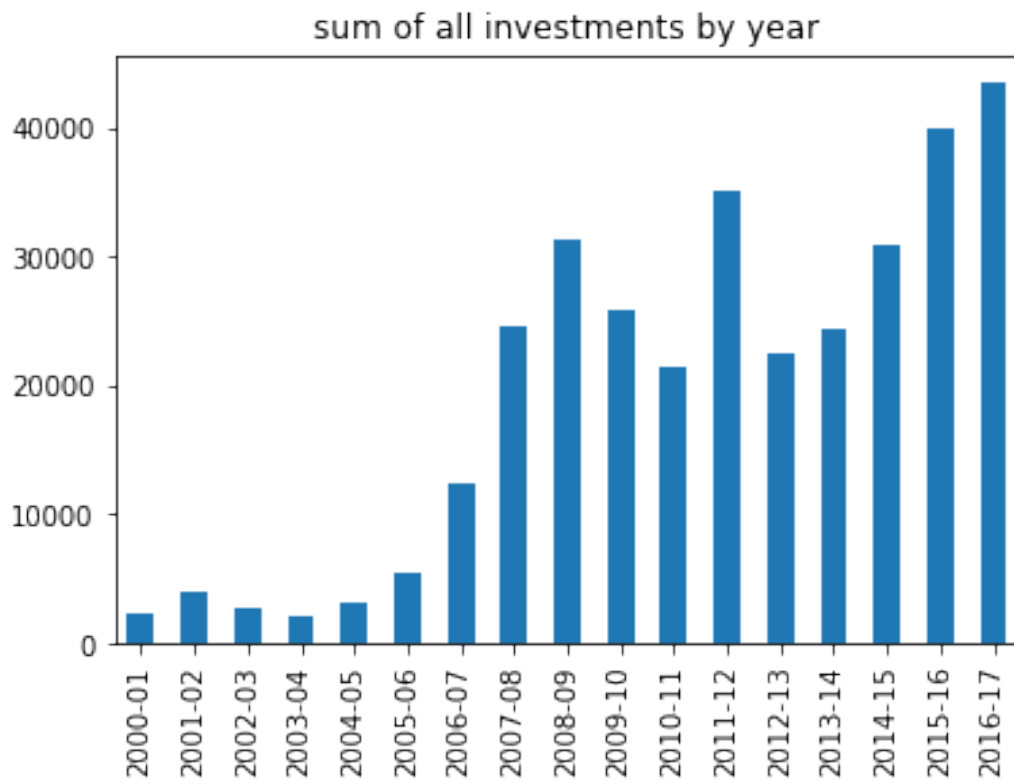
```
for i in range(0,4):
    df.iloc[i].plot(kind='bar',title=df.iloc[i].name, ax = axes[i],
figsize=(30,5))
```



## Looking at the sum of investments in all sectors by year

```
df.sum().plot(kind='bar', title='sum of all investments by year')
```

