Identifying Financial Institutions by Transaction Signatures

Noa Haas
Intuit
noa_haas@intuit.com

Shimon Shahar
Intuit

Yair Horesh
Intuit

Yehezkel S. Resheff
Intuit

ABSTRACT

Financial data aggregators and Personal Financial Management (PFM) services are software products that help individuals manage personal finances by collecting information from multiple accounts at various Financial Institutes (FIs), presenting data in a coherent and concentrated way, and highlighting insights and suggestions. Money transfers consist of two sides and a direction. From the perspective of a financial data aggregator, an incoming transaction consists of a date, an amount, and a description string, but not the explicit identity of the sending FI. In this paper we investigate supervised learning based methods to infer the identity of the sending FI from the description string of a money transfer transaction, using a blend of traditional and RNN-based NLP methods. Our approach is based on the observation that the textual description field associated with a transaction is subjected to various types of normalizations and standardizations, resulting in unique patterns that identify the issuer. We compare multiple methods using a large real-world dataset of over 10 million transactions.

KEYWORDS

Personal Finance, Financial Data Aggregators, Transactional Data Analysis

1 INTRODUCTION

Personal financial management (PFM) services and financial aggregators are software applications that collect and bring together information from multiple sources to provide users with a single stop shop for tracking and managing their personal finances [3]. For individuals with multiple bank accounts, credit cards, and utility bills, seeing the big picture and gaining insights into their financial health can be incredibly valuable. Indeed, services of this sort are used by millions of people in the US alone [2].

The rest of the paper is structured as follows: Section 2 contains a precise problem definition. Next, in Section 3 the methods are presented, followed by results on a large real-world dataset in Section 4.

2 PROBLEM DEFINITION

We formalize the problem as the recovery of the identity of the formatter program running by the transaction issuer. Consider a transaction $T$ with a set of attributes $\{a_i(T)\}$. The issuing formatter $f_s$ running by the sending FI is a mapping from $A_s \subset \{a_i(T)\}$ to a string. The receiving formatter $f_r$ running by the receiving FI is a mapping from the received string and $A_r \subset \{a_i(T)\}$ to the final description string we observe. Thus, we observe the string:

1 This information is often available to the customer in the online bank account display, but is not obtained by the PFM due to technical issues.
Table 1: Examples of the money transfer transactions and their description by the receiving entities. A small percent of transactions include the sender financial institute explicitly (oversampled here and shown in bold), the rest we attempt to infer from the structure of the string. Numbers and other identifying or private information is censored using Xs.

| date       | amount | from            | to              | description on receiving end                                      |
|------------|--------|-----------------|-----------------|------------------------------------------------------------------|
| 11.01.16   | 1,000$ | Bank of America | Bank of America | Online Banking transfer to SAV XXXX Confirmation# XXXX             |
| 12.01.16   | 1,000$ | Bank of America | Chase           | Online Transfer XXXX fromBoF main account #XXXX XXXX t            |
| 01.01.17   | 1,000$ | Chase           | Wells Fargo     | CHASE EPAY XXXX XXXX <Sender Name>                               |
| 02.01.17   | 1,000$ | Wells Fargo     | Bank of America | Payment                                                          |
| 03.01.17   | 1,000$ | ING direct      | Chase           | CAPITAL ONE N.A. CAPITALONE XXXX WEB ID: XXXX                    |

\[
 f_r(f_s(A_s), A_r) \triangleq \Pi_{s \neq r}(T)
\]

From an in-depth exploration of the data we conclude that the \( f_r \) formatters leave much of the structure produced by \( f_s(A_s) \) intact. Furthermore, we observe that transactions originating from difference FIs have uniquely identifying patterns, albeit this is a many-to-one relation (see Table 1).

Given many transaction strings \( \Pi_{s \neq r}(T) \) our goal is to recover the pairs \((s_i, r_j)\) of the sending and receiving formatters that produced them. Note that since one side of the transaction is known (this is the financial institute in which we saw this transaction), we only need to infer the other side of the transaction. In this paper we concentrate on incoming transactions, where \( r \) in known, and infer \( s \) from the transaction strings.

