Exploring Temporal Ego Networks Using Small Multiples and Tree-ring Layouts

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***Abstract*—Many of the current dynamic network visualisations methods or techniques rely on node-link force-based models that were originally developed for visualising static network snapshots. In this study, we diverge from this traditional layout approach and develop a layout for ego networks that places the time dimension in the foreground, by turning time into an element of shape. In addition to this we develop an interactive system that enables the visualisation of multiple networks simultaneously by employing small multiples. Using the proposed layout and analytical system as a grounding visual structure, we visually characterise dynamic network events in 3 different networks; the evolution of the biotechnology field, a phone call data set and a network of passenger connections of an airline. From this analysis we propose a range of ego network visual motifs that can be used as templates to identify and characterise events that are occurring in a dynamic network.**

***Keywords*-Dynamic networks, Ego networks, Small Multiples, Graph Drawing**

Social networks are dynamic systems in a state of constant change. People are born, form friendships, find partners, lose friends and die. Companies are created, merge, spilt and close. Traditionally, mainly because of the difficulties in collecting data, networks were studied by analysing a single snapshot of the network taken at a particular time. Today, dynamic network data is becoming increasingly available from sources such as social networking sites, telecommunication networks and customer transaction databases. Leading researchers in the field of network science have identified the study of *dynamic networks* as one of the next primary challenges in network theory [4].

From the very early days of social network analysis, visualisation has been a key element to the development of the field [21]. With access to dynamic network data, researchers in information visualisation are working to enhance the social scientist toolbox by developing tools and visualisation techniques that facilitate the study, understanding and exploration of network dynamics and the processes they represent.

Where dynamic social network visualisation has been studied the focus has been predominantly on new nodes entering the network, large scale networks, and the use of animation techniques to convey the dynamics within the network [5], [8], [15], [26]. Recent studies [19] comparing static and animated dynamic network tasks, have shown that contrary to common expectation, static displays are generally more effective in terms of both time and accuracy, when performing analytic tasks.

By contrast, instead of visualising dynamic networks using animation techniques we develop a system based on a *small multiples* visual interface. The principle behind small multiples design is to place several small visualisations near each other to facilitate comparison and pattern identification while maximising the ink to information ratio [35]. By displaying multiple networks simultaneously on the same page, we seek to overcome the weaknesses of animation while preserving the ability to understand the temporal nature of the network dynamics.

The motivation and tasks for this study originated from studying interactions between biotechnology companies, over a span of 10 years. The initial visualisation approach relied on using multiple node-link diagrams each representing a single year displayed on the same page as small multiples. This visualisation approach soon became impractical due to the large size of the data and scale free nature of connections. The resulting diagrams were complex, difficult to understand and poor according to most graph drawing aesthetic measures [13]. Additionally, the visualisation was cluttered because it was confined to the small space dictated by the small multiples design. Our next attempt refocussed on the analyst's tasks and asked the question, "how can the patterns of connections and events be mapped into simple visual images that can be generalised as visual motifs for dynamic network data".

We ground our study of dynamic social network visualisation in the tasks and problems faced by social scientists.

This grounding has allowed us to focus on the concept of an *ego network*. An ego network is a sub-network that focuses on an individual actor who is the subject of the network. The focal point of the network is called the "ego", whereas the other actors he interacts with are called "alters". In an ego network, only actors that are directly connected to the ego form part of the network. We describe an *event* as a change in the graph structure that occurs at a particular point in time.

A *network motif* acts as a visual fingerprint of a connection pattern. While motifs for static networks are commonly employed, especially in biology, the equivalent for dynamic networks do not exist. In [36], Welser et al address ego motifs to characterise roles in social groups. In order to visualise the temporal element of activity, they use a separate visualisation called an authorline, to supplement ego motif networks with temporal data. Here, we address the need to create a simple intuitive layout that can be used to describe temporal information in ego network motifs, a visualisation that is able to tell a story in time with a single diagram.

Our method to achieve this is through a tree-ring layout algorithm which converts several temporal aspects of data into visual shape elements. This form of visualisation provides a network analyst both a visual language for describing network motifs and the ability to focus on important changes in the links between actors in the network. New nodes and hence new edges are an important facet of dynamic network structure but so too are the nature, rhythm and pattern of interactions these new entities bring. Figure 1 shows the design of our small multiples system that combines a number of different network diagrams including traditional node link diagrams, matrix views and tree-ring ego networks, in one interface.

