Author Attribution in the Bitcoin Blocksize Debate on Reddit

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Abstract

The block size debate has been a contentious issue in the Bitcoin community on the social media platform Reddit. Many members of the community suspect there have been organized attempts to manipulate the debate from people using multiple accounts to over-represent and misrepresent important issues on the debate. The following analysis uses techniques from authorship attribution and machine learning to determine whether comments from user accounts that are active in the debate are from the same author. The techniques used are able to recall over 90% of all instances of multiple account use and achieve up to 72% for the true positive rate.

1 Introduction

The current block size debate is critical to reach consensus on issues that affect the scalability and overall future of the Bitcoin network. The process for consensus is one that typically involves Bitcoin core developers, miners, merchants and other experts and stakeholders, but there has been difficulty reaching a viable agreement on the block size. The wider community on the social media site Reddit has been eager to support the side of the debate they believe is best for the future of bitcoin. But this has only served to add a lot of noise to the debate and many bitcoin experts who are active in the Reddit community believe that there are even organized attempts to manipulate the outcome of the debate by people using multiple accounts, also known as *sock puppets*. Two members have gone as far as offering a bounty for an in-depth analysis indicating the presence (or absence) of multiple accounts used to manipulate debate. As part of a submission for this bounty, this report seeks to identify cases of multiple account use on the Bitcoin subreddit. To do this in an unbiased way, it will use established techniques from authorship attribution studies and machine learning. Assuming the intended audience may not have much background in statistics or machine learning, this report will forego many of the technical details, in favor of discussing the intuition and purpose of the techniques used. Enough technical details and references will be provided that the analysis can be reproduced. The full project is available at `https://github.com/aehaynes/reddit_authorship`

The main idea behind authorship attribution is that by computing some text based features we can distinguish among texts from different authors [1]. Authorship attribution research is typically concerned with building generative models for each candidate author, however, this analysis simply aims to construct a discriminative model to determine whether comments from a given pair of Reddit users originated from the same author. It will use tools from natural language processing and statistics to engineer features that will measure how similar two users are based on what they talk about (topical similarity) and how they talk about it (syntactic similarity). These features will then be used to train a Random Forests classifier on the binary classification task of predicting whether or not the topical and syntactic similarity scores indicate the comments from the two users are from the same author.

In Section 2 we will discuss the methodology behind data gathering, feature engineering and classification tasks. Section 3. will discuss the results and give a brief discussion on their performance. The main report aims to be as objective as possible, however, identifying cases of manipulation will rely on some reasonable but subjective assumptions. For this reason, any discussion of identifying cases of manipulation is left for Appendix I., where we give three examples of multi-account use for manipulation. The main report will focus on identifying possible cases of multiple account use.

2 Methodology

2.1 Data

The data was collected from the Bitcoin subreddit using the Reddit API to retrieve all threads matching a given list of keywords related to the block size debate (see Appendix IV. for more details). All user comments were retrieved from the matching threads and stored in a database. Since the block size debate has been most active over the last year, comments were split into two groups: the first group treated as 'seen' data, containing all comments before 1st June 2014, used to train and test the Random Forests classifier; and the second group containing all comments from 1st June 2014 to 10th June 2015, treated as 'unseen' data and used in post-modeling investigation to determine whether there are in fact authors with multiple user accounts who are active in the debate.

For both groups only users with 10 or more comments were considered for analysis. This was done to eliminate possible sources of noise and strengthen assumptions that rely on large samples for some statistical features in the feature engineering phase. The comments were pre-processed to remove: common words — also known as stop words — (e.g. "and", "the"), URLs, text tagged as quoted comments, and some special characters including HTML escape codes.

In this analysis we aggregated all comments for each user to form a *profile*, and used it to compute a cumulative representation of that user's tendencies. This is in contrast to *instance* based approaches that consider each item of text from an author individually. The instance based approach is sensitive to variations in style of writing across different contexts — as is the case if the author was writing for different audiences [1]. Since the data was limited to one community on Reddit with a relatively fixed audience, it was assumed that there was no significant variation in writing style across a given user's comments. The goal is to represent the general style of each user and not the separate style of each individual comment. Furthermore, since comments are often brief, building a profile of a user's comments helped to avoid missing or ambiguous measurements for features that were sparse in individual comments. For example the number of times a semi-colon occurs may be close to zero for individual comments, but may be higher in an aggregated set of comments.

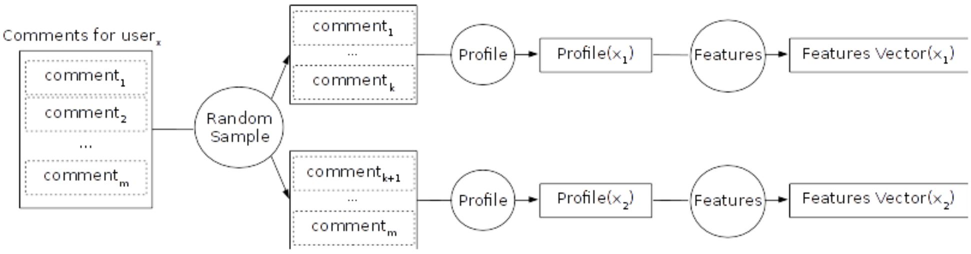

Figure 1: Data flow for creating a profile.

