

Social network Graph Link Prediction - Facebook Challenge

Problem statement:

Given a directed social graph, have to predict missing links to recommend users (Link Prediction in graph)

Data Overview:

Taken data from facebook's recruiting challenge on kaggle <https://www.kaggle.com/c/FacebookRecruiting> (<https://www.kaggle.com/c/FacebookRecruiting>)

data contains two columns source and destination eac edge in graph

- Data columns (total 2 columns):
- source_node int64
- destination_node int64

Mapping the problem into supervised learning problem:

- Generated training samples of good and bad links from given directed graph and for each link got some features like no of followers, is he followed back, page rank, katz score, adar index, some svd fetures of adj matrix, some weight features etc. and trained ml model based on these features to predict link.
- Some reference papers and videos :
 - <https://www.cs.cornell.edu/home/kleinber/link-pred.pdf>
(<https://www.cs.cornell.edu/home/kleinber/link-pred.pdf>)
 - <https://www3.nd.edu/~dial/publications/lichtenwalter2010new.pdf>
(<https://www3.nd.edu/~dial/publications/lichtenwalter2010new.pdf>)
 - https://kaggle2.blob.core.windows.net/forum-message-attachments/2594/supervised_link_prediction.pdf
(https://kaggle2.blob.core.windows.net/forum-message-attachments/2594/supervised_link_prediction.pdf)
 - <https://www.youtube.com/watch?v=2M77Hgy17cg> (<https://www.youtube.com/watch?v=2M77Hgy17cg>)

Business objectives and constraints:

- No low-latency requirement.
- Probability of prediction is useful to recommend ighest probability links

Performance metric for supervised learning:

- Both precision and recall is important so F1 score is good choice
- Confusion matrix

In [2]:

```
#Importing Libraries
# please do go through this python notebook:
import warnings
warnings.filterwarnings("ignore")

import csv
import pandas as pd#pandas to create small dataframes
import datetime #Convert to unix time
import time #Convert to unix time
# if numpy is not installed already : pip3 install numpy
import numpy as np#Do arithmetic operations on arrays
# matplotlib: used to plot graphs
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns#Plots
from matplotlib import rcParams#Size of plots
from sklearn.cluster import MiniBatchKMeans, KMeans#Clustering
import math
import pickle
import os
# to install xgboost: pip3 install xgboost
import xgboost as xgb

import warnings
import networkx as nx
import pdb
import pickle
```

In [4]:

```
# reading the grapg
if not os.path.isfile('data/after_eda/train_woheader.csv'):
    traincsv = pd.read_csv('data/train.csv')
    print(traincsv[traincsv.isna().any(1)])
    print(traincsv.info())
    print("Duplicate entruess nubers: ", sum(traincsv.duplicated()))
    traincsv.to_csv('data/after_eda/train_woheader.csv', header=False, index=False)
    print("saved the graph into file")
else:
    g=nx.read_edgelist('data/after_eda/train_woheader.csv', delimiter=',', create_using
=nx.DiGraph(), nodetype=int)
    print(nx.info(g))
```

Name:

Type: DiGraph

Number of nodes: 1862220

Number of edges: 9437519

Average in degree: 5.0679

Average out degree: 5.0679

In [5]:

```
# displaying the sub-graph
if not os.path.isfile('train_woheader_sample.csv'):
    pd.read_csv('data/train.csv', nrows=50).to_csv('train_woheader_sample.csv', header=
False, index=False)

subgraph=nx.read_edgelist('train_woheader_sample.csv', delimiter=',', create_using=nx.D
iGraph(), nodetype=int)

pos=nx.spring_layout(subgraph)
nx.draw(subgraph,pos,node_color='#A0CBE2',edge_color='#00bb5e',width=1,edge_cmap=plt.cm
.Blues,with_labels=True)
plt.savefig("graph_sample.pdf")
print(nx.info(subgraph))
```

Name:

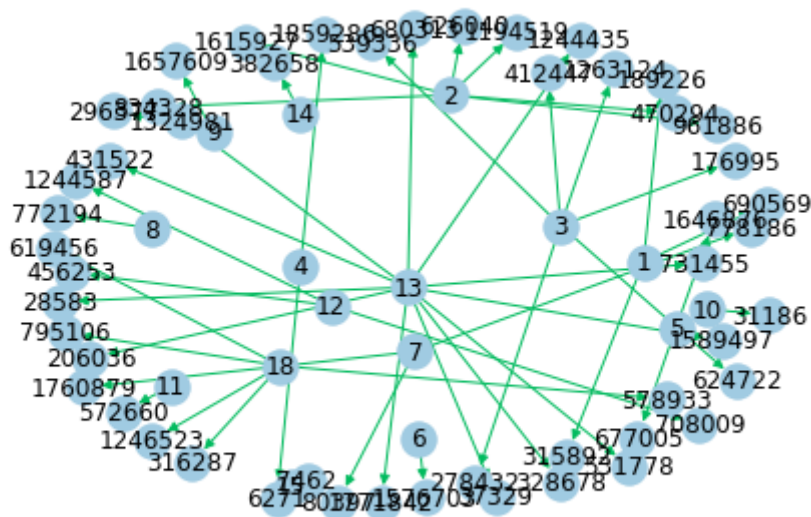
Type: DiGraph

Number of nodes: 66

Number of edges: 50

Average in degree: 0.7576

Average out degree: 0.7576



Exploratory Data Analysis:

In [6]:

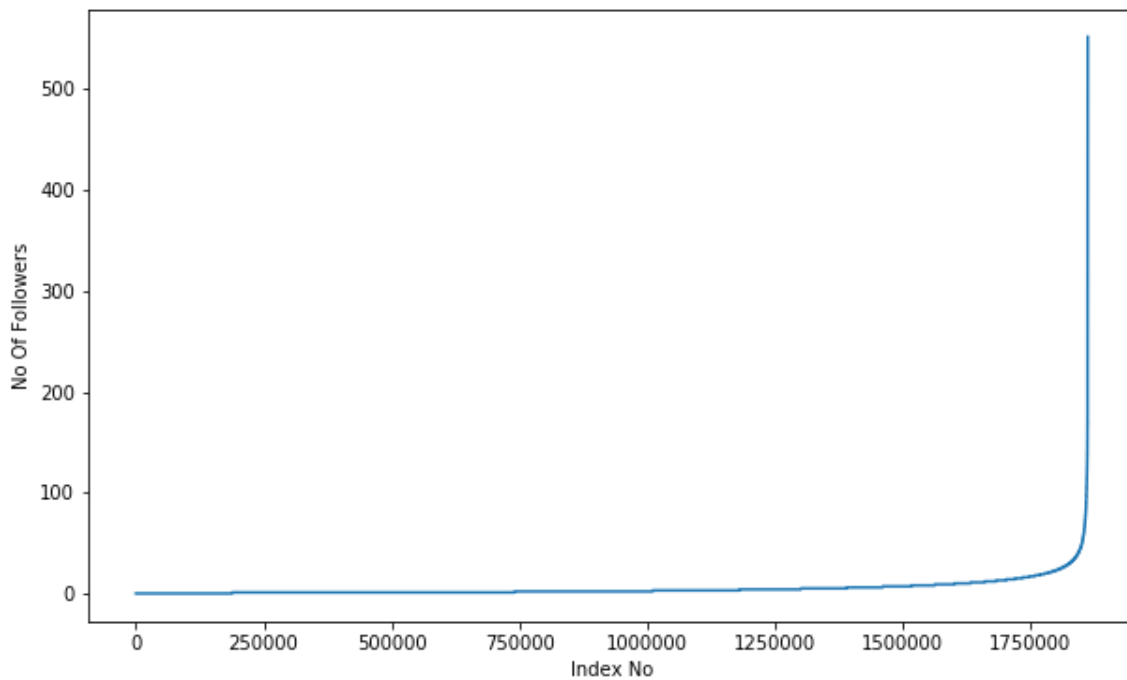
```
# unique perdons
print("The number of unique persons", len(g.nodes()))
```

The number of unique persons 1862220

No of followers for each person

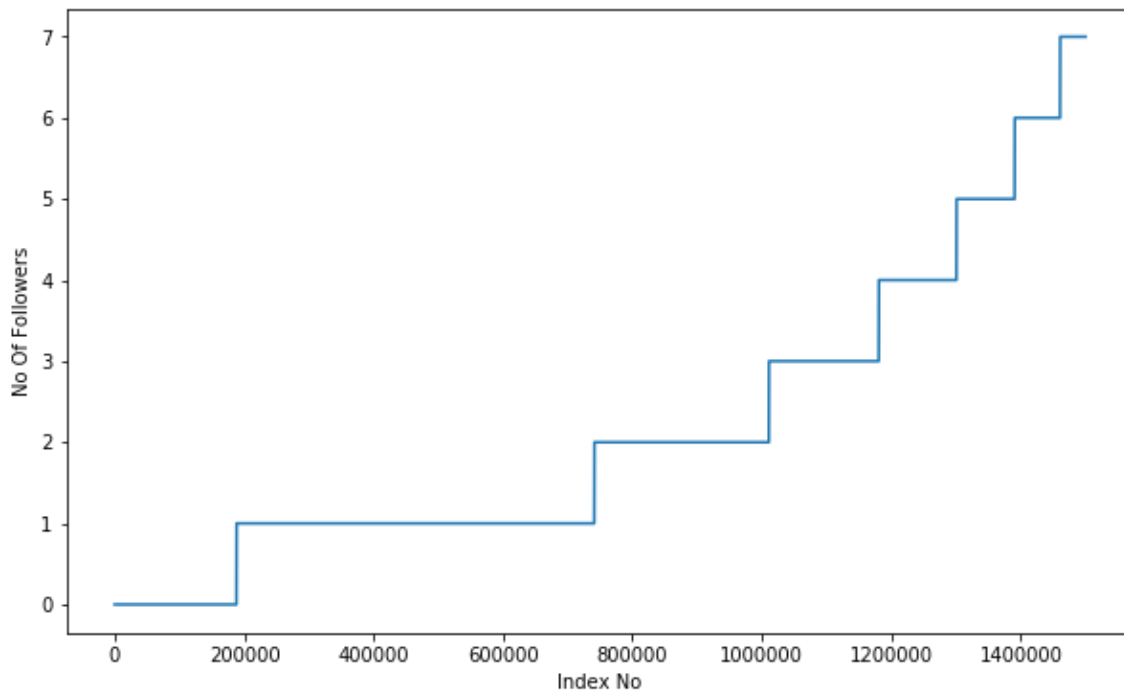
In [7]:

```
indegree_dist = list(dict(g.in_degree()).values())  
indegree_dist.sort()  
plt.figure(figsize=(10,6))  
plt.plot(indegree_dist)  
plt.xlabel('Index No')  
plt.ylabel('No Of Followers')  
plt.show()
```



In [8]:

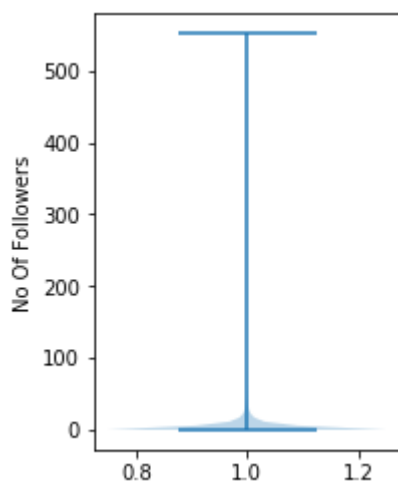
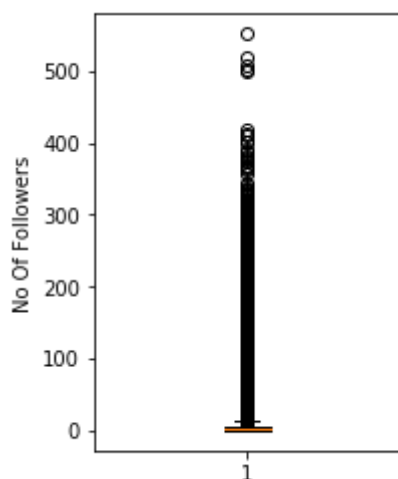
```
indegree_dist = list(dict(g.in_degree()).values())  
indegree_dist.sort()  
plt.figure(figsize=(10,6))  
plt.plot(indegree_dist[0:1500000])  
plt.xlabel('Index No')  
plt.ylabel('No Of Followers')  
plt.show()
```



In [15]:

```
#plt.figure(figsize=(10,6))
plt.subplot(1,2,1)
plt.boxplot(indegree_dist)
plt.ylabel('No Of Followers')
plt.show()

plt.subplot(1,2,2)
plt.violinplot(indegree_dist)
plt.ylabel('No Of Followers')
plt.show()
```



In [16]:

```
# 90-100 percentile  
  
for i in range(0,11):  
    print(90+i, 'percentile value is', np.percentile(indegree_dist, 90+i))
```

```
91 percentile value is 12.0  
91 percentile value is 13.0  
91 percentile value is 14.0  
91 percentile value is 15.0  
91 percentile value is 17.0  
91 percentile value is 19.0  
91 percentile value is 21.0  
91 percentile value is 24.0  
91 percentile value is 29.0  
91 percentile value is 40.0  
91 percentile value is 552.0
```

99% of the data having folowers of 40 only.

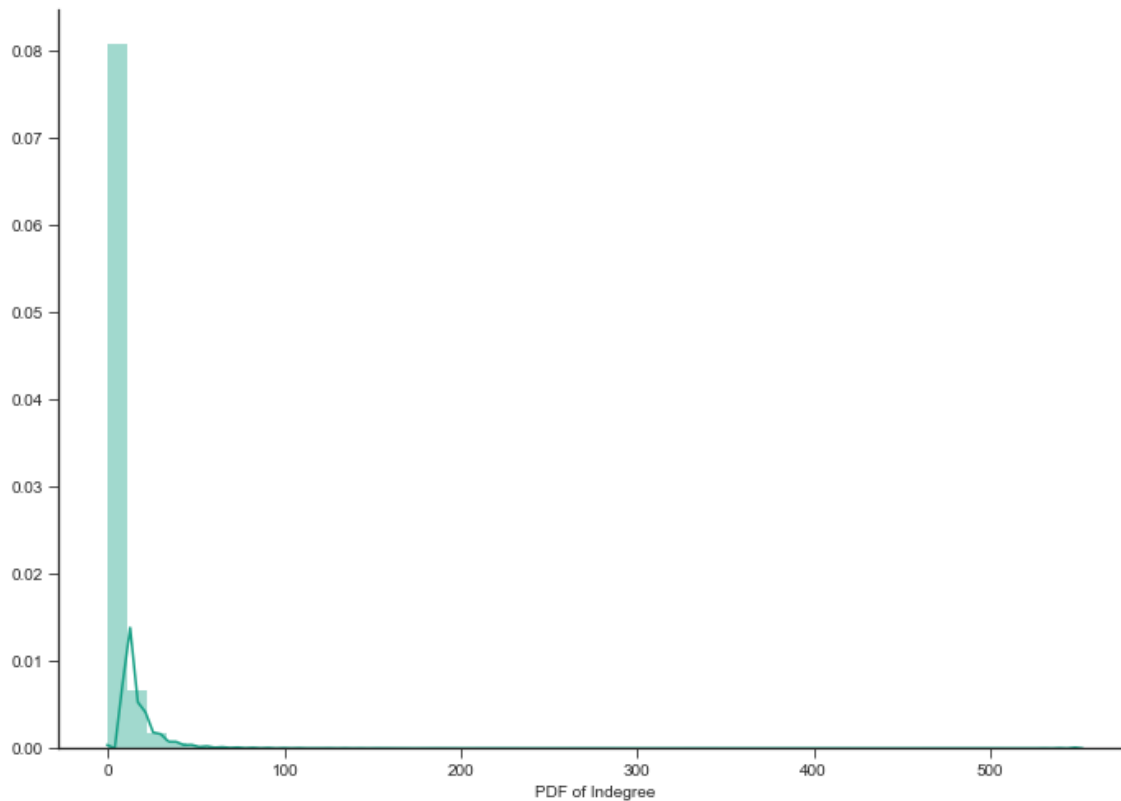
In [19]:

```
## 99 - 100 percentile  
for i in range(10, 110,10 ):  
    print(99+(i/100), 'percentile value is:', np.percentile(indegree_dist, 99+(i/100)))
```

```
99.1 percentile value is: 42.0  
99.2 percentile value is: 44.0  
99.3 percentile value is: 47.0  
99.4 percentile value is: 50.0  
99.5 percentile value is: 55.0  
99.6 percentile value is: 61.0  
99.7 percentile value is: 70.0  
99.8 percentile value is: 84.0  
99.9 percentile value is: 112.0  
100.0 percentile value is: 552.0
```

