Facebook Friend Recommender

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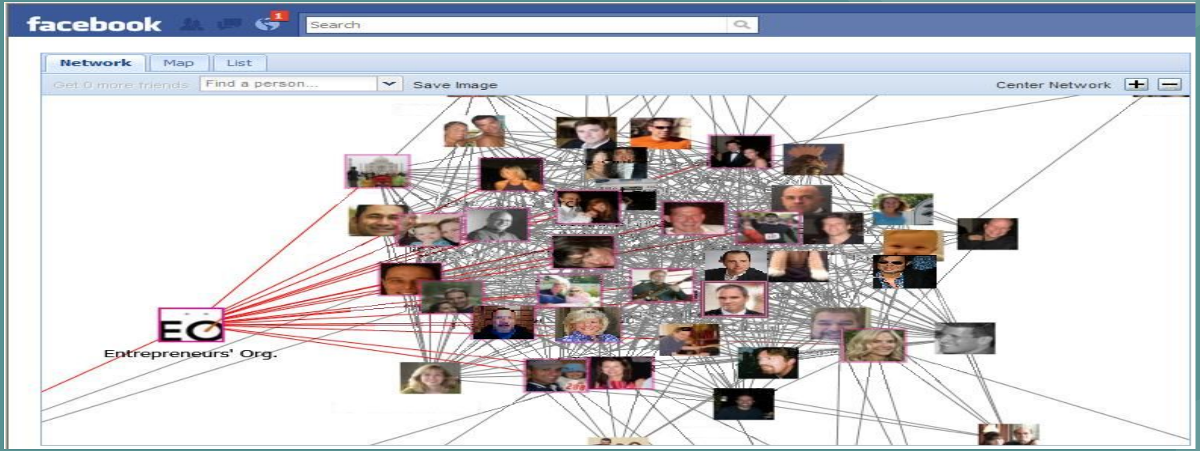
Problem

- Networking & connecting with others is one of the most important features among many social media platforms
- Facebook and other social media platforms need people to be able to connect users based on their common interests, degrees of separation, etc.



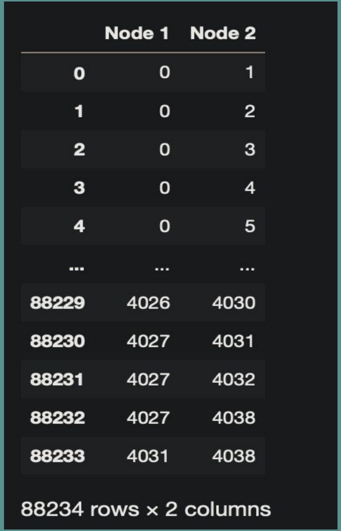
http://www.fmsasg.com/socialnetworkanalysis/facebook/

Data

- https://snap.stanford.edu/data/ego-Facebook.html
- [Number] corresponds to file names: '0','107','348','414','686','698','1684','1912','3437','3980'

1. facebook_combined.txt -> Gives all of the connected node pairs
2. [Number].featnames -> Gives the feature type, semicolon, followed by specific feature value characterized by a number
3. [Number].feat -> Gives the row of '1's or '0's for each node indicating whether the node has a feature or not in the corresponding [Number].featnames file rows

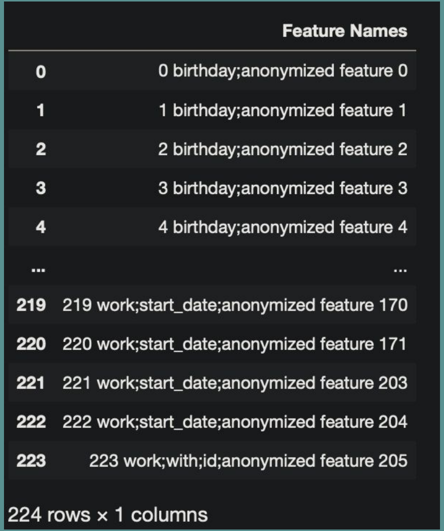
1.



	Node 1	Node 2
0	0	1
1	0	2
2	0	3
3	0	4
4	0	5
...	...	...
88229	4026	4030
88230	4027	4031
88231	4027	4032
88232	4027	4038
88233	4031	4038

88234 rows × 2 columns

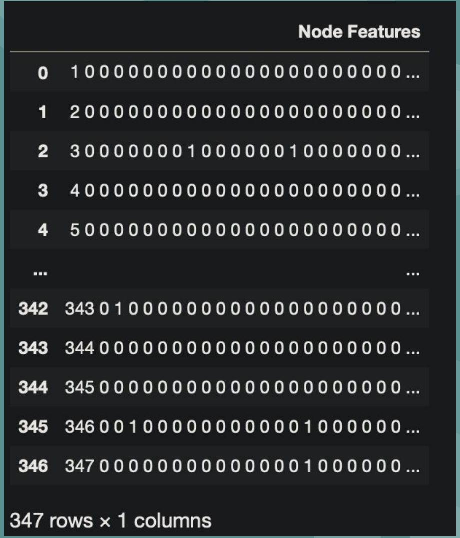
2.



	Feature Names
0	0 birthday;anonymized feature 0
1	1 birthday;anonymized feature 1
2	2 birthday;anonymized feature 2
3	3 birthday;anonymized feature 3
4	4 birthday;anonymized feature 4
...	...
219	219 work;start_date;anonymized feature 170
220	220 work;start_date;anonymized feature 171
221	221 work;start_date;anonymized feature 203
222	222 work;start_date;anonymized feature 204
223	223 work;with;id;anonymized feature 205

224 rows × 1 columns

3.

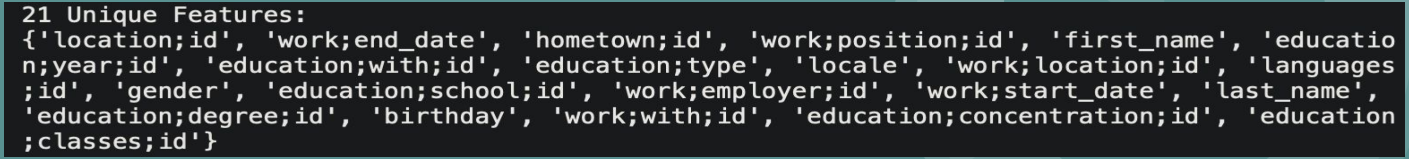


	Node Features
0	1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
1	2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
2	3 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 ...
3	4 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
4	5 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
...	...
342	343 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
343	344 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
344	345 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
345	346 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 ...
346	347 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 ...

