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# An Exploratory Visual Analytics Tool for Multivariate Dynamic Networks

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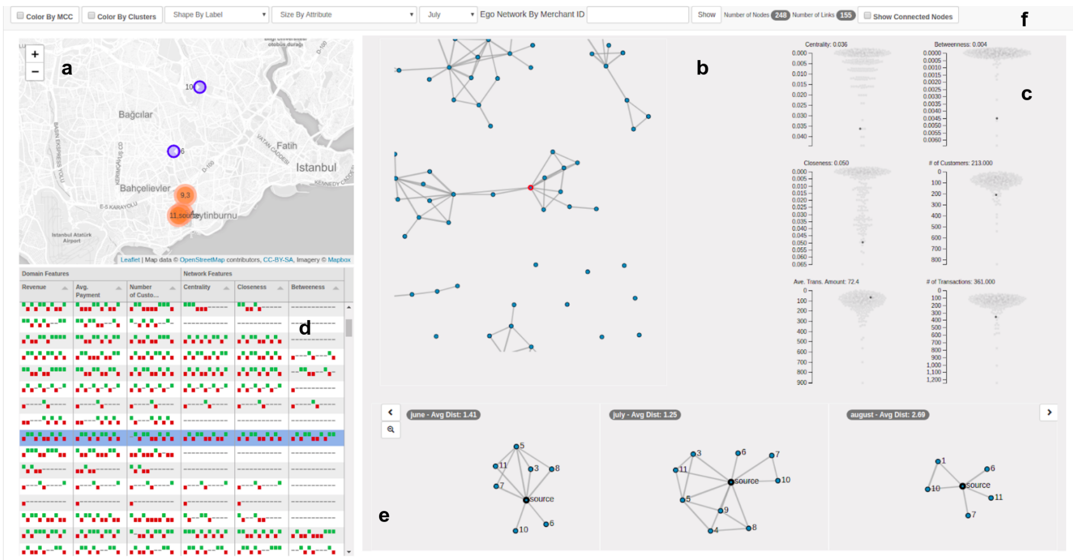

**Figure 1:** *The designed user interface. a) The spatial component depicts the encoding between the network and a geographical map. b) The general network overview. c) The distribution component for domain and network features. d) The pixel display component to visualize temporal changes in the domain and network features. e) The ego-network component to display the ego-network evolution. f) Visual encoding and filtering component.*

**Abstract**

*Visualizing multivariate dynamic networks is a challenging task. The evolution of the dynamic network within the temporal axis must be depicted in conjunction with the associated multivariate attributes. In this paper, an exploratory visual analytics tool is proposed to display multivariate dynamic networks with spatial attributes. The proposed tool displays the distribution of multivariate temporal domain and network attributes in scattered views. Moreover, in order to expose the evolution of a single or a group of nodes in the dynamic network along the temporal axis, an egocentric approach is applied in which a node is represented with its neighborhood as an ego-network. This approach allows users to observe a node's surrounding environment along the temporal axis. On top of the traditional ego-network visualization methods, such as timelines, the proposed tool encodes ego-networks as feature vectors consisting of the domain and network attributes and projects them onto 2D views. As a result, the distance between projected ego-networks represents the dissimilarity across the temporal axis in a single view. The proposed tool is demonstrated with a real-world use case scenario on merchant networks obtained from a one-year-long credit card transactions.*

**CCS Concepts**

• ***Human-centered computing*** → ***Visualization; Visual analytics;***





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## 1. Introduction

Network data is ubiquitous. Networks consist of entities, nodes that are connected to each other over relations named links. In a real-world scenario, nodes in a network may represent many different entities such as users, locations and routers; while links stand for the relationship between them such as friendship, roads and signals. Understanding the topological structure within the network help analysts to acquire useful insights such as clusters within the network. However, nodes or links in the network may have domain related multivariate attributes that have the potential to reveal more insights to the analyst. In addition, the network topology alters as the time forwards; new nodes and links emerge while some die. The network alteration can be captured within temporal snapshots and stored in a dynamic network. Essentially, a multivariate dynamic network consists of chronologically ordered multivariate networks, depicting the transitions between consecutive time steps in terms of topological and domain attributes is a challenging task.

Existing multivariate dynamic network exploration tools focus on the evolution of the overall network. However, narrowing down to a particular or a group of nodes in the network may reveal invaluable insights. An ego-network consists of an ego node with its directly connected neighbors and links connecting them. For instance, in a social network such as Facebook, the ego-network of a user consists of other users who are directly connected. The demographic attributes of the connected users help analysts to better understand the environment in which the select user is located. Analyzing the ego-network of the selected user along a time span, in which new connections occur and existing ones die, would depict the evolving environment around the selected user. For example, Halgin et al. [HB12] analyze the interactions between customers with the help of ego-networks over the course of a time period to observe collective churn behaviors. There exist many studies on the evolution of ego-networks, especially in social sciences [CNJV18, DCYS17, FC16]. For instance, Fares et al. [FC16] study ego-network evolution to analyze the difference between healthy and diseased people in terms of the perception of care. And furthermore, Lucia et al. [LF14] utilize ego-networks to classify text messages.

