Temporal Motifs for Financial Networks: A Study on Mercari, JPMC, and Venmo Platforms

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Abstract. Understanding the dynamics of financial transactions among people is critical for various applications such as fraud detection. One important aspect of financial transaction networks is temporality. The order and repetition of transactions can offer new insights when considered within the graph structure. Temporal motifs, defined as a set of nodes that interact with each other in a short time period, are a promising tool in this context. In this work, we study three unique temporal financial networks: transactions in Mercari, an online marketplace, payments in a synthetic network generated by J.P. Morgan Chase, and payments and friendships among Venmo users. We consider the fraud detection problem on the Mercari and J.P. Morgan Chase networks, for which the ground truth is available. We show that temporal motifs offer superior performance to several baselines, including a previous method that considers simple graph features and two node embedding techniques (LINE and node2vec), while being practical in terms of runtime performance. For the Venmo network, we investigate the interplay between financial and social relations on three tasks: friendship prediction, vendor identification, and analysis of temporal cycles. For friendship prediction, temporal motifs yield better results than general heuristics, such as Jaccard and Adamic-Adar measures. We are also able to identify vendors with high accuracy and observe interesting patterns in rare motifs, such as temporal cycles. We believe that the analysis, datasets, and lessons from this work will be beneficial for future research on financial transaction networks.

1 Introduction

Financial relationships become increasingly important in today's society. The quick development of online payment services, such as Apple Pay, PayPal, Stripe,

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and Venmo, has revolutionized people's daily financial activities. Online payment services have become the most widely used payment method and generate a tremendous amount of transactions every day. Critical applications, such as fraud detection, anti-money laundering, and link prediction, require a thorough understanding of the dynamics in financial transaction networks in various media.

One key characteristic of financial transactions is temporality. The order of transactions, time differences, and the way those appear within the graph structure can offer crucial insights. Temporal motifs, defined as a set of nodes that interact with each other in a short time period, are shown to be a powerful tool in this context [21,22,16,30,10,25]. Temporal motifs are used in various domains such as communication networks [39], trading [4], human contact networks [38], and others [7,8,13,17,18,35].

In this work, we study fraud detection, link prediction, and node classification problems by using temporal motifs on three novel temporal financial networks:

- **Transactions in Mercari, an online marketplace.** We build the consumer-to-consumer online marketplace network of Mercari, which is one of the largest e-commerce platforms in Japan. We obtain the network through personal correspondence. An event (u, v, t) denotes that user u sells an item to user v at time t. It is illegal to sell certain items, such as weapons, medicine, and used underwear, and the sellers of those items are marked as fraudulent users.
- **Payments in a synthetic network generated by J.P. Morgan Chase (JPMC).** We consider a synthetic payment network generated by JPMC [3], obtained via personal correspondence. The network preserves many unique features observed in the real transactions and has been used for JPMC internal research. Importantly, each transaction contains a monetary amount information and marked as licit or fraudulent. A user is a fraudster if s/he receives at least one fraud payment.
- **Payments and friendships among Venmo users.** We identify 600 most active users in a public dataset of seven million Venmo transactions [28] and collect the transaction history of these users using the Venmo API. We also collect the friendship relations among all the users. Each transaction comes with the IDs of sender and receiver, the timestamp, and a payment note.

We study fraud detection on the Mercari and JPMC networks using temporal motifs from one-hop egocentric networks. Each user is represented by a feature vector based on motif counts. Using logistic regression, SVM, random forest, and XGBoost, we show that temporal motif features outperform baselines—simple graph features [14], LINE [31], and node2vec [9]—reaching up to 0.89 AUC on Mercari and 0.82 on JPMC. On Venmo, we explore friendship prediction, vendor detection, and temporal cycles. Motif-based features outperform heuristics in predicting friendships. For vendor detection, we manually label users and release the dataset. We also identify rare cyclic patterns ($A \rightarrow B \rightarrow C \rightarrow A$) linked to behaviors like poker games. Our results and datasets offer valuable insights for future research.

Our contributions can be summarized as follows:

- We study three novel financial transaction networks, Mercari, JPMC, and Venmo, which are a diverse set of media for financial activities.
- We utilize temporal motifs for fraud detection on the Mercari and JPMC networks where the fraud activity is defined differently.
- We investigate the interplay between financial and social relationships on the Venmo network by using temporal motifs. We consider friendship prediction and vendor identification problems, and also analyze temporal cycles.
- We release financial transactions, friendships, and vendor labels for Venmo network, and also share the codes at `https://github.com/erdemUB/ASONAM25`.

