Deanonymizing Bitcoin

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Abstract

.....Graph approaches are better becuase they can use features that represent physical properties.....whatever....sailing is chill.

1 Introduction

Since several years ago, we have lived in the epoch of crytocurrency: decentralized, digitial forms of payment with encryption at their cores. Its adoption was catalyzed by a clever solution to the double-spending problem (the use of the same currency for multiple transactions): Bitcoin [**?**]. A public ledger (blockchain) hashes and stores every transaction made with the currency. Its allure and subsequent popularity, however, is perhaps attributed to its anonymity. Transactions never demand the identification of either the vendor or customer. Hence increased privacy concerns in our daily lives have driven the rise of Bitcoin. One side effect is the security it provides to criminals including, for example, sellers of illicit goods (Silk Road [**?**]), and hackers (Ransomware [**?**]). Authorities may therefore seek ways to undermine the privacy granted by bitcoin in efforts against such threats.

One approach is identification of latent structure within the available bitcoin transaction data. While actual names are not recorded, the blockchain tracks spenders and recievers through addresses linked their virtual wallets. Patterns can be extracted from these entries (e.g. an address that conistently recieves payments is likely an organized vendor). This paper uses machine learning techniques to make predictions of transactions by training on a one-year time interval of blockchain data, and hence tests the viability of different algorithms to identify underlying information in massive yet sparse datasets.

2 Data and Methods

Our dataset consists of pairs of sending and receiving addresses and the number of interactions between them over a time span from March 2012 to March 2013 (corresponding to blocks 170000 to 225000). There are 444,075 addresses and 3,348,026 recorded pairs. The number of possible transactions ($\sim 2 \times 10^{11}$) yields a sparsity of $\sim 10^{-5}$. We seek to train our models on this data to predict whether a pair of addresses will have a transaction in the future. We take two distict approaches. The first is factorization of the blockchain sparse matrix, which lets us identify eigenvalues representative of the strongest transaction patterns. The second is a graph-based analysis, in which we derive features from nodes and edges corresponding to addresses and transactions. These are two prominent and well-studied techniques, and therefore serve as the foundation of our analysis.

2.1 Matrix Factorization Methods

Factorization (Decomposition) of a matrix involves numerically approximating it as a product of two or more matrices which contain feature information. One may set a small number of features to significantly reduce dimensionality of the component matrices, which is extremely useful since it extracts the strongest latent signals from otherwise noisy data and improves prediction accuracy. We test two decomposition models that support sparse matrices. **Singular Value Decomposition** (SVD) determines three component matrices. The outer two are unitary and are comprised of basis vectors. The central one is diagonal and contains the singular values. **Non-negative Matrix Factorization** (NMF) assumes a non-negative input matrix, and determines two constituent matrices by minimizing the Frobenius norm [**?**]. Thus vectors are always superpositions of the components. These models are summarized in Figure 2.

2.2 Graph Feature Extraction

An entirely separate approach to the data involved extraction of a number of features from the directed-graph representation of the blockchain. Using the python graph-processing package NetworkX [**?**], each transaction in the training data was modeled as a directed edge from the node representing sending address to the node of the receiver, with the number of transactions stored as an attribute of the edge. A subset of the graph can be seen visualized in Figure 4. A number of features were then extracted from this graph to simulate the two classes of address pairs: that is future transaction or no future transaction.

To simulate a pair in the no-transaction (negative) class, two random addresses were selected at random, repeating the selection if they already had a directed edge between them. Then using the methods from NetworkX, the following features were compiled: out-degree of the sending address, in-degree of the receiving address, total number of transactions of each address, and the length of the shortest directed path between the two. The positive class was simulated by selecting a transaction from the training list at random, and temporarily removing the directed edge from the graph, then computing the same features without the transaction in question, and re-adding the link before computing another pair. Promisingly, histograms for these features tended to segregate the two classes noticably, as seen in Figure **??**. These features were calculated for one hundred thousand random pairs, keeping the class-priors consistent with the inflated test data: 10% positive and 90% negative. The same features calculated above were calculated for each pair of addresses in the test set.