347 rows × 1 columns

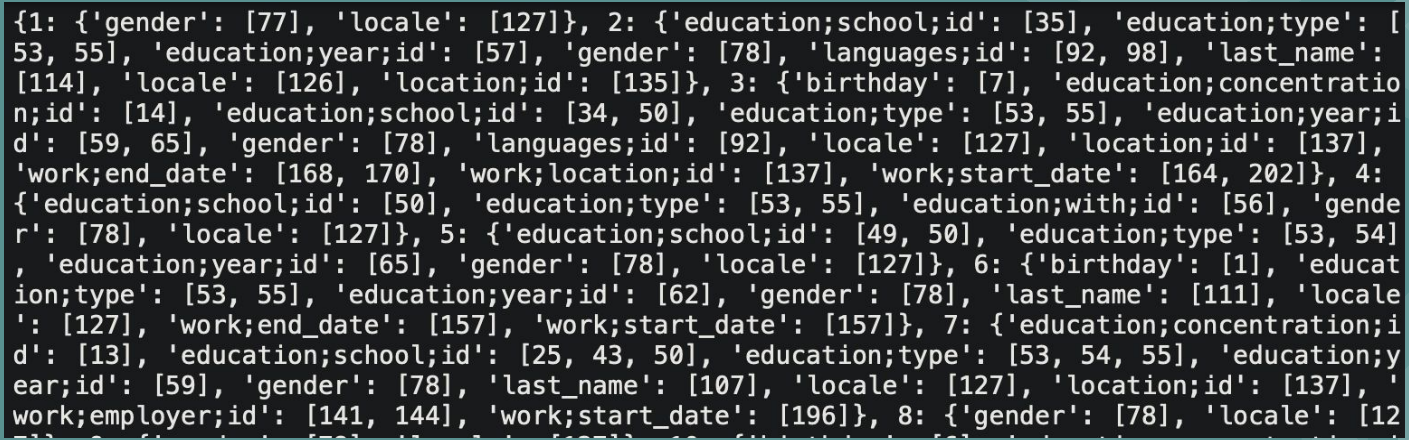
Data Wrangling

- I discovered there were 21 unique feature types by parsing through the [no.].featnames files



```
21 Unique Features:
{'location;id', 'work;end_date', 'hometown;id', 'work;position;id', 'first_name', 'educatio
n;year;id', 'education;with;id', 'education;type', 'locale', 'work;location;id', 'languages
;id', 'gender', 'education;school;id', 'work;employer;id', 'work;start_date', 'last_name',
'education;degree;id', 'birthday', 'work;with;id', 'education;concentration;id', 'education
;classes;id'}
```

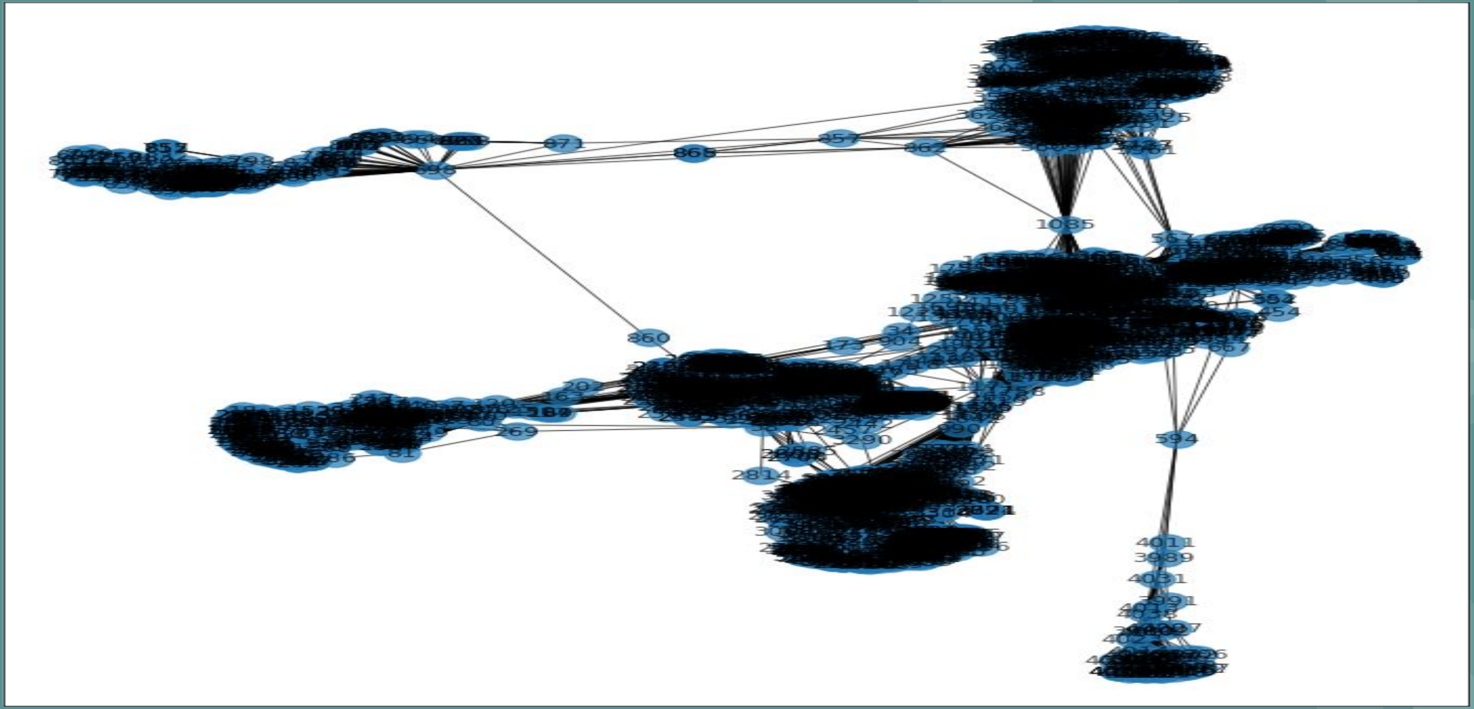
- I iterated through different node files and their attributes & values and linked them together in a dictionary. I then used the dictionary to create a graph using the networkx library.



```
{1: {'gender': [77], 'locale': [127]}, 2: {'education;school;id': [35], 'education;type': [
53, 55], 'education;year;id': [57], 'gender': [78], 'languages;id': [92, 98], 'last_name':
[114], 'locale': [126], 'location;id': [135]}, 3: {'birthday': [7], 'education;concentratio
n;id': [14], 'education;school;id': [34, 50], 'education;type': [53, 55], 'education;year;i
d': [59, 65], 'gender': [78], 'languages;id': [92], 'locale': [127], 'location;id': [137],
'work;end_date': [168, 170], 'work;location;id': [137], 'work;start_date': [164, 202]}, 4:
{'education;school;id': [50], 'education;type': [53, 55], 'education;with;id': [56], 'gende
r': [78], 'locale': [127]}, 5: {'education;school;id': [49, 50], 'education;type': [53, 54]
, 'education;year;id': [65], 'gender': [78], 'locale': [127]}, 6: {'birthday': [1], 'educat
ion;type': [53, 55], 'education;year;id': [62], 'gender': [78], 'last_name': [111], 'locale
': [127], 'work;end_date': [157], 'work;start_date': [157]}, 7: {'education;concentration;i
d': [13], 'education;school;id': [25, 43, 50], 'education;type': [53, 54, 55], 'education;y
ear;id': [59], 'gender': [78], 'last_name': [107], 'locale': [127], 'location;id': [137], '
work;employer;id': [141, 144], 'work;start_date': [196]}, 8: {'gender': [78], 'locale': [12
```

Exploratory Data Analysis

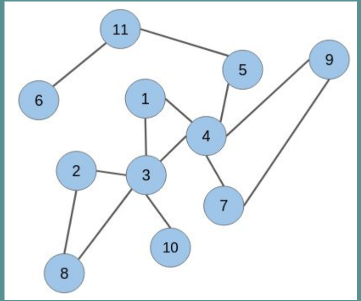
- Image of a spring layout graph of the network of people



Node2Vec Pre-Processing

- The goal was to generate features for the model to be able to use with a supervised learning model to predict if a pair of nodes are connected or not
- The Node2Vec algorithm generates features for a node but first needs to learn how to generate those features, and it does so by understanding the graph structure and the nodes. So, a Node2Vec model will be created with an input of the graph & other hyperparameters to base its feature generation on
- Instead of creating a Node2Vec Model on the entire graph (1), I created the Node2Vec model based on a new graph (2) with some deleted edges / node pairs that wouldn't change the fundamental structure of the graph since it wouldn't eliminate any nodes nor split the graph