Remark. We conduct experiments on three datasets: Mercari, JPMC, and Venmo. These data are acquired from real-world financial systems and may reveal the financial activities of users. To address this potential risk, all user identities of the Mercari and JPMC data have been encrypted by the corresponding owner companies prior to our use. We are not able to share the Mercari and JPMC datasets but we are releasing the Venmo network. Although Venmo transaction information is publicly available to anyone by the default user settings, we anonymized the users' names and IDs to prevent potential leakages of user information.

2 Related Work

We first briefly summarize the previous work on financial networks and fraud detection. Then we outline the related work on temporal network motifs.

2.1 Financial Networks and Fraud Detection

Advances in machine learning and data mining have introduced various computational methods for detecting financial fraud. When labeled data is available, classifiers are trained on features like transaction amount, user segmentation, and text [34,1,27]. However, such features can be easily manipulated by fraudsters.

To address this, researchers have turned to network-based methods. Savage et al. used anomaly detection to identify money laundering through community structures [29]. Van Vlasselaer et al. integrated intrinsic and network features like degrees and neighborhood similarity [32]. Li et al. developed metrics for detecting high-volume money flows [19]. Kodate et al. applied random forests to local network properties for e-commerce fraud detection [14]. However, most methods ignore event chronology, which can be vital for identifying fraud.

Graph embedding methods also offer promise [31,9]. Liu et al. applied GNNs to heterogeneous graphs of accounts and devices [23], while Yu et al. used random walks and auto-encoders to detect anomalies in dynamic graphs [36]. These methods, though powerful, are computationally intensive and often lack explainability. Nonetheless, we include LINE [31] and node2vec [9] in our experiments.

Beyond fraud, network analysis aids in studying financial systems. Zhang et al. analyzed Venmo's transaction graphs, identifying distinct patterns in user-to-user and user-to-vendor communities [37]. They compared graph metrics like degree, assortativity, and reciprocity but did not use transaction timestamps. They inferred vendor roles based on user behavior with strangers, without verifying vendor status. In contrast, our work predicts friendship ties using only transaction data, leverages temporal motifs to detect complex vendor patterns, and validates findings using vendor labels.

2.2 Temporal Network Motifs

Motifs have proven valuable in various domains involving temporal networks. Extending static motifs [24,26], several works adapted motifs for temporal contexts using snapshots. Jin et al. introduced trend motifs based on dynamic node weights, applying them to financial and protein networks [12]. Chechik et al. used activity motifs—ordered combinations of chains, forks, and joins—to study gene interactions in yeast [7]. Zhao et al. developed communication motifs to analyze synchronous/asynchronous information flow in CDR and Facebook networks [39]. Bajardi et al. modeled cause-effect chains in cattle trade movements [4], and Zhang et al. analyzed diverse human interactions through extensive motif-driven studies [38]. Kosyfaki et al. proposed flow motifs for edge-weighted temporal networks such as bitcoin, transit, and Facebook data [15].

The first temporal motif model for event streams was proposed by Kovanen et al., introducing temporal adjacency [16]. Song et al. framed event pattern matching for streaming data, allowing partially ordered motifs [30]. Hulovatyy et al. extended graphlet-based motifs with relaxed constraints on and support for event durations [10]. Paranjape et al. presented a practical model bounded by a time window [25]. Liu et al. surveyed and unified these models by combining temporal adjacency with time window constraints, and explored correlations between consecutive events [21].

3 Background

We explore temporal networks that we represent as $G = (V, E)$, where V is the set of nodes, and E is the set of time-stamped events. Each event $e_i \in E$ is a 3-tuple (u_i, v_i, t_i), which represents a directed relation from the source node u_i to the target node v_i that occurs at time t_i. The set E is a time-ordered list of $|E|$ events such that $t_1 \leq t_2 \leq t_3 \leq \cdots \leq t_{|E|}$. The set of neighbors of a node u in $G = (V, E)$ is defined to be $\Gamma(u) = \{v \mid (u, v, t_i) \in E \text{ } or \text{ } (v, u, t_j) \in E\}$ for some t_i and t_j, i.e., we consider all the incoming and outgoing neighbors. The one-hop egocentric network of a node u is defined as $G_u = (V_u, E_u)$ where $V_u = \{u\} \cup \Gamma(u)$ and E_u is the set of edges (w, x) such that $w, x \in V_u$.

A temporal network can be projected to a static network by discarding the timestamps of the events. Formally, $\bar{G} = (V, \bar{E})$ is a (directed) static projection of $G = (V, E)$ iff $(u, v) \in \bar{E}$, then $(u, v, t) \in E$ for some t. Here we distinguish edges and events, where the edge $\bar{e} = (u, v)$ is the static projection of an event $e = (u, v, t)$. There can possibly be multiple events occurring on the same edge at different times.