2.2 Feature Engineering

The author discrimination model uses representations of what users comment about (topics), and the written style of their comments (syntax), as a basis for judging the similarity between two users. The representations used, view the collection of texts, also known as a *corpus*, as a bag-of-words i.e. a collection of words with no inherent ordering. The bag-of-words approach is used to generate a family of models known as Vector Space Models. These provide an algebraic representation of a corpus as a collection of vectors, where each dimension corresponds to terms that occur in the corpus. The weights of each component of the vector are typically given by the frequency of the corresponding term in the source text, but there are other weighting schemes such as term frequency-inverse document frequency (tf-idf). Tf-idf is a cross-entropy transformation that gives more weight to terms that are frequent in a text but infrequent across the corpus, and lower weight to terms that are common across all texts in a corpus, as well as terms that are uncommon across the corpus [2]. In this way, tf-idf re-weights the frequency vector representation of a text, so that terms that are over used (e.g. in this case, words like "bitcoin", "blocksize" etc.) or rarely used have a lower weight. By comparison, terms that are not common nor infrequent (e.g. "BIP100") are weighted with a higher value. This gives a kind of term-relevance model.

2.2.1 Topical Features

Vector space models can also be used to do topic modeling i.e. to identify a collection of words that best represent salient topics in a corpus. Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA) represent two such techniques. To keep this discussion brief and non-technical, refer to [3] and [4] for the technical details of these algorithms. It is worth noting that they determine topics by identifying latent structure in term co-occurrences across a corpus.

LDA is a parametric model that in this context would try to represent each comment as a mixture of topics, where each topic has a particular probability distribution over the terms in the corpus. LDA requires that the number of topics, and the prior or initial distribution of topics across comments (i.e. the probability each topic occurs in a comment) is given at the outset. On the other hand, LSA only requires that you choose the number of topics. In this context, it uses singular value decomposition to compute the hidden relationships between comment vectors in the vector space model for the corpus [4]. It is also worth noting that transforming the word vectors using tf-idf before applying LSA to the corpus can give significant improvements over using LSA on an untransformed corpus.

Once the topic representations were computed, users topics were compared using Hellinger distance for LDA and cosine similarity for LSA (See Appendix II. for definitions). Hellinger distance measures the distance between two probability distributions and is more appropriate for LDA since it gives topics as a probability distribution over words. Cosine similarity gives the normalized Euclidean distance between two vectors in the LSA space, and was used to measure how close the latent topics of users' comments were.

Summary of Features and Similarity Measures			
Type	Feature	Transformation	Similarity Measure
Topical	word frequency vector	tf-idf	cosine distance
	LSA topics vector	tf-idf	cosine distance
	LDA topics vector	none	Hellinger distance
	vocabulary set	none	Jaccard distance
Syntactic	character 4-grams	tf-idf	cosine distance
	commas per sentence	none	Welch t-test p-value
	semi-colons per sentence	none	Welch t-test p-value
	colons per sentence	none	Welch t-test p-value
	ellipses per sentence	none	Welch t-test p-value
Summary	total words	none	generalized Jaccard distance
	total vocab	none	generalized Jaccard distance
	net word diversity	none	generalized Jaccard distance
	word diversity per sentence	none	Welch t-test p-value
	words per sentence	none	Welch t-test p-value

Table 1: Features and similarity measures used to judge user similarity.

2.2.2 Syntactic Features

The goal of including syntactic features is to develop representations that correlate with writing style, and compare them across users for similarity. Table 1. has a list of the syntactic features and corresponding similarity measures used to compare users for similarity (see Appendix II. for definitions). A few of these features are worth mentioning in more detail.

Character n-grams view each comment as a collection of n-character sequences. For example, the text “block size” would generate the following sequence of character 4-grams:

{“bloc”, “lock”, “ock ”, “ck s”, “k si”, “ siz”, “size”}

Character n-grams are able to capture the nuances in writing style, including persistent grammatical mistakes and unusual uses of punctuation. A user who has a habit of writing “block-size”, will have several of the previously mentioned 4-grams in common with a user who writes “block size”, but will clearly have more in common with other users who have the same stylistic preference. See [1] for a more detailed discussion of character n-grams and why 4-grams perform well in practice. Similar to the vector space model of terms, a user’s comments were modeled using a vector of 4-gram sequences weighted by frequency. The vectors were transformed using tf-idf, and cosine distance was used to measure the similarity between users.

Also worth mentioning are the features for punctuation rates per sentence. Consider the number of commas per sentence for a user as a random variable. The distribution of this random variable is not Gaussian, however, over a large sample of sentences, Central Limit Theorem implies that the average number of commas per sentence converges to a Gaussian distribution. Suppose it is reasonable expect that user accounts controlled by the same author would have a similar distribution in the number of commas per sentence over a large sample. A statistical hypothesis test can be constructed to determine if the difference in the average rate or commas between two users is significant. The most appropriate test for this is the Welch t-test, since it allows for the standard deviation of the commas per sentence to be different for the two users. It is important to note that the resulting *p-value* is not a valid distance or similarity measure. The most that can be said of a small p-value is that it suggests there is no evidence to reject the assumption of no difference in the average comma rate between the two users. Although the p-value is not a valid measure of similarity, it is certainly *informative* in judging whether two users are similar in the relevant features.

2.3 Classification

A random sample of 60% of the users from the ‘seen’ data was used to generate training data for binary classification. The remaining 40% was used to test and compare the classification accuracy under different conditions. Keeping the users in the training and test set distinct allows us to determine how well the patterns of similarity learned in the training users generalize to predicting similarity for a new set of users.

To generate labeled instances of multi-account use for training, each user’s comments from the training data was randomly and evenly split into two profiles, as shown in Figure 1. The features of all user profiles were compared to each other (pairwise) using the corresponding similarity measures. Cases where the comparison was between two profiles from the same user were assigned {Label = 1}. These represented a true comparison from the same user. All other cases representing comparisons between different users were assigned {Label = 0}.

