A State Transition Approach to Understanding Users' Interactions

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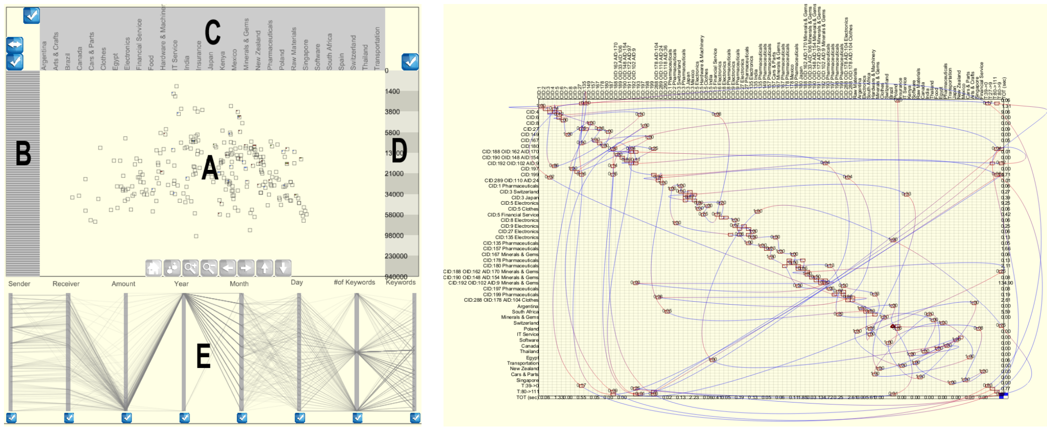

(a) (b)

Figure 1: Overview of InteractionViz. It consists of two windows as a Relation Window (a) and a Transition Window (b). The Relation Window consists of multiple coordinated views to show the relationships among keywords, accounts, and transactions. Experts' findings on transactions are represented in the Relation Window and their overall semantic-level interactions (i.e. keywords, accounts, and transactions) are displayed in the Transition Window by following a state transition approach.

Abstract

Understanding users' interactions is considered as one of the important research topics in visual analytics. Although numerous empirical user studies have been performed to understand a user's interaction, a limited study has been successful in connecting the user's interaction to his/her reasoning. In this paper, we present an approach of understanding experts' interactive analysis by connecting their interactions to conclusions (i.e. findings) through a state transition approach.

1 Introduction

Although many useful visualization applications have been designed, how much the designed systems are useful in solving analytical questions is regarded as a research challenge. In the visualization community, researchers discussed to find possible research directions in understanding users' interactions by connecting to their reasonings [1]. From the discussion, one of the promising research directions was to use an eye-tracking device, with which an user's interaction can be analyzed by tracking one's visually processed visual elements. Although this is a quite promising approach in understanding users' interactions, how to connect the user's interaction to her reasoning and how to analyze the captured eye-tracking data is still unknown. In contrary to this approach, we performed an expert evaluation to see how user interactions encode experts' reasoning [3]. From the study, we found that by examining financial analysts' interactions (semantic-level interactions), about up to 79% of their findings can be recovered through the use of a visual analytical tool. This indicates that the user's interaction logs (e.g. semantic-level interactions such as keywords, accounts, and transactions) are somewhat connected to one's reasoning behind the analysis process. In addition, we observed that financial analysts have different opinions on each financial transaction as suspicious, unsuspicious, and inconclusive. Although they have different ideas and sometimes contradict each other on determining each transaction, we found that finding the evidence how they ended up with their conclusions is difficult.

In this paper, we propose an approach to understand the analysts' interactions. To extract their interactions and discover the reasoning behind the analysis processes, we used a state transition approach by creating a state transition matrix (i.e. Markov Chain [5]). In here, each user-created interaction is regarded as a state. Depending on the number of semantic information, a $m \times m$ transition matrix is generated by referencing the overall user's interactions. With this transition matrix, the user's reasoning can be recovered. This paper begins with describing the designed visual analytics system, then moves to explaining how the user's interactions can be analyzed by connecting them to her reasoning through the system.

2 System Design

In our previous study [3, 4], we performed an experts' user study based on a well-known financial visual analytics system (called WireVis [2]). From the study, we observed that financial analysts have different opinions on each financial transaction as suspicious, unsuspicious, and inconclusive. Since their decisions are often based on experiences, it is difficult to understand how they concluded with their decisions. To understand how they ended up with different conclusions, we designed a system (called InteractionViz)

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by following a coordinated multiple views approach. As shown in Figure 1, InteractionViz consists of two windows as a Relation Window and a Transition Window. The Relation Window represents the relationship among accounts, keywords, and transactions. And the Transition Window shows how the user transits from one state to another while performing a visual exploration on financial data.