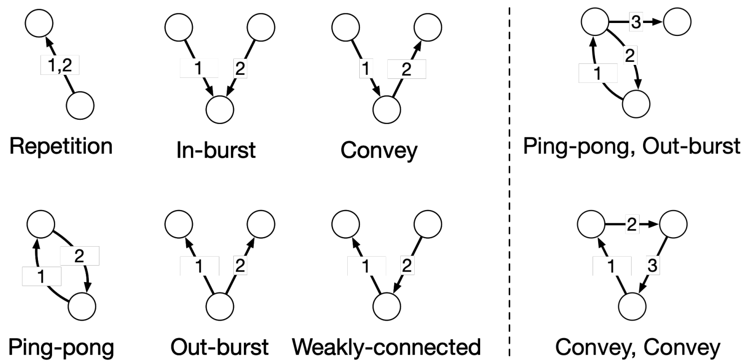


Fig. 1: [Left] All 2-event motifs, which are six types of consecutive event pairs. [Right] Two examples of 3-event motifs denoted by the sequence of event pairs.

Temporal Motifs Given a temporal network $G = (V, E)$ and an inter-event time threshold Δ_C, we define a k-node l-event temporal motif ($k \geq 2$ and $l \geq 2$), $M = (V', E')$, as a temporal subgraph in G such that

- $|V'| = k$, $|E'| = l$, $V' \subseteq V$, and $E' \subseteq E$.
- $E' = \{(u'_1, v'_1, t'_1), \ldots, (u'_l, v'_l, t'_l)\}$ for $t'_1 \leq t'_2 \leq \cdots \leq t'_l$
- For any pair of consecutive events (u'_i, v'_i, t'_i) and $(u'_{i+1}, v'_{i+1}, t'_{i+1}) \in E'$ such that $\{u'_i, v'_i\} \cap \{u'_{i+1}, v'_{i+1}\} \neq \emptyset$, it holds true that $t'_{i+1} - t'_i \leq \Delta_C$.
- For any pair of events $(u', v', t') \in E'$ and $(u'', v'', t'') \in E'$, $t' \neq t''$.

Using a larger Δ_C threshold allows us to discover more temporal motifs. However, a large Δ_C has less power to control the relevance between consecutive events in the motif, especially for temporal networks with short timespans or inter-event times. In addition, increasing the Δ_C value will also exponentially increase the computation cost. To address this trade-off, we choose Δ_C based on two characteristics of the temporal networks: the mean inter-event time and the connectivity rate of the consecutive events. For a temporal network with $|E|$ events, the mean inter-event time (δ) is the average arrival time of consecutive events:

$$\delta = \frac{1}{|E| - 1} \sum_{i=1}^{|E|} (t_{i+1} - t_i)$$

We define the connectivity rate of a temporal network (γ) as the ratio of the number of consecutive events pairs (u_i, v_i, t_i) and $(u_{i+1}, v_{i+1}, t_{i+1})$, such that $\{u_i, v_i\} \cap \{u_{i+1}, v_{i+1}\} \neq \emptyset$, to the total number of consecutive event pairs in the temporal network (i.e., $N - 1$). We set $\Delta_C = \delta/\gamma$ so that $\frac{\Delta_C}{\delta} \times \gamma = 1$. In other words, within the time interval of Δ_C, we are expected to find a pair of events that are consecutive and share a node. For convenience, we round the calculated Δ_C value up to an hour in our experiments.

The 2-event motif is the simplest temporal motif by our definition, which is a pair of consecutive and connected events. Figure 1 shows all types of 2-event motifs, named as repetitions, ping-pong, in-burst, out-burst, convey, or

Network	Nodes	Edges	Events	Fraudsters	Time span	δ	γ	Δ_C
Mercari	741,879	876,413	1,000,000	22.76%	3/22/18-3/30/20	0.05s	72.6%	1hr
JPMC	18,361	17,442	58,263	9.05%	2/2/21-10/2/22	900.51s	8.0%	3hr

Table 1: Properties of the Mercari and JPMC networks.

weakly-connected event pairs in [22]. A motif with l events can be described as a sequence of $l-1$ event pairs. Figure 1 gives an example of a 3-node 3-event motif which can be represented as a sequence of ping-pong (first and second events) and out-burst (second and third events), and a temporal cycle that is a sequence of two convey motifs.

4 Fraud Detection

In this section, we consider two datasets in which the fraud activity is defined differently: (1) financial transactions from an online marketplace, Mercari, where the fraudsters are the sellers of illegal items, and (2) a synthetic financial transaction network used by J.P. Morgan Chase, where the fraudsters are defined as the beneficiaries of the fraudulent transactions. For both datasets, we utilize temporal motifs to detect fraudulent users. We extract temporal motif features from the egocentric networks and compare them against several baselines.