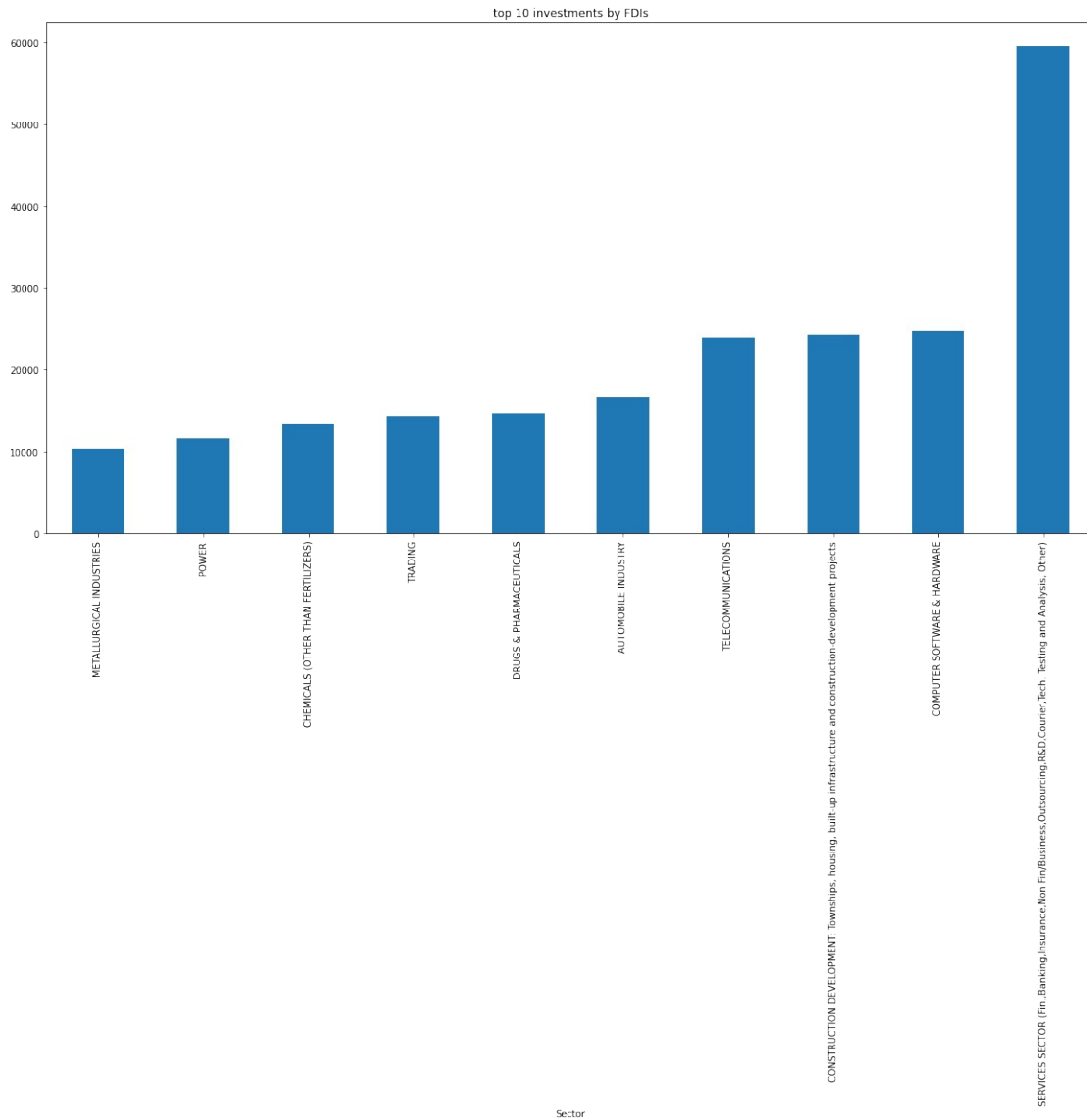
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7dd126a8d0>
```



Plotting the sum of investments of all years by their sector (top 10 sectors)

```
df_trans = df.transpose()  
df_trans.sum().sort_values()[-10:].plot(figsize=(20,10),kind='bar',  
title = 'top 10 investments by FDI's')
```

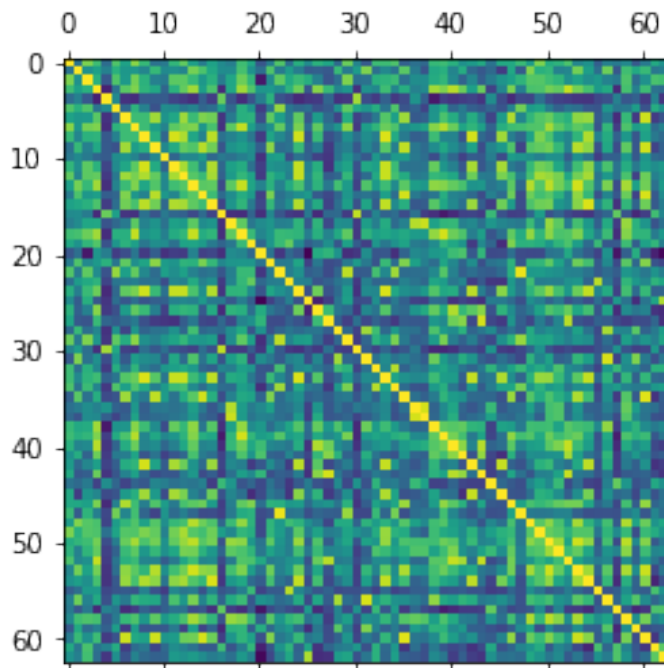
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7dd1190c50>
```