In this paper, we make two main contributions. The first contribution is the development of a new visualisation based upon a tree-ring metaphor that fits well within a small multiple design and is more structured and intuitive than traditional force based node link diagrams for displaying dynamic networks. The second contribution is the design of a small multiples based network exploration system that displays multiple network visualisations at the same time.

Traditionally small multiple visualisations focus on displaying attribute based visualisations such as scatter plots or bar charts. Here the small multiples system is used in favour of animation to visualise dynamic networks. The small multiples are intended to assist with the exploration of different relationships between actors in a network and help identify different roles and types of actors based on their individual connection patterns. With the help of this visualisation technique and interactive system we study 3 different data sets and provide analytical insights into the networks and the data within the networks. We also show examples of how the ego network motifs can be used to identify divergent or atypical patterns in the data.

I. Dynamic network tasks

Prior to proposing any new visualisation design for dynamic networks, one has to clearly understand the questions and tasks that the visualisations are intended to assist with. Past research in information visualisation has grouped user tasks into taxonomies according to the type of data in question. Robert Amar et al [2] and Plaisant et al [25] have extended the general study by Shneiderman [31] to attribute data and graphs respectively. As yet, there is no published taxonomy tailored towards dynamic network tasks, so in this section we attempt to describe the most common dynamic network concepts and tasks drawn from previous studies of such data.

Network structures can change in a variety of ways. However, the dynamic processes behind network evolution can be categorised in three overarching categories; *formation*, *rewiring* and *dissolution* [30]. These three general principles apply to both the atomic elements of the network (actors, links) and compound structures within the network, such as groups or communities [29].

If we consider the whole network structure, the formation of the network describes how the network was formed to exhibit the structure that it currently holds. If a time component is added to any structural feature in a static network, the temporal formation of that feature can be explored. This is the most basic means of enhancing a network with temporal information.

A more significant aspect of change occurs when there is rewiring within a structure manifested as a change in the links between actors. The term rewiring groups all changes that alter the connections within the current structure, possibly changing the type of the structure. For example, rewiring can include a split or a merge between members of a community. Rewiring is significant in the context of network evolution because these rewiring changes can raise important questions and lead to insights into the processes that are underlying the change.

Dissolution describes the process of any structural component or network member disappearing from the network structure. An example of dissolution is a scenario in which an actor in the network does not continue to from a part of the network after a certain time period. The propagation of a dissolution effect on the network is sometimes referred to as churn [12].

While the above types of change relate to changes in network structure, the properties of the members or actors of the network can also change. This type of change is important especially if it occurs as a result of the connections in the network. Christakis and Fowler investigate this type of change in their studies on obesity [10] and smoking habits [11]. In the biotechnology field evolution study by Powell et al [30], the authors use the term *multivocal* to describe the behaviour of actors that perform different roles

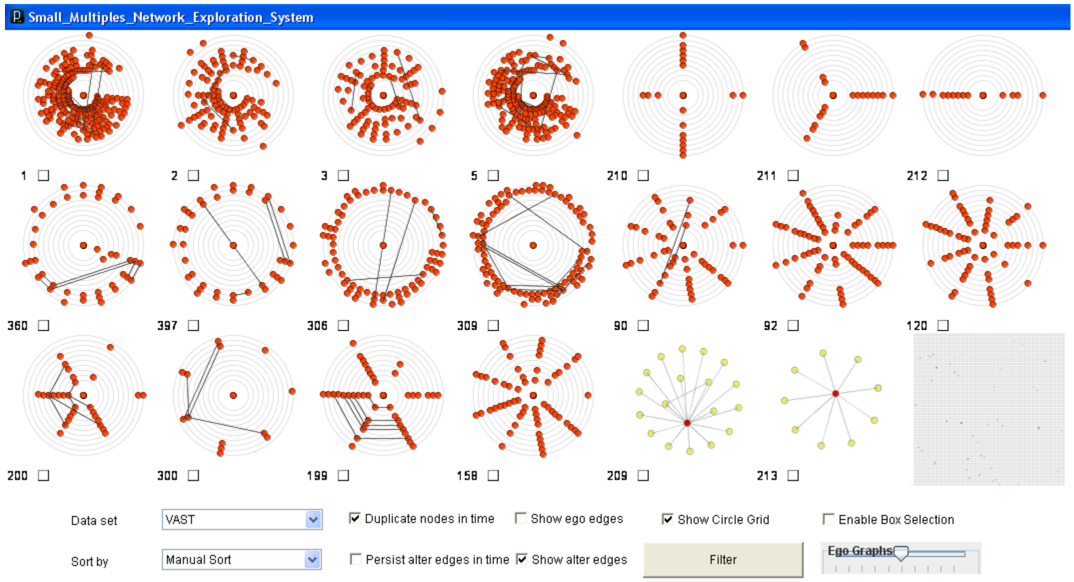

Figure 1. Small Multiples Network Exploration System

throughout the data collection period.

