Exploring Insider Trading Within Hypernetworks

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Abstract—Insider trading can have crippling effects on the economy and its prevention is critical to the security and stability of global markets. It is hypothesized that insiders who trade at similar times share information. We analyze 400 companies and 2,000 insiders, identifying interesting trading patterns in these networks that are suggestive of illegal activity. Insiders are classified as either routine or opportunistic traders, allowing us to concentrate on well timed and highly profitable trades of the latter. Using trade classification and analyzing each trader’s role in a hypernetwork, reveals cliques of opportunistic and routine traders. This idea forms the basis of a graph based detection algorithm that seeks to identify traders belonging to opportunistic cliques. The ideas of trade classification and trading cliques present interesting opportunities to develop more robust policing systems which can automatically flag illegal activity in markets, and predict the likelihood that such activity will occur in the future.

Index Terms—Insider trading, anomaly detection, graph mining, hypergraphs

I. INTRODUCTION

Insider trading is formally defined by the Securities and Exchange Commission (SEC) as the buying or selling of a security, on the basis of material, non-public information about the security. Insiders are typically company officers, board members or large shareholders within a company. In this paper we analyze the trading activity of those who engage in such insider trading.

A well known example of insider trading is the infamous case of Martha Stewart and Samuel Waksal, C.E.O of the pharmaceutical company IMClone. When it was rumored that an important drug produced by the company would not be passing FDA trials, Waksal and Stewart both sold a large portion of their shares in IMClone. Waksal dumped 5.5 million dollars worth of his shares just days before the announcement. Acting on Waksal’s information, Stewart dumped a substantial portion of her shares and made over 250,000 dollars on the sale. When insiders act illegally they create an unsafe environment for other investors and undermine the public’s confidence in the stock market. This has damaging affects on government institutions and businesses that rely on the stock market as a means of growth and sustenance.

Detecting illegal insider trading is not a simple task. In 2003, the daily average number of insider trades of interest to the National Association of Securities Dealers (NASD) was 5,5 million, involving over 16,000 stocks [1]. In 2015, with the cutting-edge software of the day, the Marketwatch team at the NASDAQ exchange reviewed almost 400,000 suspicious trades and had to manually refer some portion of that to the SEC for further investigation.

It is therefore imperative that we devise a method for detecting illegal insider trading on a large scale. Goldberg et al. proposed SONAR [1], a software used by the NASD that automates a large part of the detection process of suspicious insider trades. It monitors a number of stock markets and correlates daily pricing and volume data for a given stock to company-related news in order to assign likelihood scores to trades. A score reflects the probability that a trade was made illegally and if that score is above a threshold, that trade is flagged so that analysts can collect more information about it. However, SONAR appears to process all the trades of every insider. It is unable to intelligently distinguish between informative and non-informative trades, until the trade goes through its entire pipeline. Kulkarni et. al [2] first proposed the use of hypernetworks to model insider trading data. This work expands on this idea by exploring the relationships between cliques of insiders as a means of automated detection. As far as we are aware, this paper is the first to explore the significance of trading cliques and their connection to company-related news.

A. Contributions

In light of the shortcomings of existing models for detecting insider trading, we make the following contributions.

• We show that insider trading in many cases is not an individual act but involves cliques of traders.
• We show that the trades of insiders who belong to cliques are related to forthcoming company news.
• We argue that the use of hypergraphs over graphs better isolates suspicious trading patterns.
• In detecting illegal trades, we argue for the use of trade classification in order to produce more accurate results.

II. RELATED WORK

Graph-based outlier detection is a context-sensitive problem. We might define a general graph-based anomaly detection problem as the task of identifying the graph objects (nodes, edges or substructures) that are less frequently observed than
standard objects. Due to the context-sensitive nature of outlier detection, several distinct methods have been developed. Structural methods and community methods are two such examples. Structural approaches aim to identify rare structures, in terms of either connectivity or attributes. Community-based methods try to identify members of a community who are the most different, either by connectivity or attributes [3]. These methods cannot be applied to insider trading without first developing an understanding of how the anomalies are distributed. This will heavily factor into the methodology we pursue for automated detection. So in order to understand how to approach the problem of anomaly detection, we must develop an understanding of insider trading patterns.