4.1 Online Marketplace Transactions

Data. We build the consumer-to-consumer online marketplace network of Mercari, which is one of the largest e-commerce platforms in Japan[8]. Each user is represented as a node in the network and an event (u, v, t) denotes that user u sells an item to user v at time t. Table 1 shows the statistics of the Mercari network. The original data contains 84,285,577 trading transactions among 2,248,209 users from 3/31/2018 to 3/30/2020. In this study we select one million most recent transactions which cover the trading activities among 741,879 users in 8 days. There are 61,718 connected components in this sample, and the largest (weakly) connected component contains 80.0% of the nodes in the network. It is illegal to sell certain items in the Mercari marketplace, such as weapons, medicine, and used underwear. The sellers of the prohibited items are considered as fraudulent users. Our goal is to identify the fraudulent users based on their trading interactions with their neighbors. We do not have access to any other information about user features or item properties, such as monetary amount or whether an item is illegal or not.

Temporal motif features. We utilize the temporal motif features to distinguish whether a user is fraudulent or not in the online marketplace. For each user u, we first construct its egocentric network $G_u = (V_u, E_u)$, where V_u contains u and its one-hop neighbors, and E_u includes all the events among nodes in V_u.

[8] Mercari, Inc. approved the use of the data for this study.

Then we create the temporal motif features from G_u. In particular, we create a feature vector from d types of temporal motifs $X_u = [x_1, x_2, x_3, \ldots, x_d]$ s.t.

$$x_i = \frac{|M_u^i|}{|M_u^i| + |M_{\neg u}^i|}. \tag{1}$$

In Equation (1), $|M_u^i|$ is the number of type M^i motifs in G_u that contain node u, and $|M_{\neg u}^i|$ is the number of type M^i motifs in G_u that do not contain the node u. We create the feature vectors for the Mercari users based on all the 42 types of 2-event and 3-event motifs, with at most 3 nodes, hence $d = 42$. Equation (1) allows us to identify users who show significantly different trading patterns (M_u^i) than their neighbors ($M_{\neg u}^i$). Another benefit of Equation (1) is that it naturally standardizes the count of different types of motifs in a range between 0 and 1, preventing the commonly observed motif patterns from being over-amplified. The mean inter-event time of Mercari network is 0.05 seconds and the connectivity rate of consecutive events is 72.6% (see Table 1), hence we set $\Delta_C = 1$ hour. According to [25], the time complexity of counting 3-event temporal motifs is the number of static triangles times the number of temporal edges. Given an input temporal graph with $|V|$ nodes, $|\bar{E}|$ static edges, and $|E|$ events, the average degree of a node is $2|\bar{E}|/|V|$, and the maximum number of static edges in a one-hop egocentric graph is $O(|\bar{E}|^2/|V|^2)$. Therefore, the number of static triangles in the egocentric network is $O((|\bar{E}|^2/|V|^2)^{1.5}) = O(|\bar{E}|^3/|V|^3)$. Since each edge has $|E|/|\bar{E}|$ events on average, the number of events in the egocentric network is $O((|\bar{E}|^2/|V|^2) \times (|E|/|\bar{E}|)) = O((|\bar{E}| \cdot |E|)/|V|^2)$. We repeat this for each node's egocentric network, so the time complexity of building temporal motif features is $O(|V| \times (|\bar{E}|^3/|V|^3) \times (|\bar{E}| \cdot |E|)/|V|^2) = O((|\bar{E}|^4 \cdot |E|)/|V|^4)$. Note that real-world networks are often sparse, hence $|\bar{E}| << |V|^2$, and also the financial transaction networks in our datasets have $|\bar{E}| \approx |V|$ as shown in Table 1.

Baselines. We compare our method with three baselines: (1) simple graph features [14], (2) LINE embeddings [31], and (3) node2vec embeddings [9], all computed on the static projection of the graph. Following [14], we extract ego-centric features for each node u: degree k_u, event count s_u, event per edge s_u/k_u, edge and event direction ratios k_u^{out}/k_u, s_u^{out}/s_u, local clustering coefficient, and cycle probability CYP_u. These features are used for fraud classification. Triangle counting dominates the computation with $O(|E|^{1.5})$ complexity. We train LINE and node2vec embeddings on the static undirected graph. node2vec uses 128 dimensions, walk length 80, 10 walks, $p = q = 1$; runtime is $O(P(|V|+|E|))$. LINE uses 128 dimensions, batch size 1024, 11 epochs, $K = 5$ negative samples, and has complexity of $O(dK|E|)$. We use the GraphEmbedding implementation [9].

Experimental setup. We performed all the experiments in this work on a Linux operating system running on machines with Intel(R) Xeon(R) Gold 6130 CPU processor at 2.10 GHz with 128 GB memory.

