Graph-based Coupled Behavior Analysis: A Case Study on Detecting Collaborative Manipulations in Stock Markets

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***Abstract*—Coupled behaviors, which refer to behaviors having some relationships between them, are usually seen in many real-world scenarios, especially in stock markets. Recently, the coupled hidden Markov model (CHMM)-based coupled behavior analysis has been proposed to consider the coupled relationships in a hidden state space. However, it requires aggregation of the behavioral data to cater for the CHMM modeling, which may overlook the couplings within the aggregated behaviors to some extent. In addition, the Markov assumption limits its capability to capturing temporal couplings. Thus, this paper proposes a novel graph-based framework for detecting abnormal coupled behaviors. The proposed framework represents the coupled behaviors in a graph view without aggregating the behavioral data and is flexible to capture richer coupling information of the behaviors (not necessarily temporal relations). On top of that, the couplings are learned via relational learning methods and an efficient anomaly detection algorithm is proposed as well. Experimental results on a real-world data set in stock markets show that the proposed framework outperforms the CHMM-based one in both technical and business measures.**

I. Introduction

Human behavior (interchangeable with 'behavior' in this paper) refers to an action from a human and usually is coupled with behaviors of his/her own and other actors. 'Coupled' in this paper means behaviors have certain relationships and not independent. The couplings within an actor can be defined as intra-coupled relationships ('intra-couplings') while inter-coupled relationships ('inter-couplings') are between behaviors of different actors [1]. Taking the couplings into account for anomaly detection is critical in many real-life scenarios whereas most of existed behavior analysis methods simply ignore these coupled relationships or only consider part of them (please see II for a brief review). Take the behaviors of investors in stock markets for example. 'Place a buy order' ('buy' for short), 'place a sell order' ('sell' for short) and 'generate a trade' ('trade' for short, as an effect of matching a buy against a sell) are three typical trading behaviors. Intuitively, these behaviors are heterogeneous and not independent. In other words, if these trading behaviors are abnormal, they are coupled with each other and analyzing them individually cannot uncover the anomaly underlying these coupled behaviors. (please see Section III-A for further details about how manipulations are coupled with each other.). Analyzing such kind of behavioral anomaly should not ignore these characteristics.

Recently, the group-based coupled behavior analysis (CBA) [1] was proposed to provide an innovative framework to comprehensively analyze both intra- and inter-couplings between behaviors of a group of actors. As an initial attempt, the group-based CBA suggests a method to implicitly represent the couplings in a statistical model, coupled hidden Markov model (CHMM) [2]. For instance, suppose there are some trading behaviors as depicted in Fig. 1(a), where $buy_i (1 \leq i \leq 4)$, $sell_i (1 \leq i \leq 4)$ and $trade_i (1 \leq i \leq 3)$ denote the corresponding 'buy', 'sell' and 'trade' behaviors. To capture the couplings between these behaviors, [1] proposed to generate homogenous time intervals using a sliding window and aggregate these behaviors according to the time intervals. As can be seen from Fig. 1(a), buy_i, $sell_i$ and $trade_i$ are converted to the corresponding aggregated behaviors $buy_i^{'}$, $sell_i^{'}$ and $trade_i^{'}$. On top of that, three chains Φ_B $(buy_1^{'}, \cdots, buy_3^{'})$, Φ_S $(sell_1^{'}, \cdots, sell_3^{'})$ and Φ_T $(trade_1^{'}, \cdots, trade_3^{'})$ are constructed and a CHMM is set up to model the coupling relationships between the above behaviors via the hidden state space. The structure of the CHMM is shown in Fig. 1(b). For each aggregated behavior at one time stamp t (i.e., $buy_t^{'}$, $sell_t^{'}$ and $trade_t^{'}$) there are corresponding hidden states to each behavior (i.e., s_t^B, s_t^S and s_t^T). The coupled relationships between $buy_t^{'}$, $sell_t^{'}$, $trade_t^{'}$ and $buy_{t-1}^{'}$, $sell_{t-1}^{'}$, $trade_{t-1}^{'}$ are reflected in the dependency of the hidden states s_t^B, s_t^S, s_t^T and s_{t-1}^B, s_{t-1}^S, s_{t-1}^T (similar situations to other time stamps). This is feasible to some extent and the underlying assumption is that coupled behaviors could be modeled as a CHMM process. This solution, however, has some limitations: e.g., segmentation and aggregation of the behaviors may lose important coupling information within these aggregated behaviors; The first order Markov assumption (i.e., only considers the couplings between the aggregated behaviors of the current and previous time stamps) may not be a good approximation of real coupled behaviors.

To overcome these weaknesses of the CHMM-based CBA, this paper proposes a graph-based framework to capture richer coupled relationships between behaviors and detect anomaly. The framework mainly consists of three stages. The first stage is to represent the behaviors in a graph structure. Fig. 1(c) describes the proposed graph structure for representation of the coupled behaviors. It has two main advantages compared to the CHMM-based framework: firstly, the behaviors are not aggregated and this avoids the possible loss of coupled relationship information in the aggregated behaviors; secondly, the coupled relationships are not limited to the temporal Markov assumption and in Fig. 1(c) the possible coupled relationships between behaviors are indicated by directed links. These links are generated by some behavioral properties of the behaviors (for further details, please refer to IV), which indicate possible coupled relationships. For example, the behaviors are made at neighboring time stamps or the behaviors are made by the investors belonging to the same branch. On the basis of this graph-based coupled behavior model, in the second stage, relational learning methods [3] are adopted to capture more comprehensive coupled relationships of the normal behaviors. After that, the third stage further detects abnormal coupled behaviors (e.g., manipulations in stock markets) using the learned coupling model of the normal behaviors.

