Assignment 1 Writeup

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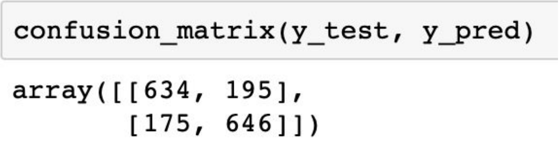
Part I: Find predictors of influence

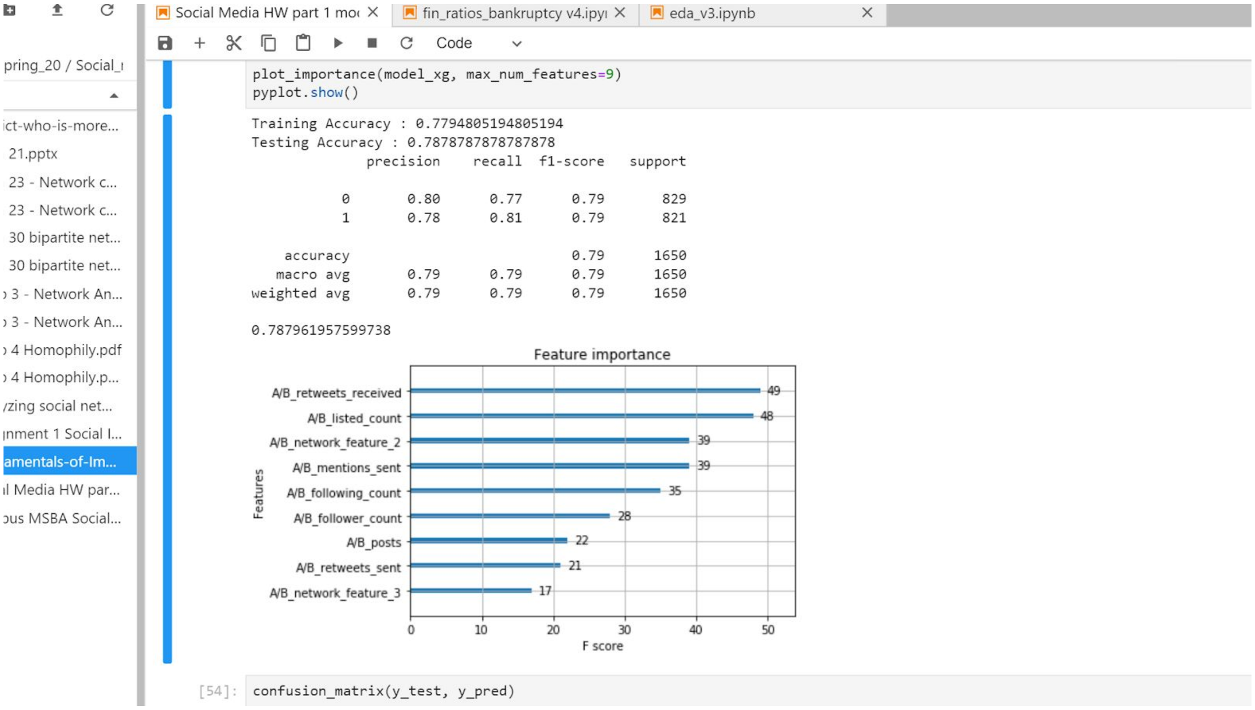
We tried three models: logistic regression, Random Forest and XGBoost. Among them, XGBoost has the highest accurate rate of 78.8%.

Confusion matrix of the XGBoost model and best predictors of influence:



```
confusion_matrix(y_test, y_pred)
```

```
array([[634, 195],
       [175, 646]])
```



```
plot_importance(model_xg, max_num_features=9)
pyplot.show()
```

```
Training Accuracy : 0.7794805194805194
Testing Accuracy : 0.7878787878787878
              precision    recall  f1-score   support

           0       0.80      0.77      0.79       829
           1       0.78      0.81      0.79       821

    accuracy                           0.79      1650
   macro avg       0.79      0.79      0.79      1650
weighted avg       0.79      0.79      0.79      1650

0.787961957599738
```

```
[54]: confusion_matrix(y_test, y_pred)
```

The best 5 predictors of influence at **retweets_received, listed_count, network_feature_2, mentions_sent, and following_count**. Retweets indicate engagement whereas following count does not, so we expect retweets to be ranked higher. However, it is surprising that following count ranks higher than follower count, because we thought how many people followed you would affect others’ perception of your influence more than how many people you follow.

A business can use the ranked features of what makes a person influential online as a guide to deciding who to partner with on social media.

Calculating the *financial value* of the model

(Assumption: each user appears only once in the data, hence each row has two new names. Hence out no. of users is twice the numbers of rows in the data)

<u>Net profit without using analytical model:</u>

We assume either A or B is an influencer and the other is not. The average number of followers is 667,686 for all A’s and B’s.

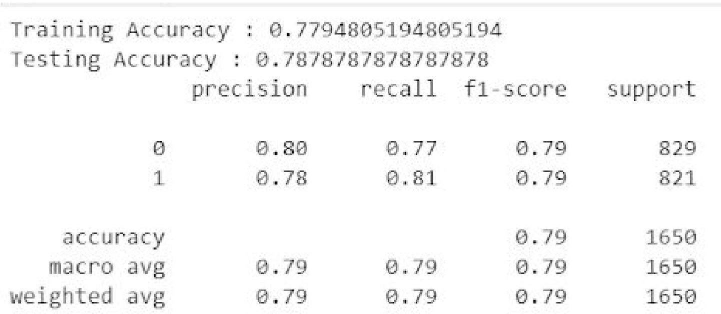
Revenue - costs = profit

=> [Profit margin per unit * .01% chance buy * no of average followers across all users - payment to each user]

=> [$10 * .01% * 667,686 - $5] = **$662.69 per paid user**

<u>Net profit using our analytical model:</u>

The confusion matrix and testing accuracy for our model is shown below. The Testing accuracy multiplied by $10 is the expected value of a follower viewing the paid person’s tweets.



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Training Accuracy : 0.7794805194805194
Testing Accuracy : 0.7878787878787878
              precision    recall  f1-score   support

           0       0.80      0.77      0.79       829
           1       0.78      0.81      0.79       821

    accuracy                           0.79      1650
   macro avg       0.79      0.79      0.79      1650
weighted avg       0.79      0.79      0.79      1650
```

Our net profit is the weighted average of the Profit from true influencers + loss from false influencers, using the average follower count of our predicted influencers:

Expected value = .78* [$10 * .015% * 1,087,897 - $10] + (-$10)*(1-.78) = **$1,262.84 per user**

Lift in expected net profit using analytical model:

$1,262.84 - $662.69 = $600.15 per user

Net profit using a perfect analytic model:

Lift in expected net profit using perfect analytical model:

In this case, the odds of correctly predicting an influencer is 100%

=> net profit = 100% * ($10 profit per unit * 0.015% * Average no of followers of influencers that tweet twice) -$10 payment
=> $10 * .015% * 1,087,897 - $10 = **$1,621.85 per user**

Perfect model vs No analytics lift
$1,621.85 - $662.69 = **$959.16 per user**

Part II: Finding influencers from Twitter

We collected tweets related to the flat earth conspiracy theory from Twitter using Tweepy.

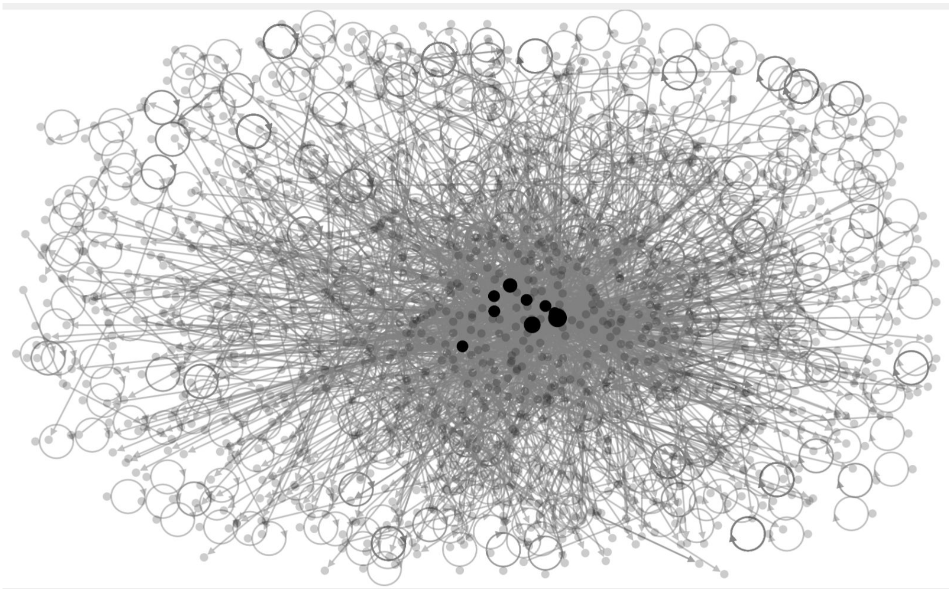
We then parse the tweets to construct a csv File with user1, user2 and the type of tweet (Tweet/ Re-tweet). On constructing a directed graph using networkx, we get a digraph as follows:

1. Number of nodes: 1499
2. Number of edges: 2419
3. Average in degree: 1.6137
4. Average out degree: 1.6137

We then calculate centrality metrics - degree, betweenness and closeness using networkx.

By using NodeXL to visualize the graph, we get the following graph:

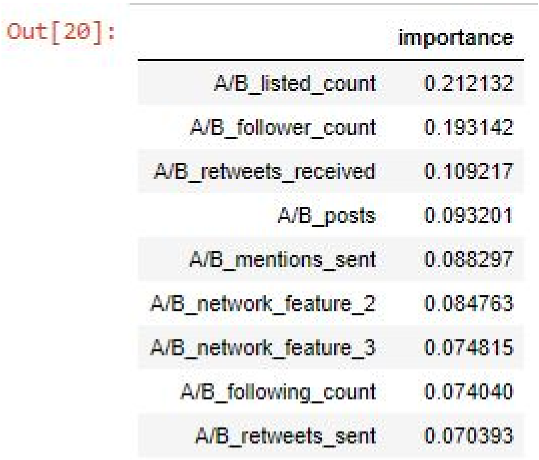
Figure 1: NodeXL Graph visualization



We can clearly see that the nodes in black act as the key influencers. The graph was constructed by considering in-degree as the determining measure.

List of Top 50 Influencers

In order to create a list of the top 50 influencers, I had to refer to the features that Part 1 of the presentation deemed to be the most important.



Out[20]:

	importance
A/B_listed_count	0.212132
A/B_follower_count	0.193142
A/B_retweets_received	0.109217
A/B_posts	0.093201
A/B_mentions_sent	0.088297
A/B_network_feature_2	0.084763
A/B_network_feature_3	0.074815
A/B_following_count	0.074040
A/B_retweets_sent	0.070393

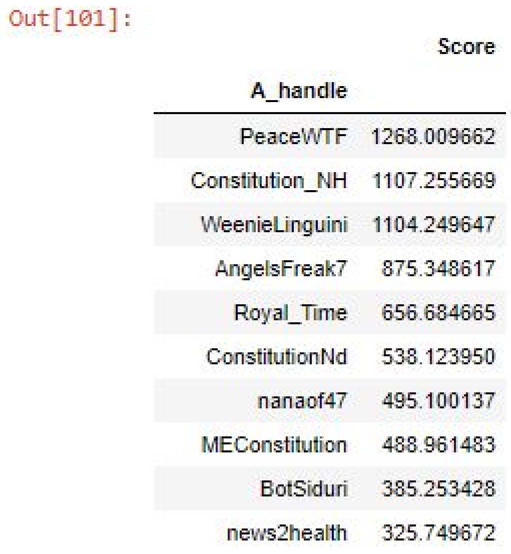
However, not all of these features existed in our dataset, and couldn't be calculated. Therefore, we simply chose the top features that exist in our data: "A/B_listed_count", "A/B_follower_count","A/B_posts","A/B_network_feature_2".

Using these, we created a new feature that consisted of a score which was calculated from the following formula: .4*A/B_listed_count + .3*A/B_follower_count + .2* A/B_posts +

.1*A/B_network_feature_2. The coefficients were chosen in order to favor features that had a higher importance.

In order to handle the fact that the same interactions between 2 users occurred multiple times, we simply summed up the scores of each interaction.

The top ten Influencers were as follows:



Out[101]:

	Score
A_handle	
PeaceWTF	1268.009662
Constitution_NH	1107.255669
WeenieLinguini	1104.249647
AngelsFreak7	875.348617
Royal_Time	656.684665
ConstitutionNd	538.123950
nanaof47	495.100137
MEConstitution	488.961483
BotSiduri	385.253428
news2health	325.749672

To see the full list of all 50 influencers, please refer to the code.