In [21]:

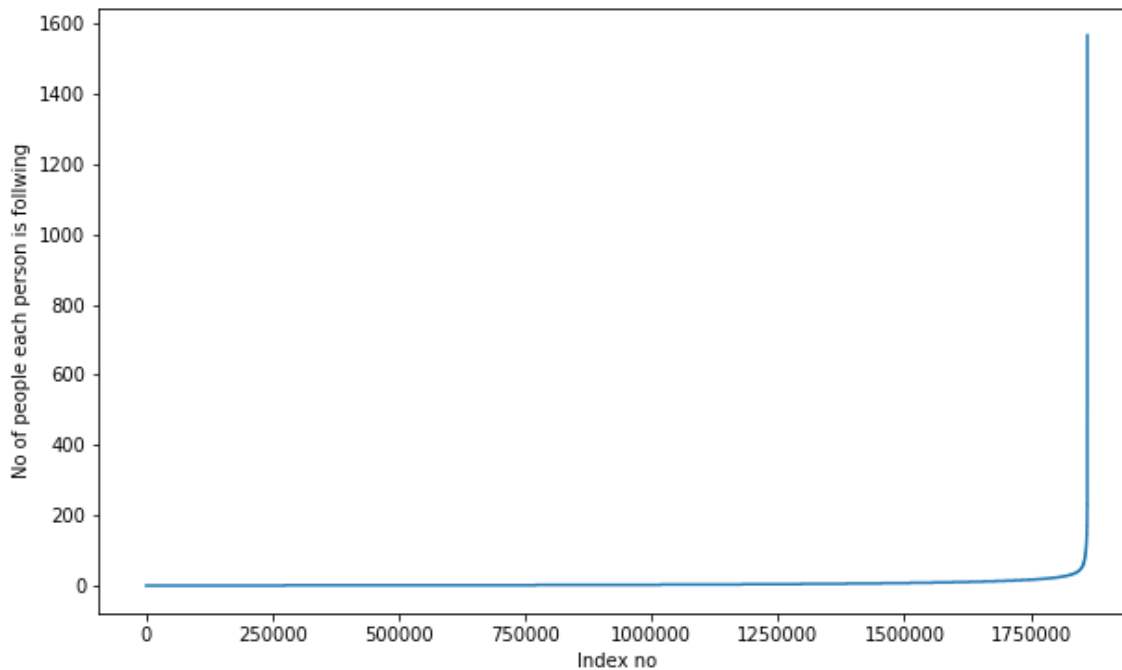
```
% matplotlib inline
sns.set_style('ticks')
fig, ax=plt.subplots()
fig.set_size_inches(11.7, 8.27)
sns.distplot(indegree_dist, color='#16A085')
plt.xlabel('PDF of Indegree')
sns.despine()
```



No of people each person is following

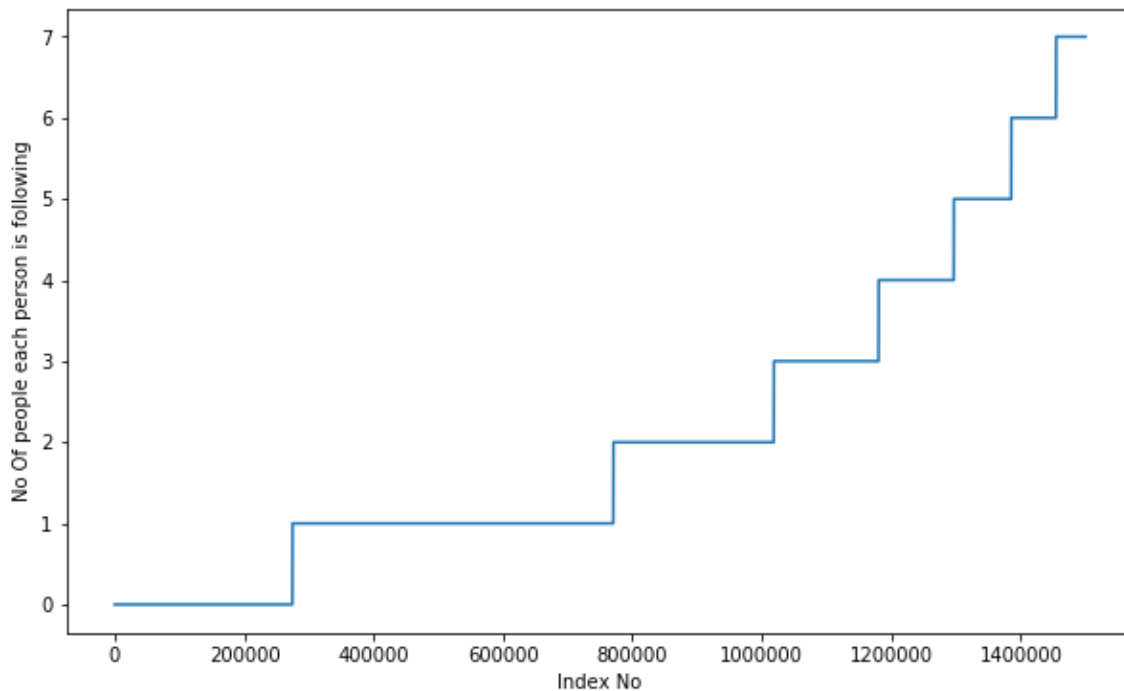
In [9]:

```
outdegree_dist = list(dict(g.out_degree()).values())
outdegree_dist.sort()
plt.figure(figsize=(10,6))
plt.plot(outdegree_dist)
plt.xlabel('Index no')
plt.ylabel('No of people each person is following')
plt.show()
```