A. Contributions

While the coupled behaviors can be found in many real-world fields, such as group-based manipulations in stock markets and criminal behaviors, only limited efforts have been done for such behavior analysis. In this paper, a novel graph-based CBA framework has been proposed and a case study is presented to detect abnormal coupled behaviors (manipulations) in stock markets under the proposed framework. The main contributions of this paper are summarized as following.

- The introducing of a graph-based representation for coupled behavior analysis. More specifically, this paper has made a first attempt to explain and model coupled relationships between behaviors based on a graph-based stucture, to the best of our knowledge.
- We further explore how to learning the coupled relationships between behaviors in the graph-based CBA framework, including how to preprocess the transactional data and model the coupled relationships via relational learning. In addition, this paper also proposes the corresponding anomaly detection techniques.
- Extensive experiments on a real-world data set from an Asian stock market have been done as a case study. From both the views of technical and business performance, the experiments explore the comparison of the proposed framework and the previous CHMM-based framework. Different anomaly scores are compared as well.

B. Structure of this paper

The rest of this paper is organized as follows. Firstly, related work is given in Section II. In Section III, the CBA problem is illustrated by a case study of detecting abnormal coupled trading behaviors in stock markets and a CHMM-based framework is reviewed. Then section IV describes our proposed framework of representing the behaviors in a graph and modeling the Couplings via relational learning algorithms and how to perform anomaly detection within the framework. Experimental results on a real data set of Asian stock market are given in Section V. Section VI concludes this paper.

II. Related Work

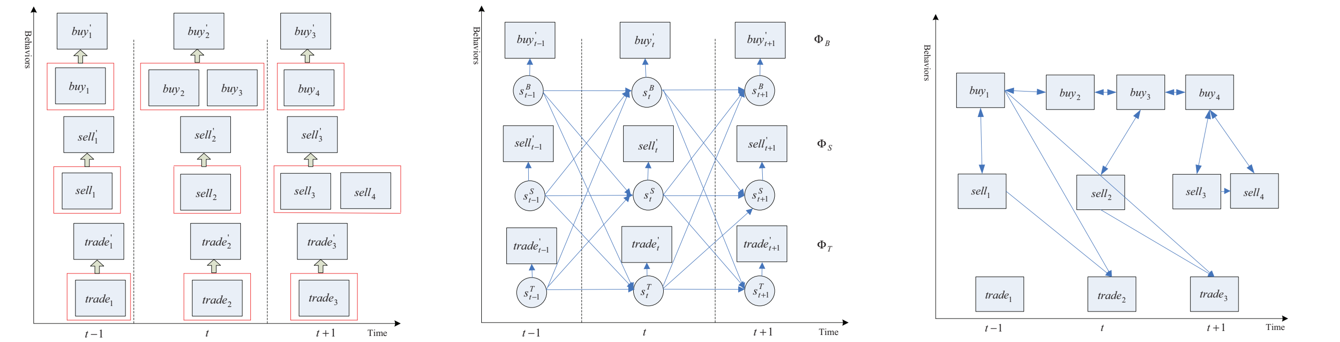
Below we briefly list a few related fields of our work. Coupled behavior analysis and anomaly detection are closely related to this paper in the sense of solving similar problems while statistical relational learning (SRL) is related to this paper in terms of methodologies.

A. Coupled Behavior Analysis.

One closely related area is group-based CBA proposed by [1], [4]. From the perspective of CBA, there are intra- and inter- couplings relationships between behaviors, as mentioned in Section I. Most of existing researches on behavior studies, however, focus mainly on discovering intra-relationship between behaviors. For example, frequent pattern mining [5], a popular data mining technique in market basket analysis and custom behavior analysis, only considers the intra-couplings. For example, frequent itemset mining [6], [7] only consider the intra-couplings within each single transaction. Similarly, frequent sequence mining [8], [9] only considers the intra-couplings within a behavioral sequence of an individual, resulting in absence of analyzing the coupled relationships between different behavioral sequences. A comprehensive analysis of intra and inter relationships is beyond most of the current individual behavior analysis techniques, to the best of our knowledge. As an initial attempt, [1], [4] suggested a CHMM-based framework and indicates the couplings in a hidden state space. Although its success to some extend, as mentioned before, it is limited by the coupling information loss because of the transformation of behavioral data (in order to suit the structure of CHMMs) and the Markov assumption. Thus, an alternative modeling strategy is necessary, which is one of the main motivations of this paper.

B. Anomaly Detection.

Another field related to this paper is anomaly detection [10]. According to [10], this paper could fall into the category of collective anomaly detection, which means a collection of related instance (i.e. behaviors in this paper) is anomalous with respect to the entire data set. Most work of this category only consider intra-coupled relationships, such as [11] and [12], which means the behaviors are analyzed individually for each actor. By contrast, this paper explores the anomaly not only in intra- but also inter-couplings. In addition, this paper is also operate in semi-supervised mode [10], assuming that only the normal class has been labeled for training. This is reasonable and applicable because the abnormal behavioral data is usually hard to obtain.



