SUPPORTING THE VISUALIZATION AND FORENSIC ANALYSIS OF NETWORK EVENTS

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Abstract

The flow of traffic among computers on the Internet, the exchange of goods and services between countries, or the propagation of an epidemic in a population are all examples of causally connected measurable events in a network. Understanding the behavior of such networks often requires the ability to discover temporal connections among the events in a large data set. The problem is that relevant events are hard to identify automatically, so the investigator must organize events into a narrative sequence by hand. The investigation process often requires backtracking and multiple comparisons, which is not well supported by current tools. This dissertation contributes new interactive visualization techniques for analyzing, organizing, and presenting network event data at multiple levels of detail for the purpose of forensic analysis - tracking down causal sequences of importance.

The first contribution is a technique that supports event analysis, called *progressive multiples*. We combine ideas from *progressive disclosure*, which reveals data to the user on demand, *small multiples*, which allows users to compare many images at once, and Bertin's *reorderable matrices*. Analyzing events requires inspecting the communication history of the network and the ability to change the investigative focus through pivoting. Dynamic event plots and timelines provide visual recognition of temporal patterns and comparisons through juxtaposition. Affordances are provided to explore the space of events. A structured layout provides a history of exploration and supports backtracking. Our techniques are instantiated in a system for network incident investigation, *Isis*, which we validated with a long-term collaboration and

deployment with the principal network analyst of the EE and CS departments at Stanford University.

The second contribution is a technique for *automatically generating flow maps*, which present summaries of network topology and behavior at a higher level than event plots and timelines. Cartographers have long used flow maps to show the movement of objects from one location to another. Hierarchical clustering is used to generate the maps much faster than was previously possible. Our technique has been adopted by a diverse group of users to depict the flow of computer networks, documents, and international ecological trade.

Acknowledgments

A dissertation is attributed to a single person, but the reality is that it would be impossible without the support of many individuals, only some of whom are listed in this section.

I'd like to thank my adviser, Terry Winograd, for his guidance in helping me to get to this point. My inclination has always been to plan the perfect system before doing anything else; Terry has always pushed me to try rough designs with real users. Without his help, I might still be in my office, thinking about the right design, and very far from finishing. He has even provided housing for me in my last quarter, above and beyond the normal duties of an adviser.

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The friends that I made in graduate school are incredible and I'm very fortunate to have met them. We've had adventures real and virtual, in snow and in sunshine, and on land and at sea (well, the beach, in any case). Our long discussions about research, life, and Wikipedia facts provided much-needed laughter and support. I only hope that I have been as good an influence on their lives as they have been on mine. Thanks to Leith Abdulla, Billy Chen, Jim Chow, Kayvon Fatahalian, Tal Garfinkel, Gaurav Garg, Neel Joshi, Jeff Klingner, Augusto Román, Dan Morris, Merrie Ringel Morris, Joel Sandin, Vaibhav Vaish, Bennett Wilburn, Sue Xia, Ron Yeh, and many, many others in and out of graduate school.

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For my family,

who have always loved me.

Contents

List of Tables

List of Illustrations

1 Introduction

A network models digital, economic, physical, or other connections among its members. The flow of traffic among computers on the Internet, the exchange of goods and services between countries, or the propagation of an epidemic in a population are all examples of measurable events in a network. An event describes a single transaction between two members of the network that occurs at a specific time. When a network behaves unexpectedly, an investigation is conducted to reconstruct the sequence of events that explains this behavior. The goal of the forensic analysis is to identify the extent of the anomaly as well as its cause, so that malicious behavior does not reoccur.

However, conducting a forensic analysis of an anomalous event can be very difficult. It is hard to identify relevant events because their number is usually very small compared to the total number of events on the network. Although there are many research projects for classification of network traffic, these systems are imperfect and cannot perform as well as a human expert. For example, a recent system for network traffic classification achieved up to 90% coverage with 95% accuracy [27]. The problem is that automated systems may still produce a large number of false positives, which must be inspected by hand. In addition, these systems tend to only classify single events; the extraction of relevant sequences is still an open research problem. Since automatic systems cannot extract these patterns effectively, we developed visualization systems that would augment the pattern-recognition abilities of a human analyst engaged in the iterative process of forensic analysis.

Information visualization is the use of computer-supported, interactive, visual representations of abstract data to amplify cognition [10]. Dynamic visualizations take advantage of a person's ability to discern visual patterns that programmatic techniques might not be able to recognize. Mapping data to a graphical representation can allow more data to be presented than would be possible with text. The challenge is to design an interactive graphical representation that makes the information of interest visually apparent. This dissertation developed visualization representations by observing dozens of investigations conducted by a network analyst over a two-year period.

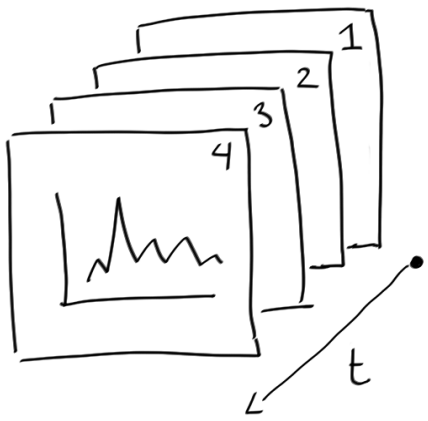


Figure 1.1 When the parameters of a visualization are changed, some systems completely replace the contents of the screen which makes it hard to compare previous results with the current one.

Our observations produced a cognitive task analysis of the investigation process. We concluded that investigation is difficult because forensic analysis involves inspecting many events which may turn out to be unrelated to the anomalous behavior. As a result, evidence that can explain the behavior is often collected out of order. The extensive backtracking that accompanies this process is not well supported by current systems. Figure 1.1 illustrates a problem that can occur in visualization systems, where changing the parameters of the visualization changes the entire screen. This makes it very difficult for analysts to remember what they have already explored, which is exacerbated by limited working memory [37].

This analysis led us to design a system that would serve as a form of external cognition by making the history of exploration apparent. Prior network visualizations have often focused on node-link representations that emphasize the topology of the

network [7, 18]. We found the problem with topological representations is that their emphasis on the structure of the network instead of its time-varying behavior makes them unsuitable for event analysis.

1.1 Contributions

1. A technique for exploring the historical behavior of a network by visualizing its events with event plots and timelines, which we call *progressive multiples*. This was developed in a long-term collaboration and deployment with the principal network analyst of the EE and CS departments at Stanford University. It provides:
    a. Visual recognition of temporal patterns by using time for the horizontal axis, which allows users to compare query results through juxtaposition.
    b. Affordances for exploring the space of events and their relationships with pivoting and brushing.
    c. Reorderable rows which allow the user to organize the display and reveal traffic structure and patterns.
2. A technique for *automatically generating flow maps*, which can combine network topology with a high-level summary of its historical behavior.

Our first contribution, progressive multiples, is designed for an analyst who is investigating unexpected behavior on the network [45]. We combine ideas from progressive disclosure, which reveals data to the user on demand, small multiples, which allows users to compare many images at once, and Bertin's reorderable matrices [8], where rows are rearranged to reveal visual structure in the data through juxtaposition. Our technique uses two linked representations of temporal sequences of network flow traffic: the *timeline* and the *event plot*. In both representations, categorical values are on the vertical axis and time is on the horizontal axis. Timelines show an aggregate value over all events, while event plots reveal the patterns of individual events. We

tested our ideas by developing and deploying a system for network security analysts, called *Isis* [44].

Our second contribution is a technique to automatically generate flow maps, which have been long used by cartographers to show the movement of objects from one location to another [46]. Flow maps trade off an exact representation of network topology in order to show a summary of network behavior by changing the width of outgoing edges from a source node [16, 53]. Most flow maps are drawn by hand, which is slow. Our method rapidly generates flow maps using hierarchical clustering, given a set of nodes, positions, and flow data between the nodes.

1.2 Dissertation Roadmap

Chapter 2 discusses related work in graphic design, visualization, and security. Chapter 3 introduces network incident investigation and presents a case study of Isis in use. Chapter 4 discusses how the progressive multiples technique can be generalized. Chapter 5 provides an evaluation of the technique using a simulated epidemic scenario and results from our deployment with network security analysts. Chapter 6 describes our technique for automatically generating flow maps and provides examples of how they can be used to summarize network behavior. Chapter 7 concludes with design recommendations for visualizations that support forensic analysis and directions for future work. Appendix A: Investigation Task Analysis provides a detailed task analysis of the investigation process used by administrators. Appendix B: Epidemic User Study Materials provides the handouts given to participants in our user study.

2 Related Work

This dissertation research builds on prior work in a number of areas. This chapter describes this prior work, how it has inspired this dissertation, and the contributions that this dissertation offers beyond existing research.

2.1 Data Graphics

Visualization draws upon work in statistics on data graphics, which can be used for presentation or exploration of the data. William Playfair, a political economist, published the first known time-series of economic data in 1786. Edward Tufte describes Playfair as being responsible for developing or improving all the fundamental graphical designs [59]. Tufte's work on data graphics [58-60] described a theory of data graphics that emphasized maximizing data-ink ratio in order to maximize the amount of relevant information.

The use of data graphics for the purpose of exploration was advocated by John Tukey. He proposed using exploratory data analysis (EDA) to gain rapid insight into data by using simple pictures instead of worrying about the quality of the graphics [61]. EDA is described as numerical or graphical detective work, which generates hypotheses about the data which can then be evaluated using confirmatory statistics. He distinguishes the collection of evidence (exploratory data analysis) from the evaluation of that evidence's strength (confirmatory data analysis).

2.2 Exploratory Visualization

Research in information visualization combined data graphics with computer systems. This has allowed the development of interactive data graphics and the ability to quickly plot larger amounts of data than is possible by hand.

Rao and Card describe Table Lens (Figure 2.1), which allows users to interactively make sense of large tables of data [48]. A user-chosen distortion maps some of the rows and columns to a graphical representation which allows more rows and columns to be displayed than possible with a text table. Siirtola describes an implementation of interactive reordering matrices (Figure 2.1) which directly translated Bertin's example to a computer [52]. The pilot study showed that novice users were able to discover some correlations in the data using the tool. Kincaid [29] describes VistaClara, a system to look for correlations in microarray data by rearranging rows and columns. VistaClara provides an extension to sort rows and columns by different similarity metrics. The primary difference between Isis and these systems is that Isis supports an iterative investigation process.

