Proposed_Model

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#

Network Science

##

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Proposed Approach:

```
Following steps has been used to implement the proposed model.

Steps:
1) Data Preparation
   In this step, we first split the data into train and test interval. Futher, we compute nega

2) Feature Engineering
   We computer the features like jaccard, cosine, common_neighbors, resource_allocation etc. fo

3) Model Training
   We considered the CatBoost algorithm to perform this task(i.e. link/contacts prediction) as

4) Model Performance
   Model has been evaluated using ROC_AUC score.
```

Import required packages

[3]:
```
import numpy as np
import pandas as pd
import networkx as nx
from tqdm.notebook import tqdm
import random
from sklearn.model_selection import train_test_split
import math
from catboost import CatBoostClassifier
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
import seaborn as sns
import community
plt.xkcd()
```

[3]: <matplotlib.rc_context at 0x7f46b06e1850>

0.1 1. Data Preparation

[4]:
```
def split(data):
    """split the data into train and test interval"""
    # delete negative time data
    data = data[~(data['time'] < 0)]
    # consider the nodes with degree >= 5
    hist = pd.concat([data.userID_1, data.userID_2]).value_counts()
    sign_nodes = hist[ hist > 4 ].keys()
    data = data[(data['userID_1'].isin(sign_nodes) & data['userID_2'].
 ↪isin(sign_nodes))]
    #
    train_int = data[(data['time'] <= np.median(data['time'])) ].
 ↪drop_duplicates()
    test_int = data[(data['time'] > np.median(data['time'])) ].drop_duplicates()
    # Drop time attribute
    train_int = train_int.drop(['time'], axis=1).reset_index(drop=True)
    test_int = test_int.drop(['time'], axis=1).reset_index(drop=True)
    return train_int, test_int
```

[5]:
```
flickr = pd.read_csv('contacts.txt',
                     header=None,
                     sep=' ',
                     names = ['userID_1', 'userID_2', 'time'])
```

[6]:
```
train_int, test_int = split(flickr)
```

[7]:
```
G_train = nx.from_pandas_edgelist(train_int,
                                  'userID_1', 'userID_2',
                                  create_using = nx.Graph())
```

[8]:
```
cc = nx.number_connected_components(G_train)
print(nx.info(G_train),'\n',
      'Number of Connected Componets: ', cc, sep='')
```

```
Name:
Type: Graph
Number of nodes: 106664
```

```
Number of edges: 1198072
Average degree:  22.4644
Number of Connected Componets: 2466
```

Generate Negative Examples Negative examples are such pairs of users that have not occured together during training and testing intervals

[9]:
```
lookup = dict()
for index, user in train_int.append(test_int).iterrows():
    lookup[(user[0], user[1])] = 1
    lookup[(user[1], user[1])] = 1
```

[10]:
```
neg_example = set([])
nodes = list(G_train.nodes)
pbar = tqdm(total = 1198072, desc='Finding Negative Examples')

while (len(neg_example)<1198072):
    user_1 = random.choice(nodes)
    user_2 = random.choice(nodes)
    found = lookup.get((user_1,user_2),0)
    try:
        sp = nx.shortest_path_length(G_train,source=user_1,target=user_2)
    except:
        sp = 1198072
    if found == 0 and user_1!=user_2 and sp>2:
        if (user_1,user_2) not in neg_example and (user_2,user_1) not in␣
 ↪neg_example:
            neg_example.add((user_1,user_2))
    pbar.update(1)
```

[11]:
```
df_neg = pd.DataFrame(list(neg_example),
                      columns=['userID_1', 'userID_2'])
```

[12]:
```
df_neg['is_Connected'] = 0
```

[13]:
```
train_neg, test_neg  = train_test_split(df_neg, test_size=0.2)
```

Positive Examples Positive examples are such pairs of users that haven't been formed during training interval but have been formed by testing interval.