### Visualizing the correlation among sectors

```
corr = df_trans.corr()  
plt.matshow(corr)
```

```
<matplotlib.image.AxesImage at 0x7f7dd10d4ed0>
```



Lets look at the top 10 correlated sectors

```
def get_redundant_pairs(df):
    pairs_to_drop = set()
    cols = df.columns
    for i in range(0, df.shape[1]):
        for j in range(0, i+1):
            pairs_to_drop.add((cols[i], cols[j]))
    return pairs_to_drop

def get_top_abs_correlations(df, n=5):
    au_corr = df.corr().abs().unstack()
    labels_to_drop = get_redundant_pairs(df)
    au_corr =
au_corr.drop(labels=labels_to_drop).sort_values(ascending=False)
    return au_corr[0:n]

print("Top Absolute Correlations")
get_top_abs_correlations(df_trans,10)
```

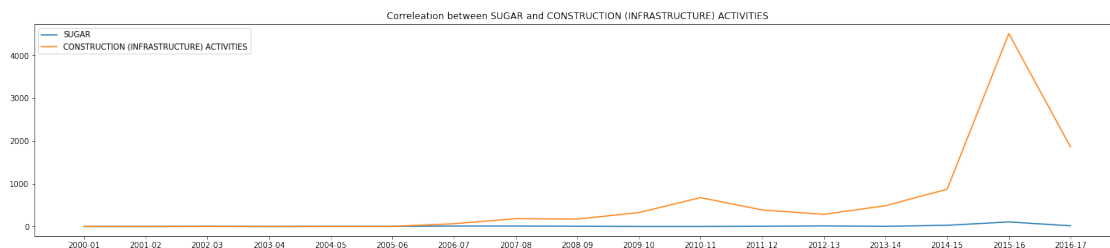
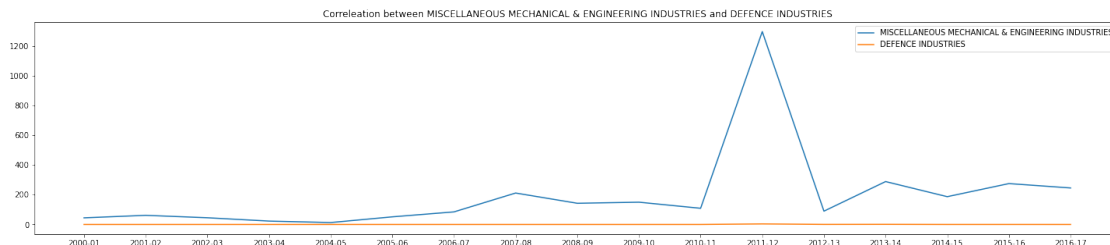
Top Absolute Correlations