Shneiderman's information-seeking mantra for designing interfaces [50] is "Overview first, zoom and filter, then details-on-demand." Flow maps, timelines, and event plots follow this mantra by providing different levels of detail of time-varying

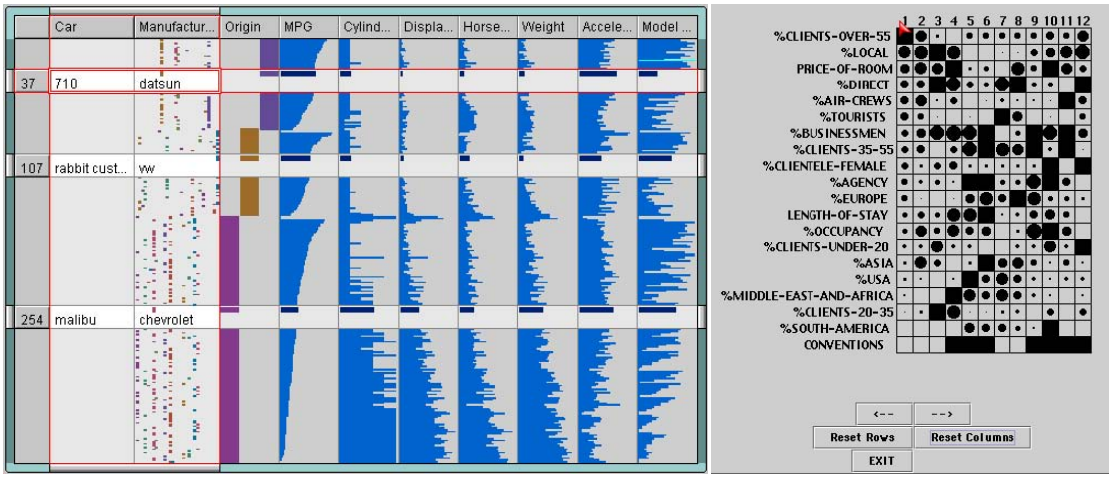


Figure 2.1 Table Lens *(left)* and Siirtola's interactive matrix *(right)*

network behavior. Flow maps are the highest level of detail, providing a network connectivity map with an aggregated view of traffic for all IP addresses. A timeline focuses on the traffic for a single IP address, and its connections can be explored through pivoting and brushing. In a timeline, the details about each partner IP's communications is still aggregated into each bin. Event plots provide a breakdown of traffic by placing the communications for each partner IP on a separate row.

Stolte's system, Polaris, allowed users to graphically explore a relational database instead of using text. Images are interactively constructed by selecting the dimensions and measures of a data set that should be displayed [54]. Polaris extends Mackinlay's APT, a system that automatically generated presentations based on the types of the data and the desired communicative intent [35]. Isis also allows users to explore a relational database, but for a more limited domain than Polaris. These constraints on the data allow Isis to support pivoting and brushing over the data set.

The notion of brushing was introduced by Becker and Cleveland in their work on brushing scatterplots [6]. Their goal was to inspect multidimensional data by using a matrix of scatterplots. Each plot showed two different dimensions of the data set. When a user hovered over a point in one plot, the same point was highlighted in the other scatterplots. This idea was extended by Ahlberg et al. [3, 4] in Homefinder and Filmfinder. Their idea of using tight coupling, which emphasizes progressive refinement, is extended in progressive multiples. Instead of having each refinement step change the display completely, each step becomes a new row in the display, which makes it easier to compare the results of different refinements.

2.3 Visualizing Time and Events

Some visualization systems have limited their focus to time and events. Plaisant et al. [47] describe Lifelines (Figure 2.2), a system for visualizing personal histories as timelines. They apply their system to youth records for juvenile justice and to medical

records. Aspects such as medical conditions appear as horizontal lines and discrete events such as physician consultations appear as icons. Other temporal event plots with categorical values on the vertical axis are the Gantt and PERT charts used in job shop and project scheduling. These differ in that events are the categorical variables whereas in Isis, events are the marks in our plots. This makes the event plot similar to the medical event chart (Figure 2.2) used to track disease progression and treatment [31].

TimeSearcher is a system by Hochheiser and Shneiderman [23] for graphically querying a single time series in the domain of molecular biology. Their system can be used to look for trends and features in a single time-series. Their techniques could enhance the interaction with a single timeline in progressive multiples.

2.4 Communication-Minded Visualization

In the process of developing tools for network security administrators, we observed that their workflow does not end with the moment the analyst gains an insight. Often the result of their analysis must be conveyed to an interested third party. A system that conveys this analysis has been termed a communication-minded visualization (CMV) by Viégas and Wattenberg [63]. In our system an analyst may reorder exploration

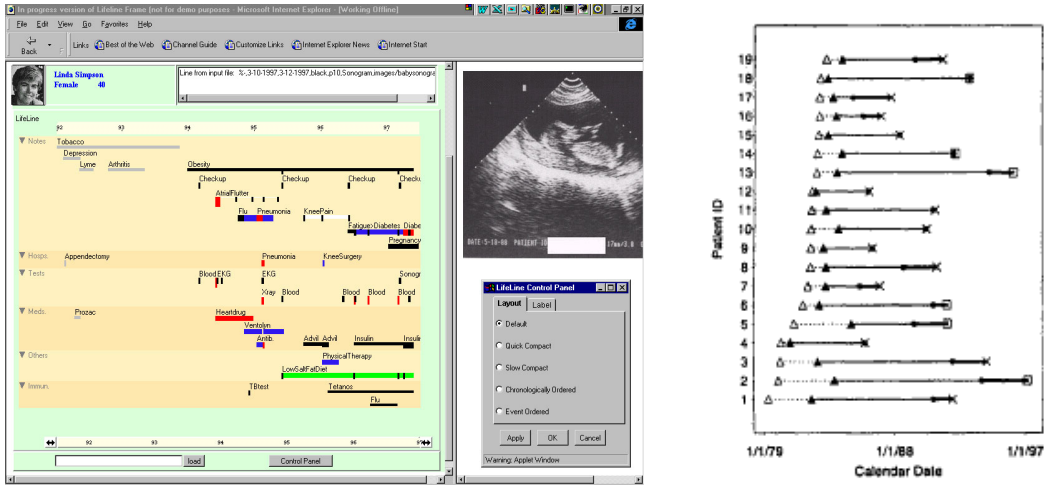


Figure 2.2 Plaisant et al.'s Lifelines *(left)* and a medical event chart *(right)*

history and interact with event plots to present narrative sequences that illustrate the chain of events that lead to a failure in the network.

Recent work in CMV research by Heer et al. [22] has presented techniques that allow users to share visualizations asynchronously by allowing users to create, share, and annotate visualizations through the Web. These techniques could enhance the ability of progressive multiples to provide collaboration among analysts.

2.5 Network Visualization

Prior work in network visualization has used node-link representations as it is natural to apply graph-drawing techniques to a network. Eick and Wills [18] describe a system that can be used to explore hierarchical networks such as email networks. HierNet allows nodes to be placed according to the weights of the links between the nodes, instead of by geography. Viewing parameters can be adjusted and brushing is used to link the graph display with other informational displays.

Other visualization systems attempt to represent network flow, topology, and geography in a single image. This is challenging because displaying a large number of connections with lines results in visual clutter. SeeNet (Figure 2.3) lets users adjust the visualization parameters of the map to manually reduce clutter and provides alternative designs to link maps [7]. Node maps eliminated links and displayed connection data as node size. The volume of traffic to or from a location is represented as the size of the square at that location. Matrix displays removed the geographic layout and encoded data by color. A mark is placed at the (source node, destination node) pair if the two nodes are communicating. Other work tried to minimize clutter by using an extra dimension. SeeNet 3D [13] and work by Munzner [41] on MBone visualization, drew links as variable-height arcs over a 2D map, where the height was encoded as the traffic volume (Figure 2.4). Unfortunately, these techniques still produce cluttered maps when encoding geographic detail, connectivity, and traffic volume on one map.

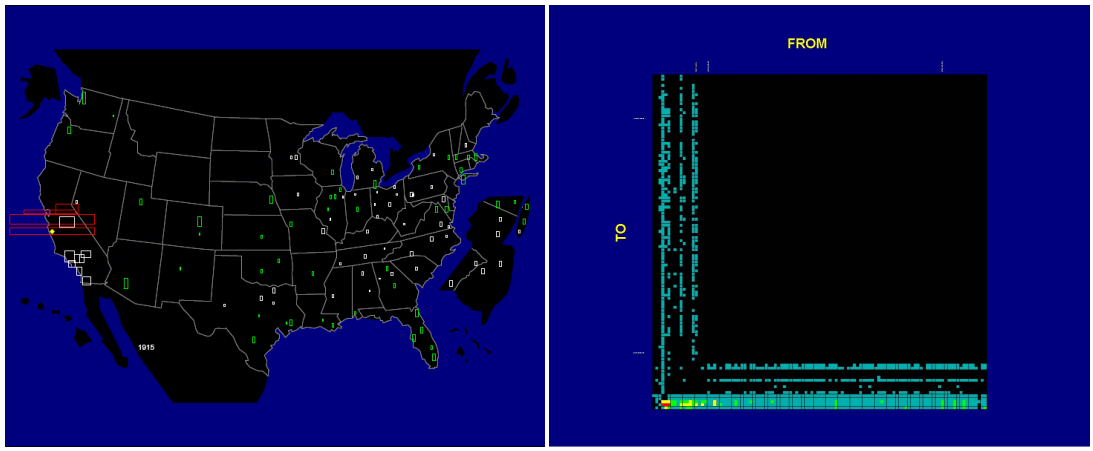


Figure 2.3 Node maps in SeeNet *(left)* and matrix displays *(right)*

Cartographers have solved this problem with flow maps, which illustrate the movement of objects among locations. A flow map shows the spatial distribution of univariate geographic phenomena [53]. Lines of varying width which represent the number of objects being transferred are overlaid on the map. Visual clutter is reduced by merging edges that share destinations. The first flow map was created by Henry Drury Harness in 1837, which illustrated rail ridership in Ireland [19]. Flow maps were later popularized by Charles Joseph Minard. Since then, cartographers have used flow maps to depict migrations, trade, and any data set with a from-to relationship [16]. Tobler [56] was the first to use computers to automatically generate flow maps in 1987 to show migration among different states. However, the generated maps were visually

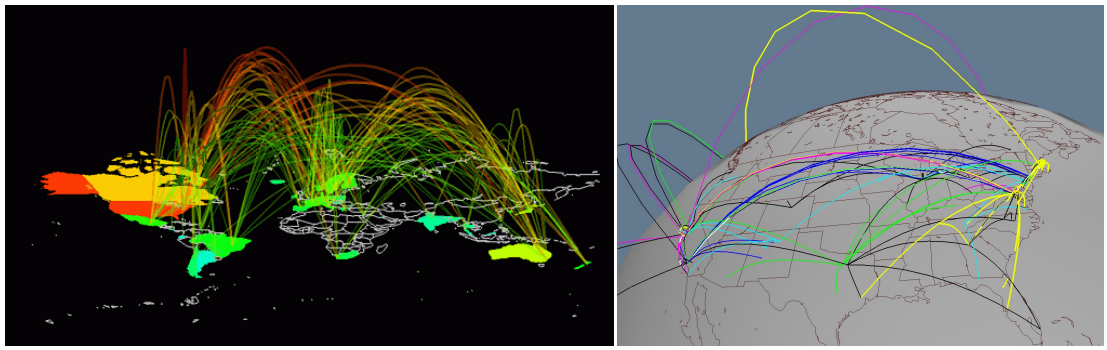


Figure 2.4 SeeNet 3D *(left)* and Munzner's Mbone Map *(right)*

cluttered because they did not take advantage of graph-drawing techniques to minimize edge crossings.

2.6 Evaluating Visualizations

Human-computer interaction has traditionally evaluated interfaces using the standard metrics of time to task completion and task efficiency. While this technique is useful for simple tasks that can be studied in a lab setting, it may not be suitable for more complex problem-solving tasks that may require expert users and or more time to learn and use an expert interface effectively.

Shneiderman and Plaisant [51] propose a strategy for doing evaluation of visualization by moving away from laboratory studies to long-term real world usage scenarios. They call this a multi-dimensional in-depth long-term case study. Instead of relying on simple quantitative measures they suggest documenting many aspects of a visualization system. They suggest recording a history of tool evolution, determining what constitutes professional success for the tool, creating a regular schedule of observations and interviews with users, tool instrumentation to provide usage data, log books to allow users to keep diaries, and documentation by designers of successes and failures with the tool. The evaluation of our work has followed the approach outlined by Shneiderman and Plaisant.

2.7 Network Security

There are many examples of applying visualization to improve monitoring and situational awareness of a network. Lakkaraju et al. [30] describe a tool called NVisionIP, which visualizes flows using three levels of granularity: a galaxy view, which shows the whole network, a small multiples view which shows the information for a selected set of hosts, and a view which shows the behavior of one machine. Similarly, Yin et al.

describe VisFlowConnect [65], which uses parallel coordinates to monitor the state of a network.

To represent time, some systems [30, 42] have used animation instead of allocating an axis. Among those with spatial layouts of time, PortVis [36] visualizes port activity with time on the y-axis and IDS Rainstorm [1] which visualizes alarms from an IDS for a large IP space in columns where the x-axis of each column is time. Livnat et al. [32] describe polar layouts with time on the radius while Radial Traffic Analyzer [28] uses an angular measure for time.

Isis differs from the preceding visualizations in that its focus is incident investigation using network flows. VIAssist [14] is a framework also designed for escalation and correlation analysis. It integrates multiple data sources, visualizations, and sup-

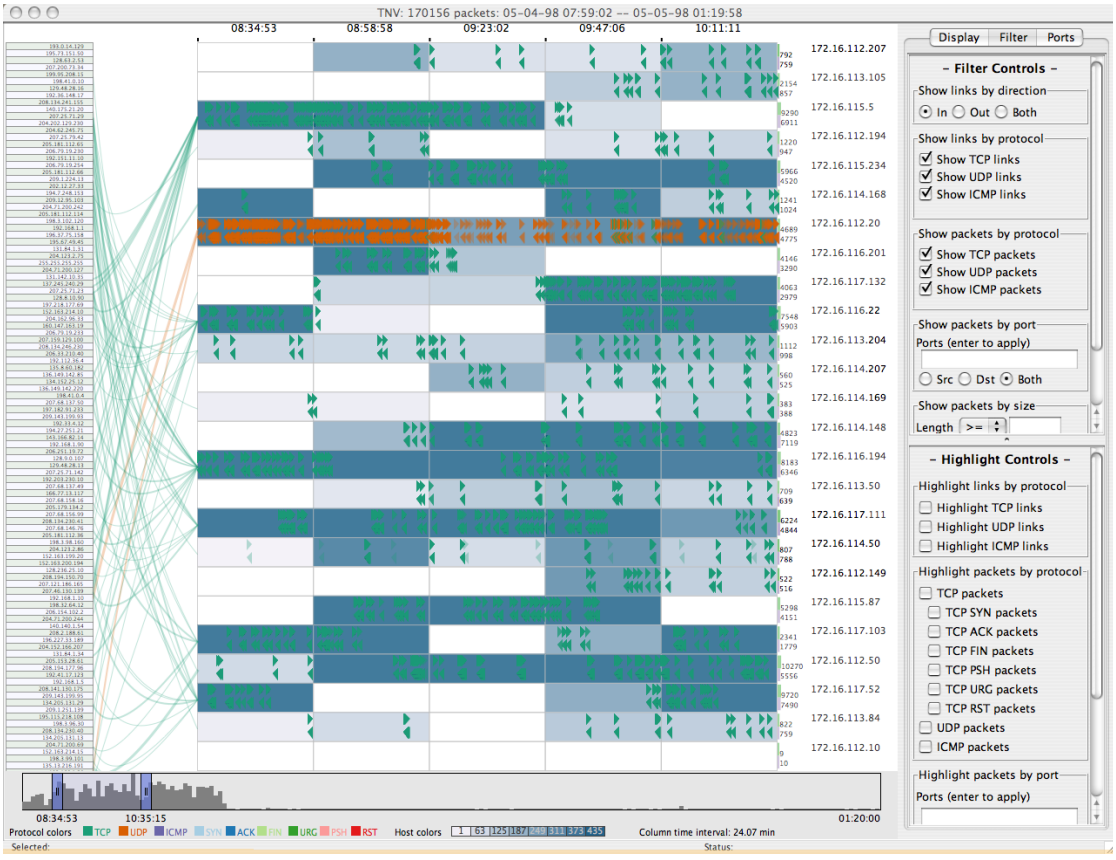


Figure 2.5 A screenshot of Goodall's TNV showing a portion of a dataset containing 170,000 packets.

ports collaboration among analysts. The timelines and event plots of Isis are not found in VIAssist, but could be incorporated into such a framework.

Goodall et al. describe TNV (Figure 2.5) which maps each IP address to a row to produce a timeline of activity [20]. Connections between IP addresses are drawn as lines among rows, in contrast to Isis, which maps an aggregate over connections for a specific IP address as a bar in a bin on a single timeline, or maps connections into marks along the x-axis of an event plot.

3 Network Incident Investigation

Networks are a critical part of modern communications infrastructure and ensuring their performance, stability, and security is an ongoing challenge. As the size and use of networks increases, it becomes more difficult for administrators to understand their behavior, since any reasonable traffic volume will generate a significant amount of data in the form of system logs, network flows, and packet traces. Developing techniques for incident investigation on a computer network provides insight into the development of more general event analysis systems.

For the last two years, we have been researching visual tools to aid network security investigations by working with the principal network analyst for the EE and CS departments at Stanford. The analyst is trying to decide if some suspicious behavior is the result of an intrusion. Intrusions are usually caused by a remote attacker who is trying to gain control of local machines in order to conduct some malicious activity. Some possible uses of compromised machines would be to cause denial-of-service attacks as part of a botnet, to host illegal software, or to attempt to steal personal information. In the period from September 2005 to November 2007, there were 43 investigations of intrusions reported on the Stanford EE and CS security mailing list. This list is used by network administrators to communicate information about ongoing security threats or incidents that have been resolved.

The analyst must isolate the vector of the intrusion by reconstructing the sequence of connections made to and from computers at Stanford. This allows them to understand the vulnerability that was exploited so that other systems may be updated

to prevent the intrusion from reoccurring. The analyst must also determine the scope of the intrusion to decide if there was collateral damage to other systems. Depending on the sensitivity of the data stored on the compromised systems, the analyst may need to verify that data was not lost to comply with privacy laws. Once the analyst understands the vector and the scope of the intrusion, she will need to make sure the compromised systems are clean. For regulatory compliance or to have a historical record, she may write a report that summarizes the intrusion and the actions taken.

This chapter describes Isis, a system that uses progressive multiples of timelines and event plots to support the iterative investigation of intrusions by experienced analysts using network flow data. The visual representations make temporal relationships apparent, allow classification of events with dynamic brushing, and enable users to organize their visualizations to reveal structure and patterns by reordering rows. Isis combines visual affordances with SQL to provide a flexible tool for investigation. We present an annotated case study using anonymized data of a real intrusion that demonstrates the features of Isis.

3.1 Network Flow Data

The data for our visualizations are the routed ICMP, UDP, and TCP network flows, captured by a sensor at the network gateway, and stored in a relational database. Each flow summarizes the time and duration of a network connection at the transport layer. Packet counts and bytes are stored, but the contents are not. To be useful for the analysis of network incidents, flows must be organized for fast searches over the tens of millions of daily flows. The EE and CS buildings at Stanford participate in 0.5 to 3 million flows per hour, with daily accumulations in the tens of millions of events. A MySQL database stores the flows, which provides the analyst with a flexible and familiar interface for specifying queries.

3.1.1 Flow Sensor

Flow records can be uni-directional or bi-directional. Bi-directional flows collapse the two uni-directional flows of a conversation into one record, with separate fields for the port, packet and byte counts. Bi-directional flows are used because they are more compact. We are using the open source Argus flow system which is configured to create bi-directional flows for routed ICMP, UDP, and TCP traffic [5]. Each flow is defined by the 5-tuple key of protocol, source/destination IP, source/destination port. The orientation of a flow is determined by the srcIP in the packet that created the flow. For long-running connections, a flow record is generated every 60 seconds, but any connection which is idle for more than 300 seconds will be dropped. It is re-established as a new flow if subsequent packets are seen.

3.1.2 Database Repository

Many incidents begin with a report of anomalous behavior involving a local IP address. As a result, the analyst will issue a query for all the traffic associated with that focus IP. Once the analyst locates a suspect IP that contacted the focus, he will often want to retrieve the suspect IP's communication with other local IPs. We call this a *pivot* from the focus IP. Because flows are relatively modest in size compared to the traffic they summarize, both the flow sensor and the database repositories can be housed on inexpensive commodity hardware.

Initially we directly mapped flow record fields to table columns, but this resulted in unsatisfactory performance. More importantly, it did not match up well with the analyst's needs so we modified the schema. The problem is that a SQL table constructed with columns directly mapping raw flow record fields will have srcIP and dstIP columns. Obtaining all the traffic for a single IP would require two queries of the database, one with the IP as the source and one with the IP as the destination using

Local IP, Remote IP	Local Port, Remote Port, Destination Port	Locality	Role	Virtual LAN	ASN	Measures

Table 1 The columns for each flow that is stored in the database.

expensive OR or UNION clauses. The investigation process is easier to reason about in terms of local and remote addresses.

To improve query performance, we transform all the src/dst fields in flow records into local and remote columns in the database table. This allows us to issue a single query for either a local IP or a remote IP. To preserve the critical orientation information of the src/dst relationship, we add a column that specifies the role played by the local IP in each flow. Because we capture some local traffic, there can be flows with two local addresses. In this case we arbitrarily choose the destination as the local IP. Using local and remote designations makes a query about a flow's destination port more complex, because the client often uses an ephemeral port and the server uses a fixed port. The destination port is usually mapped to the fixed port and is included as a convenience column.

The database schema also incorporates metadata reflecting aspects of the structure of the network. Our local network is subdivided along lines reflecting the administrative and technical groups. Since analysts are responsible for these logical subnets, called VLANS (for virtual LANS), the database allows queries to be restricted by VLAN. A similar segmentation is made for remote IPs because the Internet is divided into Autonomous System Numbers (ASNs) which define responsibility for IP address ranges. Since an ASN is roughly equivalent to an Internet Service Provider (ISP) and resolving network incidents is usually done at the ISP level, the database also associates ASNs with an IP address.

3.2 The Investigation Process

Network security incidents can be triggered in a variety of ways: by an automatic alert generated by Intrusion Detection Systems (IDS), by an e-mail complaint from an administrator at a remote network, or by a user noticing that a machine has started behaving oddly.

Once a report has been received, analysts perform a variety of tasks [15] while engaging in an iterative process of hypothesis generation and evaluation: *Triage* to decide whether a report merits investigation; *Escalation* to determine method of compromise and its extent; *Correlation* to compare this incident with those of the past; *Threat Analysis* to search for attacker identity and motivation; *Incident Response* to recommend or implement a course of action; and *Forensic Analysis* to gather and preserve evidence. Our tools support the escalation, correlation, threat analysis, and forensic analysis stages.

The network flows collected by the sensor show details of the times and extent of communications among machines and so are valuable for triage and escalation. If sufficiently fast access to historical data is available, they may also be used for correlation analysis. During an investigation, analysts are trying to identify flows that comprise an intrusion out of a vastly larger set of flows. By providing filtering, sorting, and compact visualization of the flows, Isis can help the analyst build a mental model of the network activity to distinguish intrusion flows from normal flows.

An analyst begins an investigation focused on the IP thought to be compromised. The analyst inspects all of the traffic looking for sources of possibly malicious traffic. The analyst would then pivot to focus on the suspect IPs and inspect their traffic. If that traffic indicated additional possible compromises, he would pivot again. This process is described in Appendix A: Investigation Task Analysis. *(Step 11) Action: Get Traffic Overview and Inspect Connections*, is simplified as follows:

For each IP to investigate

i. Inspect its traffic to determine it is related to the intrusion
ii. Compare its traffic to others for correlations in time and attributes
iii. Refine the query by adding filters if necessary
iv. Pivot to see related traffic if necessary

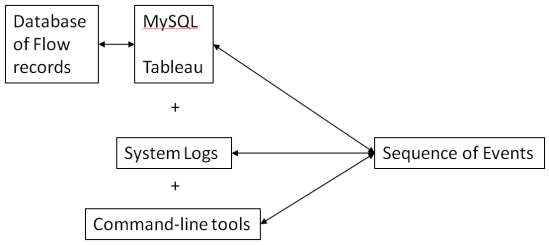


Figure 3.1 A block diagram showing all the tools available to a network administrator for reconstructing a sequence of events,

Analysts typically use a variety of tools to conduct an investigation (Figure 3.1). To interact with the database of flow records, analysts either use a command-line MySQL client or a graphical query tool like Tableau [55]. The problem with the MySQL client is that it is difficult to see patterns using raw text. Tableau avoids this problem by presenting a graphical query result, but the problem is that it does not support the investigative process very well. The problem is that adjusting a query parameter in Tableau causes the entire display to be refreshed with the new result, which makes it difficult for an analyst to keep track of what she has already investigated.

Flows are not the only source of information. System logs that are stored on individual machines provide records of who has used the system. Since flows do not contain any contents, analysts use `grep` to search system logs for confirmatory evidence. Analysts also use command-line tools such as `nmap` and `whois` to find open ports on a system or to look up the registration information for an IP address.

3.3 A Case of Mysterious IRC Traffic

To better understand the investigation process and how Isis supports it, we describe an investigation using an anonymized data set which contains a real intrusion. This intrusion was not found using Isis, but has been recreated to illustrate its features.

Each step in the investigation is labeled by a bolded number, separating the actions taken by the analyst, the features of Isis that support those actions, and discussion of design rationale for those features.

1 – Action: Look at traffic of local machine. After looking at a routine summary of network activity, an analyst noticed that there was a high level of IRC traffic to a server in northern Europe from a local machine, 75.64.71.22. Since hackers often use an IRC channel to control a bot on a compromised host, she decided to look at the last 24 hours of the machine's traffic by providing Isis with a focus IP, time window, aggregation function, and filter string. The aggregation and filter are specified as SQL expressions.

1 - Feature: View query results as a timeline. Figure 3.2 shows the result of a query of 75.64.71.22 with the aggregation: `max(l_pkt + r_pkt)` which maps the height of each bar to the flow in that bin with the largest total number of packets.

1 - Design Discussion. To ensure the entire query result fits on the screen, events are binned and shown as bars. The height of the bars is controlled by the aggregation expression, which can be any expression that returns a non-negative scalar value, such as the min, max, or average of the number of packets. The aggregation expression `count(*)` will count the rows satisfying a query and creates a timeline where the bar heights are proportional to the number of connections in each bin. In

Figure 3.2 Timeline using an aggregation expression that shows the maximum total packets to and from the local IP that is suspected to be compromised.

Figure 3.3 Timeline using an aggregation expression that shows the total number of connections to and from the local IP that is suspected to be compromised.

network incidents, the existence of a connection is often as important as its size or duration so it is a common for an analyst to use this aggregation to begin exploring traffic. Figure 3.3 shows the result of a query of using `count(*)` to get an overview of the traffic spanning the last day. The use of timelines is discussed further in 4.2.1.

2 – Action: Understand what ports were used. The analyst can see the temporal distribution of traffic with a timeline. However, the timeline does not make apparent what ports were used in that time period.

2 – Feature: Use tearoff window to see traffic by another dimension. Figure 3.4 shows the tearoff window which lists the ports that were used. This list can be sorted by the aggregate value. The analyst is able to see that port 6667, an IRC port, has approximately 63,000 flows.

3 – Action: Understand when ports were used. The analyst needs to see when different ports were used in order to locate the time when IRC traffic began. She believes that the intrusion most likely occurred very close to the beginning of the IRC traffic.

3 – Feature: Brush to see temporal distribution of a tearoff menu. The analyst can see how activity on the port is distributed in the timeline by brushing its cell. If she sees a value of interest, she can create new timelines that

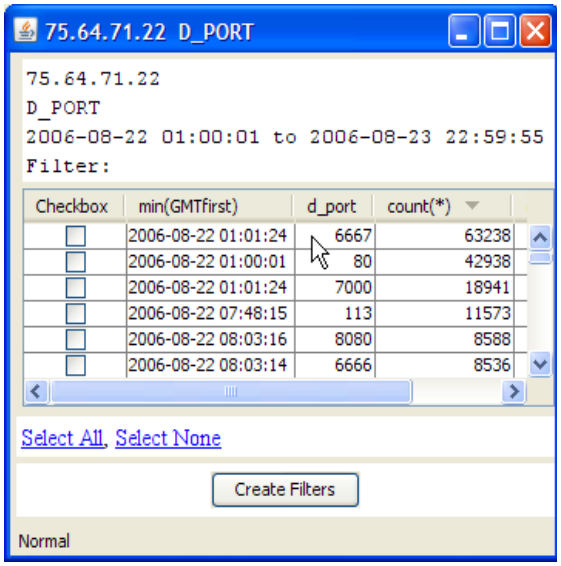


Figure 3.4 A tearoff menu showing the distribution of traffic by destination port.

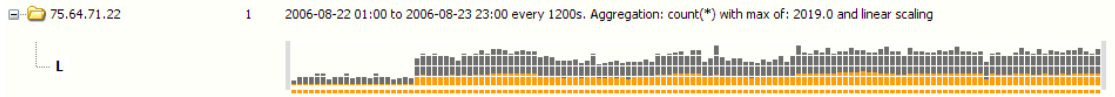


Figure 3.5 A brushed timeline where the orange highlighting indicates the presence of connections to IRC servers on port 6667 that extends over the whole period.

filter traffic on these ports. Figure 3.5 shows the results of brushing port 6667. Orange highlighting is overlaid on all of the existing timelines. The height indicates the proportion of traffic using port 6667. Orange marks underneath the bins indicate the presence of port 6667 traffic, even if the height of the orange may not be visible in the bar. As a result, the analyst can see that IRC traffic has been present over the whole time period.

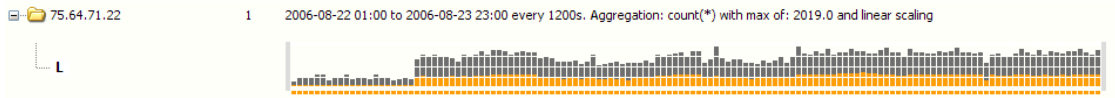


Figure 3.6 A brushed timeline where the orange highlighting indicates connections to IRC servers on a different port, 6666.

Figure 3.6 shows a brush from the same tearoff menu for port 6666, which is another IRC port. This reveals a different connection to an IRC server that is correlated with the spike in activity. Since the goal is to determine the first incidence of IRC traffic, the analyst makes a mental note to come back and look at the traffic on port 6666 at a later time.

3 – Design Discussion. The analyst can bring up tearoff menus for several dimensions that have been found to be useful: partner IPs, ports, role, ASN, locality, or Vlan. From the IP tearoffs, the analyst can also pivot to new IPs and create new timelines for those IP addresses.

4 – Action: Locate the beginning of IRC Traffic. The analyst realizes that the IRC traffic began more than 24 hours ago. She must look further back in time to locate the beginning of the IRC Traffic.

4 – Feature: Create new timelines that span earlier periods. Figure 3.7 shows a progression of queries the analyst generates to discover the beginning of the IRC

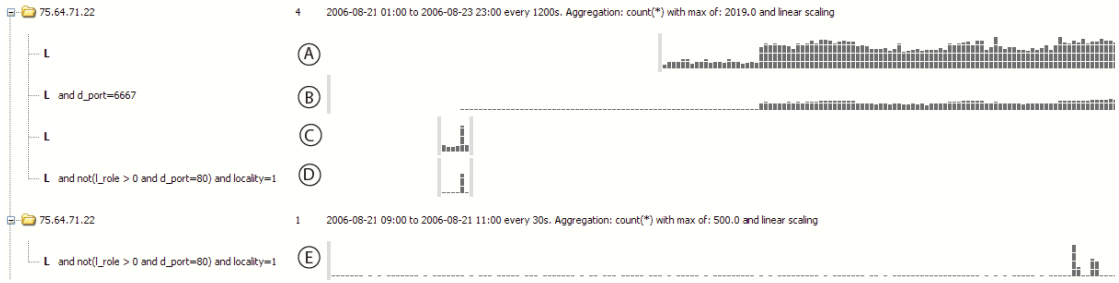


Figure 3.7 A progression of queries generated in the timeline display showing how the user has narrowed the time window from a two-day period to two-hour period. The letters in circles used in the text description to describe the individual rows.

traffic. To determine when the IRC traffic began, she limits the traffic to port 6667 and changes the time window to be another day earlier, which produces row B, and shows the beginning of the IRC traffic. To look for the source of the compromise, she queries for all traffic in a two-hour window centered on the beginning of the IRC traffic, resulting in row C. Since the focus IP is a web server, the analyst removes all web traffic served by the focus. She restricts the traffic to be nonlocal, as local traffic is usually benign. This is done using the filter `not(l_role>0 and d_port=80) and locality=1`, resulting in row D.

4 – Design Discussion. Timelines in the same folder share a common bin size and aggregate, which makes it easy to juxtapose rows and compare query results. Since the bin size of the larger folder is constrained by the earlier queries, the analyst moves row D to new folder on row E. The bin sizes are recalculated, and changes the binning to 30 seconds. Each folder has different bin sizes and aggregates so that the system can display a wider dynamic range of data. 4.2.2 discusses small multiples and how it relates to the creation of new timelines. 4.2.3 discusses how to create new timelines through the use of pivoting.

5 – Action: Look at individual flows to locate intruder's connection. Now

l_weekday	l_hour	GMTfirst	duration	locality	l_role	proto	l_asn	l_vln	inet_ntoa(l_ipn)	l_port	r_asn	r_vln	inet_ntoa(r_ipn)	r_port	d_port	l_pkt	l_byte	l_abyte	r_pkt	r_byte	r_abyte
2	2	2006-08-21 09:00:02	0.002	1	-3	1	32	71	75.64.71.22	8	26101	24288	66.94.230.32	8	0	2	196	128	2	196	128
2	2	2006-08-21 09:00:13	5.588	1	3	6	32	71	75.64.71.22	25	760	33280	131.130.70.75	25	25	30	3128	1124	28	9630	7814
2	2	2006-08-21 09:00:27	0.002	1	-3	1	32	71	75.64.71.22	8	26101	24288	66.94.230.32	8	0	2	196	128	2	196	128
2	2	2006-08-21 09:00:45	7.4	1	3	6	32	71	75.64.71.22	25	702	63744	212.249.195.196	25	25	72	5002	1098	138	91984	84516

Figure 3.8 An example of the sortable event table that is generated when the analyst looks at the raw data.

that the analyst has narrowed her focus to a two-hour window, she must look at all the individual flows to locate the connections made by the intruder.

5 – Feature: Use event table to see raw data. She creates an event table to look at the raw data, which has approximately ~1600 flows, the first few rows of which are shown in Figure 3.8. Each row in the table is a flow between the focus and partner IP.

5 – Design Discussion. The problem with an event table is that too many rows of text make it hard to see any structure in the data. Isis allows the analyst to change the visual representation to make the temporal structure more clear.

6 – Action: Locate Initial SSH Connection. To isolate the initial intrusion, she looks for an SSH connection that occurs before the start of traffic to the IRC servers.

6 - Feature: Use event plot to isolate SSH connection. The analyst changes to the event plot seen in Figure 3.9 which maps each row in the table to a mark. The horizontal position of the mark is determined by a row's timestamp. Each row of the event plot represents a different partner IP address. She can find the SSH connection by using the sidebar, which provides a breakdown of the traffic into its constituent parts. The sidebar supports the same dimensions as the tearoffs in the timeline display: ASN, Port, Vlan, Locality, and Role. Hovering over port 22 (SSH) in the sidebar causes the system to highlight all the rows in the event plot that contain flows with that destination port, revealing SSH server connections from two IPs as seen in Figure 3.10.

To keep permanent track of port 22, the analyst colors its sidebar entry a shade of blue, seen in Figure 3.11. The system allows the user to color marks by any of the sidebar dimensions. The color space for each dimension is global, so marks in other event plots with port 22 will now also be colored blue. A mark is only colored by one dimension at a time to avoid conflicts in displaying a mark that has had multiple attributes colored.

6 – Design Discussion. The event plot is discussed further in 4.4.

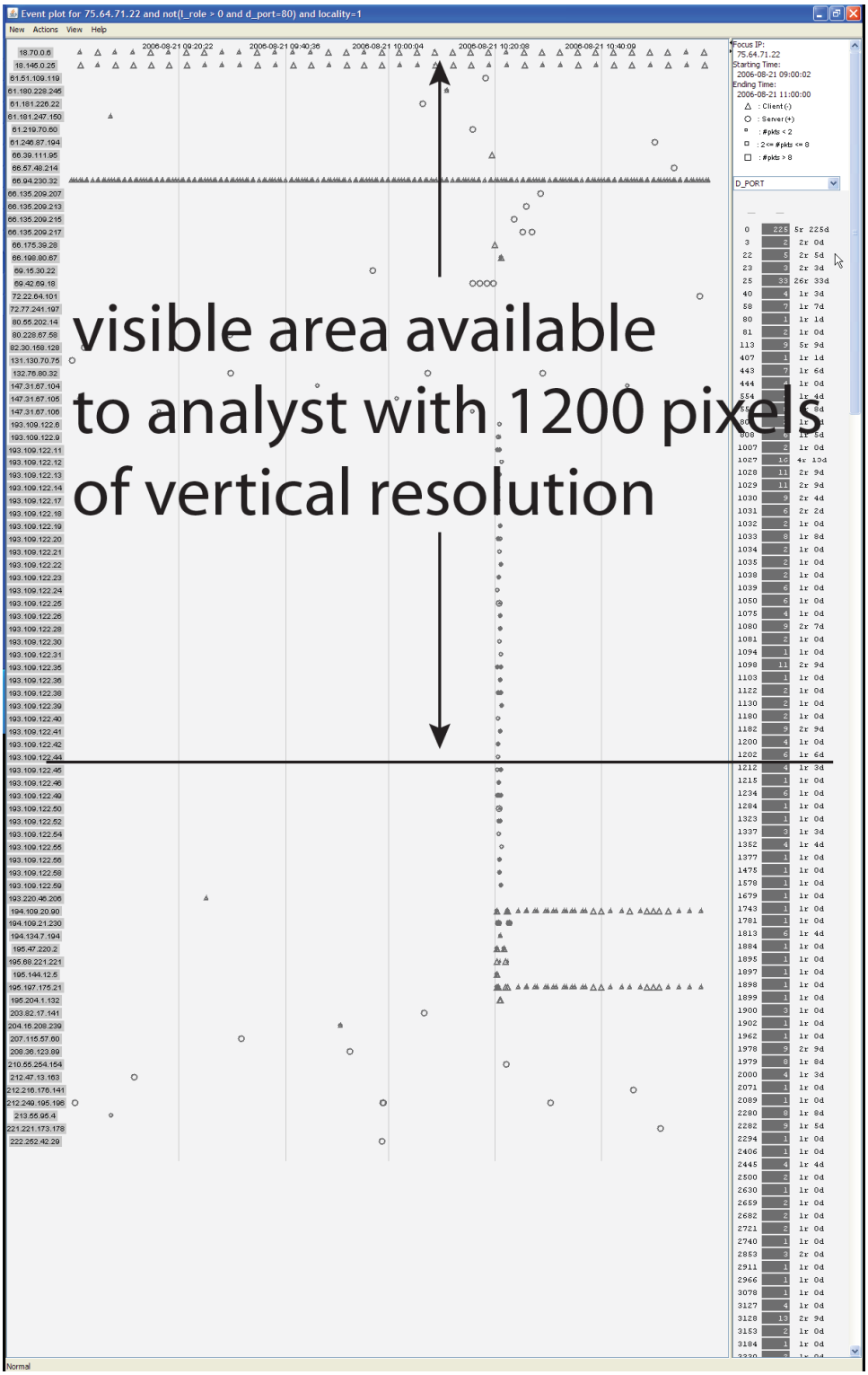


Figure 3.9 An event plot generated by Isis of a two-hour time window containing around 1600 events. Notice that many events lie off-screen, due to limited resolution. We introduce the ability to collect a brush to allow analysts to make off-screen elements visible.

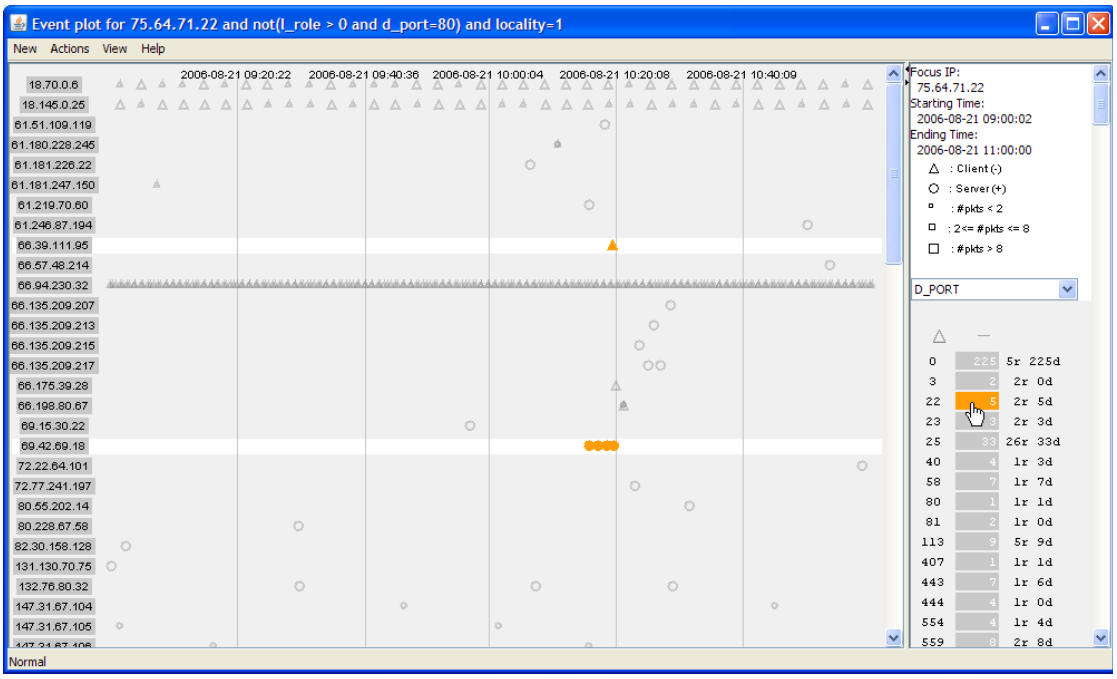


Figure 3.10 Brushing the sidebar on port 22, which highlights two rows containing suspicious SSH connections.

7 – **Action: Locate IRC Traffic.** She wants to see if there is a correlation with

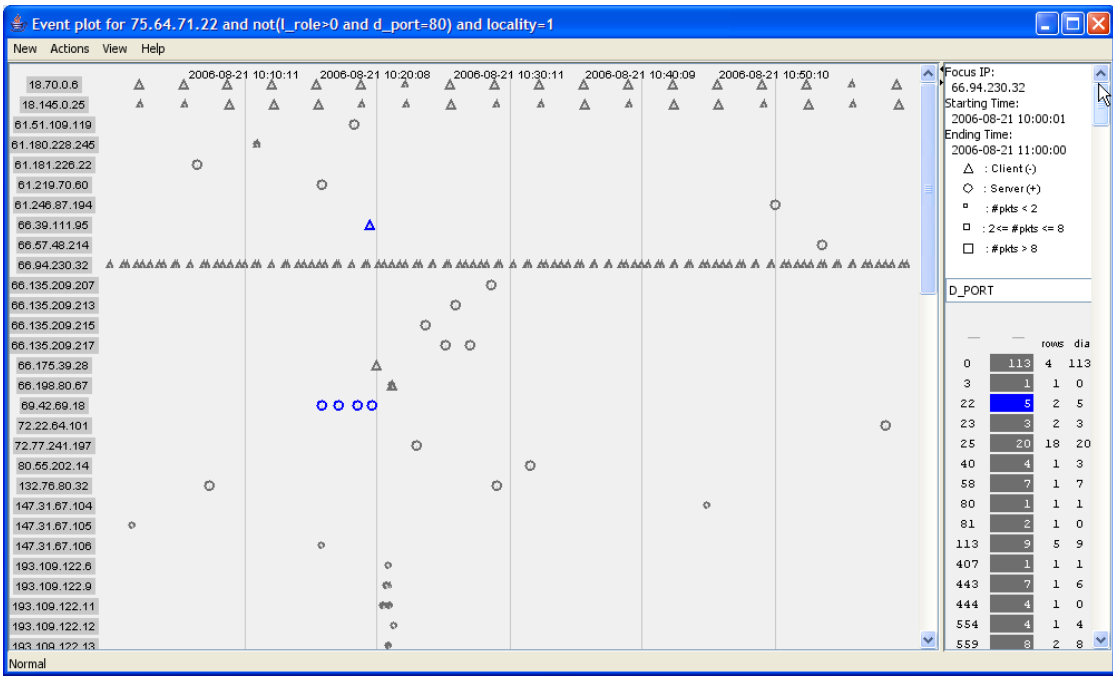


Figure 3.11 The left event plot shows the results of coloring port 22 a shade of blue.

the beginning of the SSH and IRC traffic. The analyst brushes over port 6667, but does not see any highlighting. The problem is that the number of rows that need to be displayed can exceed the physical limitations of the screen. Note that Figure 3.9 is 1920 pixels high, but she only has 1200 pixels, or 60% of that vertical resolution. When a user brushes a dimension, off-screen rows are logically highlighted but are not visible.

7 – Feature: Collect a brush. The system allows users hovering over a dimension to "collect a brush", to force all brushed rows to move to the top of display. This also allows her to easily group IP addresses by their different attributes in order to organize the display visually. In Figure 3.12, we see her collect the brushed rows for IRC port 6667, which are moved to the top of the display. She also marks the IRC traffic in red for future reference.

7 – Discussion. Please see 4.4.1 for discussion about collecting a brush.

8 – Action: Locate download of client tools. After coloring the marks for port 6667 in red, she now searches for the prior download of the IRC tools themselves. The

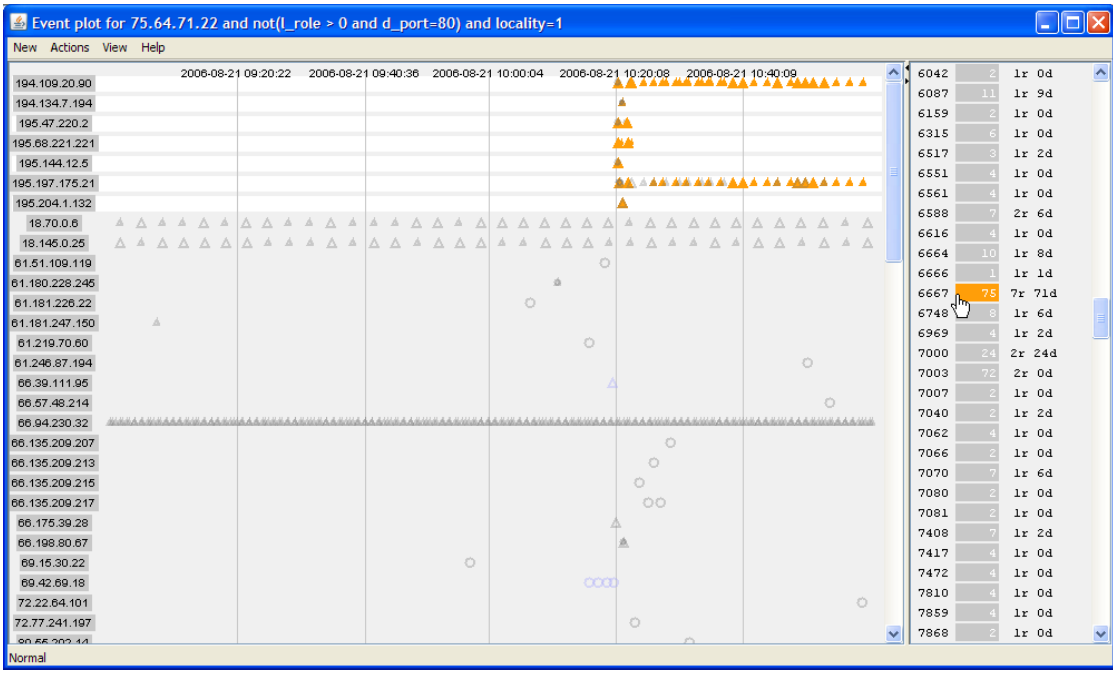


Figure 3.12 The event plot shows how the analyst has brushed port 6667 and used the "collect a brush" action to bring the IPs with flows on port 6667 to the top of the display so they can be made visible.

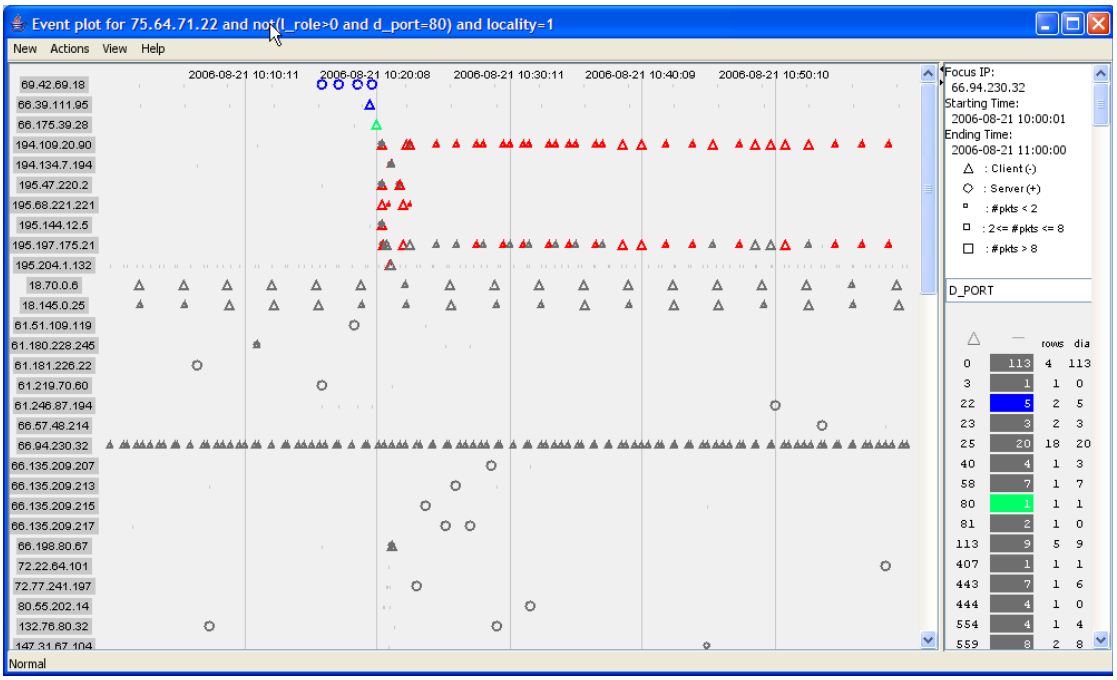


Figure 3.13 An event plot where the analyst has colored SSH connections on port 22 in blue, web traffic on port 80 in light green, and IRC traffic on port 6667 in red. She has also reordered the rows so that the flow of events can be more easily read in a left-to-right and top-to-bottom manner.

analyst knows that once an intruder logs in via SSH, he will usually download a set of exploit tools via a web server or ftp. The analyst selects web traffic on port 80 in the sidebar and colors it light green.

9 – Action: Make display readable. At this point the analyst has a good idea of the intrusion sequence, but the display does not yet reflect this structure.

9 – Feature: Reorder rows. The system allows her to reorder rows to create visual structure out of the events. Figure 3.13 shows the results of the analyst moving the rows containing SSH traffic (port 22) and Web traffic (port 80) so that the image can be read top-to-bottom, left-to right. The juxtaposition allows her to compare the behavior of different IP addresses or group IP addresses by their role in an intrusion.

9 – Design Discussion. Further discussion of reordering may be found in 4.2.4.

10 – Action: Make sure sequence of events is complete. The analyst needs to make sure that the sequence of events she has discovered is a complete representation of what occurred during the intrusion.

10 – Feature: Switch to ordinal time. Up to this point the analyst has been working with the event plot scaled with a traditional continuous time axis. To make more space for the events, the analyst switches the view to be ordinal, as seen in Figure 3.14. This reveals a gap between the SSH connections and the onset of IRC connections suggesting that there may be interesting events in the off-screen flows. Scrolling down, the analyst discovers that the spacing is due to the presence of proxy scans from computers presumably controlled by the intruder which are mapping the compromised computer. Figure 3.15 shows the cause of the gap.

10 – Design Discussion. The advantage of continuous time is that the horizontal distance between marks is linearly related to the number of seconds between those flows. This allows her to get a sense of how events are clustered or distributed in time.

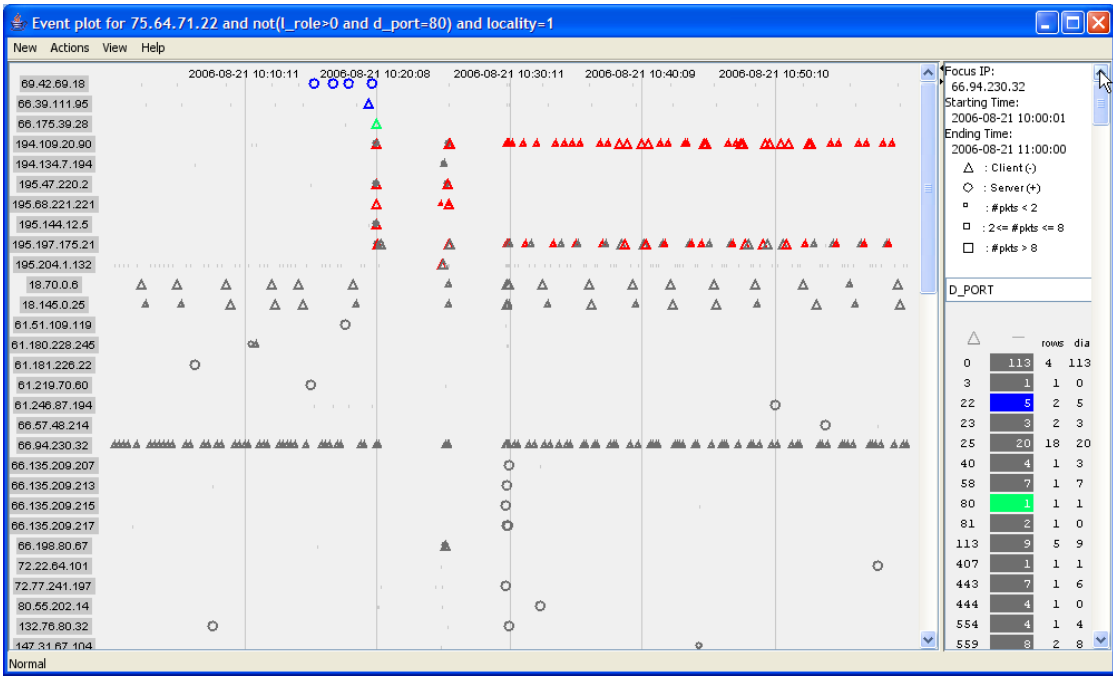


Figure 3.14 An plot with the same data as Figure 3.13, but uses an ordinal space which distributes marks evenly across the x-axis, instead of with continuous time.

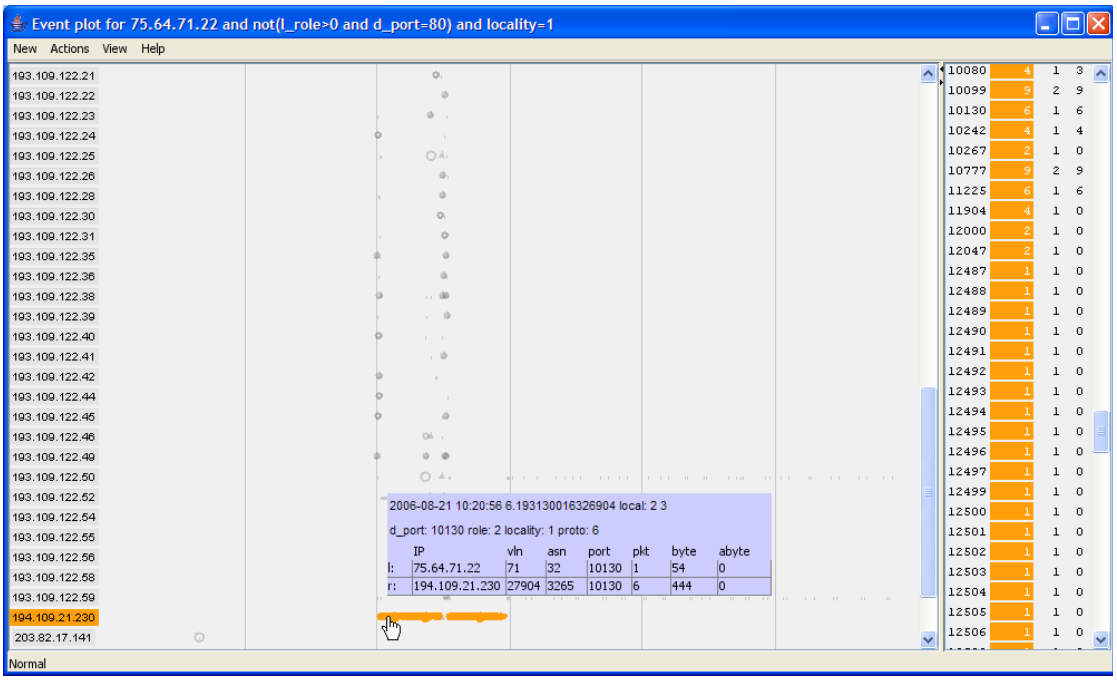


Figure 3.15 An ordinal event plot where the rows have been reordered to show a string of proxy scans from machines presumably controlled by the intruder.

Since intrusion events often occur in a small time interval, a continuous view of time can result in overplotting and reduced visibility. Overplotting occurs when multiple marks are drawn on the same screen location, causing some marks to be occluded.

To reduce the effects of overplotting, the system can show events in an ordinal space. This distributes them evenly across the x-axis such that the distance between the marks does not encode the number of seconds between events. However, because understanding the ordering of events is often more important than knowing the precise time at which they occurred, the ordinal view can be very useful. This is discussed further in 4.4.2.

11 – Action: Emphasize intrusion events and de-emphasize uninteresting events. Now that the analyst has established a sequence of events for the intrusion, she wants to precisely adjust the spacing of the marks so as to create a narrative.

11 – Feature: Adjust gridlines to allocate more space to interesting events. The system allows her to interactively edit and adjust the location of the temporal

gridlines to segment the event plot and make it easier to read visually. This allows her to create multiple regions with different horizontal distortion, similar to the technique offered by Table Lens and other systems [48].

Figure 3.16 shows the result of adjusting gridlines to allocate more space to the events that make up the intrusion. The SSH connection in blue circles indicates a remote login from 69.42.69.18. The analyst concludes that it is the IP that is likely to be responsible for the initial intrusion and that IRC bot tools were downloaded from 66.175.39.28 by the flow in yellow. The remaining connections in red are the client connections to the IRC servers. The gray connections are the proxy scans.

12 – Action: Investigation additional compromised machines. The analyst wants to understand what other machines were affected by the intrusion.