[9] `https://github.com/shenweichen/GraphEmbedding`

Method	Classifier	Mercari							JPMC						
		Fraud			Non-Fraud			AUC-ROC	Fraud			Non-Fraud			AUC-ROC
		Pre.	Rec.	F1	Pre.	Rec.	F1		Pre.	Rec.	F1	Pre.	Rec.	F1	
LINE	LR	0.105	0.543	0.176	0.893	0.453	0.601	0.498	0.028	0.395	0.052	0.972	0.605	0.746	0.500
	SVM	0.107	0.346	0.164	0.896	0.663	0.762	0.504	0.031	0.285	0.056	0.971	0.728	0.832	0.506
	RF	0.000	0.000	0.000	0.894	1.000	0.944	0.500	0.000	0.000	0.000	0.970	1.000	0.985	0.500
	XGBoost	0.000	0.000	0.000	0.895	1.000	0.944	0.500	0.000	0.000	0.000	0.974	1.000	0.987	0.500
node2vec	LR	0.141	0.583	0.227	0.922	0.582	0.713	0.582	0.128	0.681	0.216	0.989	0.860	0.920	0.770
	SVM	0.220	0.502	0.306	0.931	0.791	0.855	0.646	0.094	0.644	0.165	0.989	0.837	0.907	0.740
	RF	0.359	0.001	0.002	0.896	1.000	0.945	0.500	0.000	0.000	0.000	0.972	1.000	0.986	0.500
	XGBoost	0.304	0.010	0.019	0.894	0.997	0.943	0.503	0.471	0.133	0.208	0.977	0.996	0.986	0.565
Simple graph	LR	0.820	0.640	0.720	0.850	0.940	0.890	0.789	1.000	0.020	0.040	0.810	1.000	0.900	0.509
	SVM	0.670	0.220	0.330	0.730	0.950	0.830	0.586	0.000	0.000	0.000	0.810	1.000	0.890	0.500
	RF	0.820	0.810	0.810	0.910	0.920	0.920	0.863	0.360	0.180	0.240	0.820	0.920	0.870	0.552
	XGBoost	0.820	0.810	0.820	0.920	0.920	0.920	0.868	0.380	0.190	0.250	0.830	0.930	0.870	0.558
Temporal motif	LR	0.940	0.710	0.810	0.880	0.980	0.930	0.844	1.000	0.650	0.790	0.920	1.000	0.960	0.825
	SVM	0.940	0.760	0.840	0.900	0.980	0.940	0.871	1.000	0.640	0.780	0.920	1.000	0.960	0.820
	RF	0.940	0.810	0.870	0.920	0.980	0.950	0.892	1.000	0.650	0.790	0.920	1.000	0.960	0.825
	XGBoost	0.950	0.800	0.870	0.920	0.980	0.950	0.890	1.000	0.650	0.700	0.920	1.000	0.960	0.825
Simple graph and temporal motif	LR	0.960	0.880	0.920	0.950	0.980	0.960	0.930	1.000	0.650	0.790	0.920	1.000	0.960	0.826
	SVM	0.960	0.710	0.820	0.880	0.990	0.930	0.848	1.000	0.610	0.760	0.920	1.000	0.960	0.807
	RF	0.950	0.950	0.950	0.980	0.980	0.980	0.962	0.860	0.670	0.750	0.930	0.970	0.950	0.820
	XGBoost	0.960	0.950	0.950	0.980	0.980	0.980	0.964	0.860	0.660	0.750	0.920	0.980	0.950	0.818

Table 2: Classification results on the Mercari and JPMC datasets for logistic regression, support vector machine, random forest, and XGBoost on five different variants: (1) LINE embeddings, (2) node2vec embeddings, (3) simple graph features, (4) temporal motif features, and (5) both simple graph and temporal features. Precision, recall, and F1 scores are given for both the fraud and non-fraud classes.

Results. We use four different classifiers—logistic regression, support vector machine, random forest, and XGBoost—on five different variants: (1) LINE embeddings, (2) node2vec embeddings, (3) simple graph features, (4) temporal motif features, and (5) both simple graph and temporal features. In XGBoost classifier, we use max depth as 3, choose 100 estimators, and set learning rate to 0.01. For logistic regression, we use *L2* penalty. For random forest we use 100 estimators. All classifiers are implemented using scikit-learn[10] and all remaining parameters set as default in the corresponding implementations. For each run we use 75% of the data for training and the remaining 25% for testing. For each configuration, we repeat the experiments 100 times and report the average precision, recall, and F1 scores for fraud and non-fraud classes, along with the AUC-ROC scores. Table 2 presents the results.