### 3 METHODS

#### 3.1 Generating the Labeled Dataset

Data used for this work was collected by a large financial data aggregation service. During registration, users provide credentials that allow us to continuously obtain transaction data from over 25,000 financial institutions including banks and credit card companies. A record describing a transaction typically contains the date of the purchase, a dollar amount, and a description string explaining the nature of the transaction. Overall, available data contains over 15 billion transactions per year, arriving from over 10 million users. This represents several percent of all private transactions in the US.

In our experiments, we use slices of this data pertaining to money transfer between known financial institutes. All experiments were conducted with data from the year starting November 2016.

In order to generate a labeled dataset of transactions between known financial institutes we use transactions for which both sides are visible to the data aggregation service. More specifically, we concentrate on transactions where both the source and the destination are within the same user account. In such cases we are able to obtain the identity of both financial institutes, as well as the descriptions produced by both of them.

The labeled dataset obtained this way contains 10.87 million records, from 88,000 users. Each record consists of the name of the sending and receiving financial institute, a dollar amount and date, and the description of the transaction as recorded both by the sender and the receiver (see illustrative examples in Table 1). Experiments reported here were conducted using a random sample of 500,000 records from this dataset.

### 3.2 Tokenization, Feature Crafting, and Models

Description strings were tokenized using a standard (NLTK [1]) tokenizer, limited to a dictionary of size 10,000. No text pre-processing was performed, other than replacing digits with Xs (this was done so that tokens representing number lengths would be formed to replace individual numbers).

In addition to the tokenized representation of the description strings, additional hand-crafted features describing textual patterns that are not expressed as token were computed. These features include indicators (ex. is all the string upper case?), and more complex regular expression patterns found to be useful for this task.

We compare the following classification methods and baselines:

- **max-label baseline**: as a baseline for all other methods we use the proportion of data from the largest FI in the set under consideration.
- **logistic-raw**: logistic regression on the distribution of tokens only.
- **logistic-features**: logistic regression with the additional computed features and the raw token distributions combined.
- **LSTM/GRU**: The model structure for all RNN based methods used here consists of a token embedding layer (in all cases the embedding size is 20), followed by a single LSTM or GRU layer. The final output of the RNN is then fed into a cascade of 2 dense layers, and a softmax readout of the identity of the financial institute. In the RNN setting only the tokenized sequence is used (with no hand-crafted features). Description string length was limited to 20 tokens (longer ones were truncated).

#### Table 2: Accuracy of the various methods tested in prediction of financial institute from transaction description. Columns show results when limiting to the most common 10 / 100 / 1000 FIs.

| Method            | 10-class | 100-class | 1000-class |
|-------------------|----------|-----------|------------|
| Baseline-max      | 28.80    | 20.51     | 16.90      |
| Logistic-raw      | 82.01    | 72.72     | 67.47      |
| Logistic-features | 82.47    | 73.26     | 68.04      |
| LSTM              | 99.13    | 90.81     | 84.15      |
| GRU               | 99.11    | 90.72     | 84.13      |
4 RESULTS AND DISCUSSION

In an exploratory phase, we examined the manner in which the distribution of tokens in descriptions reflects the relations between financial institutes in the US. After tokenization we observed the association between financial institutes as pairwise distances with respect to token distribution. Plotting a clustered heatmap of these distances (see figure 1) reveals that the textual data is useful in revealing associations between different banks.

For example, the token distribution seems to easily capture the relatedness of different branches or divisions of the same bank, as in the case for Citibank and Chase bank (including Amazon award visa which Chase operates). This view of the data also surfaced mergers and acquisitions in the FI market, such as Capital One’s acquisition of ING Direct division. Finally, we learned that the descriptions may also generate geographical attributes, as demonstrated by the moderate similarity between CIBC and National Bank of Canada, which are two distinct institutes. The later observation raises the potential of learning more characteristics of financial institutes through their transaction descriptions. This might also imply a limitation on the

learnability of the mapping from description strings to FIs. More precisely, it indicates that we are likely to have to rely on structure and deeper features of these strings, and not just the distributions of tokens. This notion is reinforced by the results presented below.