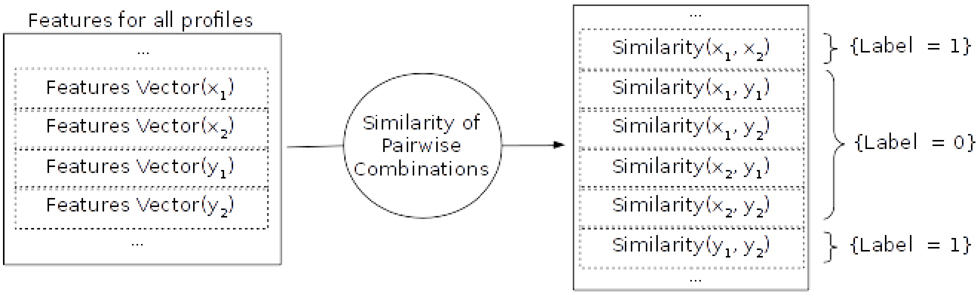

Figure 2: Data flow for constructing training and test data from profile features.

In the training data there are 1616 users with more than 10 comments. Splitting each user's set of comments into two profiles gives 3232 profiles. This leads to $\frac{(3232)(3231)}{2} = 5,221,296$ unique comparisons, out of which only 1616 have {Label = 1} ($\approx 0.03\%$). This is known as class imbalance and presents an interesting challenge for both training a classifier and judging its classification accuracy. Since {Label = 0} is the dominant class, a uniform random sample of the training data would result in a classifier that is able to predict instances of {Label = 0} well, but not {Label = 1}. Furthermore, a classifier that predicts {Label = 0} for all comparisons would have a prediction accuracy of over 99%, for predictions on a uniform sample of the test set. Given our goal, this is clearly not useful.

To address the problem for training, we designed our training set by first specifying r, the ratio of {Label = 1} samples to {Label = 0} comparisons. All comparisons where {Label = 1} were chosen, and a random uniform sample of n_r comparisons from {Label = 0} was taken such that,

$$r = \frac{|\{\text{Label} = 1\}|}{n_r}$$

A Random Forest classifier was trained on this data and prediction accuracy was judged on a random sample of the test set with an equal amount of class {Label = 1} and {Label = 0} comparisons.

Another useful set of measures to judge the performance are precision and recall. In the context of this problem, precision measures what proportion of comparisons predicted as having {Label = 1}, were actually cases of the same user. Recall on the other hand measures what proportion of comparisons that are actually cases of the same author, were predicted to have {Label = 1}. A recall score of 1 therefore implies that all cases of {Label = 1} were predicted to have {Label = 1}; and a precision score of 1 implies that all cases that were predicted to have $\{\text{Label} = 1\}$ are actually cases of the same user.

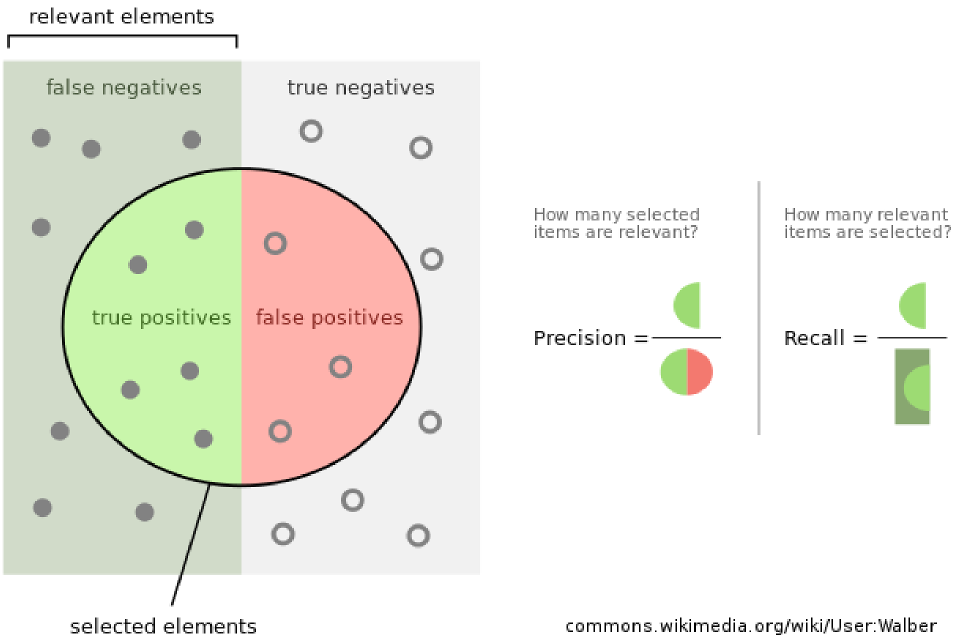
relevant elements
false negatives
true negatives
true positives
false positives
selected elements
How many selected items are relevant?
Precision =
How many relevant items are selected?
Recall =
commons.wikimedia.org/wiki/User:Walber

Figure 3: Precision and Recall.

Additionally, a precision vs recall curve can be used to assess how precision and recall vary over different decision thresholds. The decision threshold is the value used as a cutoff for the probability of the class prediction. e.g. at a threshold of 0.5 a binary classifier would predict $\{\text{Label} = 1\}$, if the predicted probability of $\{\text{Label} = 1\}$ (given the data) is ≥ 0.5. Precision vs Recall curves were used to choose the sample ratio and threshold that gave the best precision. In this problem, it is more useful to have a 'cleaner' list of suspects of multi-account use (high precision), than it is to have a list of suspects that include all multi-account users and a potentially large number of false positives (high recall).

3 Results

3.1 Topics

Figure 4. shows the top 5 (of 100) topics computed using LSA for the ‘seen’ data. Within each topic, words of similar color can be thought of as being more related to each other, while diverging colors represent weaker word associations. The first topic in LSA is typically interpreted as the most frequent words across all topics in the corpus; subsequent topics are interpreted as salient groups of semantic relations. Topic 4 appears to be related to bitcoin wallets, addresses and private keys, as well as a diverging discussion related to Electrum wallets and passwords. Topic 3 on the other hand appears to be entirely related to tipping via changetip.