Classifiers trained on temporal motif features consistently outperform those using simple graph features, LINE, or node2vec embeddings. They achieve up to 0.870 F1 for fraud, 0.950 for non-fraud, and 0.892 AUC. Temporal motifs also show robust performance across all classifiers. Adding simple graph features improves performance slightly, especially for XGBoost, which reaches 0.964 AUC.

The most important simple graph feature is s_u^{out}/s_u, while the most predictive motif is the out-burst. Fraudulent users appear in 1.256 out-burst motifs on average, compared to 0.233 for non-fraudulent ones, suggesting rapid, repeated sales by fraudsters, see [20] for details.

The overhead of temporal motif computation runtime for Mercari data is significant but not impractical when compared to the embedding times: motif counting is faster than LINE embedding computation by ∼50 mins and is slower

[10] `https://scikit-learn.org/stable/index.html`

than node2vec embedding by ∼30 mins. Regarding the classification runtimes, SVM is the costliest one, taking ∼17 hours on node2vec embeddings. However, it takes only a few minutes on temporal motif features as the number of dimensions is much less when compared to the embedding methods (42 vs 128), see [20] for details. Overall, temporal motifs are preferable to all the other methods.

4.2 Synthetic Payment Transactions

Data. We consider a synthetic payment network generated by J.P. Morgan Chase (JPMC)[11] using the characteristics of the real payment data [3]. This is a high-fidelity synthetic data that preserves many unique features observed in a real transaction system. The data includes 58,263 transactions among 18,361 users from 2021 to 2022 (see Table 1). In addition to the transaction time and the anonymized IDs of the sender and receiver, each transaction also includes the monetary amount, the type of the payment method, and the users' countries of residence. [12] Payment fraud occurs when a fraudster deceives others to receive fraud payment to the fraudster's account. We mark a user as a fraudster if they receive at least one fraud payment. Among 18,361 users in the JPMC data, 1,663 are labeled as fraudsters. Similar to our approach for the Mercari data, we extract the temporal motif features and simple graph features from the one-hop egocentric network of each user, and also run LINE and node2vec embeddings. We train logistic regression, support vector machine, random forest, and XGBoost classifiers to predict if a user is a fraudster or not. The mean inter-event time of the JPMC network is 900.51 seconds, and the connectivity rate of consecutive events is 8.0% (see Table 1). Hence, we set $\Delta_C = 900.51/0.08 \approx 3$ hours when counting the 2-event and 3-event temporal motifs.

Results. Temporal motif features significantly improve fraud detection on the JPMC dataset (Table 2), achieving up to 0.790 F1 for fraud and 0.960 for non-fraud, with 0.825 AUC. Simple graph features perform poorly—SVM fails entirely, and LR performs weakly. Embedding methods underperform, especially for fraud detection. Unlike in Mercari, adding simple features to motifs does not help, likely due to JPMC's smaller size (58K vs. 1M events).

The out-burst motif is observed to be the most important temporal motif feature to support the decision of the fraud detection models. All simple graph features appear to have similar influences, while the number of events for each node s_u and the ratio of out transactions s_u^{out}/s_u are more important than the other features (details are in [20]).

Regarding the runtime performance, the overhead of temporal motif counting is 40% less than node2vec embedding, which suggests that the superior classification performance of temporal motif features is also practical. Also, the classi-

[11] J.P. Morgan grants us the non-transferable limited license to use the data solely for this project.

[12] Incorporating monetary amount in the classification does not yield any improvement, details are given in [20].

Network	Nodes	Edges	Events	Time span	δ	γ	Δ_C
Venmo Transactions	19,141	18,559	131,206	5/21/15-2/9/21	1721.61s	17.8%	24hr
Venmo Friendships	19,141	62,965	N/A	N/A	N/A	N/A	N/A

Table 3: Properties of the Venmo transaction and friendship networks.

fication runtimes are less than a second for all temporal motif trainings whereas it takes up to 19 seconds to train node2vec embeddings.

5 Interplay Between Transaction & Friendship Networks

Social and financial interactions are often intertwined—friendship may influence transactions and vice versa. Financial institutions leverage various networks, including social ones, to enhance fraud detection [5]. In this section, we analyze Venmo data to explore the link between transaction and friendship networks using temporal motifs. We construct both networks via Venmo's public API and use motif features to (1) predict friendships based on transactions and (2) identify vendor users by combining transaction and friendship data. We also examine rare temporal motifs and associated payment notes for behavioral insights.

5.1 Data

Venmo, a leading digital payment platform, processes over a billion USD in monthly transactions. Users can publicly share transactions and form friend connections. We selected 600 highly active users from a public dataset of seven million Venmo transactions [28] and collected their full transaction histories using the Venmo API. This yielded 131,206 transactions among 19,141 users between 5/21/2015 and 2/9/2021. Each transaction includes sender and receiver IDs, timestamp, and a required message (though not the transaction amount).

Table 3 presents summary statistics for the Venmo transaction and friendship networks. Friendship data is treated as static and undirected, as the API only indicates current friend status. The transaction network contains 227 connected components, with the largest covering 81.6% of nodes. In contrast, the friendship network is more fragmented, with 1,271 components and a largest component covering 24.8% of nodes.

5.2 Supervised Friendship Discovery

We use temporal motifs to predict whether two Venmo users are friends based on their transactions. For each node pair (u, v), we count the number of 2-event and 3-event motifs that include both users. Only pairs with at least a transaction or friendship relation are included, totaling 52,021 pairs—86% of which are friends. The average inter-event time is 1,721.6 seconds, and 17.8% of consecutive events are temporally connected. Given the five-year timespan, we set the motif time window $\Delta_C = 1$ day, slightly larger than δ/γ, to capture meaningful patterns.

Temporal motif distributions. We first examine if the motif counts between friend and non-friend node pairs show different patterns. For each pair of nodes that are involved in an interaction (transaction or friendship), we count all the 2-event and 3-event temporal motifs and then investigate how the friend node pairs compare against non-friends. We observe that motifs containing repetition, ping-pong, convey, and weakly-connected (remember Figure 1) are more dominant between friends, while motifs containing in-bursts and out-bursts occur more often between non-friend pairs. More details are available in the extended version [20]. We do not observe any non-friend node pair that has more than 5 ping-pong motifs, while nearly 50% of the friend node pairs are contained in at least 5 ping-pong motifs. On the other hand, in-burst motifs are more common in the non-friend node pairs than the between friend node pairs.

Features and baselines. Based on our observations above, we extract features from the Venmo transaction network to predict the friendship relationship between users. For each pair of nodes u and v, we create a feature vector $X_{u,v} = [M^1_{u,v}, M^2_{u,v}, \ldots, M^d_{u,v}]$ where $M^i_{u,v}$ is the number of M^i motifs containing both u and v. We use all 2- and 3-event temporal motifs ($d = 42$). We train the logistic regression classification model with the temporal motif features to predict the friendship between two users. We also consider two baseline models by applying the logistic regression model on the Jaccard (JC) coefficient [11] and Adamic-Adar (AA) index [2], which are commonly used heuristic scores for link prediction tasks. For a pair of nodes u and v, the Jaccard coefficient is $J(u,v) = \frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|}$ and the Adamic-Adar index is measured as $A(u,v) = \sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{\log |\Gamma(w)|}$, where we remind that $\Gamma(u)$ is the set of neighbors of u. Note that these two scores do not consider temporality and work on the undirected static projection of the graph. For classification, we use 75% of the data to train and the rest to test.

Results. Using temporal motif features achieves the best performance, with 0.86 precision, 1.0 recall, and 0.92 F1 scores. All three models are able to capture all the friend node pairs (with 1.0 recall scores), whereas temporal motifs yields less false positives than Jaccard and Adamic-Adar indices.

5.3 Unsupervised Vendor Discovery

As described in [37], Venmo users can be considered as customers or vendors, and friend transactions often show clear person-to-person patterns and stranger transactions usually indicate vendor-customer relations. Identification of vendors, who do not declare themselves as such, can be an important application for more accurate tax verification purposes as the current practice simply relies on a threshold on the number of transactions or the total amount received [33]. Here we utilize temporal motifs to identify vendor users. We categorize Venmo transactions into two: 106,315 transactions between friends (TF) and 24,891 transactions between non-friend users (TN). Our goal is to develop an unsupervised approach to identify vendors in the Venmo network.

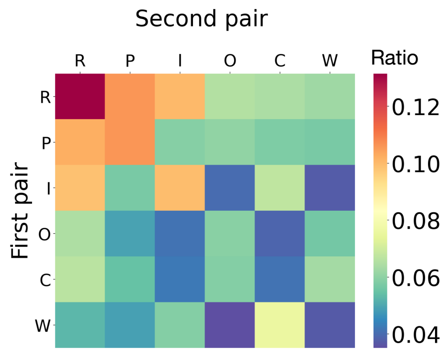
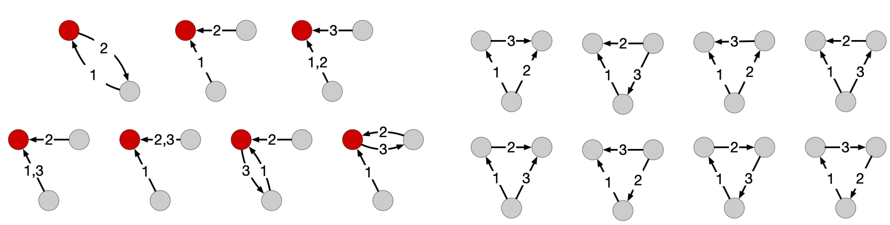


Fig. 2: Ratios of the number of TN motifs to the number of TF motifs. Each block represents a type of three-event motif; the row shows the first pair of events (first and second) and the column shows the second pair (second and third). The ratios are color-coded. R, P, I, O, C, and W are repetition, ping-pong, in-burst, out-burst, convey, and weakly-connected, respectively.