In dynamic social network visualisation, many of the current techniques focus on showing the formation of the structure over time [23]. In this study we fill in a gap for the task of analysing actor rewiring. Our visualisation addresses the question, "how can we visually describe the choice and change of partner preference over time". Along with this we also try to facilitate the understanding of how nodes change their properties or exhibit multivocal behaviour over time.

II. Tree Ring Layout

The proposed node layout algorithm for dynamic ego network motif exploration was inspired by tree rings. Dendrologists study tree rings to determine the age of a tree and the amount of new growth of a tree in a year. In the tree ring layout, the ego node is first placed in the centre of the drawing (black node in Figure 2). From the central ego node a number of concentric circles, akin to tree rings, are drawn. Each concentric circle represents a time period in the network data (t_1 to t_4 in Figure 2). The alters are then placed on the concentric circles according to the time when the interaction between the alter and the ego takes place. The earlier the interaction, the closer to the centre the alter is placed. All alters are placed equidistantly from each other based on the total number of nodes in the ego network through the networks' timespan. In Figure 2 the first group of nodes that interact with the ego are the red node and two green nodes on ring 1. On ring 2, only green nodes interact with the ego, while on rings 3 and 4, a mixture of green and blue nodes interact with the ego.

The alter nodes start being positioned from the angular

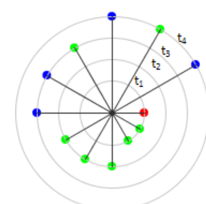

Figure 2. Tree ring ego network layout principle

position zero with respect to the ego. In Figure 2 this position is occupied by the red node on time ring 1. The desirable visual characteristic here is to position the majority of alters that interact with the ego at one time point, close together in a logical ordering. The ordering of the alters within the same time period can be changed using the layout parameters (see Section II-B).

Each alter has a unique angular position with respect to the ego position in the centre. The uniqueness of this constraint avoids overlapping of the same nodes across different time periods. Assigning a unique angular position to each node also enables nodes to be replicated at each time point, when there is an interaction with the ego. For example, if a node interacts with the ego at time t_1 and time t_4 then the node can be shown both on the ring representing time t_1 and the one showing time t_4. The node is shown at the same angular position thus aligning it in a straight line with the first time the node was displayed. An example of this can be seen in Figure 3 label 2, where the orange node is replicated across 4 time periods.

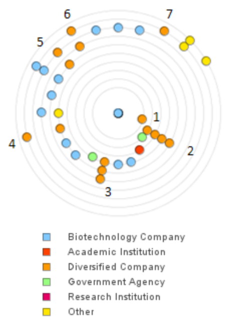

Figure 3. Example of the ego network of a biotech company

Rings do not necessarily have to represent a year in time or a uniform time pattern. A single ring can contain an aggregate number of time periods in it. If each ring is representing a time aggregate, then any node placed on the ring means it interacted with the ego during that time period. For instance, if the data set contains a range of a 100 years each time ring can be used to aggregate a uniform number of years, in this case 10 rings each representing 10 years. Alternatively, a period of years can be compressed on one ring and the others expanded in the rest of the rings. In this example, the first 90 years can be represented in the inner ring while the last 10 years can be displayed in their own individual rings.

A. Motivational Example

Figure 3 is an example of an ego network from the data analysed in the biotechnology case study (discussed in detail in Section IV-A). The explicit edges from the ego to the alters are omitted to evidence the node positioning of the layout and the meaning behind the ordering. The first interaction of the ego, a dedicated biotechnology company represented by a blue node, is with a diversified company, represented by an orange node (label 1). Notice how this node has the smallest angular position with respect to the ego. In the second year there is no more interaction with this company, but the ego interacts with a new diversified company (label 2). This relationship continues for the next four years. In year four, the ego interacts with another diversified company (label 3), for a duration of 3 years. Within this time period the relationship with diversified company 2 terminates. In the fourth year the ego also interacts with another diversified company (label 4), however the relationship has a two year gap which could have possibly been filled by the other diversified companies labelled 5, 6 and 7. In the fifth year when company number 2 is dropped three diversified companies 5, 6, 7 are introduced.