Ego-network visualization literature focuses on displaying the topological evolution across the temporal axis. However, depicting the evolution of the domain attributes reveal additional invaluable insights for the analysts. In this paper, an exploratory visual analysis tool is developed to display multivariate dynamic networks from an egocentric approach. The developed tool focuses on displaying both domain and network attributes. In addition, the evolution display of ego-networks aims to answer both mesoscopic and microscopic questions [WPZ*16]. Lastly, to further expose the relationship between nodes in the network, a spatial encoding component is incorporated into the tool. With the help of the spatial encoding component, users are able to observe the proximities between nodes in the network.

## 2. Related Work

A multivariate dynamic, $D$, is a finite sequence of chronologically ordered temporal multivariate networks, $\langle G_0, G_1, ..., G_t \rangle$, in which, temporal snapshots, $G_i$, possess a finite set of attributes, $A = \{a_1, a_2, ..., a_n\}$, assigned to each node and/or edges. The objective is to display the topological and domain-specific attribute evolution along the temporal axis. To this end, juxtaposed timeline views [GBD09, BVB*11] and animated transitions [BBL12, BPF14] are proposed by researchers to display the temporal evolution. However, scaling and cognitive load is the primary drawbacks involved in these methods. In order to alleviate these problems, a hybrid approach [HSS11, SMM13] is applied in which users are able to iterate over a pre-defined time window between temporal snapshots.

Existing visual ego-network studies are based on the previously mentioned visualization techniques [FHQ11, HZL*16]. In ego-network studies, the objective is to display the evolution throughout the entire time span for the focal node and its alters. Shi et al. [SWW*15] propose a 1.5D visualization for ego-network evolution, in which temporal axis is displayed as a vertical axis that is divided into distinct time slots, corresponding to ego-networks. The alters and domain-related attributes are displayed alongside the vertical axis, resulting in an additional dimensionality. In a similar manner, Zhao et al. [ZGC*16] deploys temporally segmented horizontal lines, representing alters in an ego-network, that stores the connections with the focal node and the other alters in the ego-network, so that the users are able to observe how the topology changes over time. Lastly, Liu et al. [QHS*15] incorporate domain-related event information on top of the temporal axis. However, as the number of time steps increase, the cognitive load on the users increases as well due to the linear time projection.

[WPZ*16, LWB18] propose spatial layouts that encapsulate the state of an ego-network in timestamp $t$ as a position in a 2D view. Wu et al. [WPZ*16] extract the topological features for each temporal ego-network and store them as feature vectors. The resulting feature vectors are then projected onto 2D views so that the proximity between observations represent similarity. Instead of extracting raw topological features, Law et al. [LWB18] focus on the events that capture the temporal changes among the domain attributes. As a result, the users can observe similar ego-networks that possess similar evolution patterns with respect to their domain attribute changes over the temporal axis. In the proposed tool, the ego-network component is based on both traditional hybrid approaches and spatial layouts. However, compared to the previous studies, topological network features are combined with domain-specific attributes so that the evolution along the entire temporal axis can be depicted in a single view.

## 3. Design Rationale

The goal of the developed exploratory tool is to help users form and test hypotheses and observe certain patterns, trends, and outliers present in the multivariate dynamic network with an egocentric approach. In order to achieve this goal, the multivariate dynamic network must be comprehensively displayed in various aspects. The changes in the domain and network attributes must be available for a particular or a group of node(s) in the network. In addition, the visual display of ego-network evolution should answer mesoscopic and microscopic [WPZ*16] questions. The mesoscopic questions deal with comparisons among a group of nodes' ego-network evolution similarities. For instance, how do a group of nodes' domain and network specific attributes evolve along the temporal axis? To what do they extent they drift from each other? These are some of the exemplary questions regarding the mesoscopic analysis. On the other hand, microscopic questions focus on a particular node's ego-network evolution.