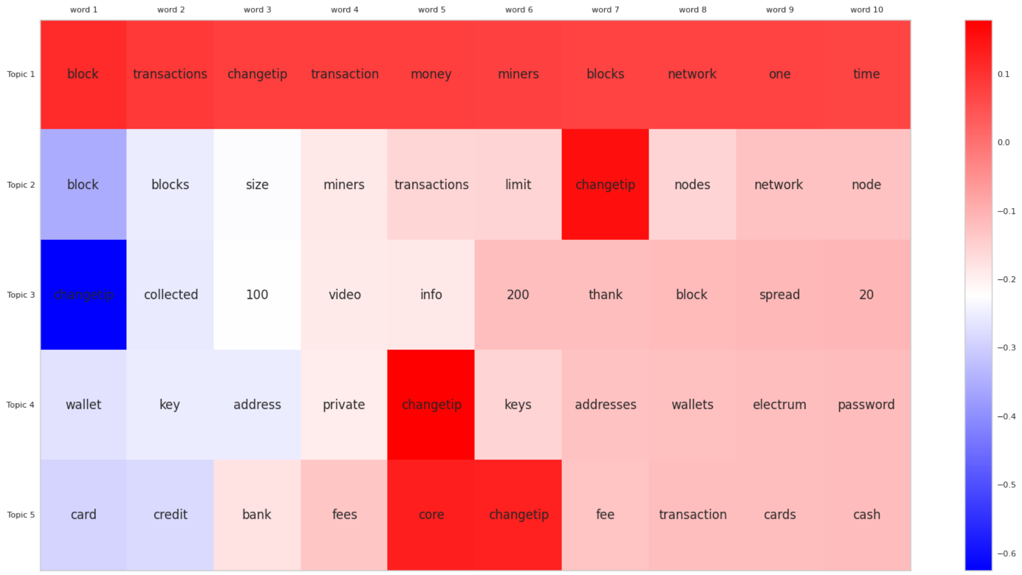

Figure 4: LSA topics for the ‘seen’ training data.

Topics from LDA did not produce as many meaningful results. This may be due to not using aggressive stop word removal. This was done to allow character 4-grams to capture more syntactic nuances. However, LSA appears to be extremely robust to lack of aggressive stop word removal. Overall, the 100 LSA topics captured around 24% of the variability in the ‘seen’ corpus.

Figure 5. shows the top 5 (of 100) topics using LSA on the ‘unseen’ data. As expected, there is a fair amount of overlap between topics in the ‘seen’ data (i.e. comments prior to June 2014) and the ‘unseen’ data. There are noticeable differences: Topic 5 represents trending discussions related to Counterparty, and core developers working on sidechains. Topic 4 seems suggests that over the last year, the Trezor device has become more popular.

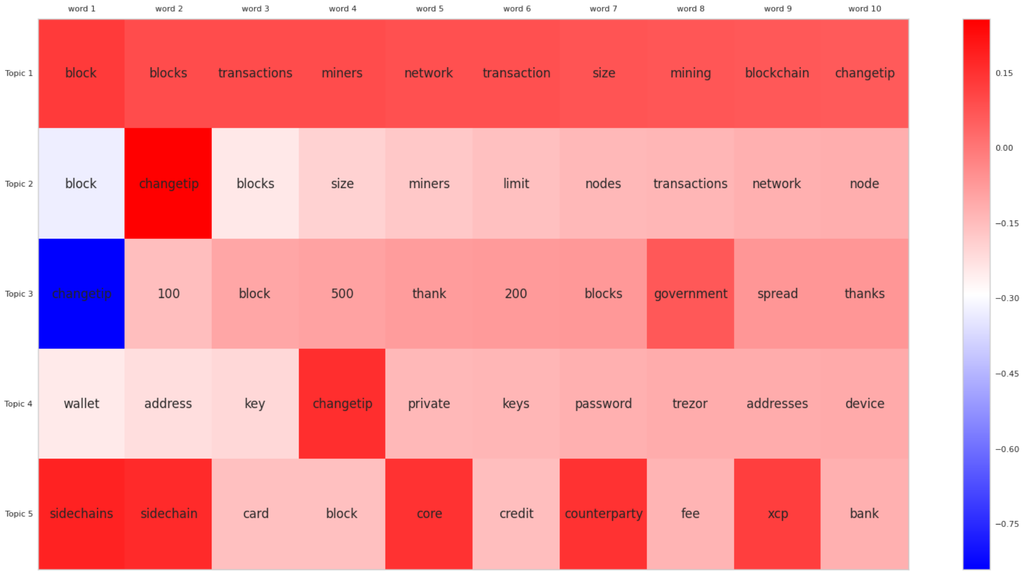

Figure 5: LSA topics for the 'unseen' data.

Each user's set of comments are represented as a linear combination of the 100 LSA topics, and in this way LSA can be used to represent what each user *tends* to talk about. As was the case with the 'seen' data, LDA did not lead to many meaningful topic words, however, LDA was still included as a feature for classification. The optimal number of topics for LDA were selected using the Arun measure (see [6] for more details). To ease the computation and storage constraints, the number of LSA topics were chosen as the minimum of 100 and the number of topics that explained 50% of the variation.