B. Layout Parameters and Interaction

The general layout description specifies that all the nodes that interact with the ego during a time period should be displayed on the same tree ring, however it does not impose an ordering of nodes on the same ring. The order of the nodes could follow a temporal structure. If each time ring represents a time aggregate, for instance a year, the nodes can be ordered by the day when they first interact with the ego. Alternatively, nodes can be ordered using an attribute of the data set, such as, the type of the node. This has the effect of visually clustering together nodes of the same visual or logical characteristic.

Nodes can also be ordered based on graph drawing aesthetic criteria, particularly edge crossings between the alters. Since each node in the tree ring layout occupies its own layer, a layer crossing minimising algorithm similar to Sugiyama's approach [33] or Brandes et al [7], can be used to reduce edge crossings. Alternate intra layer node layout techniques may also be adopted.

A number of parameters can be used to control the visual encodings of the elements in the visualisation. Explicit edges such as those connecting the ego to all the alters can be displayed or hidden (this is the case in most of the figures in the paper). Alter nodes and edges can be set to persist through the time period from the first time they interact with the ego. When persistence is enabled the elements in the network aggregate over time to produce a composite view of the network. The edges between alters can also be turned on or off or altered in intensity based on either edge importance or time properties.

In tree rings, the size of each ring is proportional to the growth of the tree during the year. This concept can also be visually applied to the layout by mapping the size of each concentric circle to the activity in the time period. This can be used to allow for the nodes to be spread out further in time. Intermediate time rings can also be introduced in between other time periods to improve the readability of dense time periods.

Interactive techniques can also be used to overcome issues with the selection and aggregation of time periods displayed in the ego network. If there are more time periods than the layout can support in a small multiple view, a brushing interactive motion on an ego network can let the analyst scroll thorough time periods to display activity in other time steps. A movement from the ego out towards the periphery would scroll forward in time, while a movement from the periphery towards the centre could scroll back in time. The time periods that are out of range can be aggregated on the first or last ring if required. Once this motion is complete for the reference network it can be easily applied to all the other small multiples.

III. Small multiples interactive system

A generic small multiples framework was developed to allow different types of visual representations in each individual small multiple. We extend this paradigm that is traditionally used to visualise attribute based data [20], to

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visualise network data. Figure 1 shows an example of a display where the majority of the diagrams are tree ring diagrams and the last 3 diagrams on the bottom right show traditional node link and matrix visualisations respectively.

When designing the small multiples based system we follow the design mantra of Shneiderman et al [31] of overview first, filter and details on demand as a guiding framework for interaction and exploration. In the overview stage the small multiples can be reduced in size to maximise the number of data elements that can be displayed and provide an overview of the data. In this stage different aggregations and abstractions of the network can also be used to visualise the overall structure of the network and its components. From these visualisations the analyst can interact with the system to select individual visualisations or filter the data by the properties of the network in order to focus on the elements of interest. To get more detail on individual elements within the visualisation, individual elements in the visualisation can be selected to obtain further information.

Each small multiple image consists of a visual representation in a small window and all images are displayed in a grid similar to a photo album. The number and size of the images can be controlled by the user at run time to balance between the amount of information displayed and the detail in each image. The image sizes range from 150x150 pixels up to 300x300. When displaying the ego networks at their smallest size one can get an *overview* of a 400 node network in 10 frames. All the images in a small multiples display are traditionally of the same size and this system follows this design pattern.

The ego networks can be sorted by different criteria such as; the node degree at a time period, node attributes, activity within the time period and the relative age of the ego. When paging through the list of multiples, the user can select a number of small multiples by selecting a checkbox near each image. Upon confirming the selection the display can be reconfigured to display the selected ego networks next to each other on the same page. This interactive features shows how *filtering* can be used from the small multiples display to enable the comparison and study of interesting networks. If more *details* are required for an individual image, the analyst can select the image and display that image at full size instead of showing that image in a small multiple view.

Apart from interacting with the visualisation as a whole, one can also interact directly with the node link visualisations. If a node is double clicked and that node exists in other ego networks on the same page, then the node is highlighted in all the other small multiples. To evidence this highlighting, all the the other node types can be faded and shown in the same colour. If the node is right clicked, the small multiples on the page change to show all the ego networks of which the clicked node is a member. A group of nodes can also be selected to change the small multiples displayed to the ego networks of the selected nodes. It is also possible to interact with the individual node elements to view information tooltips and/or node labels, depending on the available data.