## 4. System Description

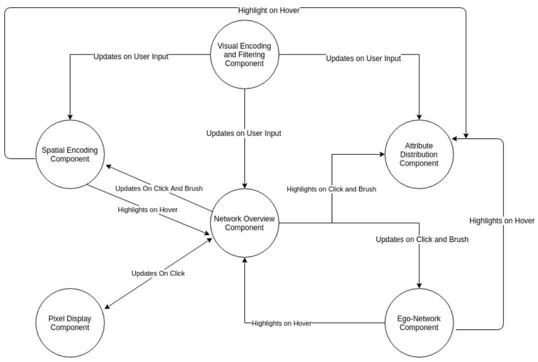


**Figure 2:** *Interaction schema among the components.*

In Figure 1, the designed interface, consisting of six visual components, can be observed. The main component of the interface is the temporal network area (part b in Figure 1) in which a snapshot $G_t$ of the multivariate dynamic network is depicted to achieve overview and zoom/filter functions. Although there exists other network layouts, such as matrix notation [GGK*11] or 3D networks [GZD*15], node-link layout [Dud13, MH15] is chosen due to its simplicity and understandability. A temporal snapshot of the network allows the users to focus on the dynamics of the current time step. Users are able to select temporal snapshots of the network with the help of The visual encoding and filtering component which is depicted in Figure 1-f. Moreover, a velocity Verlet based force-directed layout is deployed for the node-link representation. The next component, part a, displays the spatial attributes of each node on a map. The component on part c displays the domain and network attribute distributions with swarm plots for a particular network snapshot. In addition, the brush selection on the network overview component yields the temporal attribute evolution as in Figure 4. In order to display the temporal increases and decreases in both domain and network attributes, a pixel display is utilized in part d. In this component, the direction of change is encoded with colors in each time step as small rectangular glyphs. Each row in the table corresponds to a node in the network, with its domain and topological attributes displayed in the columns. The users are able to directly perceive the change between consecutive time steps. Moreover, they can still obtain the raw value with a hover action the desired time step. Lastly, the visual encoding component, part f, help users assign domain and network attributes to specific visual encodings.

The visual display of ego-network evolution takes place in part e in Figure 1. A timeline view [Tuf90] is deployed in which a node's ego-networks are juxtaposed to each other as small multiples. Moreover, on-demand by the user, a spatial layout is displayed, in which a connected scatter plot [vdEHBvW16] depicts the similarities between each ego-network $U_k^t$ of focal node $k$ at time step $t$. The ego-network component incorporates two different views for the users. By default, the juxtaposed temporal ego-network snapshots as node-link layouts are displayed to the user. The distance preserving spatial layout is displayed with a click event on a switch button located on the top left corner. Finally, to compare a group of nodes' temporal domain and network attributes, sparklines [GBWI17] are utilized in the temporal attribute component.

On top of the network features such as, *centrality* and *closeness*, domain attributes are added to the feature vectors as well to represent an ego-network in a particular timestamp $t$. In order to project the computed temporal feature vectors, dimensionality reduction techniques are utilized. Among the existing studies, Multidimensional Scaling stands out as the frequent choice [BSH*16, LWB18, WPZ*16], since it aims to preserve the original distances in the temporal feature space. As a result, metric MDS is utilized in this paper as well since feature vectors are consisting of quantities measured in terms of coordinates.

MDS expects a dissimilarity matrix as the input to project multidimensional features onto a 2D plane. The distance metric in the dissimilarity matrix plays a crucial role in encapsulating the dissimilarities. The selected distance metric should be sensitive to small changes. Canberra distance, $\sum_{i=1}^{d} \frac{|P_i - Q_i|}{P_i + Q_i}$, is an effective distance metric to discriminate changes near zero [BKEF12]. Consequently, MDS is utilized with a distance matrix computed with Canberra distance.

## 5. Use Case: Merchant Networks

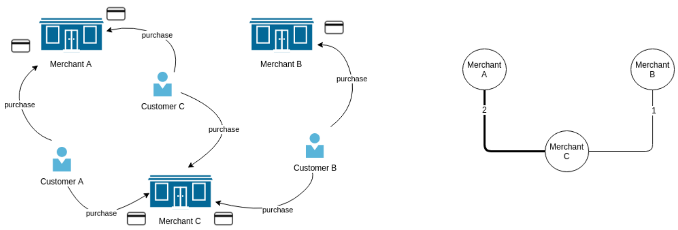


**Figure 3:** *Multivariate dynamic network creation from transaction data set.*

Small and medium-sized enterprises, SMEs, constitute a significant segment in the majority of the economies. Existing approaches for predicting an SME's well-being are based on financial criteria, for instance, earnings per asset and equity per asset [FF09]. A research team in Sabanci University proposed a novel set of attributes solely based on credit card transactions and created a merchant network in which merchants are nodes and shared customers are edges.

The credit card transaction data was provided by a private bank operating in Turkey. In the data set, transactions are made by registered customers in registered merchant venues. The officials of the bank anonymized required fields such as customer and merchant identification values. The dataset contains amount, location, category, and timestamp for each transaction between July 2014 and

June 2015 belonging to nearly 5K customers. In addition, the demographic attributes, such as age and education level, of customers were provided by the bank as well.