3.2 Classification Performance

As mentioned in Section 2., care was needed in designing training and test sets due to the class imbalance problem. Class $\{\text{Label} = 1\}$ represented less than 1% of the data, therefore a classifier that simply predicts $\{\text{Label} = 0\}$ for all test cases would achieve a prediction accuracy of over 99% if prediction accuracy is judged naively on a uniform sample of the test set. Similarly, training the classifier on a uniform sample of the training set would not give the classifier enough cases to learn the class $\{\text{Label} = 1\}$ effectively. To investigate the effect of class imbalance on prediction, the Random Forest classifier was trained on training samples with different ratios of $\{\text{Label} = 0\}$ to $\{\text{Label} = 1\}$. For each sample with sample ratio $= r$, all training cases with $\{\text{Label} = 1\}$ are chosen, and cases with $\{\text{Label} = 0\}$ are uniformly sampled such that:

$$n_r = \#\text{ of samples with } \{\text{Label} = 0\} \;\; = \frac{\#\text{ of observations with } \{\text{Label} = 1\}}{r}$$

Prediction accuracy was judged on a balanced test set with equal samples of $\{\text{Label} = 0\}$ and $\{\text{Label} = 1\}$.

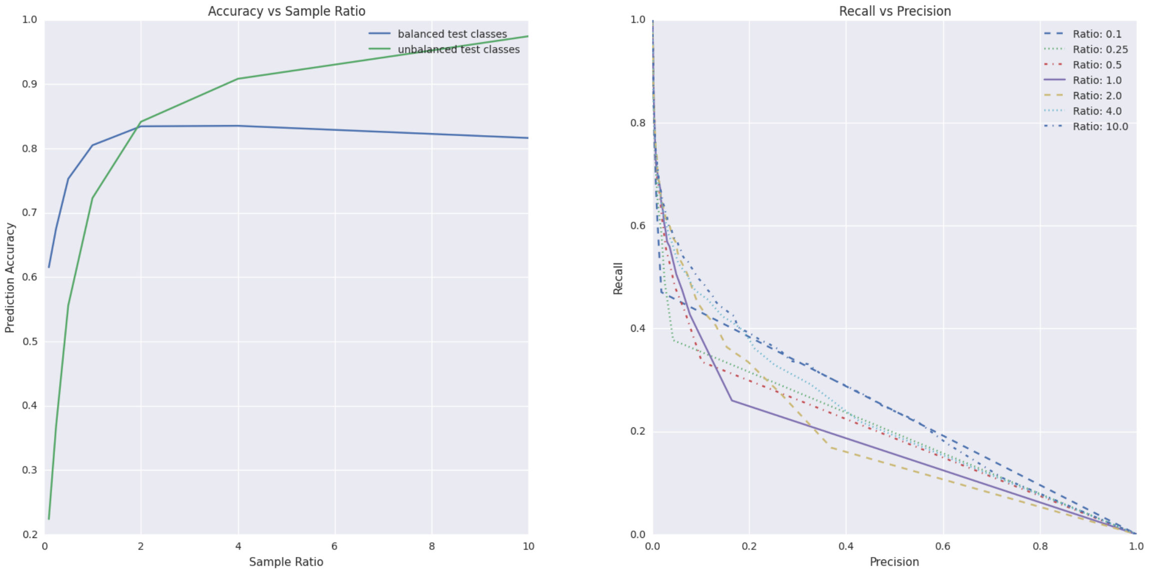

Figure 6: Prediction accuracy and Precision/Recall curves for ‘seen’ test data.

Figure 6. shows how prediction accuracy varies with the sample ratio, r, for balanced and unbalanced test classes. Prediction accuracy peaks around $r = 2$ on the balanced test samples. The monotonic improvement of the prediction accuracy on the unbalanced test classes may be due to seeing more training samples overall as r is increased. As mentioned in Section 2., the precision and recall measures are a better judge of performance in the context of this problem.

Sample Ratio	Best Precision	Recall	Threshold
0.1	0.019	0.470	0.99
0.25	0.043	0.377	0.99
0.5	0.103	0.335	0.99
1	0.165	0.260	0.99
2	0.370	0.168	0.99
4	0.428	0.220	0.99
10	0.722	0.110	0.99

Table 2: Best precision for each sample ratio.

Table 2. shows the best precision and corresponding recall and threshold for the sample ratios used. The classifier trained on samples with $r = 10$ gave the best precision of 0.72 at a threshold of 0.99. However, this was only able to retrieve approximately 10% of the relevant cases of multi-account use. Instead, the classifier selected for investigating the ‘unseen’ data was trained with $r = 10$, and a threshold of 0.96 was used for prediction. This gave a precision of 0.476 and recall of 0.250 on the ‘seen’ test sample. Therefore, this classifier can be expected to recover at most one quarter of the relevant cases of multi-account use in the ‘unseen’ data, with at most half of the recovered cases being actual instances of multi-account use. Appendix I. further discusses ranking cases of multi-account use to identify manipulation.