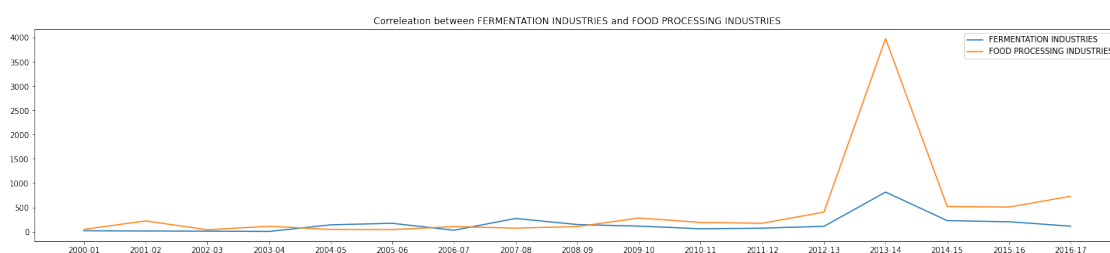
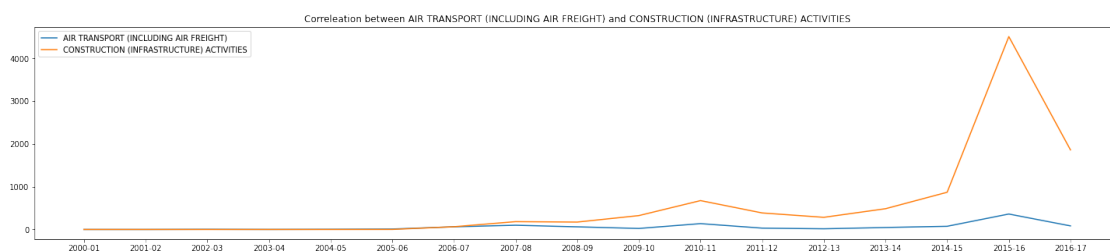
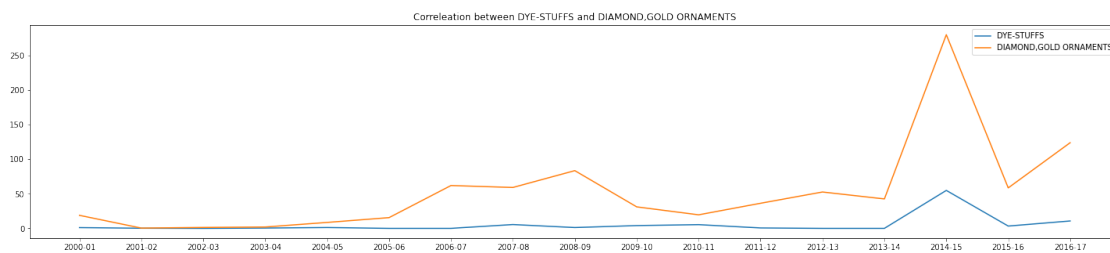
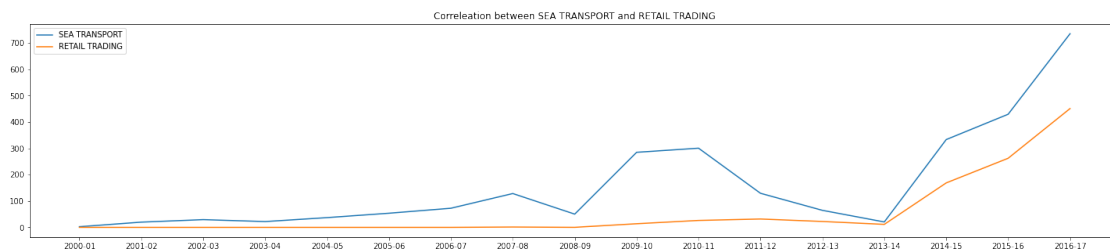
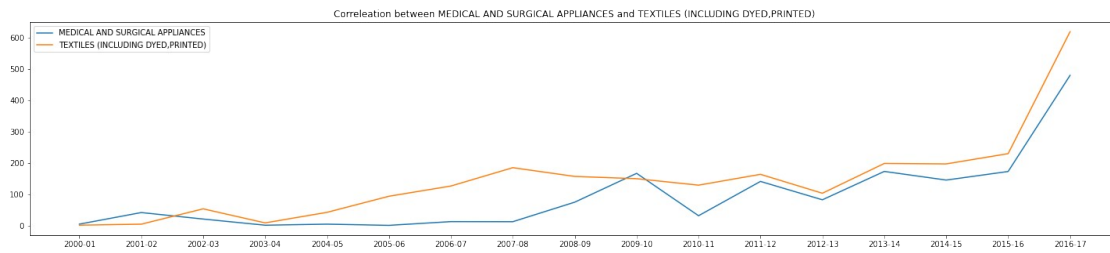
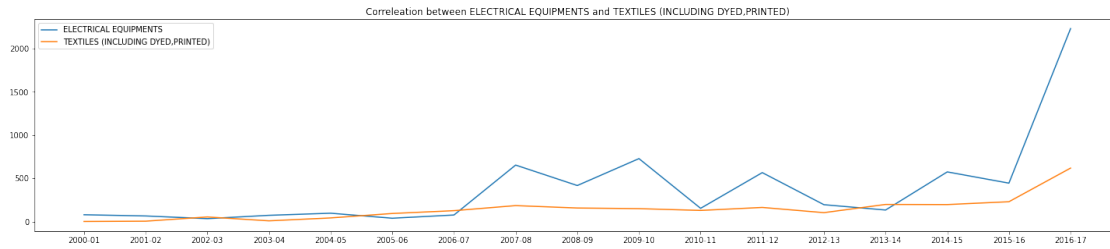
Sector	Sector
MISCELLANEOUS MECHANICAL & ENGINEERING INDUSTRIES	DEFENCE INDUSTRIES
0.958449	
SUGAR	CONSTRUCTION
(INFRASTRUCTURE) ACTIVITIES	0.937258
ELECTRICAL EQUIPMENTS	
DYED,PRINTED)	0.926705
	TEXTILES (INCLUDING