Insider trading has been explored in a variety of contexts. Cohen et al. perform a large scale study of insider trading, profiling a large number of insiders by their trades. They find that all insiders fall into two classifications, routine and opportunistic traders. The study concludes that opportunistic trades tend to have higher predictive power. Specifically, there is a causal relationship between opportunistic trades, market trends, and SEC prosecution activity [4]. Tamersoy et al. explore insider trading from a network centric perspective. They focus on using algorithms to construct and mine networks of traders, in order to better understand trading patterns. The insights gained from both studies are presented and built upon in this work. Following the work of Cohen, we want to be able to perform similar analysis on insiders in our network. Also building on the work of Tamersoy, we wish to know if there is a way to profile our traders into cliques or smaller groups where trading patterns are more routine or opportunistic respectively. This would allow us to formalize what distribution of traders are worth investigating.

We note that in several cases brought before the SEC, several insiders were prosecuted jointly, all having acted on the same information illegally. We are particularly interested in exploring the relationship between activities of trading cliques (groups of two or more traders) and company news in order to provide insight into how insiders trade.

### III. Dataset

We use the same dataset in [2] but we are specifically interested in networks that are modeled as hypergraphs.

Formally, a hypergraph is a generalization of a graph $H = (X, E)$, where $X$ is the set of vertices $\{x_1, \ldots, x_N\}$ and $E$ is a nonempty set of edges s.t. $E \subseteq P(X)$; $P(X)$ is the power set of $X$. Hypergraphs capture the notion of trading cliques more accurately than traditional graphs, allowing us to focus on a pattern of trades that may reveal insight into company related news. Consider the example illustrated in Figure 1. Nodes in the network represent insiders and they are linked based on the similarity of their trading dates [2].

In the first scenario, depicted on the left, three insiders share three different trade sequences. In the second scenario, shown on the right, three insiders share the same trade sequence. If we were to model this using a graph, in both cases, we would see a single clique with three nodes. Modelling trading patterns using a hypergraph would allow us to distinguish between the two different scenarios. In a hypergraph, the first scenario would be represented as three different cliques of size two and the second would be a single clique of size three. The ability to distinguish between the two different scenarios allows us to observe the significance of a sequence of trades shared by a group of traders, as opposed to just two. Importantly, paying attention to trades that follow the same chronological sequence allows us to distinguish between different types of trading behaviors.

We partition the data by company because the vast majority of insider trades tend to occur among insiders in a single company [5]. Since the reasons that insiders buy or sell stock vary, it is not helpful to represent both types of transactions in a single network. Instead, each company is partitioned into two networks. A purchase network models all of the purchases associated with that company’s stock, and a sale network models all of the sales associated with that company’s stock.

A hypernetwork is constructed from the data, for purchase and sale networks, for each company, as follows: Given a specific threshold $t$, let any number of insiders that share at least $t$ trade dates form an edge [2]. The parameter $t$ represents the minimum length of the longest common subsequence (LCS) of trade dates between any group of traders. Experimenting with different values of $t$ will produce hypergraphs with different sizes for each company. Figure 2 depict the change in distribution of edges in each company’s hypernetwork as we vary the threshold parameter, $t$. We get a larger number of graphs with over ten edges per hypernetwork when $t$ is smaller, since more traders tend to share a smaller sequence of dates. Although choosing $t = 3$ would allow us to examine a greater number trades, significantly more cliques will involve just three trades and would make it more difficult to distinguish between routine and opportunistic trading – see IV-A. We also lose the ability to capture the rarity of larger trading cliques. Table 1 shows the difference between the number of all companies in the dataset, and the number of companies which have at least one clique of traders who share five trading dates. We can observe that since such trading patterns are rarer, significantly fewer companies can be modeled as hypernetworks when $t = 5$. In this paper, we adopt $t = 5$ for sale networks and $t = 10$ for purchase networks.

We also interestingly observe that sales are more common transactions (Figure 3). This is because insiders are awarded grants and equity and will often sell portions of their holdings to balance their portfolio [5].