In [10]:

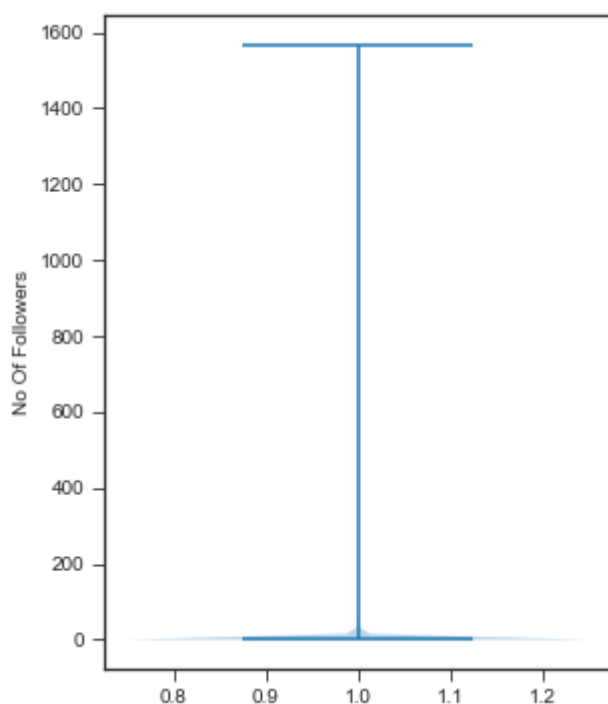
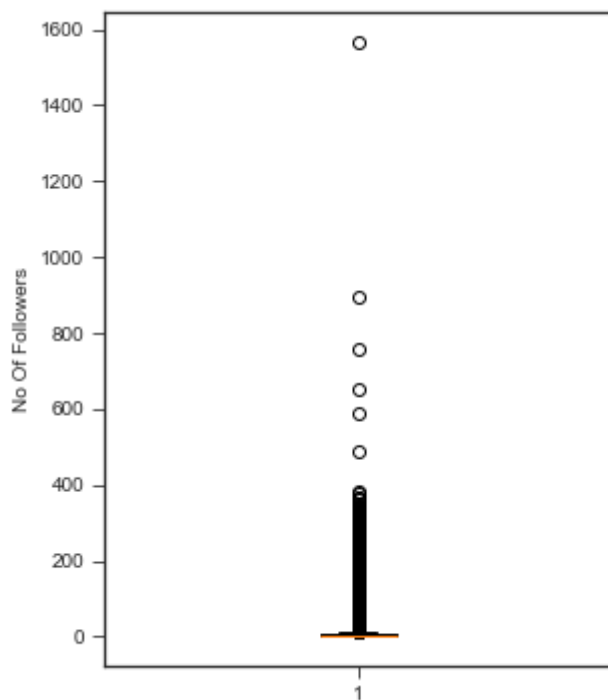
```
indegree_dist = list(dict(g.in_degree()).values())
indegree_dist.sort()
plt.figure(figsize=(10,6))
plt.plot(outdegree_dist[0:1500000])
plt.xlabel('Index No')
plt.ylabel('No Of people each person is following')
plt.show()
```



In [26]:

```
plt.figure(figsize=(10,6))  
plt.subplot(1,2,1)  
plt.boxplot(outdegree_dist)  
plt.ylabel('No Of Followers')  
plt.show()
```

```
plt.figure(figsize=(10,6))  
plt.subplot(1,2,2)  
plt.violinplot(outdegree_dist)  
plt.ylabel('No Of Followers')  
plt.show()
```



In [27]:

```
### 90-100 percentile
for i in range(0,11):
    print(90+i,'percentile value is',np.percentile(outdegree_dist,90+i))
```

```
90 percentile value is 12.0
91 percentile value is 13.0
92 percentile value is 14.0
93 percentile value is 15.0
94 percentile value is 17.0
95 percentile value is 19.0
96 percentile value is 21.0
97 percentile value is 24.0
98 percentile value is 29.0
99 percentile value is 40.0
100 percentile value is 1566.0
```