[14]:
```
# Authors in train_set and test set
```

```
unique_train = pd.concat([train_int['userID_1'], train_int['userID_2']]).
 ↪unique()
unique_test = pd.concat([test_int['userID_1'], test_int['userID_2']]).unique()
# Common authors in train_set and test_set
inter = np.intersect1d(unique_train, unique_test)
#
test_int = test_int[(test_int['userID_1'].isin(inter) & test_int['userID_2'].
 ↪isin(inter))]
```

[15]:
```
train_int['is_Connected'] = 1
test_int['is_Connected'] = 1
```

[16]:
```
train_set = train_int.sample(n=train_neg.shape[0]).append(
    train_neg,ignore_index=True)
```

[17]:
```
test_set = test_int.sample(n=test_neg.shape[0]).append(
    test_neg,ignore_index=True)
```

[24]:
```
print('='*20,'TRAIN_SET','='*20)
print("Number of positive examples",
      train_set[train_set.is_Connected==1].shape[0])
print("Number of negative examples",
      train_set[train_set.is_Connected==0].shape[0])
print('='*20,'TEST_SET','='*21)
print("Number of positive examples",
      test_set[test_set.is_Connected==1].shape[0])
print("Number of negative examples",
      test_set[test_set.is_Connected==0].shape[0])
```

```
==================== TRAIN_SET ====================
Number of positive examples 958457
Number of negative examples 958457
==================== TEST_SET =====================
Number of positive examples 239615
Number of negative examples 239615
```

0.2 2. Feature Engineering

We will follow the below references to generate the new features for our link prediction model.

References:

Paper on Project recommendation system

Networkx Documentation

[25]:
```
def generate_features(G, df):
    jaccard = []
    cosine_dst = []
    num_con_s = []
    num_con_d = []
    common_neighbors = []
    adar = []
    page_rank_s = []
    page_rank_d = []
    hub_score_s = []
    hub_score_d = []
    auth_score_s = []
    auth_score_d = []
    preferential_att = []
    resource_alloc = []
    within_inter_c = []
    resource_alloc_c = []
    common_neighbors_c = []

    for r in tqdm(df.iterrows(), total=df.shape[0]):
        nb_v = set(G.neighbors(r[1]['userID_1']))
        nb_w = set(G.neighbors(r[1]['userID_2']))
        union = nb_v | nb_w
        inter = nb_v & nb_w
        ## Jaccard's coefficient
        jaccard.append(len(inter) / len(union))
        ## Cosine Distance
        cosine_dst.append(len(inter)/ math.sqrt(len(union)))
        ## Number of connection user_1 has
        num_con_s.append(len(nb_v))
        ## Number of connection user_2 has
        num_con_d.append(len(nb_w))
        ## Number of common neighbors
        common_neighbors.append(len(inter))
        ## Adamic/Adar
        a = 0
        for node in inter:
            a += 1.0 / np.log(G.degree(node))
        adar.append(a)
        ## Page Rank for user_1
        page_rank_s.append(pr.get(r[1]['userID_1'], mean_pr))
        ## Page Rank for user_2
        page_rank_d.append(pr.get(r[1]['userID_2'], mean_pr))
        ## Hub score for user_1
```

```
        hub_score_s.append(hits[0].get(r[1]['userID_1'],0))
        ## Hub score for user_2
        hub_score_d.append(hits[0].get(r[1]['userID_2'],0))
        ## Authorities score for user_1
        auth_score_s.append(hits[1].get(r[1]['userID_1'],0))
        ## Authorities score for user_2
        auth_score_d.append(hits[1].get(r[1]['userID_2'],0))
        ## Preferential attachment
        preferential_att.append(len(nb_v) * len(nb_w))
        ## Resource allocation
        ra = 0
        for node in inter:
            ra += 1.0 / G.degree(node)
        resource_alloc.append(ra)
        ## ratio of within- and inter-cluster common neighbors
        try:
            within_inter_c.append(
                list(nx.within_inter_cluster(G,
                    [(r[1]['userID_1'], r[1]['userID_2'])]))[0][-1])
        except:
            within_inter_c.append(0)
        ## Resource allocation using community information
        resource_alloc_c.append(
            list(nx.ra_index_soundarajan_hopcroft(G,
                [(r[1]['userID_1'], r[1]['userID_2'])]))[0][-1])
        ## number of common neighbors using community information
        common_neighbors_c.append(
            list(nx.cn_soundarajan_hopcroft(G,
                [(r[1]['userID_1'], r[1]['userID_2'])]))[0][-1])

    df['jaccard'] = pd.Series(jaccard, index = df.index)
    df['cosine'] = pd.Series(cosine_dst, index = df.index)
    df['num_con_s'] =  pd.Series(num_con_s, index = df.index)
    df['num_con_d'] =  pd.Series(num_con_d, index = df.index)
    df['common_neighbors'] = pd.Series(common_neighbors, index = df.index)
    df['adar'] = pd.Series(adar, index = df.index)
    df['page_rank_s'] = pd.Series(page_rank_s, index = df.index)
    df['page_rank_d'] = pd.Series(page_rank_d, index = df.index)
    df['hub_score_s'] = pd.Series(hub_score_s, index = df.index)
    df['hub_score_d'] = pd.Series(hub_score_d, index = df.index)
    df['auth_score_s'] = pd.Series(auth_score_s, index = df.index)
    df['auth_score_d'] = pd.Series(auth_score_d, index = df.index)
    df['preferential_att'] = pd.Series(preferential_att, index = df.index)
    df['resource_alloc'] = pd.Series(resource_alloc, index = df.index)
    df['within_inter_c'] = pd.Series(within_inter_c, index = df.index)
    df['resource_alloc_c'] = pd.Series(resource_alloc_c, index = df.index)
    df['common_neighbors_c'] = pd.Series(common_neighbors_c, index = df.index)
```

```
    df['Combined_measure'] = 0.7*df['preferential_att'] + 0.3*df['adar']
    df['Combined_measure'] = 0.7*df['preferential_att'] + 0.3*df['adar']
```