(a) An Example of Some Coupled Trading Behaviors in Stock Markets

(b) The Structure of the CHMM

(c) The Structure of the Graph-based Coupled Behavior Model

Fig. 1. The Coupled Behaviors and The Corresponding Two Different Models

C. Statistical Relational Learning.

Traditional statistical machine learning approaches assume that a random sample of homogeneous objects is from single distribution and independent to others. However, the characteristics of real world data sets violate the above assumption more often than not. They usually are: (1) multi-relational, heterogeneous and semi-structured; (2) noisy and uncertain. To fill the gap between the real world and the traditional machine learning, SRL has been proposed and become increasingly concerned by both the academic and industrial fields [13]. Meanwhile, a newly emerging research area, statistical relational learning [13] has been exploring the dependence relationships in relational heterogeneous data, such as academic networks and World Wide Web, which can be utilized in the setting of coupled behavior analysis. Most of the current relational learning focus on classification of instances, given the label of some instances. Generally speaking, there are two types of SRL models in terms of inference: individual inference [14], [15] and collective inference [16], [17], [18], [19]. While collective inference model, such as relational dependency networks (RDNs) [3], utilize the related instance to infer one instance's label, individual inference models does not and thus getting rid of high computational collective inference. Individual inference models, such as relational Bayesian classifiers (RBCs) [15] and relational probability trees (RPTs) [14], [20], typically transform relational data into propositional form so that conventional machine learning techniques (e.g., Bayesian classifiers and probability tree) can be applied. In this paper, relational learning is used to learning the couplings between coupled behaviors on the basis of the graph representation.

III. Problem Formation

A. A Case Study in stock markets

In stock markets, the trading transactions are made up of trading actions from investors on their desired securities at particular trading prices, volumes and time points. As a toy example, Table I excerpts several order transactions of some investors and the corresponding trades made by them in an Asian stock market. Common sense tells us these transactional behaviors are not isolated but coupled with other in certain relationships that sometimes could be anomalous. In fact, domain knowledge experts have identified Investor (1) and (2) as cooperative manipulators in this excerpt dataset. Such sophisticated manipulators carefully place quotes with specific prices, volumes and times to maximize personal benefits. As can be seen from Table I, investor (2) first placed a large buy at 10:00:35 to mislead other buyers after his/her partner (1)'s sell. To confuse other investors, (2) further placed a sell at 10:01:23 while (1) placed a buy at 10:01:38. After that other investors such as (4) and (5) followed up by submitting buy quotes at the same price as (2)'s sell. In this way, investor (1) and (2) cooperate to mislead other investors and sell the stocks at a higher price. Thus, the trading behaviors are coupled with each other and the coupling relationships may become abnormal when manipulations happen. Analysis of such coupled behaviors is considered to be a vital point of detecting the anomaly exists in the stock markets. The next sections will review the formalization of the CBA problem.

B. Coupled Behavior Analysis Problem.

Suppose there are I actors, an actor i undertakes m_i behaviors $\mathbf{b_{i1}}, \mathbf{b_{i2}}, \cdots, \mathbf{b_{im_i}}$. Each actor i's j^{th} behavior $\mathbf{b_{ij}}$ is associated with a behavioral type $T(\mathbf{b_{ij}}) = t_{(\mathbf{b_{ij}}}$. Each behavioral type $t \in T$ has a number of associated properties $\mathbf{P^t} = (P_1^t, P_2^t, \cdots, P_n^t)(n$ may vary for different t value). Thus, each behavior $\mathbf{b_{ij}}$ is associated with a set of behavioral property value (a vector) $(p_1^{t_{\mathbf{b_{ij}}}}, \cdots, p_n^{t_{\mathbf{b_{ij}}}})$ determined by its behavioral type $t_{\mathbf{b_{ij}}}$. Then a behavior feature matrix $FM(\mathbf{b})$ for all actors for a specific period of time can be represented as follows [1]:

$$FM(\mathbf{b}) = \begin{pmatrix} \mathbf{b_{11}} & \mathbf{b_{11}} & \cdots & \mathbf{b_{1m_{\max}}} \\ \mathbf{b_{21}} & \mathbf{b_{21}} & \cdots & \mathbf{b_{2m_{\max}}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{b_{I1}} & \mathbf{b_{I1}} & \cdots & \mathbf{b_{Im_{\max}}} \end{pmatrix}. \quad (1)$$

where $m_{\max} = \max\{m_1, m_2, \ldots, m_I\}$, and for each actor i, if $m_i < m_{\max}$the corresponding element $b_{ij}(m_i <$

TABLE I
AN EXPERT OF THE 'ORDER' AND 'TRADE' RECORDS IN STOCK MARKETS

(a) Examples of buy and sell orders

Investor	Time	Direction	Price	Volume
(1)	09:59:52	Sell	12.0	155
(2)	10:00:35	Buy	11.8	2000
(3)	10:00:56	Buy	11.8	150
(2)	10:01:23	Sell	11.9	200
(1)	10:01:38	Buy	11.8	200
(4)	10:01:47	Buy	11.9	200
(5)	10:02:02	Buy	11.9	250
(2)	10:02:04	Sell	11.9	500

(b) Examples of the corresponding trades

Investor	Time	Direction	Price	Volume
(4)	10:02:04	Buy	11.9	200
(5)	10:02:04	Buy	11.9	250
(2)	10:02:04	Sell	11.9	450

$j \leq m_{\max})$ is defined as $\emptyset$, which means no action. Thus, the intra-couplings are reflected by the relationship between elements within one row of the above matrix, whereas the relationships between elements of different rows indicate the inter-couplings. Specifically, Actor i's behavior $\mathbf{b_{ij}}$ are intra-coupled with other behaviors of the same actor in terms of the corresponding function $\theta_k^i(\cdot)(1 < j \leq m_i, k \neq j)$ and inter-coupled with other actors' behaviors in terms of the corresponding function $\eta_k^i(\cdot)(1 < k \leq \mathrm{I}, k \neq i)$, with non-determinism.

Definition 1 (Coupled Behaviors): Coupled behaviors $\mathbf{b}$ refer to behaviors $\mathbf{b_{i_1j_1}}$ and $\mathbf{b_{i_2j_2}}$ that are coupled in terms of the relationship $f(\theta_{j_1j_2}^{i_1i_2}(\cdot))((i_1 = i_2) \wedge (j_1 \neq j_2))$ or $f(\eta_{i_1i_2}^{i_1i_2}(\cdot))((i_1 \neq i_2) \wedge (j_1 \neq j_2))$, where $(1 \leq i_1, i_2 \leq I) \wedge (1 \leq j_1, j_2 \leq m_{\max})$.

Theorem 1 (Coupled Behavior Analysis (CBA)): The analysis of coupled behavior is to build the objective function $g(\cdot)$ under the condition that behaviors are coupled with each other by coupling function $f(\cdot)$, and satisfy the following conditions:

$$f(\cdot) := f(\theta(\cdot), \eta(\cdot)). \tag{2}$$

$$g(\cdot)|(f(\cdot) \geq f_0) \geq g_0. \tag{3}$$

The above definitions formalize the problem of CBA and give the roadmap to solve this issue. But in real-applications, identifying both functions $\theta(\cdot)$ and $\eta(\cdot)$ and the coupling function $f(\cdot)$ is usually beyond the capability of current knowledge because of the inherent unobservable and non-deterministic properties of coupling relationships. For simplicity and efficiency, [4], [1] proposed a coupled CHMM-based approach to represent the coupling in the hidden state space, which will be reviewed in the following before the description of our proposed framework.

C. CHMM-based Coupled Behavior Modeling

CHMM [2] is a statistical model designed to model multiple processes with coupled relationships and each process is represented by a univariate or multivariate time series, which means the time interval between instances are uniform. Human behaviors (instances), though, may not meet the above condition of uniform time interval more often than not. Thus, the CHMM-based framework suggests to convert the coupled behaviors to sequences and then use sliding time window to aggregate the behavioral instances to cater for the utilization of CHMM [1], as indicated by Fig. 1(a).

In the case study of [1], they build three hidden Markov models (HMMs) [21] for one CHMM: HMM_B for buy sequence Φ_B, HMM_S for sell sequence Φ_S and HMM_T for trade sequence Φ_T, as shown in Fig. 1(b). One HMM can be denoted of a set of conditional probability densities (CPDs) in terms of A, B, C, π as follows: $\lambda^{HMM} = (A, B, \pi)$, where B is the observation probability distribution conditioned on the hidden state and π is the initial hidden state distribution and A, C is the conditional probability density of the current hidden state s_t conditioned on the previous hidden state s_{t-1} (i.e., $p(s_t|pa_{s_t})$ and the parent node of s_t is only s_{t-1}), which models the couplings between behaviors. Correspondingly, a CHMM modeling three trading sequences can be expressed as $\lambda^{CHMM} = (A, B, C, \pi)$. Then, A CHMM-based CBA framework can be built based on the following mapping relationships [1]:

$$CBA\ problem \rightarrow CHMM\ Modeling \tag{4}$$

$$f(\theta(\cdot), \eta(\cdot)) \rightarrow (A, B, C, \pi) \tag{5}$$

Meanwhile, as pointed out before, in order to build CHMM for analyzing the anomaly underlies the coupled trading behaviors [4], [1] converts the transactional data into behavior sequences and aggregating them, which makes the data suitable for CHMM-based modeling. Arguably, this kind of conversion may lose the information of important coupled relationships between behaviors. Motivated by this end, in next section, we present a novel graph-based CBA framework for a better modeling of coupled behaviors.

IV. PROPOSED FRAMEWORK

A. Preliminaries

As shown in Fig. 1(c), a group of coupled behaviors can be represented by a typed, attributed graph $G_B = (V_B, E_B)$. The nodes V_B represent behaviors (e.g., $buy_i(1 \leq i \leq 4)$, $sell_i(1 \leq i \leq 4)$ and $trade_i(1 \leq i \leq 4)$) and the edges E_B represent potential coupled relations among the behaviors (e.g., the directed edges in Fig. 1(c) and please refer to Section IV-B for how to generate them). Suppose we have a group of behaviors, each behavior $\mathbf{b_i} \in V_B$ is associated with a type $T(\mathbf{b_i}) = t_{\mathbf{b_i}}$ and each behavior type $t \in T$ has a number of associated attributes $\mathbf{X^t} = (X_1^t, \cdots, X_m^t)$ $(\mathbf{X^t} \subset \mathbf{X}$, where $\mathbf{X} = \{X_1, X_2, \cdots, X_n\}$ is the whole attribute set associated with the coupled behaviors: e.g., trading price, trading volume). An example can be seen in Fig. 2(b). There are no hidden variables in our proposed graph-based model and we directly model the couplings of behaviors by a set of CPDs of all the behavioral attributes $\mathbf{X}$ in a relational setting.

Specifically, for any specific attribute instance x_i of X_i in a behavior $\mathbf{b}$, the CPD $p(X_i = x_i|pa_{x_i})$ is conditioned on the attribute values of other behaviors linked to $\mathbf{b}$ (as well as other attribute values of $\mathbf{b}$ itself). In this sense, the couplings between behaviors are considered in the form of a set of CPDs (in a relational setting [1]) for different behavioral attribute values of the coupled behaviors conditioned on related values (similar to the A, C of the CHMM framework). Then, A relational learning-based CBA framework can be built based on the following mapping relationships:

$$CBA\ problem \rightarrow SRL\ Modeling \tag{6}$$

$$f(\theta(\cdot), \eta(\cdot)) \rightarrow p(X_i = x_i|pa_{x_i}), X_i \in \mathbf{X} \tag{7}$$

The following content describes how the proposed framework works, which includes three stages: data preprocessing, modeling coupled behaviors via relational learning and the corresponding anomaly detection algorithm.

B. Data Preprocessing

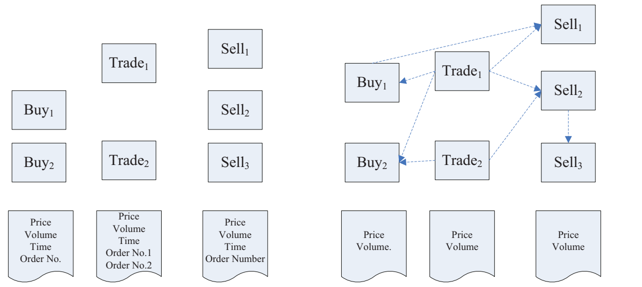
Let us review the behavior feature matrix defined in Equation 1, this feature matrix encodes all the behaviors that are coupled together for analysis. Intuitively, the space for analyze the couplings among these behaviors are almost infinite. For a coupled behavior $\mathbf{b_j}$ in n coupled behaviors, it could be possibly coupled to any one of the remaining $n-1$ behaviors and the corresponding search space is $O(C^1_{n-1})$. Generally, if considering it to be coupled to any k, $1 \leq k \leq n-1$, the possible search space could be $O(C^k_{n-1})$. Thus, if we sum up the search space and the overall search space could be $O(2^{n-1})$, which means computational complex is exponential to the increase of the number of coupled behaviors. This is intractable when the number of the coupled behaviors is large. Alternatively, we could limit the search space suggested by some reference behavioral properties of the behaviors indicating the possible coupled relationships. Then the remaining behavioral properties can be defined as analysis properties, which are used for learning the coupled relationships between the behaviors in terms of CPDs in a relational setting. The formal definition of such two properties is as following.

Definition 2 (Reference Property): A reference property R refers to the behavioral property which is used to generate the possible underlying coupled relationships between behaviors, usually user-defined.

Definition 3 (Analysis Property): A analysis property A refers to the behavioral property which is used to learn the coupled relationships between behaviors.

Let us see an example to clarify these definitions. Recall the Case Study in stock markets described in Section III. As mentioned above, there are three type of behaviors in stock markets: 'buy', 'sell' and 'trade'. These behaviors are coupled with each other and exhibit different relationships which may indicate the manipulation of the market. As shown in Fig. 2(a).

[1]This CPD is not the same as the CPD in a flat setting which only consider the dependency of intrinsic attribute values (i.e., the attribute values within the same instance), for further details, please refer to [3].



(a) The coupled behaviors with reference and analysis properties (b) Link generation using reference properties

Fig. 2. An example for illustration of reference and analysis properties

The three kinds of behaviors all have the corresponding behavioral properties. In terms of coupled behaviors, these properties can be divided into reference property (indicating possible couplings) and analysis property(for analysis of couplings under the constrain of possible couplings). For example, in Fig. 2(a), the behavioral properties of 'buy' are: 'Price', 'Volume', 'Time' and 'Order No.'. The reference property can be 'Time' and 'Order No.'. The property 'Time' may become a clue of the coupled behaviors neighboring in time. This is reasonable because beyond the time constrain the behaviors have less chance to be coupled. Consequently, these possible coupled behaviors are linked for further analysis, as shown in Fig. 2(b). Similarly, another property 'Order No.' of 'buy' and 'trade' behaviors points out the corresponding 'trade' behaviors (also have order Numbers). These possible relationships are also generated in terms of links between the behaviors. Other links between these behaviors are generated as long as users are interested in such possible couplings.

C. Modeling Coupled Behaviors via Relational Learning

After obtaining the graph structure of the coupled behaviors, we further explore the learning of couplings between the behaviors (i.e., a set of CPDs.). In some cases, estimating all the CPDs may not be of the direct interest. For example, in stock markets, the 'trade' behavior directly influence the price of a specific security and the 'buy' and 'sell' behaviors have indirect impact on the price fluctuation. In other words, in stock market, the manipulators control the market through deliberately arranging the trading prices of the securities which are decided by 'trade' behaviors directly. To detect the anomaly in stock markets, we are more interested in modeling the fluctuation of 'trade' behaviors' $price$ attribute values and its dependency on other related trading behaviors' attribute values. Thus, we alternatively model the CPD of the $price$ attribute values conditioned on other related behavioral attribute values. Consequently, we need to specify the 'target behavior' (e.g., the 'trade' behaviors) and the 'target behavioral property' (e.g., the 'price' attribute) and their formal definition is as following:

Definition 4 (Target Behavior): A target behavior $\mathbf{b_i^{(t)}}$ is determined by its behavioral type $t_{\mathbf{b_i^{(t)}}}$. Usually, one behav-

TABLE II
AN EXAMPLE OF FLAT THE COUPLED BEHAVIORAL DATA

	RF_1	RF_2	$\cdots$	RF_n
$trade_1$	rf_{11}	rf_{21}	$\cdots$	rf_{n1}
$trade_2$	rf_{12}	rf_{22}	$\cdots$	rf_{n2}

ioral type of behaviors are indicated as target behaviors by prior domain knowledge.

Definition 5 (Target Behavioral Property): A target behavioral property $X^{t_{\mathbf{b}_i^{(t)}}}$ is usually one of the properties belonging to one behavioral type and specified by prior domain knowledge as well.

In consequence, in order to model the coupled relationships among behaviors, we could estimate the CPD becomes $p(X^{t_{\mathbf{b}_i^{(t)}}} = x|pa_x)$., underlies which the coupled relations between behaviors are considered: To learn the $p(X^{t_{\mathbf{b}_i^{(t)}}} = x|pa_x)$ is challenging because the parent node of a behavioral attribute instance could be heterogenous. A possible method is to flat the parent nodes (the attribute values of linked behaviors) into relational features. [14], [15] and [3] proposed different strategies to flat data using relational features. For example, the 'trade' behaviors in Fig. 2(b) can be transformed into TABLE II by generating the relational features $RF_1, \cdots, RF_n$.

a) Modeling of Conditional Probability Distribution: Theoretically, any models learn the conditional probability distribution can be used for our task for coupled behaviors learning. Here we discuss two different conditional probability models: relational probability trees (RPTs) [14] and relational Bayesian classifiers (RBCs) [15]. The main differences between the two methods are how to generate relational features and how to use them.

b) Relational Bayesian Classifiers: RBCs are simple Bayesian classifiers to model relational data, which in this paper is coupled behavior data. Similar to the independence assumption of the naive Bayesian classifier, RBCs flat the relational data into propositional data through multiset estimators, such as average value, independent value and average probability [15]. For example, consider the 'trade' behavior as the target behavior and its $price$ property as the target behavioral property in Fig. 2(b). To estimate the relational CPD for the attribute $price$ values on behavior $trade$, the RBC considers all the attribute values associated with the related behaviors $buy, sell, trade$ and treats them as independent relational features. The CPD can be estimated as $p(x|pa_x) \propto p(x)p(rf_1|x)p(rf_2|x)\dots p(rf_n)(rf_1$ to rf_n refer to the relational feature values). Please refer to [15] for further details.

c) Relational Probability Trees: An alternative way to estimate the CPD by a RPT. The RPT algorithm uses aggregation functions (e.g, mode, count, proportion and degree) [14] to transform the relational feature to a propositional feature, which is different to the RBC algorithm. After that a probability tree is construct to select proper features to represent the desired CPD. For example, consider the 'trade' behavior as the target behavior and its price property as the target behavioral property in Fig. 2(b). A possible if-then rule generated by the RPT could be $if\ RF_1 > T_0\ then\ p(price = price_1) = 80\%$ (e.g., RF_1 could be the average price of related buy behaviors and T_0 is a constant). A set of this kind of rules could represent the CPD we want to estimate. In other words, the RPT algorithm automatically generates and selects aggregated relational features to model the CPD of the target behavioral property values (e.g., $price$ values in Fig. 2(b)) of the target behavior (e.g., the trade behavior in Fig. 2(b)) conditioned on other related behavioral attribute values. Please refer to [14] for further details.