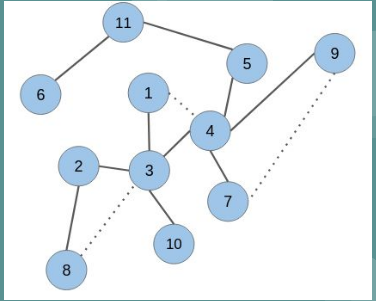
1



After Deleting Removable Edges

Dotted Edges are removable

2

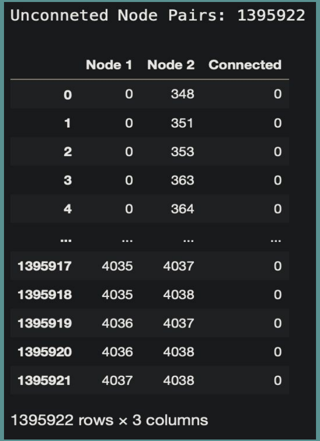


- The point of this was to have Node2Vec learn the fundamental graph structure to know how to generate features and test its accuracy by generating features on the removed & unconnected edges using a supervised learning ML model
- This would give a good indication of how well the Node2Vec Model node features are for predicting connection status when new edges form
- Although, in reality a link prediction model would constantly be retrained on the most current graph, so creating Node2Vec on the entire graph (1) would be more realistic, followed by generating features on a balanced set of of unconnected & connected node pairs, test train splitting the data, and modeling for prediction of unconnected or connected node pair status

Node2Vec Pre-Processing

1. Found the negative samples (unconnected edges / node pairs) with nodes at max path length of 2 from one another to get samples that were possibly more likely to form a connection due to having more common neighbors
2. Found the positive samples (removable edges / node pairs) - edges that could be removed while preserving the base graph structure (not eliminating nodes & not splitting the graph)
3. Found the remaining edges by removing the positive edges from the list of connected edges so we can train the Node2Vec Model on those remaining edges (base structure of the graph)
4. Combined negative & positive samples into final dataframe after reducing the # of negative samples to balance the final dataset to about equal positive & negative samples to be used for more accurate modeling
5. Used the trained Node2Vec model to generate features for each node in a pair & sum them for a final set of features for that pair. Then, I test train split the data for modeling

1.

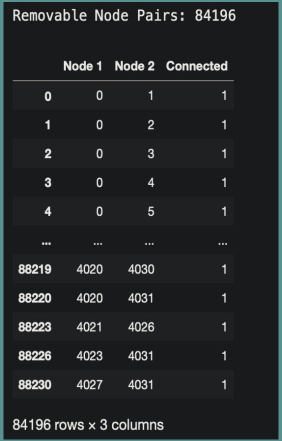


```
Unconneted Node Pairs: 1395922
```

	Node 1	Node 2	Connected
0	0	348	0
1	0	351	0
2	0	353	0
3	0	363	0
4	0	364	0
...	...	...	...
1395917	4035	4037	0
1395918	4035	4038	0
1395919	4036	4037	0
1395920	4036	4038	0
1395921	4037	4038	0

1395922 rows × 3 columns

2.

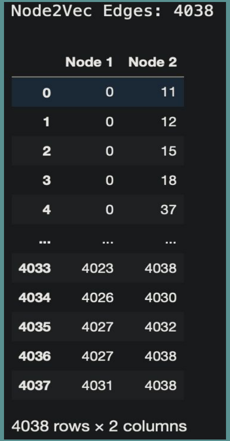


```
Removable Node Pairs: 84196
```

	Node 1	Node 2	Connected
0	0	1	1
1	0	2	1
2	0	3	1
3	0	4	1
4	0	5	1
...	...	...	...
88219	4020	4030	1
88220	4020	4031	1
88223	4021	4026	1
88226	4023	4031	1
88230	4027	4031	1

84196 rows × 3 columns

3.

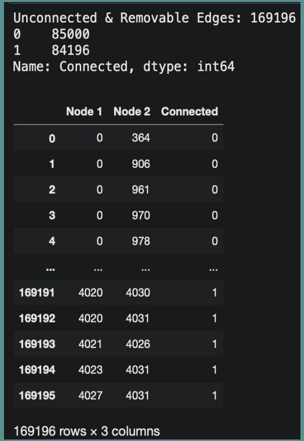


```
Node2Vec Edges: 4038
```

	Node 1	Node 2
0	0	11
1	0	12
2	0	15
3	0	18
4	0	37
...	...	...
4033	4023	4038
4034	4026	4030
4035	4027	4032
4036	4027	4038
4037	4031	4038

4038 rows × 2 columns

4.

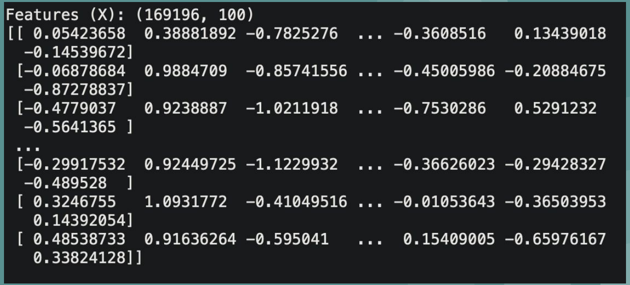


```
Unconnected & Removable Edges: 169196
0    85000
1    84196
Name: Connected, dtype: int64
```

	Node 1	Node 2	Connected
0	0	364	0
1	0	906	0
2	0	961	0
3	0	970	0
4	0	978	0
...	...	...	...
169191	4020	4030	1
169192	4020	4031	1
169193	4021	4026	1
169194	4023	4031	1
169195	4027	4031	1

169196 rows × 3 columns

5.



```
Features (X): (169196, 100)
[[ 0.05423658  0.38881892 -0.7825276  ... -0.3608516   0.13439018
  -0.14539672]
 [-0.06878684  0.9884709  -0.85741556 ... -0.45005986 -0.20884675
  -0.87278837]
 [-0.4779037   0.9238887  -1.0211918  ... -0.7530286   0.5291232
  -0.5641365 ]
 ...
 [-0.29917532  0.92449725 -1.1229932  ... -0.36626023 -0.29428327
  -0.489528  ]
 [ 0.3246755   1.0931772  -0.41049516 ... -0.01053643 -0.36503953
   0.14392054]
 [ 0.48538733  0.91636264 -0.595041   ...  0.15409005 -0.65976167
   0.33824128]]
```

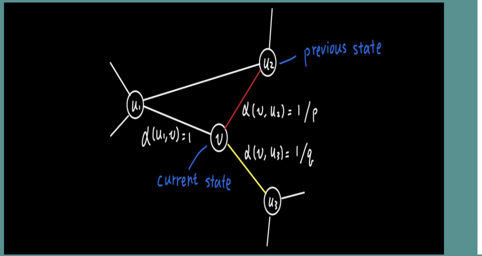
Node2Vec Process

- Node2vec algorithm can be summarized as a two-part process (2):

1. First, it uses second-order biased random walks to generate sequences of nodes or “sentences” for each node according to the hyper-parameters: walk length, # of walks, and p & q values which tune for more exploratory or local walks thus producing different similarities between nodes. (1)
2. Second, once the sequences of nodes or ‘sentences’ are generated, they are used as an input to a word2vec skip-gram with negative sampling model. The main idea is that it maximizes the probability of predicting the correct context node given the center node. The skip-gram model first generates pairs of input and context nodes given the context window size and then feeds them into a shallow two-layer neural network. Once the neural network is trained, you can retrieve the hidden layer weights as your node embeddings. The number of neurons in the hidden layer will determine the size of the embedding, or you can alter the size based on hyperparameter tuning.