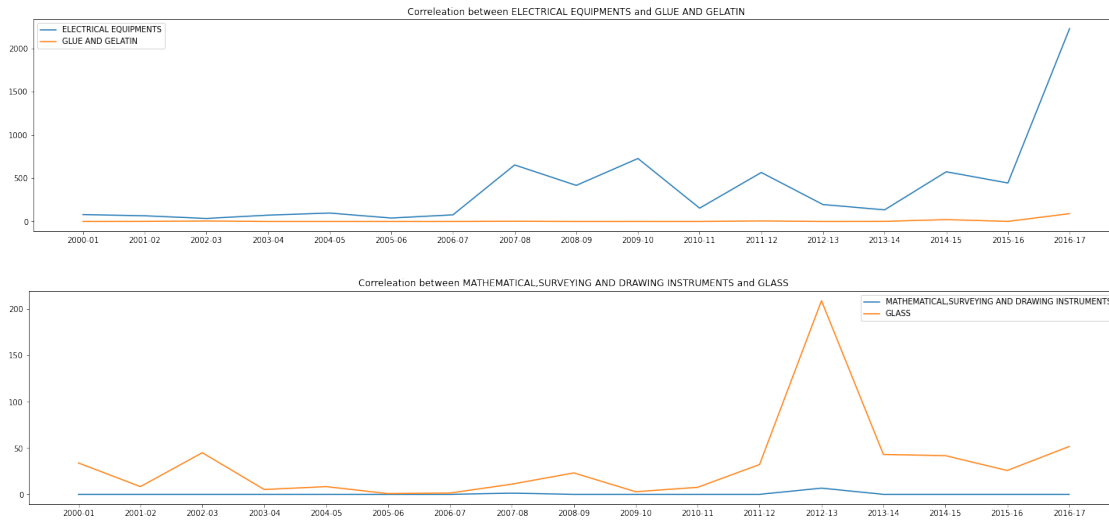
MEDICAL AND SURGICAL APPLIANCES		TEXTILES (INCLUDING
DYED, PRINTED)	0.919642	RETAIL TRADING
SEA TRANSPORT		DIAMOND, GOLD
0.918936		CONSTRUCTION
DYE-STUFFS		FOOD PROCESSING
ORNAMENTS	0.916723	GLUE AND GELATIN
AIR TRANSPORT (INCLUDING AIR FREIGHT)		GLASS
(INFRASTRUCTURE) ACTIVITIES	0.916622	
FERMENTATION INDUSTRIES		
INDUSTRIES	0.910990	
ELECTRICAL EQUIPMENTS		
0.908833		
MATHEMATICAL, SURVEYING AND DRAWING INSTRUMENTS		
0.908687		
dtype: float64		

### Plotting the Correlated Sectors

```
abs_corr = get_top_abs_correlations(df_trans, 10)
plt.rcParams['figure.figsize'] = [25, 5]
for i in range(10):
    plt.plot(df.loc[abs_corr.index[i][0]], label = abs_corr.index[i][0])
    plt.plot(df.loc[abs_corr.index[i][1]], label = abs_corr.index[i][1])
    plt.title(f'Correlation between {abs_corr.index[i][0]} and {abs_corr.index[i][1]}')
    plt.legend()
    plt.show()
```







Lets look at the 3 most correlated years

```
abs_corr = get_top_abs_correlations(df,3)
abs_corr
for i in range(3):
    plt.plot(df_trans.loc[abs_corr.index[i][0]], label =
abs_corr.index[i][0])
    plt.plot(df_trans.loc[abs_corr.index[i][1]], label =
abs_corr.index[i][1])
    plt.title(f'Correleation between {abs_corr.index[i][0]} and
{abs_corr.index[i][1]}')
    plt.legend()
    plt.show()
```