Compute the pagerank, hub score and authority score for each node in train interval graph. These algorithms are based on directed graph but networkx implementation auto convert the undirected to directed graph by converting each edge into two directed edges.

[26]:
```
pr = nx.pagerank(G_train, alpha=0.85)
mean_pr=float(sum(pr.values())) / len(pr)
hits = nx.hits(G_train, max_iter=100,
               tol=1e-08, nstart=None, normalized=True)
```

Networkx link prediction algorithms like cn_soundarajan_hopcroft, within_inter_cluster are based on community information. That's why, we added 'community' attribute in the train interval graph.

[27]:
```
part = community.best_partition(G_train)
for node in G_train.nodes:
    G_train.nodes[node]['community'] = int(part.get(node))
```

Generate new features

[28]:
```
generate_features(G_train, train_set)
generate_features(G_train, test_set)
```

[29]:
```
test_set.to_csv('test_set.csv', index=False)
train_set.to_csv('train_set.csv', index=False)
```

[30]:
```
test_set = pd.read_csv('test_set.csv')
train_set = pd.read_csv('train_set.csv')
```

[31]:
```
# Train Examples
X_train = train_set.drop(['userID_1','userID_2','is_Connected'], axis=1)
y_train = train_set['is_Connected']
# Test Examples
X_test = test_set.drop(['userID_1','userID_2','is_Connected'], axis=1)
y_test = test_set['is_Connected']
```

0.3 3. Train the Model

Link Prediction Model (CatBoost Classifier)

```
[32]: model = CatBoostClassifier(iterations=1000,
                               loss_function='Logloss',
                               eval_metric='Logloss',
                               random_state=2020,
                               verbose=100,
                               task_type="GPU",
                               od_type = "Iter",
                               od_wait = 100,
                               learning_rate=0.04,
                               depth=4,
                               l2_leaf_reg=5)
```