Comparing TF and TN motifs. We first compare the temporal motif counts in the TF and TN graphs. Hereafter we refer the motifs in the TF and TN graphs as TF motifs and TN motifs, respectively. For each type of 3-event motif, we compute the counts in both graphs by using $\Delta_C = 1$ day. We display the ratio of the count of the TN motifs to that of the TF motifs in Figure 2. We observe that motifs that consist of repetitions, ping-pongs, and in-bursts are relatively more frequent in the TF graph than the TN graph. These motifs might correspond to real-world events in which a consumer purchases multiple times from the same vendor (repetition), a consumer asks for a refund from the vendor (ping-pong), or the vendor is paid by multiple consumers (in-burst). On the other hand, triangle motifs are more frequent in the TF graph than the TN graph, where three users are friends and make transactions with each other.

Vendor score. We propose an unsupervised method to identify vendors in Venmo. For each user u, we compute a heuristic vendor score: $vs(u) = \log(|M^{+}_{TN}|+1) - \log(|M^{-}_{TF}|+1)$. Here, M^{+}_{TN} denotes seven positive temporal motifs (shown in Figure 3a) likely associated with vendor behavior—such as in-burst motifs where a receiver rapidly transacts with multiple strangers, or ping-pong motifs suggesting refunds. We select three 3-event motifs where a target node receives payments from two strangers, and two 3-event motifs where a refund is implied. As shown in Figure 2, repetition patterns are more common between strangers than friends. However, we exclude repetitive and ping-pong motifs from the



(a) Positive patterns

(b) Negative patterns

Fig. 3: Vendor motif patterns. We select seven positive patterns in which the target node (red) is likely to be a vendor user (Figure 3a), and eight negative patterns that are unlikely to contain vendor users (Figure 3b).

score since they appear too frequently in both TF and TN networks and may overshadow more indicative patterns. We define M_{TF}^{-} as eight motifs (from Figure 3b) with the lowest TN-to-TF ratio—primarily triangles among friends—used to model anti-vendor behavior. The use of log helps manage motif count scale due to exponential growth with motif size.

Results. To validate, we manually searched for profile information of the top 1,000 users by $vs(u)$. We identified 62 as vendors and 938 as non-vendors, while protecting personally identifiable data. Among the top 10 users, nine are verified vendors; among the top 20, 13 are verified. The recall drops to 23% and 6.1% for top 100 and 1,000 users, respectively. These results indicate that temporal motifs are a promising approach for vendor detection in transaction networks.

5.4 Curious Case of Temporal Cycles

Temporal motifs can also be used to identify special activities in the Venmo network. For example, 3-node temporal cycles, $A \rightarrow B \rightarrow C \rightarrow A$ (convey-convey motifs), are the rarest type of 3-event motif in the Venmo transaction network. Indeed such transactions are not expected to occur in a short time period; two transactions would be sufficient to balance all three accounts. Among 637,439 3-event motifs in the transactions between friends, only 1.04% are the 3-node temporal cycles. Similarly, out of 49,682 3-event motifs among non-friends, only 0.55% are temporal cycles. We investigate the payment notes of the transactions which are involved in the 3-node temporal cycles between friends and identify 70 transactions with a note about "poker". Venmo is indeed a popular medium (and legal in several states in the US) to exchange funds in online gambling platforms[13]. We believe that temporal cycles can be used to detect gambling activities and be helpful to law enforcement agencies in states and countries where online gambling is illegal.

6 Conclusion

This paper leverages temporal motifs to analyze financial networks and improve key applications. We extract motif-based features from users' egocentric networks and show they outperform static graph features and node embeddings in fraud detection on the Mercari and JPMC datasets. In Venmo, we use these features to predict friendships, identify vendors via an unsupervised approach, and uncover behaviors such as fund exchanges in social games. Our findings demonstrate the versatility and effectiveness of temporal motifs in understanding and modeling dynamic financial interactions.

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[13] `https://www.legalbettingonline.com/venmo/`

used resources of the CCR at the University at Buffalo [6]. We also thank Jingjing Chi and Yifan Wang for helping with the vendor labeling process.

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