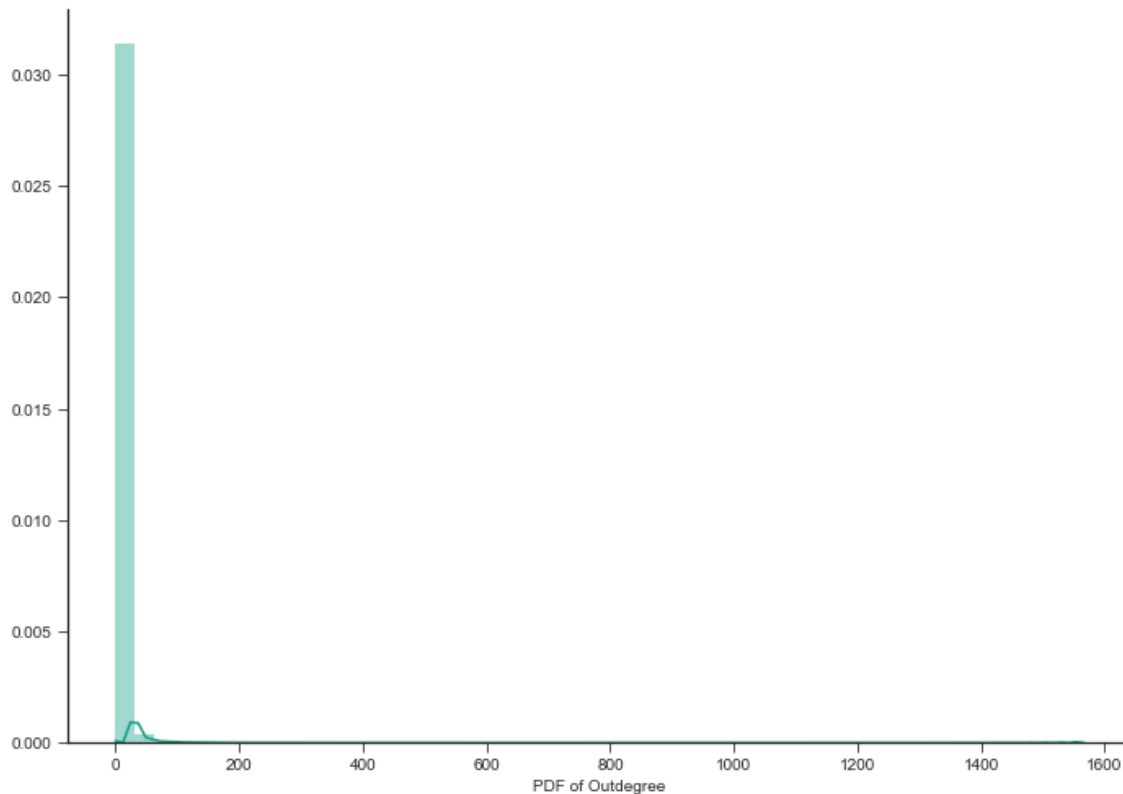
In [28]:

```
### 99-100 percentile
for i in range(10,110,10):
    print(99+(i/100),'percentile value is',np.percentile(outdegree_dist,99+(i/100)))
```

```
99.1 percentile value is 42.0
99.2 percentile value is 45.0
99.3 percentile value is 48.0
99.4 percentile value is 52.0
99.5 percentile value is 56.0
99.6 percentile value is 63.0
99.7 percentile value is 73.0
99.8 percentile value is 90.0
99.9 percentile value is 123.0
100.0 percentile value is 1566.0
```

In [29]:

```
sns.set_style('ticks')
fig, ax = plt.subplots()
fig.set_size_inches(11.7, 8.27)
sns.distplot(outdegree_dist, color='#16A085')
plt.xlabel('PDF of Outdegree')
sns.despine()
```



In [30]:

```
print('No of persons those are not following anyone are' ,sum(np.array(outdegree_dist)=
=0),'and % is',
      sum(np.array(outdegree_dist)==0)*100/len(outdegree_dist
) )
```

No of persons those are not following anyone are 274512 and % is 14.741115
442858524

In [35]:

```
print('No of persons having zero followers are' ,sum(np.array(indegree_dist)==0),'and %
is',
      sum(np.array(indegree_dist)==0)*100/len(indegree_dist)
)
```

No of persons having zero followers are 188043 and % is 10.097786512871734

In [36]:

```
count = 0
for i in g.nodes():
    if len(list(g.predecessors(i)))==0:
        if len(list(g.successors(i))) == 0:
            count +=1
print('No of persons those are not following ', count)
```

No of persons those are not following 0

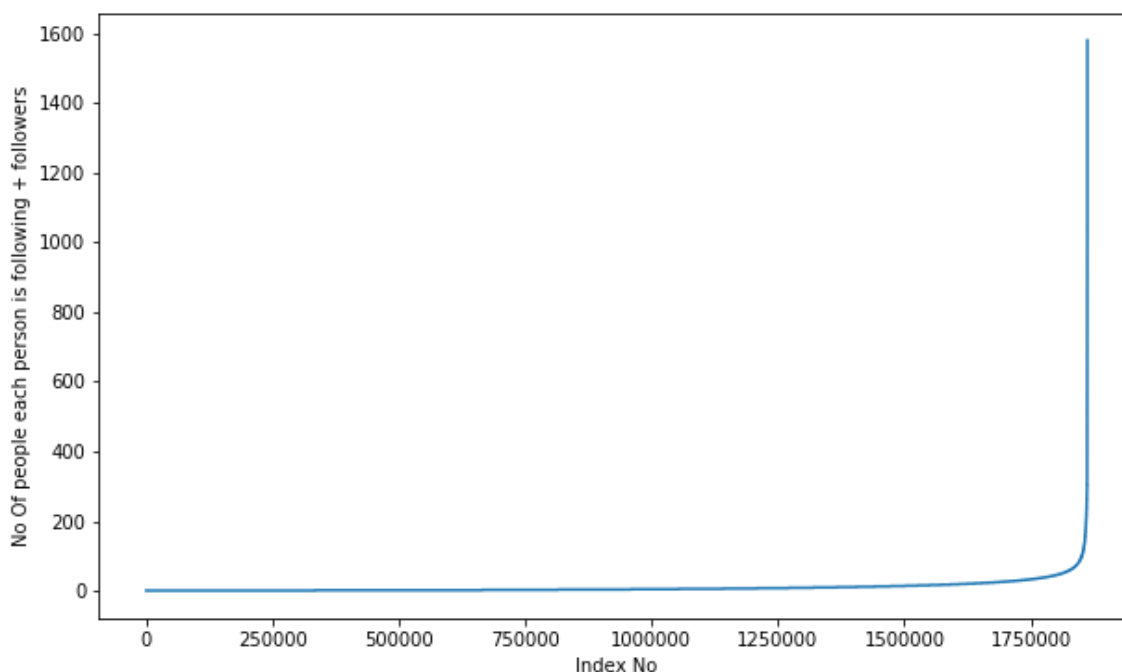
both followers + following

In [11]:

```
from collections import Counter
dict_in = dict(g.in_degree())
dict_out = dict(g.out_degree())
d = Counter(dict_in) + Counter(dict_out)
in_out_degree = np.array(list(d.values()))
```