D. Abnormal Coupled Behaviors Detection

Having modeled the normal coupled behaviors, we must further determine whether the new coming coupled behaviors are normal or abnormal. An intuitive solution to this problem is to calculation the conditional likelihood (CL) given the observations of the coupled behaviors based on the normal model M (i.e. the CPD learned), which is $CL(\mathbf{b^k}) = \prod_{\mathbf{b_i} \in \mathbf{b^k}} p(X^{t_{\mathbf{b}_i^{(t)}}} = x|rf_{1i}, rf_{2i}, \cdots, rf_{ni}; M)$. This can be also used to predict the value of the target behavior property and then compared to the true value of the property. The obtained performance measure (e.g., area under ROC curve (AUC) and accuracy) can also be used to check how well the coupled behaviors are modeled by the normal model as well. Thus, in this paper, we integrate the performance measure and the corresponding CL value as the anomaly score for the coupled behaviors.

$$AS(\mathbf{b^k}) = CL(\mathbf{b^k}) * AUC(\mathbf{b^k}) * Accuracy(\mathbf{b^k}) \quad (8)$$

The assumption is that abnormal trading behaviors are less likely to be predicted based on normal behaviors and have a low CL value.

The algorithm for detecting abnormal coupled behaviors is described in Algorithm 1. As shown in Algorithm 1, step 1 is train a normal model M_0 of all the coupled behaviors in the training set. Step 2 to 7 is a loop process to calculate the corresponding anomaly score of each group of coupled behaviors in the testing set. If the anomaly score is lower than some predefined threshold, the corresponding group of coupled behaviors is judged as anomaly. The output of this baseline algorithm is the set of anomaly.

V. EMPRICAL RESULTS

A. The Data set

The experimental data set is from an Asian stock market. It covers 388 valid trading days from 1 June 2004 to 31 December 2005. The data is partitioned into two sets suggested by domain experts. The training data set consists of transactions collected from 1 June 2004 to 31 December 2004, by filtering those transactions associated with the identified alerts. We treat it as 'normal' data. The remainder of the transactional data form the test set. The behavioral data of each trading day in the training and testing set can be seem

Algorithm 1 Model-based Anomaly Detection

Input: A Training set $\{\mathbf{b^1}, \mathbf{b^2}, \cdots, \mathbf{b^N}\}$,
A Testing set $\{\mathbf{b^1}, \mathbf{b^2}, \cdots, \mathbf{b^M}\}$,
A Model Type M,
A Threshold Th_0.
Output: An anomaly set $\mathcal{A}$.

Train one M_0 model on the training set $\{\mathbf{b^1}, \mathbf{b^2}, \cdots, \mathbf{b^N}, \}$.
for all $\mathbf{b^k}$ in the Testing set **do**
    Compute the anomaly score of $\mathbf{b^k}$ given the model M_0: $AS(\mathbf{b^k}|M_0)$
    if $AS(\mathbf{b^k}|M_0) < Th_0$ **then**
        $\mathbf{b^k} \rightarrow \mathcal{A}$
    end if
end for

as $\mathbf{b^j}$ $(1 \le j \le N)$ and $\mathbf{b^k}$ $(1 \le k \le M)$ in Algorithm 1, respectively. Those transactions with alerts are not removed from the test set so that the test set is made up of both normal and abnormal coupled trading behaviors. Alerts fired by the existing surveillance system are referred as rough benchmark for us to evaluate the performance of our proposed algorithm. Because it is very costly and time-consuming to label the data, the above evaluation method is suitable and reasonable.

B. Performance Measure

In this paper, we evaluate the performance of our proposed algorithms from both technical and business perspective. True positive TP, true negative TN, false positive FP and false negative FN are counted in terms of treating the abnormal cases as the positive class. The technical performance of a framework is then evaluated by accuracy $(\frac{TP+TN}{TP+FN+FP+TN})$, precision $(\frac{TP}{TP+FP})$, recall $(\frac{TP}{TP+FN})$, and specificity $(\frac{TN}{FP+TN})$. On the other hand, two business metrics, return and abnormal return [22], are used as indicators for abnormal dynamics surveillance of the market. Empirically, the trading days with exceptional patterns are more likely to incur a higher return and abnormal return than those without exceptional trading. Return refers to the gain or loss for a single security or portfolio over a specific period, which is calculated by $\mathrm{R}eturn = \ln \frac{p_t}{p_{t-1}}$, where p_t and p_{t-1} are the trade prices at time t and $t-1$, respectively. Abnormal return is defined as the difference between the actual return of a single security or portfolio and the expected return over a given time period. The expected return is the estimated return based on an asset pricing model, using a long-term historical average, or multiple valuations. The formula to compute abnormal return is as $\mathrm{AbnormalReturn} = \mathrm{R}eturn - (\gamma + \xi \mathrm{R}eturn^{market})$, where $Return^{market}$ is the observed return for the market index, γ and ξ are the estimated parameters using previous return observations.

C. Comparison of Different relational models and the CHMM

We tested the two different CBA framework based on two different relational models (denoted as 'CBA-RBC' and 'CBA-RPT', respectively) on the test data set and compared them to the CHMM-based CBA framework (denoted as 'CBA-CHMM')[2]. Fig. 3 shows both their technical performance. The horizontal axis (P-Num) stands for the number of detected group-based abnormal behaviors (of a trading day), and the vertical axis represents the values of technical measures (accuracy, precision, recall or specificity) or business measures (return and abnormal return). As can be seen from Fig. 3(a), Fig. 3(b), Fig. 3(c) and Fig. 3(d), both the two relational learning-based CBA frameworks perform better than the previous proposed CHMM-based framework. Specifically, when $P\!-\!num = 11$, the precision of the RBC-based framework can be 100.02% higher than that of the CHMM-based framework. Simialr trends can be seen in other measures. This proves the data transformation in the CHMM-based framework may cause information loss and lead to poorer performance. Of the two relational models, the CBA-RBC performs the best in terms of all the measures. This is may be because the way the RBC constructs relational features are more close to the real situation in this case, compared to the RPT, which may be helpful to capture more comprehensive couplings between behaviors.