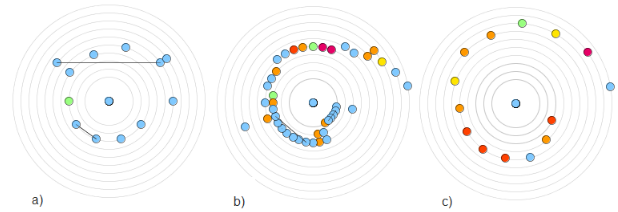

Figure 4. Homophily and multi-connectivity ego motifs

IV. Case Studies

In this section we analyse three different data sets to characterise the types of ego networks that are present in each data set and study the capabilities of using a tree-ring ego layout to develop ego network motifs. The three case studies are from thee diverse fields, the first one is from social science, the second one is a scenario based synthetic data set created for the VAST 2008 competition and the third data set is a commercial data set of airline passengers.

A. Biotechnology company data case study

In the first case study we use data from previous work in the social sciences, that studies the dynamics of “logics of attachment” in the evolution of the biotechnology field [30]. This data set contains examples of the analytical task that our visualisation sets out to assist with, i.e. changing patterns of connection.

The data used for this case study was compiled by Powell et al primarily from *BioScan*, an independent industry directory. Six types of companies are represented: dedicated biotechnology companies (2736), academic institutions (279), public research firms (177), government institutes (201), diversified companies (778) which include large pharmaceutical corporations and diversified health corporations, financial institutions and other types of companies (523). A connection between any two organisations exists whenever there is a news report that mentions a collaborative tie, alliance, contractual agreement or an exchange of resources between two or more organisations. The sample data selected covers a period of from 1988 to 1998 and the data is aggregated on a yearly basis.

The authors of the paper report that the biotechnology industry is characterised by many short term connections between companies. Once the connection is formed and the goal for which the connection was sought is achieved, then the two companies do not remain in contact with each other. For this reason, in this particular analysis the links between alters are only shown if they happen during the same time period.

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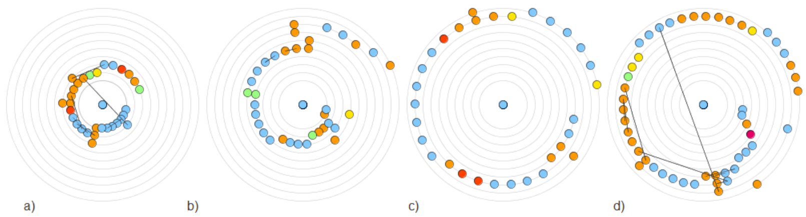

Figure 5. Different company evolution patterns

1) Network motifs and patterns: Powell et al discuss four types of partner attachment principles, *Accumulative advantage*, *Homophily*, *Follow the herd* and *Multiconnectivity*. We focus on three of these principles and explore other types of events that can be easily visualised with the tree ring visualisation. In the case study examples, each type of company is represented with a different colour and the explicit links between the ego and the alters are not displayed.

The principle of homophily [27] states that actors have a higher probability of making connections with actors that are similar to them. This sort of behaviour can be explained with the common saying "Birds of a feather flock together". On the contrary, multiconnectivity explains the behaviour when actors connect with different types of partners, thus diversifying their connections. Accordingly, organisations that exhibit homophily are more likely to connect to companies of the same type, therefore of the same colour. Conversely, multiconnectivity can be identified when companies connect to a variety of different companies, thus connecting to nodes of different colour.

Figure 4a shows an ego motif of a biotech company (blue node) exhibiting homophilious behaviour by primarily interacting with other biotech companies. Figure 4b shows an example of a biotech firm that starts out exhibiting homophilious relationships, but expands to interact with different types of companies in the later years. This pattern is a common pattern in the data set as the importance to forge connections with different types of companies increases with time. Ties with different types of companies are important for survival in such a competitive market, since different ties give access to different resources in the network. In Figure 4c the ego has a connection with different types of nodes, showing a good example of multiconnectivity.

The pattern of accumulative advantage [3] shows how actors with a high number of connections have a higher likelihood of getting new connections. This property is a feature of the entire network that is difficult to visualise when considering individual ego networks, as these do not generally provide a complete network perspective. Using the developed small multiple system, we can visualise the change in degree between the most connected nodes and the rest of the nodes. When ordering the ego networks by degree, a clear difference emerges from the first few nodes with a high degree of interconnections and the rest of the ego networks.