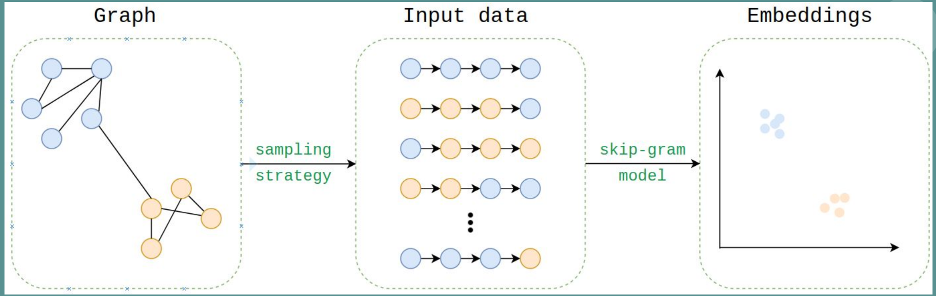
- These embeddings are a list of numbers that encapsulate the homophily or structural equivalence topological similarity in the graph, so that people closely related have similar representations & vice versa. Homophily similarity is finding nodes belonging to the same network community and structural equivalence is finding nodes that have the same structural roles. High p, low q hyperparameter values -> more depth first search / structural equivalence similarity & vice versa. (3). The embeddings are then used as features for a ML model.

1



https://towardsdatascience.com/node2vec-explained-graphically-749e49b7eb6b

2



https://towardsdatascience.com/node2vec-embeddings-for-graph-data-32a866340fef

3

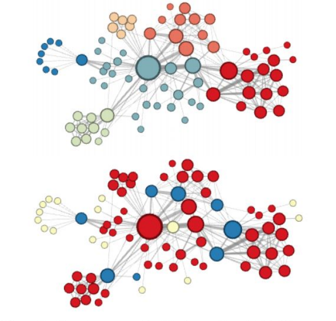
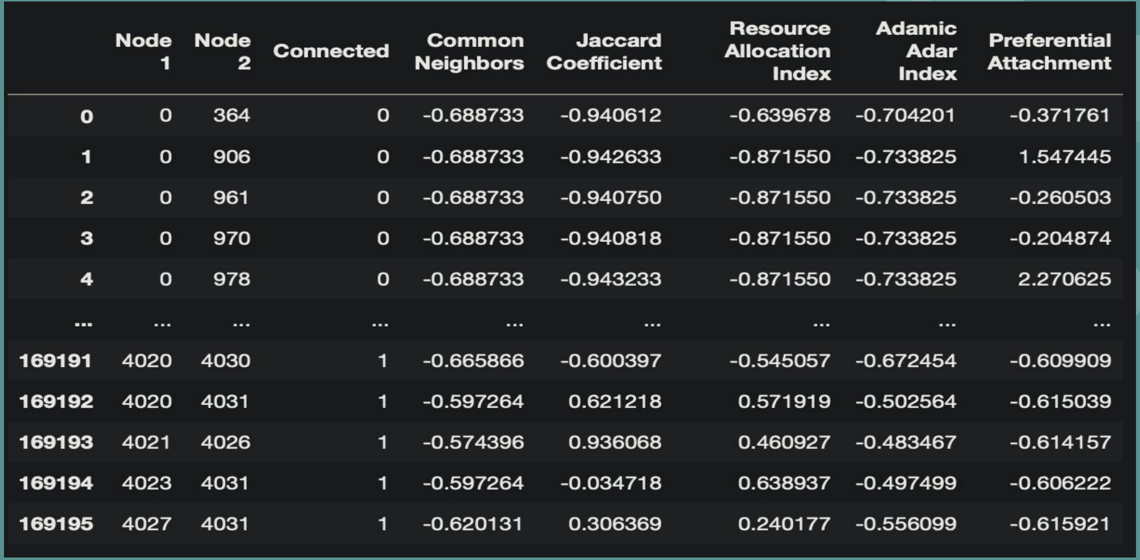


Figure 3: Complementary visualizations of Les Misérables coappearance network generated by *node2vec* with label colors reflecting homophily (top) and structural equivalence (bottom).

NetworkX Link Prediction Pre-Processing

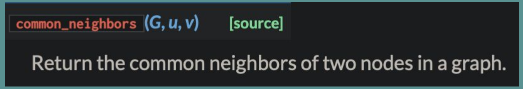
- Used the NetworkX library link prediction algorithms to calculate the link metric for each pair in the list of unconnected (negative samples) & removable edges (positive samples) to generate features that will be applied to a supervised learning approach to predict probabilities of each node pairs in forming a connection. I used the same set of negative & positive samples as in Node2Vec to maintain consistency between two approaches
- Used the following link prediction algorithms: common_neighbors, jaccard_coefficient, resource_allocation index, adamic_adar_index, & preferential_attachment
- Created & scaled the training set and testing set of data to create the final data below to be used for modeling:



	Node 1	Node 2	Connected	Common Neighbors	Jaccard Coefficient	Resource Allocation Index	Adamic Adar Index	Preferential Attachment
0	0	364	0	-0.688733	-0.940612	-0.639678	-0.704201	-0.371761
1	0	906	0	-0.688733	-0.942633	-0.871550	-0.733825	1.547445
2	0	961	0	-0.688733	-0.940750	-0.871550	-0.733825	-0.260503
3	0	970	0	-0.688733	-0.940818	-0.871550	-0.733825	-0.204874
4	0	978	0	-0.688733	-0.943233	-0.871550	-0.733825	2.270625
...	...	...	...	...	...	...	...	...
169191	4020	4030	1	-0.665866	-0.600397	-0.545057	-0.672454	-0.609909
169192	4020	4031	1	-0.597264	0.621218	0.571919	-0.502564	-0.615039
169193	4021	4026	1	-0.574396	0.936068	0.460927	-0.483467	-0.614157
169194	4023	4031	1	-0.597264	-0.034718	0.638937	-0.497499	-0.606222
169195	4027	4031	1	-0.620131	0.306369	0.240177	-0.556099	-0.615921

NetworkX Link Prediction Algorithms

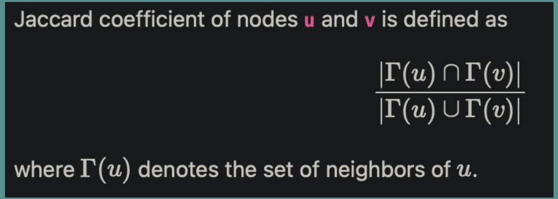
1. Common_neighbors



`common_neighbors` (G, u, v) [source]

Return the common neighbors of two nodes in a graph.

2. Jaccard_coefficient

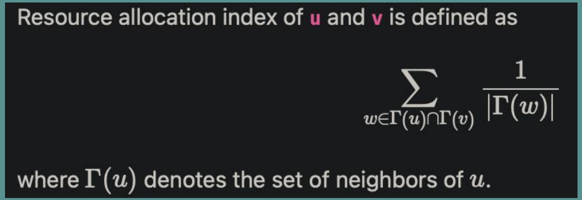


Jaccard coefficient of nodes u and v is defined as

$$\frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|}$$

where $\Gamma(u)$ denotes the set of neighbors of u.

3. Resource_allocation index

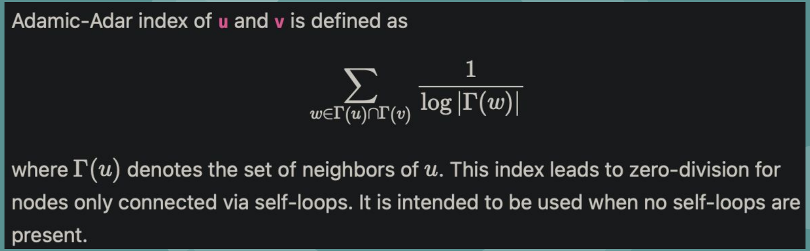


Resource allocation index of u and v is defined as

$$\sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{|\Gamma(w)|}$$

where $\Gamma(u)$ denotes the set of neighbors of u.

4. Adamic_adar_index

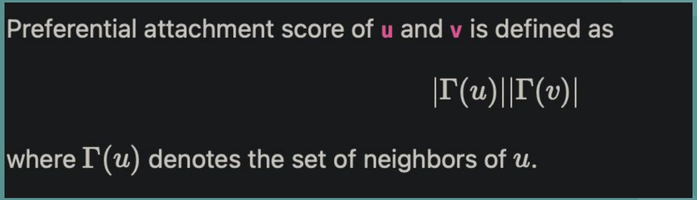


Adamic-Adar index of u and v is defined as

$$\sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{\log |\Gamma(w)|}$$

where $\Gamma(u)$ denotes the set of neighbors of u. This index leads to zero-division for nodes only connected via self-loops. It is intended to be used when no self-loops are present.

5. Preferential_attachment



Preferential attachment score of u and v is defined as

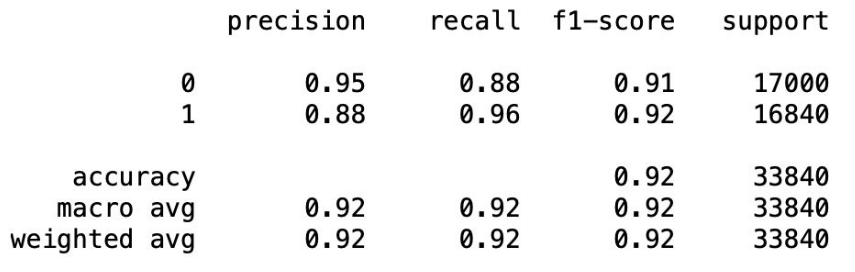
$$|\Gamma(u)||\Gamma(v)|$$

where $\Gamma(u)$ denotes the set of neighbors of u.

Node2Vec & NetworkX LP Modeling

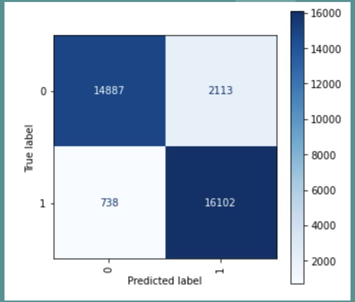
- I trained & tested 4 ML models to predict my binary classification of 1 or 0 representing connected status of connected or not connected respectively. I used logistic regression, Random Forest Classifier, Gradient Boosting Classifier, and a Multi-Layer Perceptron Classifier
- I wanted a simple & quick classifier so I picked a logistic regression classifier. Also, tree based classifiers like random forest & gradient boosting & a neural network classifier like mlp to try more complex and generally more accurate models even though they take more time to train.
- I took the following 5 steps to implement each of the 4 ML models:
  - 1. I used GridSearchCV for hyperparameter tuning to pick the best model version
  - 2. I fit the model and made predictions for the test set
  - 3. Printed the classification report displaying the accuracy, precision, recall, and F1-scores.
  - 4. Calculated the accuracy, precision, recall, F1-score, log loss score, and ROC-AUC (area under the curve) for the model
  - 5. Lastly, displayed the confusion matrix to see the distribution of predictions being made

MLP Classification Report



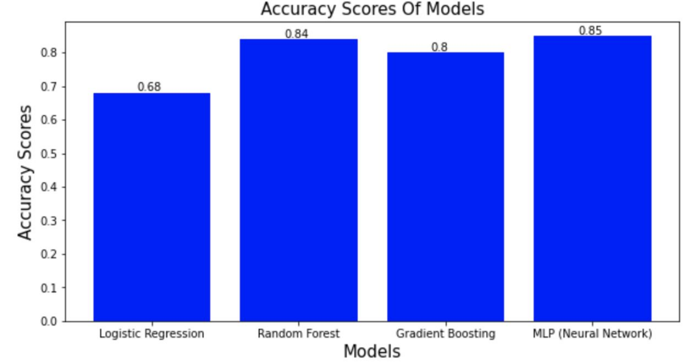
```
              precision    recall  f1-score   support

           0       0.95      0.88      0.91     17000
           1       0.88      0.96      0.92     16840

    accuracy                           0.92     33840
   macro avg       0.92      0.92      0.92     33840
weighted avg       0.92      0.92      0.92     33840
```

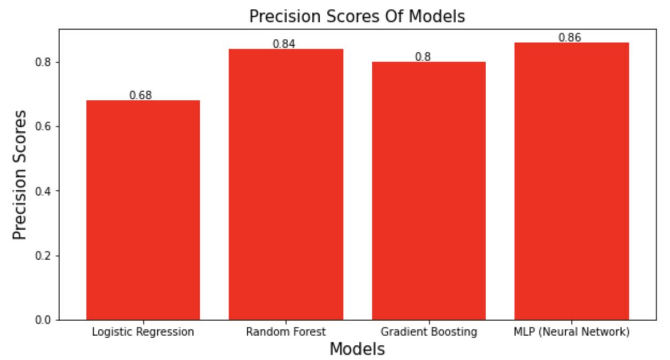
MLP Confusion Matrix

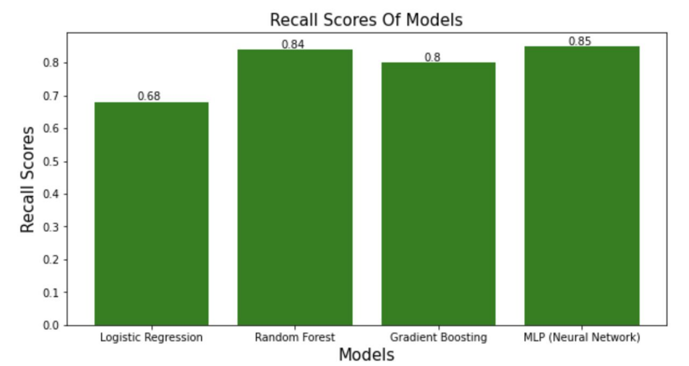


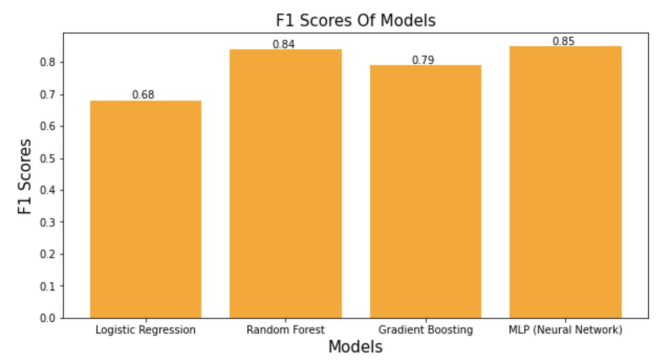
Node2Vec Model Comparison

- The best model is the Multilayer Perceptron Classifier (Neural Network Classifier)
- The accuracy, precision, recall, and F1 scores are compared for all 4 models.
- The delta between the best and worst model in accuracy: 17%, precision: 18%, recall: 17%, f1: 17%





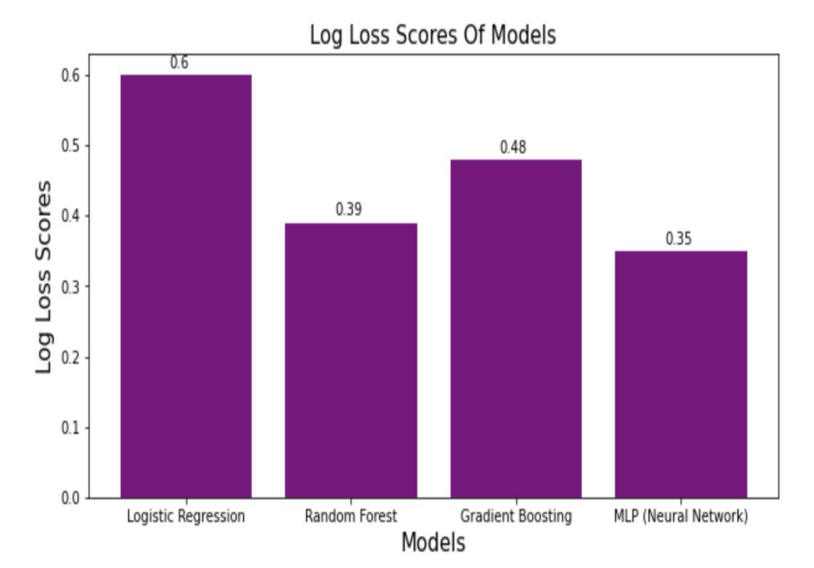


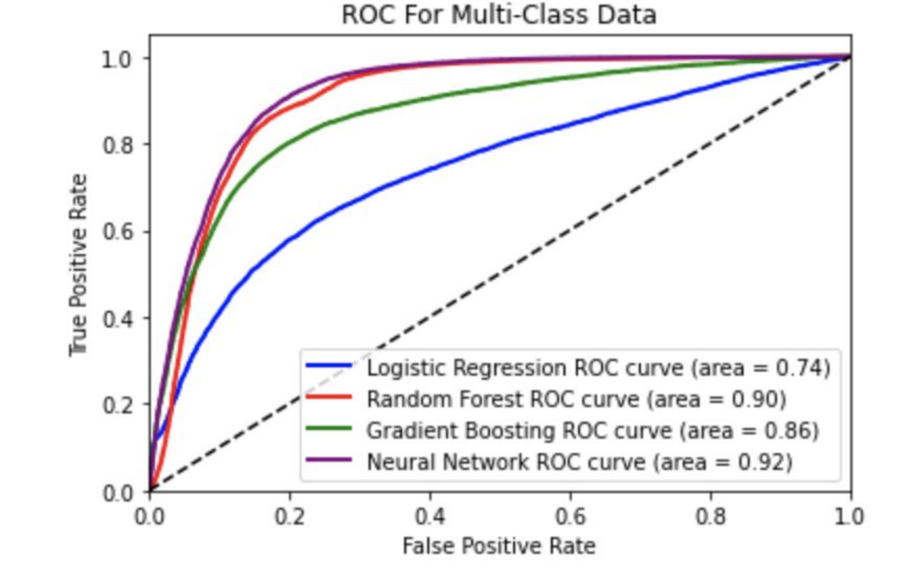


Node2Vec Model Comparison

- The lowest Log Loss score was 0.35 for the Multilayer Perceptron Classifier model

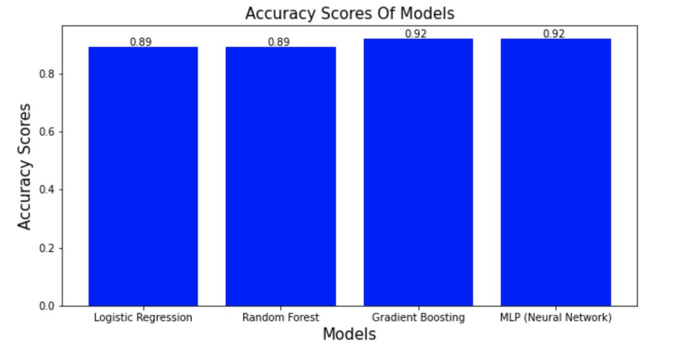
- The ROC curves and the area under the curve (AUC) is the largest at 0.92 for the Multilayer Perceptron Classifier model

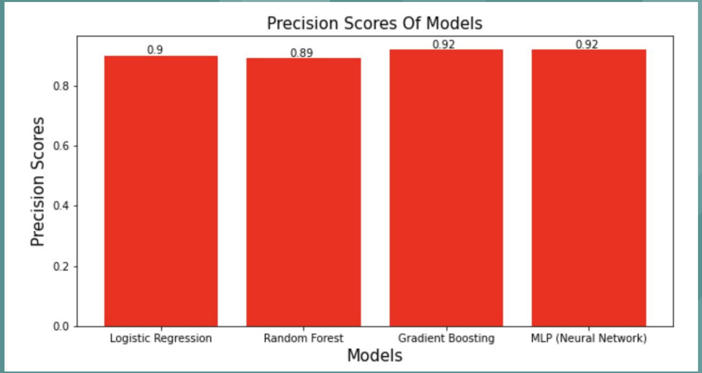


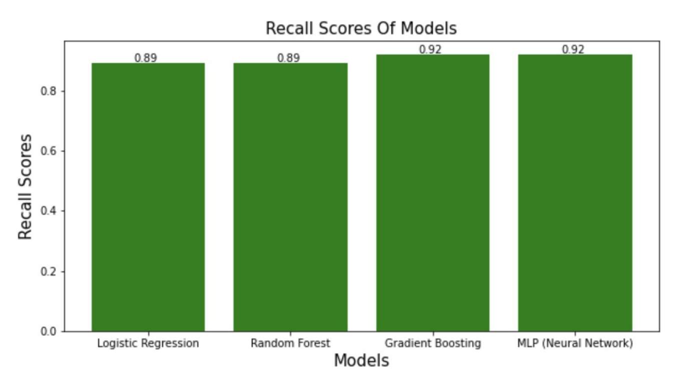


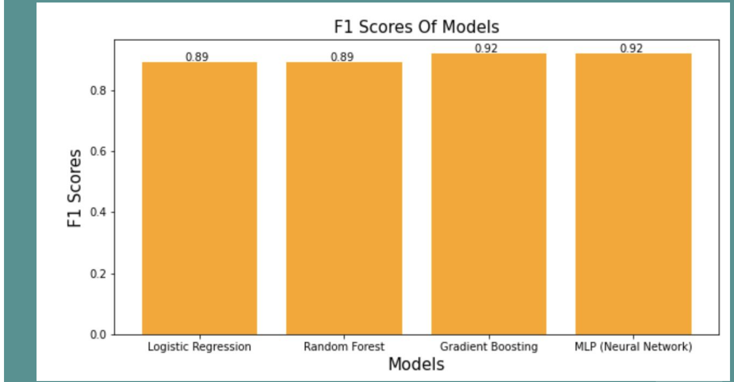
NetworkX LP Model Comparison

- The best models were the Multilayer Perceptron Classifier (Neural Network Classifier) & Gradient Boosting Classifier
- The accuracy, precision, recall, and F1 scores are compared for all 4 models
- The delta between the best and worst model in accuracy: 3%, precision: 2%, recall: 3%, f1: 3%



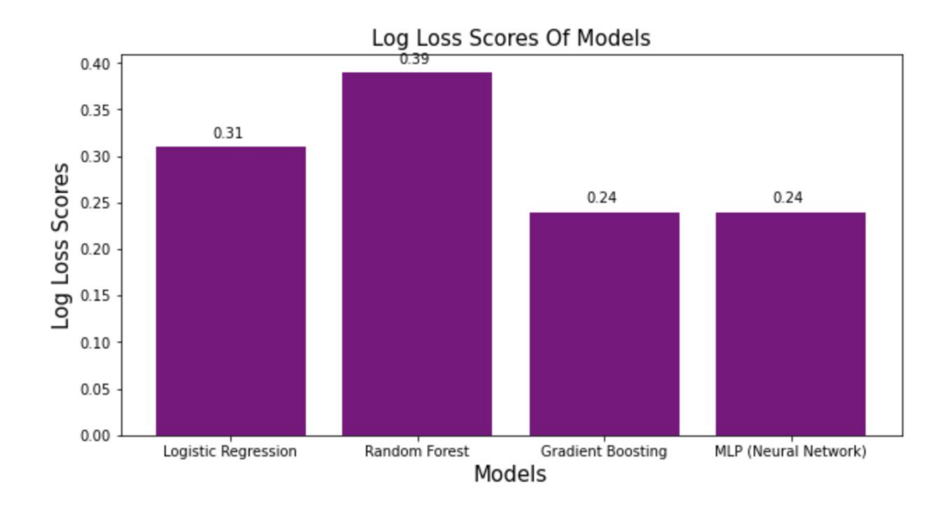


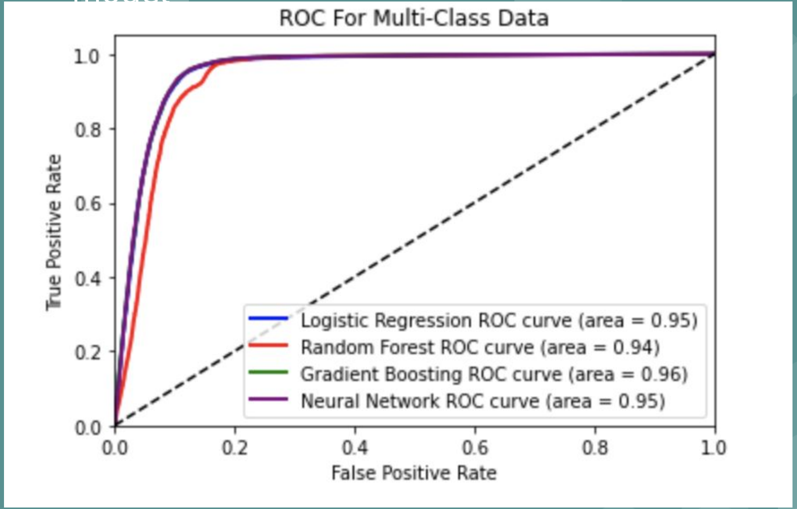




NetworkX LP Model Comparison

- The lowest Log Loss score was 0.24 for the Multilayer Perceptron Classifier & Gradient Boosting Classifier models
- The ROC curves and the area under the curve (AUC) is the largest at 0.96 for the GB model and 0.95 for the Multilayer Perceptron Classifier model & the LR model





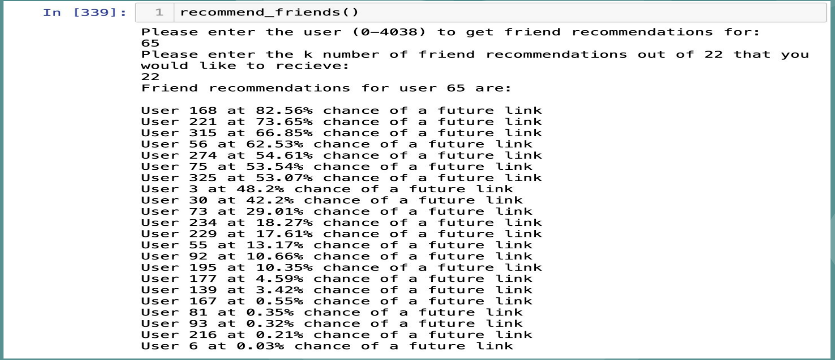
Node2Vec & NetworkX LP Recommender Functions

- Recommed_friends function gets probabilities for each unconnected pair that includes the user requested user # and prints the top k as requested by the user

Function Steps

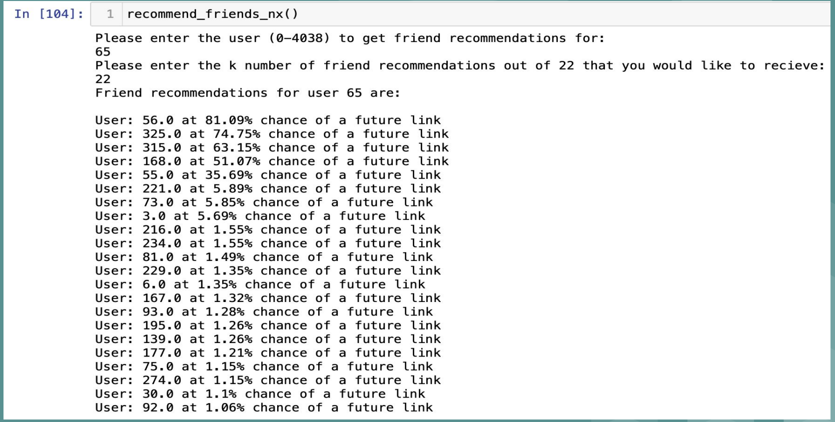
1. Prompts to pick the user # to recommend friends for
2. Prompts the user for # of recommendations
3. Uses MLP classifier & ‘predict_proba’ method to get the probabilities of all unconnected node pairs being connected
4. Ranks the probabilities and prints out the requested number of recommended friends user #s

Node2Vec Function



```
In [339]:  recommend_friends()

Please enter the user (0-4038) to get friend recommendations for:
65
Please enter the k number of friend recommendations out of 22 that you
would like to recieve:
22
Friend recommendations for user 65 are:

User 168 at 82.56% chance of a future link
User 221 at 73.65% chance of a future link
User 315 at 66.85% chance of a future link
User 56 at 62.53% chance of a future link
User 274 at 54.61% chance of a future link
User 75 at 53.54% chance of a future link
User 325 at 53.07% chance of a future link
User 3 at 48.2% chance of a future link
User 30 at 42.2% chance of a future link
User 73 at 29.01% chance of a future link
User 234 at 18.27% chance of a future link
User 229 at 17.61% chance of a future link
User 55 at 13.17% chance of a future link
User 92 at 10.66% chance of a future link
User 195 at 10.35% chance of a future link
User 177 at 4.59% chance of a future link
User 139 at 3.42% chance of a future link
User 167 at 0.55% chance of a future link
User 81 at 0.35% chance of a future link
User 93 at 0.32% chance of a future link
User 216 at 0.21% chance of a future link
User 6 at 0.03% chance of a future link
```

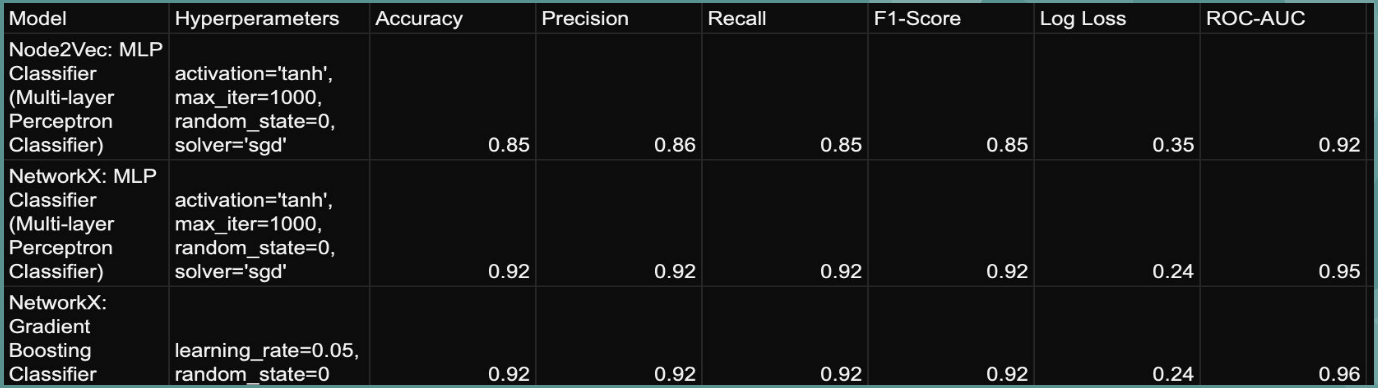
NetworkX LP Function



```
In [104]:  recommend_friends_nx()

Please enter the user (0-4038) to get friend recommendations for:
65
Please enter the k number of friend recommendations out of 22 that you would like to recieve:
22
Friend recommendations for user 65 are:

User: 56.0 at 81.09% chance of a future link
User: 325.0 at 74.75% chance of a future link
User: 315.0 at 63.15% chance of a future link
User: 168.0 at 51.07% chance of a future link
User: 55.0 at 35.69% chance of a future link
User: 221.0 at 5.89% chance of a future link
User: 73.0 at 5.85% chance of a future link
User: 3.0 at 5.69% chance of a future link
User: 216.0 at 1.55% chance of a future link
User: 234.0 at 1.55% chance of a future link
User: 81.0 at 1.49% chance of a future link
User: 229.0 at 1.35% chance of a future link
User: 6.0 at 1.35% chance of a future link
User: 167.0 at 1.32% chance of a future link
User: 93.0 at 1.28% chance of a future link
User: 195.0 at 1.26% chance of a future link
User: 139.0 at 1.26% chance of a future link
User: 177.0 at 1.21% chance of a future link
User: 75.0 at 1.15% chance of a future link
User: 274.0 at 1.15% chance of a future link
User: 30.0 at 1.1% chance of a future link
User: 92.0 at 1.06% chance of a future link
```

Takeaways

- In the Node2Vec & NetworkX features creation pre-processing approaches, the Multi-layer perceptron classifier was the best model & the gradient boosting classifier as well on the NetworkX LP approach

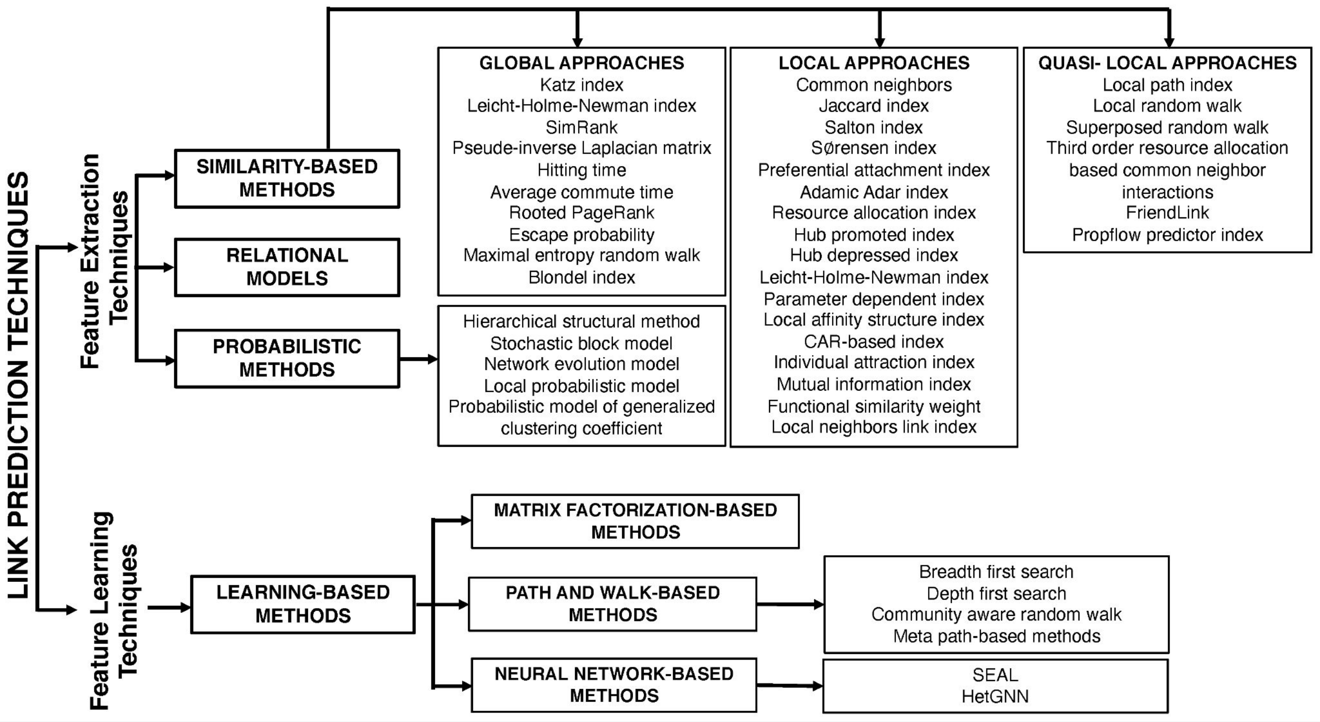


Model	Hyperperameters	Accuracy	Precision	Recall	F1-Score	Log Loss	ROC-AUC
Node2Vec: MLP Classifier (Multi-layer Perceptron Classifier)	activation='tanh', max_iter=1000, random_state=0, solver='sgd'	0.85	0.86	0.85	0.85	0.35	0.92
NetworkX: MLP Classifier (Multi-layer Perceptron Classifier)	activation='tanh', max_iter=1000, random_state=0, solver='sgd'	0.92	0.92	0.92	0.92	0.24	0.95
NetworkX: Gradient Boosting Classifier	learning_rate=0.05, random_state=0	0.92	0.92	0.92	0.92	0.24	0.96

- The features generated by node2vec don't work for predicting links as well as the features generated by the NetworkX library link prediction algorithms

Further Research

- I would try to implement different approaches to get link predictions other than the Similarity-Based Local Approaches (NetworkX LP) & Path & Walk-Based Method (Node2Vec)



LINK PREDICTION TECHNIQUES

Feature Extraction Techniques

SIMILARITY-BASED METHODS

RELATIONAL MODELS

PROBABILISTIC METHODS

GLOBAL APPROACHES
Katz index
Leicht-Holme-Newman index
SimRank
Pseude-inverse Laplacian matrix
Hitting time
Average commute time
Rooted PageRank
Escape probability
Maximal entropy random walk
Blondel index

LOCAL APPROACHES
Common neighbors
Jaccard index
Salton index
Sørensen index
Preferential attachment index
Adamic Adar index
Resource allocation index
Hub promoted index
Hub depressed index
Leicht-Holme-Newman index
Parameter dependent index
Local affinity structure index
CAR-based index
Individual attraction index
Mutual information index
Functional similarity weight
Local neighbors link index

QUASI- LOCAL APPROACHES
Local path index
Local random walk
Superposed random walk
Third order resource allocation
based common neighbor
interactions
FriendLink
Propflow predictor index

Hierarchical structural method
Stochastic block model
Network evolution model
Local probabilistic model
Probabilistic model of generalized
clustering coefficient

Feature Learning Techniques

LEARNING-BASED METHODS

MATRIX FACTORIZATION-BASED METHODS

PATH AND WALK-BASED METHODS

Breadth first search
Depth first search
Community aware random walk
Meta path-based methods

NEURAL NETWORK-BASED METHODS

SEAL
HetGNN

Thank You