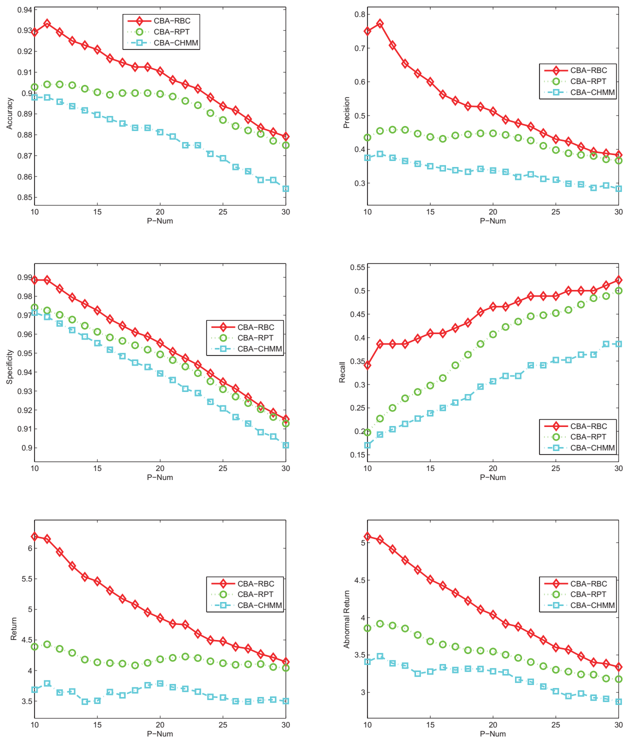


Fig. 3. Technical and Business Performance of the Four Models

D. Exploration of Different Anomaly Scores

Here we compare four anomaly scores, denoted as 'AS1', 'AS2', 'AS3' and 'AS4', respectively. The 'AS1' is defined as in Equation 8, while $AS2(\mathbf{b^k}) = Accuracy(\mathbf{b^k})$, $AS3(\mathbf{b^k}) = AUC(\mathbf{b^k})$ and $AS4(\mathbf{b^k}) = CL(\mathbf{b^k})$. The experimental results

[2]The performance results are the averaged values of different time sliding windows [4].

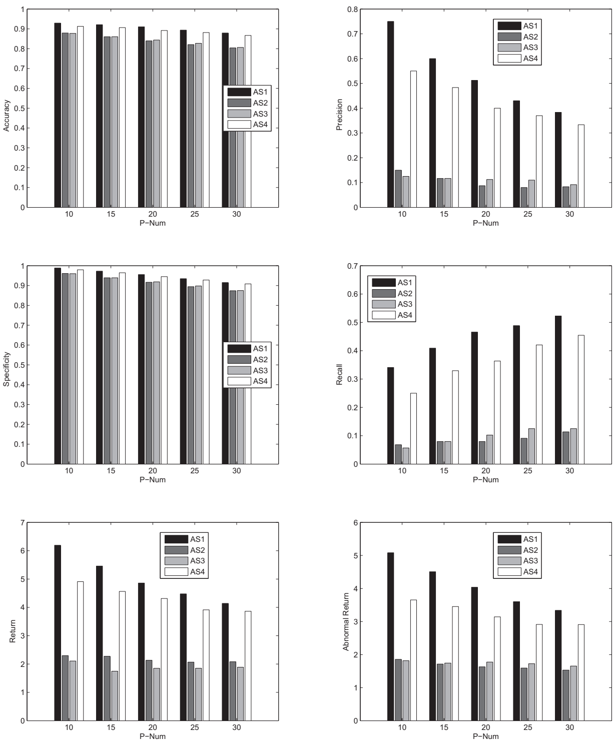


Fig. 4. Technical and Business Performance of the Four Anomaly Scores

[3] on the data set is shown in Fig. 4. The horizontal and vertical axes in Fig. 4 have the same meanings of that in Fig. 3. From the picture, we can see our proposed anomaly score ‘AS1’ performs the best. An intuitive explanation is that ‘AS1’ consider the most comprehensive aspects to in the four scores for comparison.

VI. Conclusions

We introduce a challenging issue of detecting abnormal trading coupled behaviors and propose a graph-based CBA framework. The graph model avoids the data transformation and the Markov assumption in the previous CHMM-based framework, and is expected to have a more accurate modeling of the coupled relationships between the behaviors, which is helpful to further anomaly detection. In the case study of detecting abnormal trading behaviors in stock markets, we have demonstrated that the graph-based CBA framework performs better than the CHMM-based framework and the proposed anomaly score is effective compared to alternative scores. Additional research includes applying our proposed CBA framework to other scenarios, such as social security and social welfare data mining where people’s behaviors are also coupled with each other, and investigations on capturing the dynamics of the coupled relationships between normal behaviors which may change over time.

[3]Only the performance results of CBA-RBC are reported because of limited space and other models exhibit similar trends.

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