In an aggressive domain such as the biotechnology industry, companies tend to forge alliances, merge with other companies, or acquire new companies to gain access to technology and resources. Ego evolution visualisations can be useful to identify these behavioural patterns by following the temporal outline of the visualisation. Figure 5 shows four examples of company evolution. In Figure 5a the company has a concentrated amount of activity in the early years but this activity ceases soon after. This is visually indicated by the concentration of nodes placed on the first three inner circles. This pattern is indicative of a company being bought out and replaced by another company, or a company failing and ceasing to exist. In Figure 5b the company has a consistent level of activity throughout all the years, visually indicated by a general spread of nodes on all the circles. In Figure 5c the company is a late comer, as there is no activity at all in the first 6 years and all the activity is concentrated in the last 4 years. This is of particular interest because of the high level of activity without prior build up. This pattern might be indicative of an old company opening under a new name, which will explain the significant number of connections in the last few years with no activity in the early years. A similar pattern of connection can be seen in Figure 5d, however here there is some activity in the early years, which quickly increases in later years. This pattern could be indicative of an acquisition or a merger with a bigger company that already has many connections.

The properties of actors in a network can change if data is collected over a long period of time. This change can be important both in terms of the new type of interaction and also to understand if the change occurred as an effect of network connections. In this case study, companies can fulfill different operations and take a different role that changes their type of operation, thus changing their colour. Figure 6 shows some examples of nodes that exhibit this behaviour. These nodes can be easily identified because each node is replicated on the same radius with the outermost circle. As the nodes on the radius are aligned in a straight line it is easy to identify the change in node colour of the same node.

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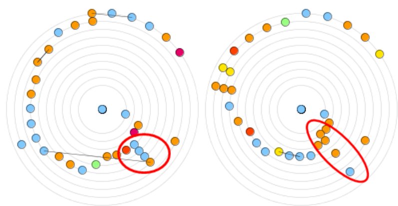

Figure 6. Actors changing type over time

B. VAST 2008 Phone Call Network

In the second case study we use the VAST 2008 phone call data set [24] that consists of a set of phone records between families in control of a controversial religious organisation. Each record has the time of the call, duration and the location of the cell tower from where the call was made. The data spanned a 10 day period and contained 400 unique cell phones.

The main analytical task in the VAST mini challenge was to characterise the change in the network occurring in the 10 day period of data collection. In this case study we use the tree-ring visualisation within the small multiples system, to categorise and characterise the different types of network actors based on their interaction patterns and their possible change in behaviour over the 10 day period. After having identified the important actors in the data set using ego network visualisation, different visual and analytical tools can be used to investigate how the interactions between these prominent nodes evolves through time [17].

Figure 1 (on page 2) shows examples of some of the most prominent actors in the VAST data set. The first set of nodes (1, 2, 3, 5) are the nodes that have the highest number of connections, however we observe that in the outer circles that represent the later time periods, the number of connections is close to zero. If we study the nodes under the first set (360, 397, 306, 309) we notice that these exhibit a similar but inverse behaviour to the first set of nodes. They are very active nodes but are only active in the last 3 days of the time period.

A very common ego network motif is the one exemplified by nodes 210, 211 and 212 where the ego regularly interacts with the same 2 or 3 alters throughout the whole 10 day period, with little or no interaction between the alters at the same time period. This is typical of scale free networks and is indicative of the same accumulative advantage pattern seen in the biotech network where only few nodes have a large number of connections and most have few connections. Other network ego motifs that are common are those exemplified by nodes 90, 92, 120, 158 where the ego interacts with a number of nodes in a regular pattern with gaps between some time periods.

Nodes 199, 200 and 300 are examples of atypical ego motifs because of the high number of interactions between alters when compared to the number of alter interactions in the other ego networks that was very limited. In the scenario description node 200 is described as an important node. From the visualisation we notice that node 300 has a similar ego network motif to node 200 which prompts us to flag is as suspicious. The geography and call duration can be encoded by colour and node size respectively. Using this representation, actors that are changing their geographic location will exhibit the same multivocal patterns as seen in Figure 6.

C. Airline Passenger Network

In the third case study we visualise a sample of an inferred network of airline passengers [16], [18]. The network is automatically inferred from the bookings records of around 430 unique passengers spanning over a period of travel of 10 weeks. The passengers are uniquely identified using an entity resolution pre-process as a unique identifier was not available for all passengers. A relation between two passengers exists if they are booked together on the same booking.