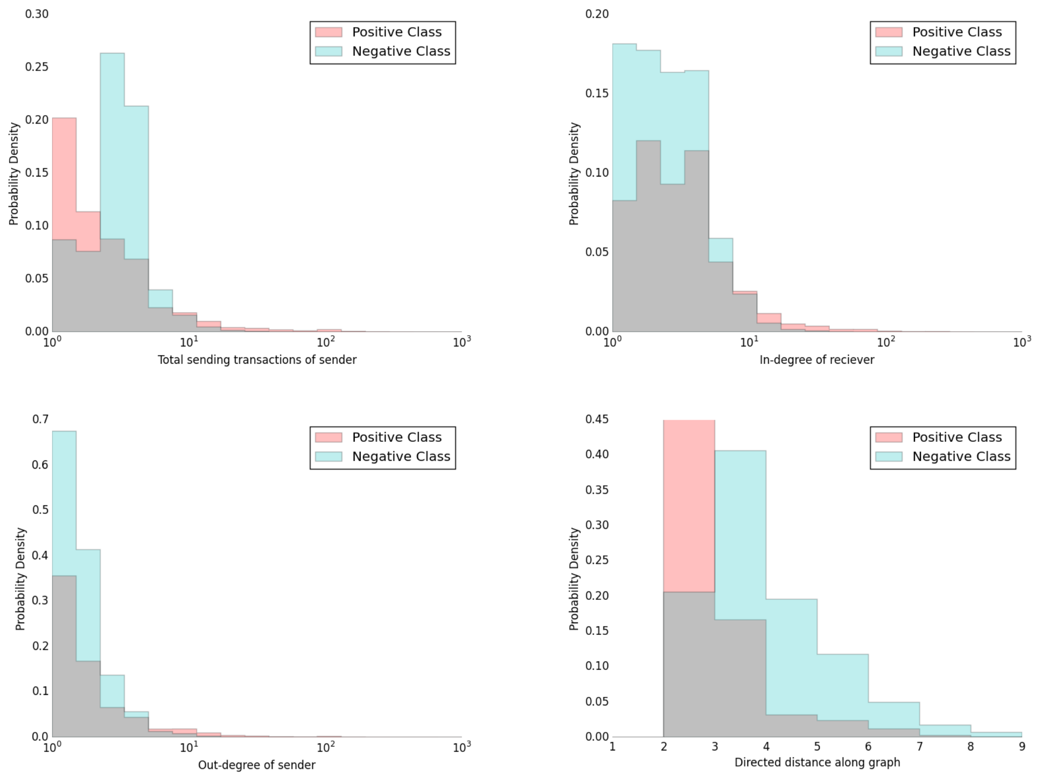


Figure 1: Histogram of graph-based features computed on the transaction network

2.2.1 Classification Methods

Several models were trained on the binary classification task using the compiled feature vectors.

- **Random Forest**
- **Multinomial Naive Bayes**

3 Results

3.1 Decomposition True Positive Rates

Here we present the performance of our two matrix decomposition methods, SVD and NMF. We also compare them against 'Random,' in which the component matrices are randomly generated with elements in [0, 1]. Both of the decomposition methods perform much better than the random case, as summarized in Figure 2. NMF performs the best consistently, perhaps because of the non-negative assumption. It successfully identifies transactions at a true positive rate of 0.51, with an erroneous false positive rate of only 0.1. Both models however are far from optimal binary classification (a point at FPR = 0, TPR = 1).