To assign an edge between two nodes in the network, the number of shared customers are computed. The majority of the customers do not make frequent transactions. In order to prevent cluttered edges and misleading results, edges are set based on a threshold value. An edge is created between two merchants if the number of shared customers is more than the threshold value.

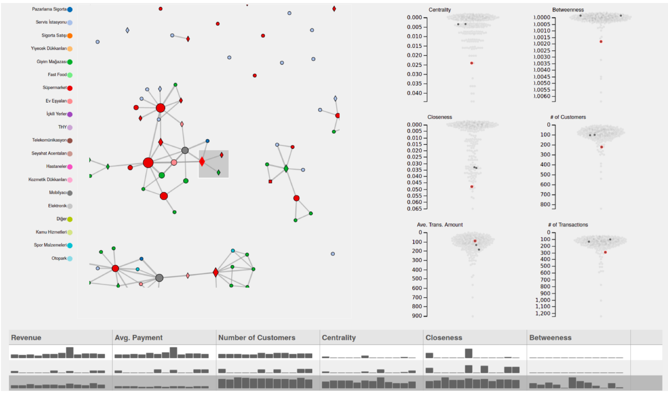


**Figure 4:** *A group of successful merchants' attribute distributions.*

On network overview and ego-network components, the merchant category is encoded by color. Moreover, well-being status is encoded by shape, diamonds representing successful merchants, while circles represent failing ones. In addition, squares stand for unknown states. The size of the nodes may encode several domain attributes such as average transaction amount, number of customers, and revenue. And lastly, the width of the links encodes the number of shared customers.

**Mesoscopic Analysis**. With the help of the attribute distribution component, users are able to observe how a group of merchants with similar attribute values are distributed in topological and spatial order. The top-performing merchants in terms of degree centrality can be brushed in the attribute distribution component.

As merchant well-being represented with shape encoding, merchant groups with the same marker shape are crucial. For instance, in Figure 4, three successful merchants are selected.The merchant with red-stroke is connected to the remaining merchants. They are located around the same district. Moreover, they share similar values in the domain and network attributes, except degree centrality. This example provides visual evidence towards the hypothesis proposing that well-being is related to the domain and network attributes; besides, the location may play an import role.

With the help of the pixel display component, users may find merchants with increasing domain and network attributes and analyze how they are located in the network overview and attribute distribution components. Locating such merchants on the network layout would reveal more insights as other domain attributes encoded on the layout. For instance, a user may relate increases and decreases in attributes with merchant well-being.

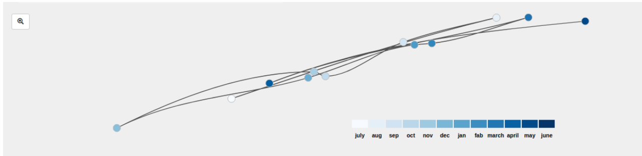

**Figure 5:** *Projection of the temporal feature vectors of the selected focal node.*

**Microscopic Analysis**. In order to extract ego-network feature vectors, financial domain-specific features are appended; namely *revenue, avg. transaction amount, number of transactions, and number of customers*. In Figure 5, a significant distance between July and August can be observed with the help of projected feature vectors. Once the distance is noticed, users can go back to the timeline view and analyze how the difference between feature vectors affects the topology between consecutive time steps. In addition, other attribute encodings can be utilized to observe the changes. In Figure 5, a significant change occurs between July and August, as many alters leave the ego-network in the following time step.

## 6. Conclusion & Future Work

In this paper, a visual analytics tool is demonstrated for the exploration of multivariate dynamic networks involving spatial attributes from an egocentric approach. In addition to visualizing multivariate temporal networks from a topological point of view, the developed tool equally depicts the evolution of domain and network attributes in multiple views. With the help of interaction methods, as mentioned earlier on integrated components, users are able to observe how the domain and network attributes of a single or a group of nodes in the network change throughout the entire time span.

The ego-network component presents a node's evolution with a time folding approach using its combined domain and network attributes as a feature vector. Users are able to observe the dissimilarities between ego-networks in different time steps based on the distance. However, the current implementation does not provide interpretable views. Users can observe how distant they are but can not grasp the reason behind it. In order to increase the interpretability, the tool may allow users to create their own feature vectors on the fly and observe the changes between them.

In this paper, there exists a single use case on the merchant network. However, the developed tool must be evaluated with more use cases involving larger networks. Moreover, user studies with detailed questionnaires must be carried out on a group of participants, and received responses must be analyzed to further evaluate the performance of the tool. And finally, the proposed tool must be compared with the existing solutions in the field so that a better evaluation of the tool can be obtained.

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