Unlike the VAST and the Biotech network data sets the airline customer data set contains many cliques between passengers travelling together. Each time three or more passengers are booked on the same booking a link is created between all the passengers in the booking, thus creating a clique connection pattern.

Figure 7 shows five representative patterns from the airline passengers data set. The first network illustrates the case where the ego travels with two parties of 4 and 5 passengers each, towards the end of the 10 week time period and a separate trip with another passenger. The second ego network is typical for most egos in that they travel once in the sampled time period but with a number of people in the same booking.

The third network illustrates an interesting pattern of a passenger travelling with the same group of people on subsequent weeks. This can be seen with the overlapping triangles shown in the top left corner. The same passenger travels with other groups of people during the other weeks.

The fourth pattern is interesting because it goes against our intuition and is quite uncharacteristic (there were only two egos with this pattern). In fact this shows the pattern of an actor who has a lot of trips with many separate people, few of which are linked. Upon further analysis of these actors we realised that this was in fact an anomaly which was showing an instance of actor misidentification in the entity resolution stage. Here more than 4 different passengers were considered to be the same person therefore the individual trips of those four people resulted in multiple sparse links in this ego network motif.

The last pattern shows an actor travelling with two groups of people in different time periods where one of the members in the group overlaps. This almost results in a diamond

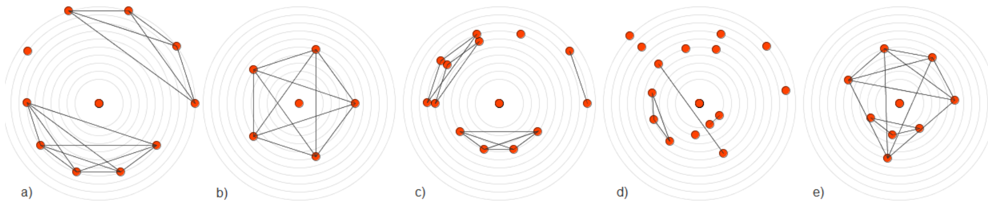

Figure 7. Airline passengers ego network nodes

shaped pattern with the extension of one of the nodes reaching out in a different time slice.

V. Related Work

The layout approach proposed in this paper is a type of radial visualisation that uses a circular pattern to position network nodes. The widespread adoption, variety and applicability of radial visualisations was the subject of a recent survey paper by Draper et al [14]. In this work, the authors categorise different radial layouts based on their visual properties. Our visualisation contains elements of three of these patterns – the star pattern, the tree pattern and, to an extent, the concentric circle pattern. The defining characteristic of the star pattern is the centre of the diagram from which edges originate. In our ego diagrams, the ego is placed in the centre and edges originate from the ego to connect the ego to all the alters. While all leaf nodes are connected to the central node with a straight line, which is a characteristic of star patterns, the inner nodes can be connected between themselves too which is a pattern exhibited in the tree pattern. Thirdly, concentric circles are a critical positioning element in the visualisations where time representation becomes a key issue. The novelty of our approach lies in the combination of a star based layout with an underlying concentric circle field that is used to encode a positional dimension for time.

Circular layouts were amongst the first types of layouts used by social scientists to draw the first social network visualisations [21]. Perhaps the most famous example is Northway's target sociogram [28] that uses a series of concentric circles to represent actor centrality and guide the placement of nodes by placing the most structurally central nodes in the innermost circle. Brandes et al [6], in their work on visualising policy networks, use Northway's original target sociogram principles and elaborate on a method to improve aesthetics when automatically drawing such diagrams. An approach that uses the tree ring metaphor to draw nodes is presented in [34]. In this layout, a hierarchical tree structure is placed along concentric circles representing different time periods.

There is further novelty in our approach of displaying the circularly laid-out ego networks as small multiples, allowing in a single visualisation, the different temporal patterns of different ego networks to be compared. Thus, the 'when' question, which by definition is central to any dynamic analysis is emphasised in each small multiple and differences in temporal patterns are easily discernible by scanning across the multiples. Our work also complements the ideas presented in [32] where the authors use node attributes, including temporal attributes, to guide the node placement.