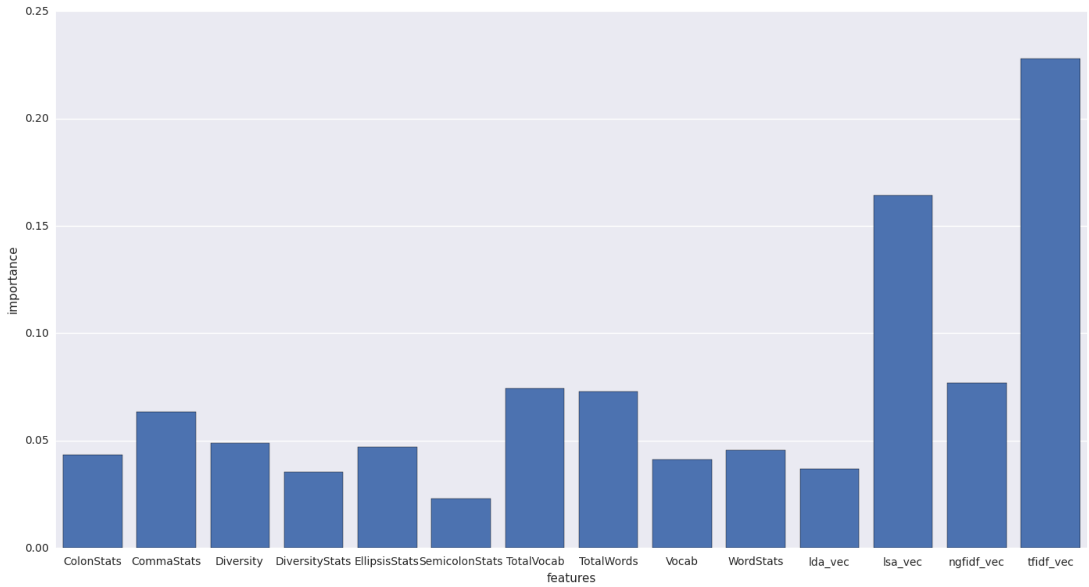

Figure 7: Feature importance scores for the Random Forest classifier.

Figure 7. shows the importance of each feature for discriminating between user accounts. The topical features were the most important judge of author similarity with the tf-idf transformed word frequency vector and the LSA topics being the most dominant. Character 4-grams and commas per sentence were the most important of the syntactic features.

4 Conclusion

The goal of the bounty was to identify manipulation of the block size debate from people using multiple accounts as 'sock puppets'. Objectively identifying instances of multi-account use gives a systematic way to approach the problem, by reducing the number of accounts that need to be further analyzed for manipulation. This analysis set out to detect multi-account use in the Reddit Bitcoin community by using topical features to represent what users talked about and syntactic features to represent their styles of writing. The resulting model suggested that topical features were the most important for discriminating whether two users are the same, but this may also be due to the setting of this problem. On Reddit, comments are usually at most a few sentences long and may not contain enough information in the syntactic features to discriminate between users effectively. Other syntactic features such as part of speech tags could be explored for efficacy, but were not in this analysis due to their high computational cost. Features that required statistical hypothesis tests to inform their similarity could also be improved by using permutation tests instead of a Welch t-test. This was not done because it would have required on $O(k \cdot m)$ computations on average; where $10 \leq k \leq 1000$ and represents the number of permutation tests required for a pair of profiles, and m is the number of pairwise comparisons for all user profiles — approximately 5×10^6 comparisons for the training data.

There is also room for improving the topic models, in particular the LDA model. Since many of the topical words in LDA were common, non-informative words, more aggressive stop word removal is likely to provide significant improvements. In practice, LDA generally performs better than LSA at detecting meaningful topics, but requires more effort to tune parameters and some subjectivity in choosing the number of topics. Non-parametric approaches such as the Hierarchical Dirichlet Process may provide improvements and less subjectivity.

In spite of these shortcomings, the classifier performed well on the discrimination task, with a peak accuracy of around 85% on the 'seen' class balanced test data. The classifier with 48% precision and 25% recall was chosen to recover as many relevant instances of multi-account use in the 'unseen' data without a large trade off in the quality of the results. Three probable cases of manipulation are discussed in Appendix I.

The true identity of Satoshi Nakamoto — the creator of bitcoin — remains an open question. An interesting direction for future work would be to use the techniques discussed in this analysis to identify probable candidates for Satoshi.

References

[1] Stamatatos, E. *A Survey of Modern Authorship Attribution Methods*

[2] Gomaa, W., & Fahmy, A. *A Survey of Text Similarity Approaches*

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[4] Deerwester, S., Dumais, S., Furnas, G.W., Landauer, T. K., & Harshman R. *Indexing by latent semantic analysis*

[5] Wallach, H. *Topic Modeling: Beyond Bag-of-Words*

[6] Arun, R., Suresh V., Veni Madhavan C. E. & Narasimha Murthy M. N., *On Finding the Natural Number of Topics with Latent Dirichlet Allocation: Some Observations*

5 Appendix I: Sock Manipulation

5.1 Ranking Manipulation

Applying the selected classifier to the 'unseen' data gave 321 pairs of users as suspects for multi-account use, over 373 unique users. Based on the classifier's precision on the 'seen' test data (0.476), this implies that at most 152 of these comparisons are true instances of multi-account use. To further investigate manipulation in the 321 suspect pairs, consider a mapping from each user to the set of users they were paired with, including the user themselves:

$$f : user_i \mapsto \{user_i\} \cup \{user_j | \forall user_j \text{ s.t. } (user_j, user_i) \text{ is a suspect pair}\}$$

This mapping along with Jaccard distance (see Appendix II.) can be used to score how related each pair of the 373 users are based on the users they have in common as suspect pairs:

$$pair\_score(user_x, user_y) = Jaccard\big(f(user_x), f(user_y)\big)$$

Under this score, a pair of suspected users who are part of no other suspect pair would have $pair\_score = 1$ and a pair of users who are not part of the same suspect pair, nor paired with common users would have $pair\_score = 0$

A number of reasonable assumptions could be made about the tendencies of users who use multiple accounts to manipulate threads on Reddit. For example, one could reasonably assume the accounts they control might have similar user names, or that the accounts are relatively new, or that they have a tendency to post around the same time of day. As reasonable as those may be, it is important to choose assumptions that are as objective as possible, and are not easily subverted by an attentive manipulator. So far this analysis has assumed that a manipulator would have a tendency to post in a similar syntactic and semantic style across multiple accounts, and that this can be discerned from the classifier we developed. It may also be reasonable to assume that a manipulator would have some tendency to post in the same threads using these multiple accounts. We can use Jaccard distance to score pairs of users based on the threads they have in common:

$$threads(user_i) = \{\text{set of all threads } user_i \text{ commented in }\}$$
$$thread\_score(user_x, user_y) = Jaccard\big(threads(user_i), threads(user_j)\big),$$

Based on these assumptions, suspect pairs were given a score which ranks their likelihood for manipulation:

$$rank\_score(user_x, user_y) = thread\_score(user_x, user_y) \cdot pair\_score(user_x, user_y)$$

The suspect mapping and sock puppet rankings are available in the project repository (suspect_dictionary.txt and sock_rankings.txt). It is hard to judge the quality of the results without having clear and irrefutable examples of manipulation. However, the ranked pairs include a few 'throwaway' accounts, some deleted accounts, and even a few account pairs that whose comments seemed to provide evidence of organized attempts at manipulation. Three selected pairs of suspects are discussed below.