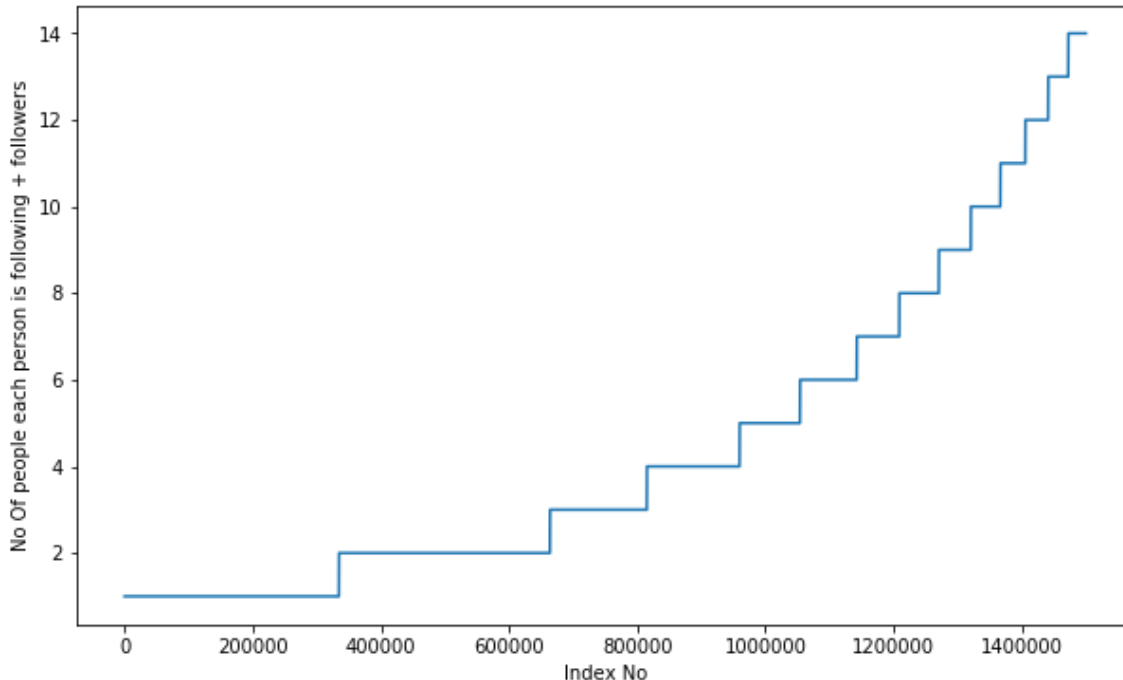
In [12]:

```
in_out_degree_sort = sorted(in_out_degree)
plt.figure(figsize=(10,6))
plt.plot(in_out_degree_sort)
plt.xlabel('Index No')
plt.ylabel('No Of people each person is following + followers')
plt.show()
```



In [13]:

```
in_out_degree_sort = sorted(in_out_degree)
plt.figure(figsize=(10,6))
plt.plot(in_out_degree_sort[0:1500000])
plt.xlabel('Index No')
plt.ylabel('No Of people each person is following + followers')
plt.show()
```



In []:

```
sns.distplot(in_out_degree_sort[0:150000], hist=False, rug=True);
```

In [40]:

```
### 90-100 percentile
for i in range(0,11):
    print(90+i,'percentile value is',np.percentile(in_out_degree_sort,90+i))
```

```
90 percentile value is 24.0
91 percentile value is 26.0
92 percentile value is 28.0
93 percentile value is 31.0
94 percentile value is 33.0
95 percentile value is 37.0
96 percentile value is 41.0
97 percentile value is 48.0
98 percentile value is 58.0
99 percentile value is 79.0
100 percentile value is 1579.0
```

In [41]:

```
### 99-100 percentile
for i in range(10,110,10):
    print(99+(i/100),'percentile value is',np.percentile(in_out_degree_sort,99+(i/100)))
```

```
99.1 percentile value is 83.0
99.2 percentile value is 87.0
99.3 percentile value is 93.0
99.4 percentile value is 99.0
99.5 percentile value is 108.0
99.6 percentile value is 120.0
99.7 percentile value is 138.0
99.8 percentile value is 168.0
99.9 percentile value is 221.0
100.0 percentile value is 1579.0
```

In [42]:

```
print('Min of no of followers + following is',in_out_degree.min())
print(np.sum(in_out_degree==in_out_degree.min()),' persons having minimum no of followers + following')
```

```
Min of no of followers + following is 1
334291 persons having minimum no of followers + following
```

In [43]:

```
print('Max of no of followers + following is',in_out_degree.max())
print(np.sum(in_out_degree==in_out_degree.max()),' persons having maximum no of followers + following')
```

```
Max of no of followers + following is 1579
1 persons having maximum no of followers + following
```

In [44]:

```
print('No of persons having followers + following less than 10 are',np.sum(in_out_degree<10))
```

```
No of persons having followers + following less than 10 are 1320326
```

In [45]:

```
print('No of weakly connected components',len(list(nx.weakly_connected_components(g))))
count=0
for i in list(nx.weakly_connected_components(g)):
    if len(i)==2:
        count+=1
print('weakly connected components wit 2 nodes',count)
```

```
No of weakly connected components 45558
weakly connected components wit 2 nodes 32195
```

Posing a problem as classification problem:

2.1 Generating some edges which are not present in graph for supervised learning

Generated Bad links from graph which are not in graph and whose shortest path is greater than 2.