The idea of using small multiples to visualise networks was explored by Chi and Card in their work on visual spreadsheets [9] where they apply the spreadsheet metaphor for visualisation. In this paper, the authors visualise complete dense scale free networks of the internet over a sequence of steps. The problem with this approach is that large scale free networks tend to be difficult to visualise using node link diagrams with the effect of reducing the readability of the networks. Adamic et al [1], use small multiples to visualise ego networks to explain the types of egos that are present in online Q&A forums. In a recent study [22], the authors use small multiples to visualise network properties such as edge count, density and degree, to facilitate network exploration, but they do not attempt to visualise relationships between nodes in their small multiple displays.

VI. Discussion

The embedding of the temporal dimension in a single network image enables us to use a small multiple design to display different egos simultaneously, showing how different types of egos evolve. The small multiples design allows the analyst to explore and identify patterns and differences in the data, however not all types of visualisation are appropriate for small multiples.

Traditional node link layouts have two disadvantages in this regard. Firstly, as traditional layouts only represent a single snap-shot in time, multiple images are required to explore the network over time. As each network is only showing one time period, the number of images is a multiple of the number of time periods. Identifying change in multiple images requires a mental comparison between multiple images which increases the cognitive load on the analyst. Secondly, certain patterns of connection can create diagrams that are too complex with many overlapping nodes and edge crossings that make the diagram unreadable.

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The limitation of space when visualising data in small multiples automatically limits the number of data elements that can be visualised. Better strategies do exist to maximise the amount of information displayed, for instance matrix representations, but the strong metaphor that the tree ring provides makes this layout very intuitive to understand and use. This is particularly beneficial when introducing a new visualisation to users who are not information visualisation specialists but rather specialists in their own fields who need tools to help them analyse their data.

Furthermore, the 'lost' space that is intrinsic in a circular shape when bin packing serves as a natural delimiter between different small multiple images. A square or rectangular shape that might enable denser packing might still require the same amount of space in between different images, to make it possible to discern between different images. It is also still not clear how small dense matrices that encode time on one of the axis can be useful to convey the path connection information between the alters. We intend to follow up with user studies on these aspects to compare the different visualisations.

In the three case studies used we make use of two real and one synthetic data set that was modelled on real networks to serve as a realistic scenario for a conference competition. In the three examples, the number of network nodes increases over time in line with what is usually observed in dynamic networks. One natural aspect of concentric ring layouts is that the inner circles are smaller than the outer circles. This visual characteristic fits well with the pattern of network evolution since the increase in the number of nodes over time is in line with the increased amount of space on the outer circles of the visualisation.

When visualising individual ego networks, the network is being decomposed into its constituent parts. This particular network perspective is tailored towards understanding the individual actors in a network rather than the network structure as a whole. Tasks suited to this technique include identifying change in connection patterns, visual characterisation of network actors based on common patterns of interaction over time, and identifying actors that diverge from those network patterns, the outliers. The majority of actors in a large scale network might not be those that an analyst might want to focus on, based on the typical connection properties of most large scale networks. The filtering and ordering interactions built in the interactive small multiples system can help the analyst focus on the more interesting actors.

The applicability of the tree ring layout can be extended and applied beyond a small multiple system. For instance, the visualisation can be used to provide details on demand when combined with a traditional node link layout. In this case, the tree-ring layout can be used to display an overlaid expanded image of a node's ego network when the node is selected. A sort of "ego lens" feature.

VII. Conclusions and Future Work

In this paper, we describe an intuitive approach to visualise dynamic ego networks using time to guide the positioning of nodes. We take advantage of the compact nature of the generated diagrams to create a system based on small multiples that allows the analyst to explore the network through ego networks. In the 3 diverse case studies, we show how different types of networks can lead to different motifs, we found some similarities and generalities between motifs and also discovered some unexpected patterns that can highlight suspicious activity or issues with data quality.

Based on these positive results we plan to further our studies of this visualisation within a small multiples design. We plan to conduct user studies to study the efficiency of this technique and are also working to provide a similar tool to social scientists to assess the applicability of this technique for other networks in their studies. As part of the user study we would like to study how this visualisation compares to traditional representations along with the effect of unwinding the circle and representing the data in a linear fashion. This should help us get a better understanding of the intuitive positive characteristics of the circular structure of the diagram.

While there are clear benefits to this type of visualisation we are aware that it is not a silver bullet for any dynamic network visualisation problem. The social scientist analysing dynamic networks should be armed with a toolbox of techniques that can be applied according to the problem being investigated and the need to solve it. The advantage that this layout technique is that it is a simple design and easy to understand based on a universally recognised metaphor which makes it a good candidate to integrate into any existing social science toolkits.

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