Name	Formula	N_{comp}	tol	ROC	$\text{TPR}_{\text{FPR}=0.1}$
SVD	$\mathbf{X} = \mathbf{USV}$	10	10^{-10}	0.64	0.39
NMF	$\mathbf{X} = \mathbf{WH}$	20	10^{-10}	0.74	0.51
Random	$\mathbf{X} = \mathbf{R}^1\mathbf{R}^2$	10	N/A	0.50	0.10

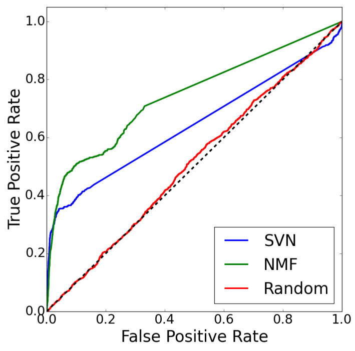
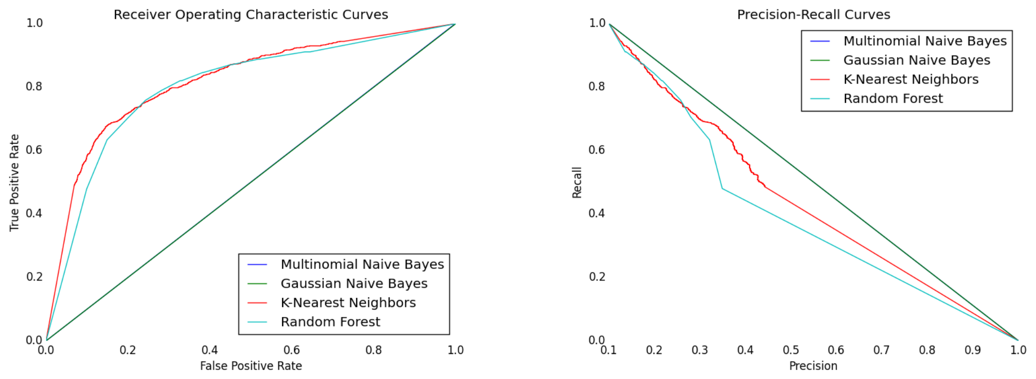


Figure 2: Properties of matrix decomposition models including name, formulation, number of components (reduced dimension), and tolerance level. Also performance including ROC area and true positive rate with at most 0.1 false positive rate. Parameters were chosen for a balance of run-time and accuracy.

3.2 Graph Classifier Performance



Model:	Gaussian Naive Bayes	Multinomial Naive Bayes	K-Neighbors	Random Forest
ROC Area	0.500	0.501	0.818	0.801
P-R Area	0.550	0.550	0.489	0.453

Figure 3: Performance of binary classifiers trained on graph features.

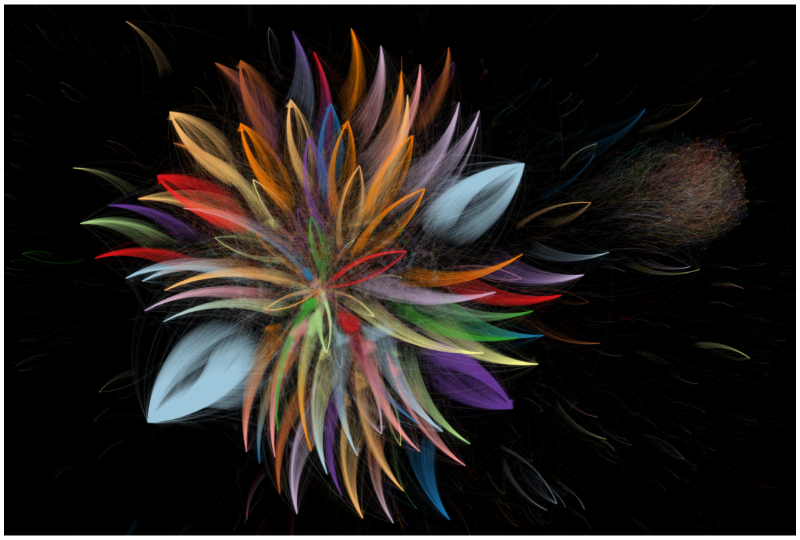


Figure 4: Visualization of 50000 randomly selected transactions. The most active nodes are clearly visible. Connections between these hubs and smaller nodes provide the basis for our graph analysis.

4 Discussion and Conclusion

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