5.2 Examples of Probable Manipulation

The following are three cases of manipulation found in sock rankings. They discuss:

1. a false positive case of manipulation
2. a case of manipulation for support
3. a case of manipulation for hostility

5.2.1 (PrimeDice, BitsByDre)

To show the shortcomings of the analysis: this pair received a high manipulation ranking, but turned out to be an obvious false positive on further investigation. These users appear to be dedicated tipping accounts. They would have been classified as the same user since all of their comments include words that engage the *changetip* tipping bot (e.g. "changetip", "bits", "sent" etc.). This would explain the high pair_score they received. The high thread_score may be due to their activity in the weekly bitcoin tipping threads. Although this is an extreme example, it demonstrates that even with the manipulation ranking, the analysis is still highly susceptible to false positives and one should not draw naive conclusions from the results.

5.2.2 (la0ban, MemoryDealers)

MemoryDealers is a known Reddit account of Roger Ver — a Bitcoin investor and well known bitcoin personality. He has used it to post on several bitcoin related threads and on other subreddits. On the other hand, *la0ban* seems to be a relatively new and unknown account. la0ban has been very active in threads related to the scandal between Roger Ver and OKCoin, and the content of la0ban's comments suggest it is someone who is privy to more information than the average Bitcoin sub-reddit poster. la0ban's posts unusually supportive of Roger Ver, and one could even go as far as saying that most of la0ban's comments have an agenda that is seemingly in-line with Ver's.

The ranking identified this as a probable case sock manipulation, and we are inclined to agree given the nature of the comments. Less rigorous support can be discerned from the name "laoban" — a Mandarin word, and popular restaurant in Singapore. The fact that Ver is frequently in Asia, and recently traveled to Singapore for a bitcoin conference is interesting, but certainly a stretch as far as reasonable evidence is concerned.

5.2.3 (throwawaybecausemod2, treeorsidechains); KeiserProfile

Apart from the fact that *throwawaybecausemod2* seems to be a 'throwaway' account by name, all three accounts have been active on threads related to Peter Todd — a Bitcoin consultant and well known community member. They typically made comments that are critical of Todd, and at times even hostile towards him. The pair ('throwawaybecausemod2, 'treeorsidechains') received a high ranking but they were also related to the user account KeiserProfile in the suspect pairs from classification. These accounts are all fairly new, and can be interpreted as having similar agendas related to Peter Todd. It is therefore probable that they represent cases of sock manipulation.

If we can reasonably say that examples 5.2.2 and 5.2.3 represent probable cases of sock manipulation, then it is likely that there are more cases in the suspect pairs from classification. Furthermore, since the classifier was shown to recover at most 25% of all relevant instances of multi-account use, it is likely that there are even more cases of manipulation that went unaccounted for. Therefore, guided by the results of this analysis, it is our opinion that there is evidence of sock manipulation on the Bitcoin Reddit, including threads related to the block size debate.

6 Appendix II: Similarity Measures

- Cosine similarity:

$$\text{cossim}(\mathbf{x},\mathbf{y}) = \frac{\mathbf{x}\cdot\mathbf{y}}{\|\mathbf{x}\|\|\mathbf{y}\|} = \frac{\sum\limits_{i=1}^{n} x_i \times y_i}{\sqrt{\sum\limits_{i=1}^{n}(x_i)^2} \times \sqrt{\sum\limits_{i=1}^{n}(y_i)^2}}$$

  where

$$\mathbf{x} = (x_1, x_2, \ldots, x_n)$$
$$\mathbf{y} = (y_1, y_2, \ldots, y_n)$$

- Jaccard similarity:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

  and

$$A = B = \emptyset \Rightarrow J(A,B) = 1$$

- Generalized Jaccard similarity:

$$J(\mathbf{x},\mathbf{y}) = \frac{\sum_i \min(x_i, y_i)}{\sum_i \max(x_i, y_i)}$$

  where

$$\mathbf{x} = (x_1, x_2, \ldots, x_n)$$
$$\mathbf{y} = (y_1, y_2, \ldots, y_n)$$

- Hellinger distance (discrete):

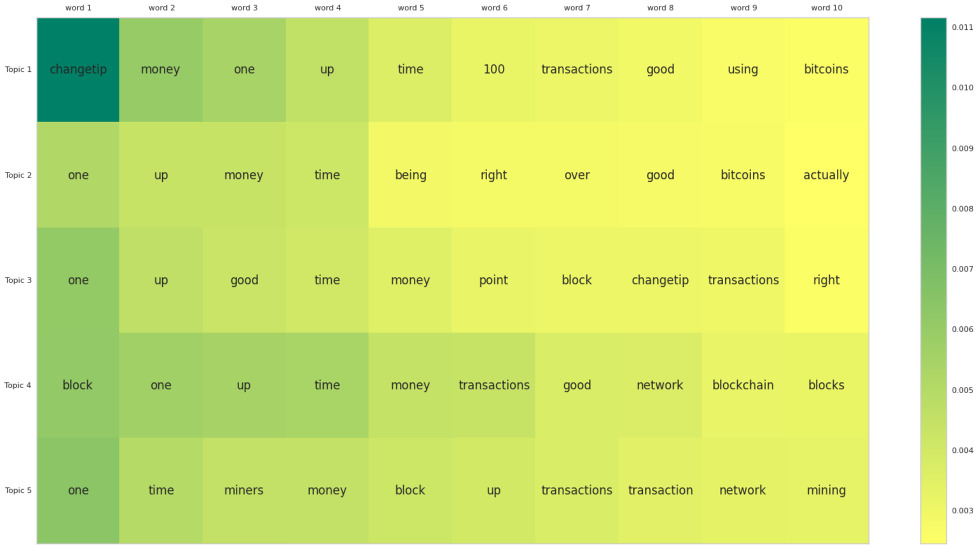
$$H(P,Q) = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{k}(\sqrt{p_i} - \sqrt{q_i})^2}$$

where P and Q are discrete probability distributions such that:

$$P = (p_1, \ldots, p_k)$$
$$Q = (q_1, \ldots, q_k)$$

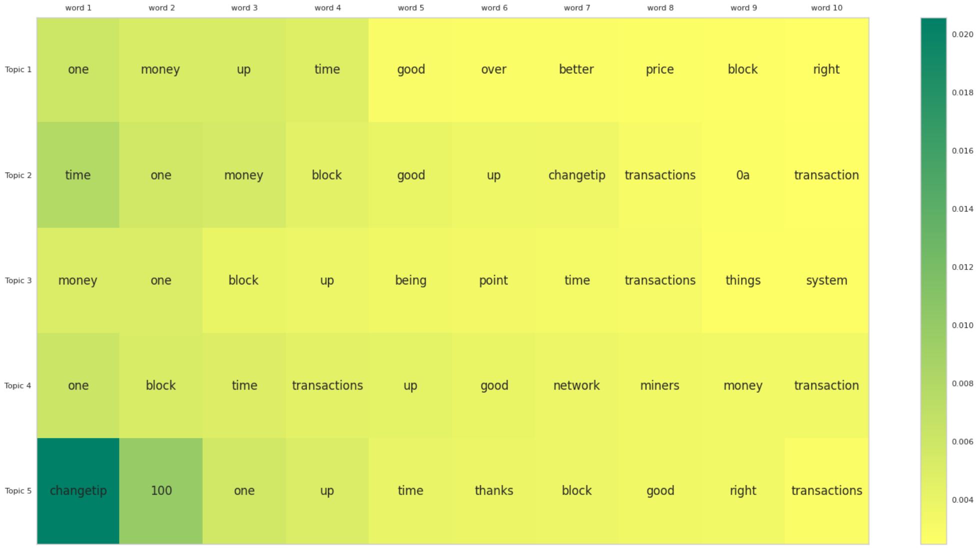
7 Appendix III: LDA Topic Words

7.1 Top 5 LDA topics for 'seen' data



	word 1	word 2	word 3	word 4	word 5	word 6	word 7	word 8	word 9	word 10
Topic 1	changetip	money	one	up	time	100	transactions	good	using	bitcoins
Topic 2	one	up	money	time	being	right	over	good	bitcoins	actually
Topic 3	one	up	good	time	money	point	block	changetip	transactions	right
Topic 4	block	one	up	time	money	transactions	good	network	blockchain	blocks
Topic 5	one	time	miners	money	block	up	transactions	transaction	network	mining

7.2 Top 5 LDA topics for 'unseen' data



	word 1	word 2	word 3	word 4	word 5	word 6	word 7	word 8	word 9	word 10
Topic 1	one	money	up	time	good	over	better	price	block	right
Topic 2	time	one	money	block	good	up	changetip	transactions	0a	transaction
Topic 3	money	one	block	up	being	point	time	transactions	things	system
Topic 4	one	block	time	transactions	up	good	network	miners	money	transaction
Topic 5	changetip	100	one	up	time	thanks	block	good	right	transactions

8 Appendix IV: Data Gathering

See the project repository (`https://github.com/aehaynes/reddit_authorship`) for the files mentioned below.

1. The top 200 matching threads for keywords in keywords.txt (one search per keyword), were retrieved for each of the following sort conditions: relevance, top, hot, new. For example, for the keyword "blocksize":

   $$Search\_Results = \bigcup \{search\_results_1, ..., search\_results_4\}$$

   where

   $$\begin{aligned} search\_results_1 &= search(\text{“}blocksize\text{”}, sort\_by = top) \\ search\_results_2 &= search(\text{“}blocksize\text{”}, sort\_by = hot) \\ search\_results_3 &= search(\text{“}blocksize\text{”}, sort\_by = new) \\ search\_results_4 &= search(\text{“}blocksize\text{”}, sort\_by = relevance) \end{aligned}$$

   Summary:

   Input: keywords list (keywords.txt)
   Output: submission id's for matching threads (submission_id.pkl)

2. Given a set of submission id's, main.py fetched all comments from the corresponding threads and stored the comments in a sqlite database.

   Database schema: (update this to actual variable names)

   See info_db.py for full schema. The database includes:

   - submissionId: reddit submission id
   - commentId: id for comment in question (= submissionId if original post comment)
   - parentId: commentId of parent comment (= submissionId if top level comment i.e. not a nested comment)
   - author: username of comment author
   - title: title of the thread
   - timestamp: UTC timestamp of when comment was made
   - upvotes: number of upvotes
   - downvotes: number of downvotes

   Summary:

   Input: submission id's (submission_id.pkl)
   Output: database of comments from the threads with corresponding submission id (redditDB.sqlite)