Train the CatBoost model

```
[33]: model.fit(X_train, y_train)
```

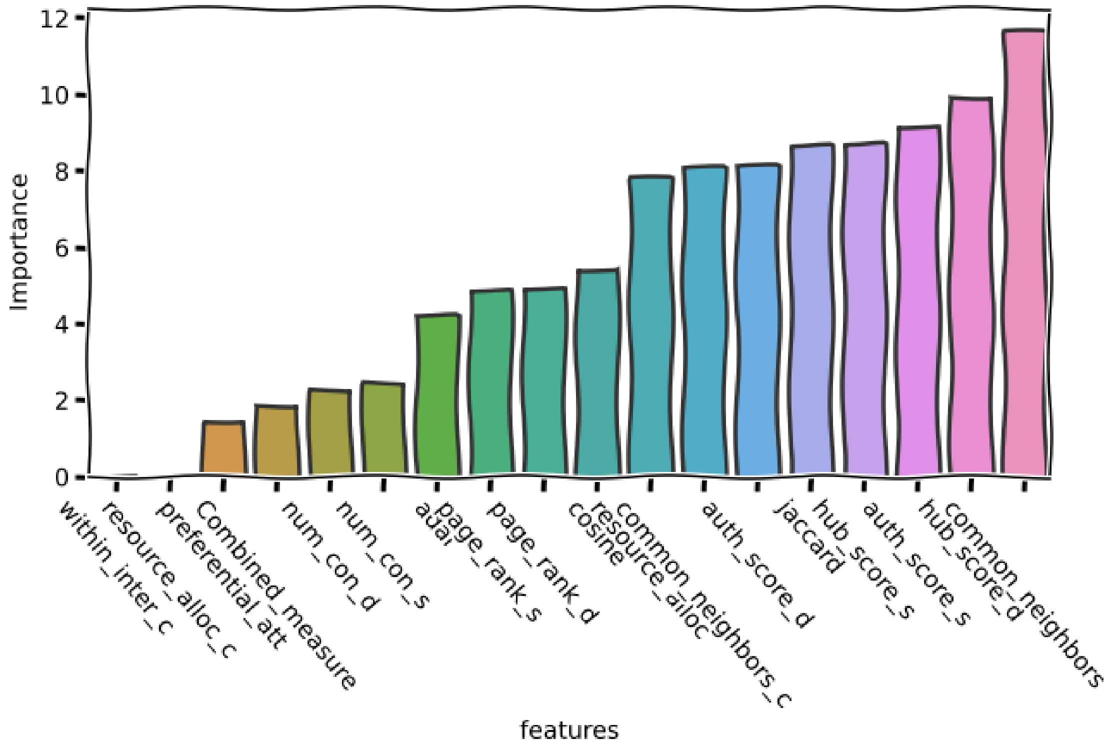
```
0:      learn: 0.5769440        total: 24.1ms   remaining: 24.1s
100:    learn: 0.0981076        total: 1.37s    remaining: 12.2s
200:    learn: 0.0903381        total: 2.7s     remaining: 10.7s
300:    learn: 0.0868843        total: 4.06s    remaining: 9.42s
400:    learn: 0.0849717        total: 5.54s    remaining: 8.27s
500:    learn: 0.0832927        total: 6.85s    remaining: 6.82s
600:    learn: 0.0819528        total: 8.18s    remaining: 5.43s
700:    learn: 0.0810649        total: 9.54s    remaining: 4.07s
800:    learn: 0.0803361        total: 10.9s    remaining: 2.7s
900:    learn: 0.0794480        total: 12.2s    remaining: 1.34s
999:    learn: 0.0788062        total: 13.6s    remaining: 0us
```

```
[33]: <catboost.core.CatBoostClassifier at 0x7f4682963e90>
```

Features Importance in the model

```
[34]: features_imp = sorted(list(zip(model.feature_names_,model.
       ↪feature_importances_)),
            key=lambda x: x[1])
```

```
[35]: fig = plt.figure(figsize=(10,5))
      ax = sns.barplot(x='features', y='Importance',
                       data=pd.DataFrame(features_imp,␣
       ↪columns=['features','Importance']),
                       linewidth=2.5, errcolor=".2", edgecolor=".2")
      plt.xticks(rotation=-50)
      plt.show()
```



Drop the features which have less importance

[37]:
```
#drop irrelevant features based on features importance
drop_features =['within_inter_c',
                'resource_alloc_c',
                'preferential_att']

X_train_new = X_train.drop(drop_features, axis=1)
X_test_new = X_test.drop(drop_features, axis=1)
```

[38]:
```
print('Number of Features: ', X_train_new.shape[1])
```

```
Number of Features:  15
```

Golden Features: Golden Features for the CatBoost Classifier which highly contribute to predict the target variable or those variables which have high importance.

[39]:
```
# index of golden_features for CatBoost Classifier
(list(X_train_new.columns).index('common_neighbors'),
list(X_train_new.columns).index('jaccard'))
```

[39]:
```
(4, 0)
```

[40]:
```
# golden_features for catboost classifier
golden_features = ['4:border_count=1024', '0:border_count=1024']
```

Pass the golden features into the CatBoostClassifier

[41]:
```
model = CatBoostClassifier(iterations=1000,
                           loss_function='Logloss',
                           eval_metric='Logloss',
                           random_state=2020,
                           verbose=100,
                           task_type="GPU",
                           od_type = "Iter",
                           od_wait = 100,
                           learning_rate=0.01,
                           depth=5,
                           l2_leaf_reg=10,
                           per_float_feature_quantization=golden_features)
```