In [4]:

```
%%time
###generating bad edges from given graph
import random
if not os.path.isfile('data/after_eda/missing_edges_final.p'):
    #getting all set of edges
    r = csv.reader(open('data/after_eda/train_woheader.csv','r'))
    edges = dict()
    for edge in r:
        edges[(edge[0], edge[1])] = 1

    missing_edges = set([])
    while (len(missing_edges)<9437519):
        a=random.randint(1, 1862220)
        b=random.randint(1, 1862220)
        tmp = edges.get((a,b),-1)
        if tmp == -1 and a!=b:
            try:
                if nx.shortest_path_length(g,source=a,target=b) > 2:
                    missing_edges.add((a,b))
            else:
                continue
        except:
            missing_edges.add((a,b))
        else:
            continue
    pickle.dump(missing_edges,open('data/after_eda/missing_edges_final.p','wb'))
else:
    missing_edges = pickle.load(open('data/after_eda/missing_edges_final.p','rb'))
```

Wall time: 5.16 s

In [5]:

```
len(missing_edges)
```

Out[5]:

9437519

2.2 Training and Test data split:

Removed edges from Graph and used as test data and after removing used that graph for creating features for Train and test data

In [6]:

```

from sklearn.model_selection import train_test_split
if (not os.path.isfile('data/after_eda/train_pos_after_eda.csv')) and (not os.path.isfile('data/after_eda/test_pos_after_eda.csv')):
    #reading total data df
    df_pos = pd.read_csv('data/train.csv')
    df_neg = pd.DataFrame(list(missing_edges), columns=['source_node', 'destination_node'])

    print("Number of nodes in the graph with edges", df_pos.shape[0])
    print("Number of nodes in the graph without edges", df_neg.shape[0])

    #Train test split
    #Spiltted data into 80-20
    #positive links and negative links seperatly because we need positive training data only for creating graph
    #and for feature generation
    X_train_pos, X_test_pos, y_train_pos, y_test_pos = train_test_split(df_pos, np.ones(len(df_pos)), test_size=0.2, random_state=9)
    X_train_neg, X_test_neg, y_train_neg, y_test_neg = train_test_split(df_neg, np.zeros(len(df_neg)), test_size=0.2, random_state=9)

    print('='*60)
    print("Number of nodes in the train data graph with edges", X_train_pos.shape[0], "=", y_train_pos.shape[0])
    print("Number of nodes in the train data graph without edges", X_train_neg.shape[0], "=", y_train_neg.shape[0])
    print('='*60)
    print("Number of nodes in the test data graph with edges", X_test_pos.shape[0], "=", y_test_pos.shape[0])
    print("Number of nodes in the test data graph without edges", X_test_neg.shape[0], "=", y_test_neg.shape[0])

    #removing header and saving
    X_train_pos.to_csv('data/after_eda/train_pos_after_eda.csv', header=False, index=False)
    X_test_pos.to_csv('data/after_eda/test_pos_after_eda.csv', header=False, index=False)
    X_train_neg.to_csv('data/after_eda/train_neg_after_eda.csv', header=False, index=False)
    X_test_neg.to_csv('data/after_eda/test_neg_after_eda.csv', header=False, index=False)
else:
    #Graph from Traing data only
    del missing_edges

```

In [7]:

```
if (os.path.isfile('data/after_eda/train_pos_after_eda.csv')) and (os.path.isfile('data/after_eda/test_pos_after_eda.csv')):
    train_graph=nx.read_edgelist('data/after_eda/train_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)
    test_graph=nx.read_edgelist('data/after_eda/test_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)
    print(nx.info(train_graph))
    print(nx.info(test_graph))

    # finding the unique nodes in the both train and test graphs
    train_nodes_pos = set(train_graph.nodes())
    test_nodes_pos = set(test_graph.nodes())

    trY_teY = len(train_nodes_pos.intersection(test_nodes_pos))
    trY_teN = len(train_nodes_pos - test_nodes_pos)
    teY_trN = len(test_nodes_pos - train_nodes_pos)

    print('no of people common in train and test -- ',trY_teY)
    print('no of people present in train but not present in test -- ',trY_teN)

    print('no of people present in test but not present in train -- ',teY_trN)
    print(' % of people not there in Train but exist in Test in total Test data are {}'.format(teY_trN/len(test_nodes_pos)*100))
```

Name:

Type: DiGraph

Number of nodes: 1780722

Number of edges: 7550015

Average in degree: 4.2399

Average out degree: 4.2399

Name:

Type: DiGraph

Number of nodes: 1144623

Number of edges: 1887504

Average in degree: 1.6490

Average out degree: 1.6490

no of people common in train and test -- 1063125

no of people present in train but not present in test -- 717597

no of people present in test but not present in train -- 81498

% of people not there in Train but exist in Test in total Test data are 7.1200735962845405 %