2.1 Relation Window

The Relation Window is designed consisting of three views: a Projection View (Figure 1(a) (A)), an Information View (Figure 1(a) (B $\sim$ D)), and a Data View (Figure 1(a) (E)). All views are coordinated in such a way that any interaction with one view is immediately reflected in all the other views (brushing & linking).

The Projection View projects all transaction data points onto a two-dimensional coordinate system based on Principle Component Analysis (PCA). The Information View has three information panels as accounts ((Figure 1(a) (B))), keywords (Figure 1(a) (C)), and the amounts of the transactions (Figure 1(a) (D)). Relevant information of highlighted or selected transactions are visualized in these panels as connected lines. The Data View shows a parallel coordinates visualization of all transactions in the original data dimensions. There are about 8 dimensions in the financial transaction data as sender account, receiver account, the amounts of the transactions, date information (year, month, and day), number of keywords, and actual keywords related to each transaction.

2.2 Transition Window

The Transition Window represents the user's semantic interactions as a state transition matrix. As we mentioned above, each interaction is regarded as a state that indicates the user's interaction with visual element(s). The changes of state indicate transitions with the probabilities associated with various state-changes. The set of all states and transition probabilities in the state transition matrix completely characterizes a Markov chain. Since the financial transaction data, which we used in our system, include 380 accounts (including account clusters), 29 keywords, 249 transactions, and 11020 account $\times$ keyword combinations, roughly a 11680 $\times$ 11680 transition matrix is created. Since all states cannot be visited by the user, non-visited states are removed from the transition matrix to increase the readability of represented visual elements. In the transition matrix, y-axis indicates current states and x-axis represents future transition states.

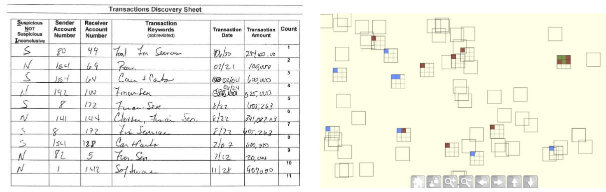
How much time the user stayed at each state by looking at transaction information is measured in seconds and mapped with a gradient blue color. Darker blue indicates the user spent more time proportionally to other states. Additionally, the user's interactions are represented as a connected spline curve (see Figure 1(b)).

3 Connecting the Users' Findings to Interactions

By investigating wire transactions, financial analysts often determine the investigated transaction(s) as suspicious, unsuspicious, or inconclusive. To show how they ended up with their decisions, the Relation Window and the Transition Window are closely connected each other to show the user's decisions (i.e. findings) and the user's interactions (i.e. reasoning), respectively.

In InteractionViz, all expert analysts' decisions (i.e. findings) and their interaction logs (i.e. semantic-level interactions) from the previous study [3] are embedded. As shown in Figure 2, the analysts' diverse opinions on each transaction are displayed inside the Projection View and colored as red ("suspicious"), blue ("unsuspicious"), and green ("inconclusive").

The user can move the mouse over the data in the information panels and the projected data elements in the Relation Window in order to allow her to focus on specific transactions and observe what specific accounts are transacting over what keywords and amounts.



(a) (b)

Figure 2: During the experts evaluation, financial analysts were requested to write down their final findings in transaction discovery sheet. Figure (a) shows an expert's transactions discovery sheet. Experts' findings in the transactions discovery sheets are mapped to a grid cell in the Projection View (b). Since the two windows are closely connected, any interaction in the Projection View will be reflected to a state transition matrix in the Transition Window.

After finding an interesting analysts' decision in the Relation Window, the user can further investigate the corresponding analyst's interactions (i.e. semantic-interactions) in the Transition Window. In the transition matrix, the user's interactions are regarded as a set of states, $S = s_1, s_2, ..., s_n$. Since the user's interactions start in one of these states and move from one state to another, an interaction is represented as a state with the probabilities p_{ij} (called *transition probabilities*). With this approach, expert analysts' interactive analysis patterns can be recovered by connecting to their findings.

4 Conclusion and Future Work

In this paper, we propose an approach of understanding financial analysts' interactions through a visual analytics application. By exploring and examining both wire transactions and the users' interactions, it is possible to find how each expert ended up with decisions on transactions as suspicious, unsuspicious, and inconclusive. The provided set of interaction and representation techniques are useful to perform interactive exploration as well as examination on the user's interactions. Since experts' decisions are diverse and sometimes contradictory to each other, tracing their reasoning can be an important process to understand their analytical procedures on wire transactions.

We believe that the system is well designed to understand the analysts' overall analytical processes. However, it is necessary to conduct an evaluation to validate the system as well as our idea of connecting the user's findings to interactions in visualization. Specifically, we are going to focus on recovering the analysts' reasoning by observing the transition matrix.

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