Train the model after dropping the irrelevent features

[42]:
```
model.fit(X_train_new, y_train)
```

```
0:      learn: 0.6627448        total: 17.7ms   remaining: 17.6s
100:    learn: 0.1278826        total: 1.7s     remaining: 15.1s
200:    learn: 0.1040905        total: 3.34s    remaining: 13.3s
300:    learn: 0.0967587        total: 5.5s     remaining: 12.8s
400:    learn: 0.0935196        total: 7.17s    remaining: 10.7s
500:    learn: 0.0907617        total: 9.07s    remaining: 9.04s
600:    learn: 0.0888684        total: 10.8s    remaining: 7.14s
700:    learn: 0.0872832        total: 12.4s    remaining: 5.3s
800:    learn: 0.0862552        total: 14.1s    remaining: 3.49s
900:    learn: 0.0854277        total: 16s      remaining: 1.76s
999:    learn: 0.0846805        total: 17.6s    remaining: 0us
```

[42]:
```
<catboost.core.CatBoostClassifier at 0x7f467c107450>
```

0.4 4. Evaluate the Model

Compute the performance of the link prediction model i.e CatBoost Classifier.

Accuracy of Link Prediction model

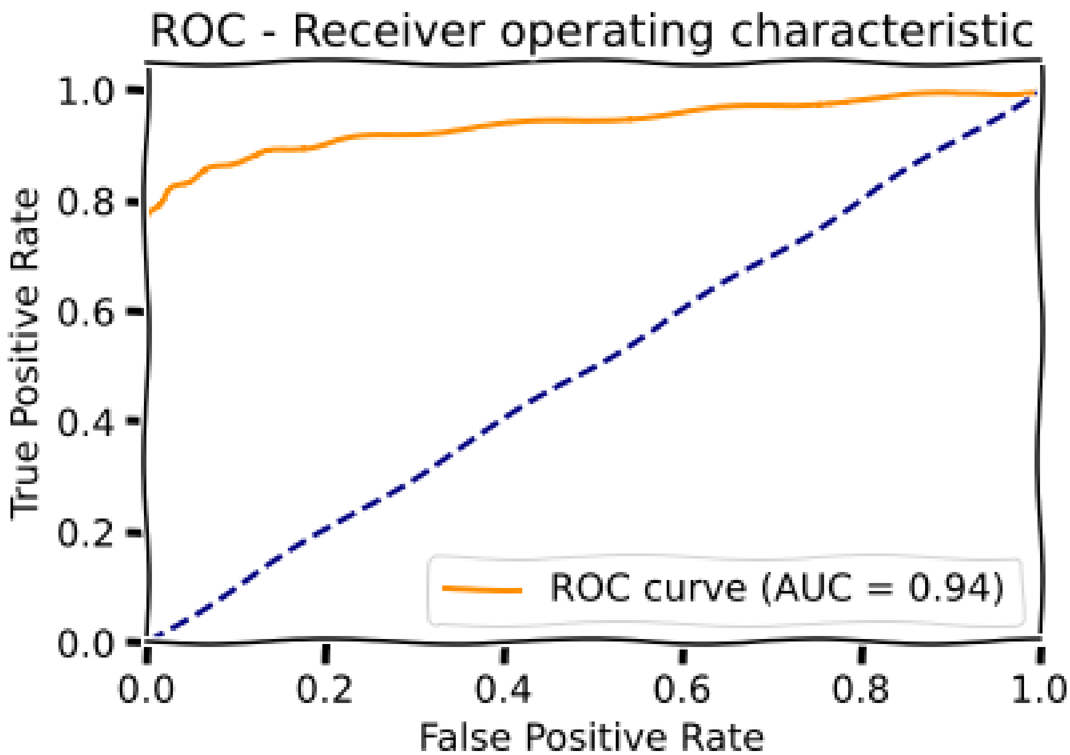
[43]:
```
model.score(X_test_n, y_test).round(2)
```

[43]: 0.89

ROC_AUC

[44]:
```
y_prob = model.predict_proba(X_test_n)
fpr, tpr, _ = roc_curve(y_test, y_prob[:,1])
roc_auc = auc(fpr, tpr)
```

[45]:
```
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC - Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



Conclusion:- Performance of proposed model for link prediction is quite high in comparison to the baseline model.

[ ]:

[ ]: