Data Mining Final Report

Introduction:

Fake accounts on social media are so widespread and prevalent now that the majority of profiles that appear on most social media platforms are likely fake. In many ways, the number of fake social media accounts has gotten so out of hand that some users may feel as if their social media platforms have been overtaken by fake accounts and given the rising sophistication of "bot" accounts it is no longer easy to distinguish fake accounts from genuine accounts. Moreover, the problems with fake accounts on social media do not end here as unlike "real" people with "real" accounts many of these "fake" accounts have little issue with engaging in behavior such as soliciting merchandise that would normally earn "real" people scorn. Due to how significant fake social media accounts have become, the social media experience is considerably degraded for many. Motivated by the mounting problems posed by fake social media accounts, our paper examines several popular data mining techniques on the tasks of detecting fake social media accounts as well as uncovering hidden patterns relating to fake and genuine accounts.

Project Setup:

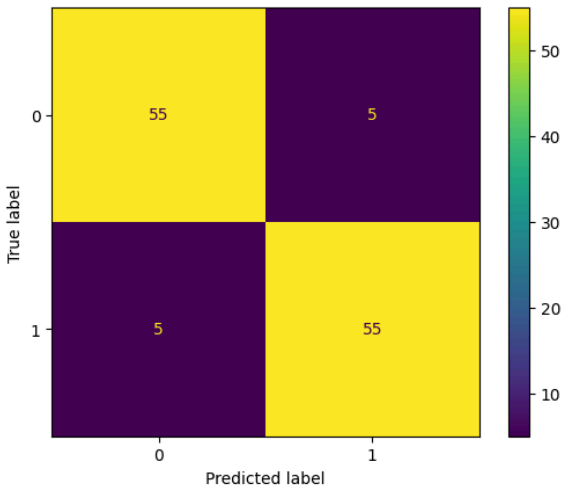
For this project, our group decided we would work on detecting fake accounts on the popular social media platform Instagram. Fake accounts on social media are of particular interest to us as a group because there are countless variations and ways in which people post fake accounts and try to pass them off as genuine. Although it may be hard to comprehend how exactly people are able to keep coming up with new ways of generating fake accounts on social media, through the direct application of data mining techniques, we can more precisely determine what kinds of common patterns and relationships exist in fake accounts and leave out conjecture. In our project, we examined a dataset on fake versus genuine social media accounts and built classification models off of that and compared model performances. Tim tested two types of algorithms on the fake/genuine social media account dataset, namely random forests and logistic regression. Additionally, Tim also analyzed the attributes present in the dataset such as "profile pic, fullname words, private, #posts, #followers" in order to find the most relevant attributes to discover patterns relating to genuine/fake accounts using apriori rule generation and binning. Lastly, Tim tested the predictive abilities of the algorithms on a few real-life Instagram accounts with the aid of a web scraper extension for Instagram and collected some interesting results. ***.Add a summary of what you did here:***

Logistic Regression and Random Forest.

In this project, the logistic regression and random forest algorithms were tested on the social media dataset and compared against each other. The reason these algorithms were selected in particular is because logistic regression and random forest represent two entirely different ways of interpreting the data and prediction making, though it should be noted that despite their differences, these two algorithms were both perfectly capable of achieving 100% accuracy in their own right at least once during K-folds cross validation.

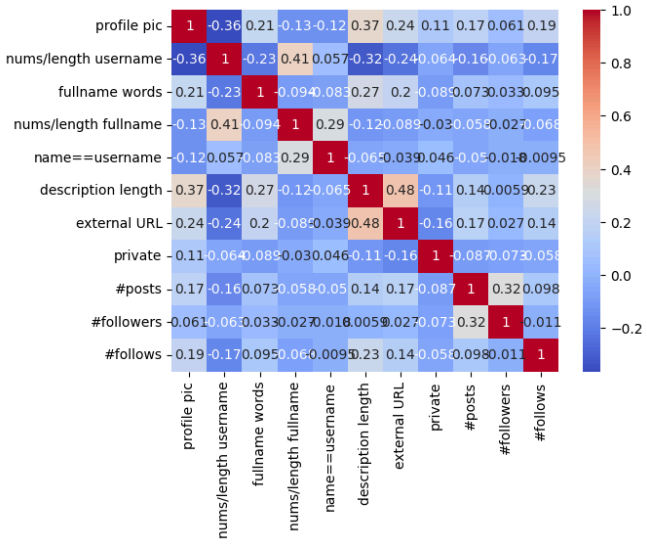
Of the two algorithms, logistic regression is probably the most intuitive to understand when envisioning how a classification algorithm should perform as it produces linear decision boundaries to separate classes similar to support vector machine. As one may guess, logistic regression is more or less a completely deterministic process as it is conceptually related to maximum likelihood estimation from statistical theory. In contrast, random forests, is a stochastic process and looks at things from an entirely different angle. Unlike most traditional classification methods, random forests is an ensemble learner with random initialization that aggregates the results of several decision trees.

Ultimately, of the two algorithms tested, random forests proved to be superior to logistic regression at the task of social media account classification with a 95% average accuracy compared to an 80% average accuracy although it should be noted again that both algorithms have the same performance ceiling of perfect classification rate. From the confusion matrix of random forests, one can see that random forests has higher accuracy and lower error rate. Moreover, since the odds of random forests making a false positive versus a false negative are the same, we do not have to worry about random forests being biased towards making either type 1 or type 2 errors.



A-priori rule association analysis:

From the correlation heat map shown below, one can see that there are a fair number of attributes in the original dataset though it is unclear just how meaningful each one these attributes are and some of these attributes may in fact be redundant. Another point that needs to be raised about the number of attributes in our datasets is that there are more attributes present than can be realistically extracted from a given Instagram profile page due to the way private profiles and the like work. Taking all of this into consideration, reducing the number of attributes in our dataset down to a set of only the most meaningful attributes might be a good idea especially if we plan on applying our models to the real world. Therefore, to accomplish this task apriori association analysis was applied to uncover the most meaningful attributes and hidden patterns in the dataset.



Before apriori,binning was applied which converted the mixture of binary and continuous data in the original dataset to binary categorical data. Here, a normal distribution was assumed and as such, the bins were divided into various grades with very low/very high representing two standard deviations above or below the mean, low/high representing one standard deviation above or below the mean, and normal representing anything within one standard deviation of the mean. After data conversion, apriori association analysis was performed with minsupport of 80% which generated the rules shown below. According to the rules generated by apriori association analysis, the most important attributes are the number of followers, length of fullname, number of posts, and number of follows which lines up with common sense. For reference distribution plots of the most important attributes are also shown below.

	support	itemsets	length
0	0.812500	(low nums/length username)	1
1	0.815972	(low fullname words)	1
2	0.909722	(low nums/length fullname)	1
3	0.861111	(low description length)	1
4	0.951389	(low #posts)	1
5	0.991319	(low #followers)	1
6	0.934028	(low #follows)	1
12	0.803819	(low #followers, low nums/length username)	2
18	0.810764	(low fullname words, low #followers)	2
21	0.862847	(low nums/length fullname, low #posts)	2
22	0.901042	(low #followers, low nums/length fullname)	2

fullname words	fake	proportion
0	0	52.631579
	1	47.368421
1	1	73.498233
	0	26.501767
2	0	78.074866
	1	21.925134
3	0	73.529412
	1	26.470588
4	0	71.428571
	1	28.571429
5	0	75.000000
	1	25.000000
6	0	100.000000
10	0	100.000000
12	0	100.000000

#followers	fake	proportion
0	1	100.0
1	1	100.0
2	1	100.0
3	1	100.0
4	1	100.0
...	...	...
3896490	0	100.0
5315651	0	100.0
6741307	0	100.0
12397719	0	100.0
15338538	0	100.0

#posts	fake	proportion
0	1	97.452229
	0	2.547771
1	1	85.714286
	0	14.285714
2	1	77.272727
...	...	...
1164	0	100.000000
1232	0	100.000000
1570	0	100.000000
4494	0	100.000000
7389	0	100.000000

Web scraper extension results:

After apriori, the random forest model was tweaked to work with only the attributes with the highest support count rather than all of the attributes in the original dataset. These changes were made to make the random forest model more applicable to real world cases in which not all of the attributes from the original dataset may be present. Logically, the next step that was carried out was testing the predictive abilities of the refined random forest model on actual fake instagram accounts with the help of the Instaloader web scraper extension. In practice, it was found that the random forest classifier can easily identify fake accounts that are obviously fake such as accounts that have no followers and posts like in the case of bot accounts. However, the tweaked random forest model failed to identify imposter accounts as fake because such accounts are often cleverly disguised. Given the already high performance of random forests, it is probably safe to assume that other algorithms would not fare much better at detecting fake imposter accounts.