We test multiple methods for determining the identity of the financial institute from which a transaction originated based on the description of the transaction (See section 3 for data and model details). Experiments show overall satisfactory results, with classification accuracy ranging from over 99% when only the top 10 FIs are considered to approximately 84% for the top 1000 (Table 2). In all cases the LSTM based classifier outperformed all other methods, followed closely by the GRU (It is noteworthy that the logistic regression operated on single token distributions and manually crafted features. Multi-grams were not tested for computational reasons). The vast superiority of both RNN based methods (which operate on the raw token sequences) over the logistic regressions which are not able to take the order of tokens into consideration indicates again that the structure of the description string has an

Figure 1: A clustering of FIs based on distance between token distribution in description strings.
important role in determining the identity of the source FI, and not just the actual tokens used.

Since the experiments presented in this paper are conducted on a subset of the available data, we test to determine the sensitivity of the classification results to the amount of training data used. Results for the LSTM based method in the 200 FI setting (Figure 2) show that performance reaches a plateau at 60% - 100% of the data used in practice, indicating that the use of additional data would be unlikely to achieve better results. We do not however rule out the possibility of utilizing the full amount of data available with more complex models, or when classifying a larger number of FIs, and leave this to future work.

Next we test the trade-off between the number of FIs we classify and classification performance. The US banking system is comprised of tens of thousands of institutions with a long tail distribution of number of customers. In the data used for these experiments the top 10 institutions are responsible for approximately 50% of all transactions, and the top 1000 for approximately 95%. The decline in performance in the LSTM based method as additional FIs are added follows this structure closely (Figure 3), with a reduction from 99.13% with 10 FIs to 90.81% for 100. The decline then slows down, and reaches 84.15% with 1000 FIs.

5 CONCLUSION

Understanding the source and meaning of transactions is a key component in the ability of financial data aggregators and personal financial management systems to deliver value through deep insights and suggestions. Money transfers are an especially important type of transaction, but the identity of the sending financial institute is not readily available in PFM aggregators systems.

In this paper we investigate the problem of supervised learning of the identity of a sending financial institute from the description string provided by the receiver. Using word embeddings, RNNs and other methods borrowed from NLP we are able to achieve excellent accuracy on this task, possibly limited only by the multiplicity of banking brands within the same family of banks. Interestingly, RNN methods with the ability to process the order of tokens in the transaction strings vastly outperform linear methods (even when additional hand-crafted features were added to the latter). This finding further supports our original hypothesis that the structure of these strings is tied to issuing FIs, and not merely the distribution of tokens.

Future work will attempt to enrich the information regarding incoming money transfers beyond the identity of the sending FI by utilizing and extending the methods presented in the current work to recover the structure of description strings and extract the attributes of the transaction embedded within them.

REFERENCES

[1] Steven Bird and Edward Loper. 2004. NLTK: the natural language toolkit. In Proceedings of the ACL 2004 on Interactive poster and demonstration sessions. Association for Computational Linguistics, 31.
[2] James R Green and Annette E Craven. 2017. Account Aggregation Tools: History and Use for the Future. Academy of Business Research Journal 1 (2017), 74.
[3] Vipul Gupta, Sameer Khanna, and Iljoo Kim. 2014. Personal Financial Aggregation and Social Media Mining: A New Framework for Actionable Financial Business Intelligence (AFBI). International Journal of Business Intelligence Research (IJBIR) 5, 4 (2014), 14–25.
[4] Mandy Korpusik, Shigeyuki Sakaki, Francine Chen, and Yan-Ying Chen. 2016. Recurrent Neural Networks for Customer Purchase Prediction on Twitter. In CBRecSys@ RecSys. 47–50.
[5] Nut Limsoopatham and Nigel Henry Collier. 2016. Bidirectional LSTM for named entity recognition in Twitter messages. (2016).
[6] Yehezkel S. Resheff and Moni Shahar. 2018. Fusing Multifaceted Transaction Data for User Modeling and Demographic Prediction. In Workshop on Multi-dimensional Information Fusion for User Modeling and Personalization. ACM.
[7] Yehezkel S. Resheff and Moni Shahar. 2018. A Statistical Approach to Inferring Business Locations Based on Purchase Behavior (2018). Manuscript submitted for publication.
[8] An-Zi Yen, Hsin-Hsien Huang, and Hsin-Hui Chen. 2018. Detecting Personal Life Events from Twitter by Multi-Task LSTM. In Companion of the The Web Conference 2018 on The Web Conference 2018. International World Wide Web Conferences Steering Committee, 21–22.