12 – Feature: Use exploration history to continue investigation. At this point, she will want to return to the timeline display to pivot upon the intruder IP to

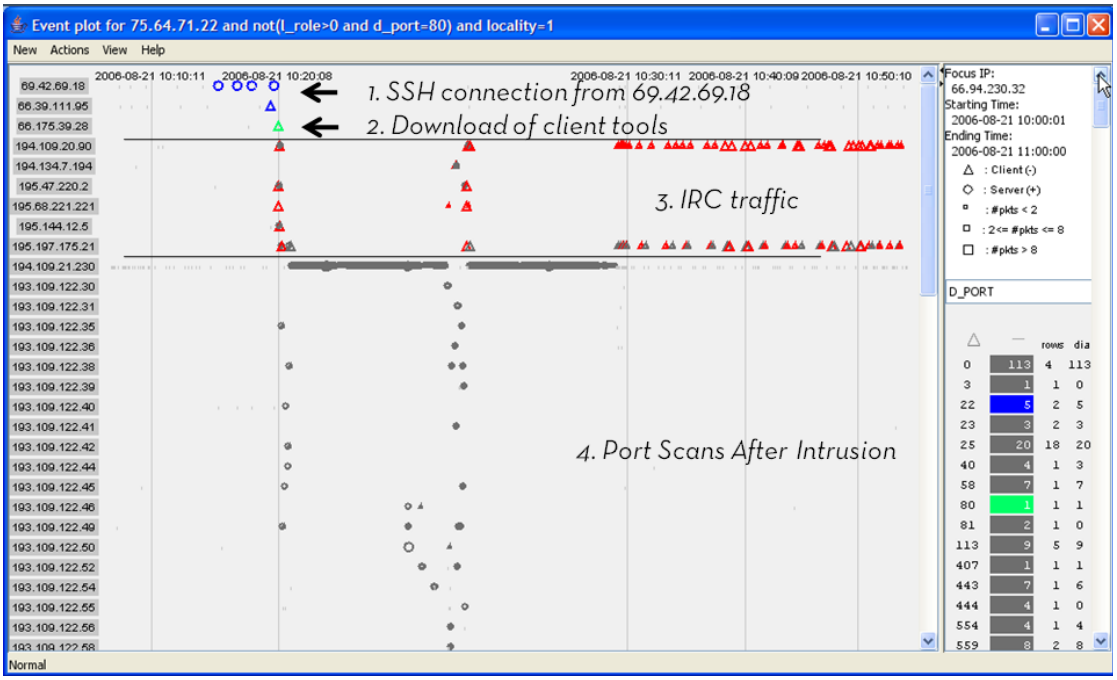


Figure 3.16 The event plot using ordinal time where the gridlines have been adjusted to show the intrusion. The SSH connection that compromised the system are the blue circles. The download of the IRC bot is in green. The red triangles show the IRC connections. The remaining traffic in grey are proxy scans.

determine if other computers have been affected and begin this process anew.

12 – Design Discussion. For more information about how the exploration history supports iterative investigation, please see 4.2.5.

This case study has demonstrated how an analyst is able to investigate intrusions using a combination of small multiples of timelines and event plots. Both representations make temporal relationships apparent and make it easy to visually classify events. Users can organize the displays to create a visual structure that can be read from top-to-bottom and left-to-right. The two displays are complementary: timelines provide overviews, navigation through pivoting, and support iteration, whereas event plots allow the analyst to classify events and create visual structure through the reordering of rows.

4 Progressive Multiples for Forensic Analysis

This chapter describes the evolution of progressive multiples from the initial flow map prototype to the final design. Although we found that flow maps were useful for obtaining overviews of traffic, they did not prove to be useful for forensic analysis. Although the system described by this dissertation targets the domain of computer network security investigation, the visualization techniques used in Isis can be applied to the forensic analysis of other kinds of networks. Progressive multiples was inspired by examples of designs from visualization and human-computer interaction, including small multiples, reorderable matrices, and progressive disclosure.

4.1 Initial Flow Map Prototype

Flow maps are a type of node-link diagram where the width of the edges encodes the number of objects that are moving among nodes on a network. Our first attempt to visualize network intrusions used flow maps to show the number of connections to and from computers at Stanford.

Cartographers have long used flow maps to illustrate the movement of objects among locations. A flow map shows the spatial distribution of univariate geographic phenomena [53]. Lines of varying width which represent the number of objects being transferred are overlaid on the map. Visual clutter is reduced by merging edges that share destinations. We developed an automatic flow map layout technique that simulated the effects of a hand drawn map. This technique is described in more detail in Chapter 6. Unlike the majority of the maps in Chapter 6, which primarily used geo-

graphic layout, these maps used a radial layout where time was the primary factor, to allow analysts to understand the sequence of events.

Figure 4.1 shows the radial flow maps used to visualize the intrusion. Each flow map shows the communication from a single computer at Stanford to external ASNs, which represents multiple IP addresses. We use ASNs in order to reduce the number of nodes that we would have to plot. The focus IP is centered at the bottom of the display. The ASN nodes are arrayed in a semicircle around the focus, where time increases clockwise. The position of the ASN nodes reflects the first time that an IP from that ASN contacted the focus node. The width of the edge from the ASN to the focus node represents the number of connections between the focus and the ASN during a given time period.

We developed a prototype to allow analysts to create flow maps of network behavior. The analyst could specify the IP and time period of interest to get a map that showed the behavior of the focus IP. The analyst could modify the query using a SQL expression to show different subsets of the traffic. The analysts found that the flow maps could generate very striking images for presenting intrusions. The problem was that it was only possible to select the correct parameters after the fact. There were two reasons why it was difficult to discover these parameters in the first place. First, node-

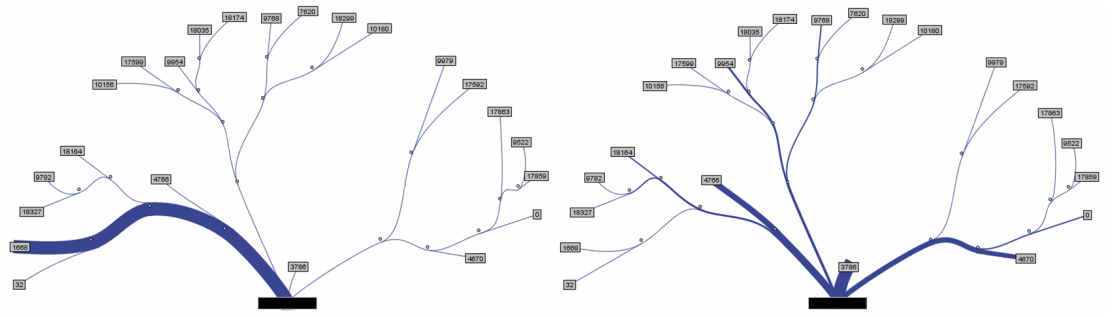


Figure 4.1 Radial flow maps with the ASN nodes contacted by the focus node arrayed in a semicircle. Time increases clockwise, and the ASN node positions are determined by the first time that they contacted the focus. The attacker is the second node on the left and the thick edge shows the initial scan made by an attacker *(left)*. The outgoing scans made by the compromised victim at a later time *(right)*.

link diagrams are not compact visual representations, which make them ill suited for investigation, as we have previously discussed. Second, node-link diagrams and flow maps emphasize network topology instead of the time-varying nature of its events. The lack of a consistent scale for time across flow maps made it hard to compare the traffic of different computers.

Flow maps can encode the number of events between nodes in the network, but cannot provide additional detail about individual events. The radial flow map encodes the time of the first connection with the position of the ASN node, but this does not distinguish between a single connection and multiple connections. Using multiple nodes for each connection to an ASN (or IP) would result in overplotting and make the visualization less compact. We considered using animation, but decided that it would be ineffective. Research in cognitive psychology has shown that it can be difficult to comprehend animations because they are often too complex and too fast to be accurately perceived by a user [62].

4.2 Design Rationale

Our experience with the flow map prototype suggested that a node-link diagram was inappropriate for forensic analysis on a network. We set out to design a visualization that would be compact and afford comparisons more directly than a flow map. Our technique, which we call progressive multiples, combines small multiples, reorderable matrices, and progressive disclosure.

4.2.1 Use row-based timelines

Figure 4.2 illustrates a node-link diagram, which shows the communication from a focus IP A to nodes B, C, D, and E. The problem with this diagram is that

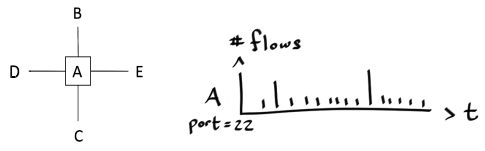


Figure 4.2 A node-link diagram that shows the traffic from computer "A" *(left).* A timeline that shows the traffic from computer "A" *(right)*

it only depicts one point in time, similar to our flow map, which only could show when each ASN first contacted the focus IP. This does not provide enough detail to understand the sequence of communications. The topology of the network is not important for event analysis because in general, the network is completely connected. Progressive multiples uses multiple timelines to show communication over a whole time range, instead of a single moment in time or an aggregation over time, as with node-link diagrams.

If the timeline uses a continuous view of time, and multiple events that occur at the same point in time, which often occurs, the events must share the same position on the horizontal axis. The system aggregates events into bins, and each bin is drawn as a bar on screen. By default, the height of the bars counts the number of events in the bin, but it is possible to count some other aspect of each event; in the network security case this could be the number of unique connections, or the average number of packets of the events in that bin. The choice of this aggregation is made by the administrator.

The aggregation string is passed directly to the database and can be any valid SQL expression that returns a scalar value in the SELECT clause. This allows the administrator to take advantage of SQL's expressivity. For example, although overall traffic volume using the query `count(sequence_id)` is an obvious choice for the analyst, it can be useful to use other aggregations. If the analyst is concerned that one of his machines may be infected and attacking others, he could use `count(distinct remote_ip)` to identify local machines

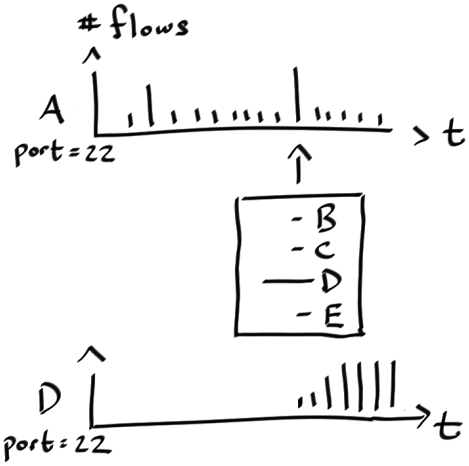


Figure 4.3 Timelines are compact and may be stacked for comparisons. Users control what timelines by interacting with existing timelines using popup menus or by issuing new queries.

with unusually large numbers of remote partners which would indicate that a machine may be scanning the network.

This aggregation in the timeline allows the system to place as many timelines on screen as possible. To make the timeline space efficient, we place additional information in a dynamic popup menu. Figure 4.3 illustrates how clicking on a bin reveals a popup menu which lists the names of the partner nodes.

4.2.2 Small multiples for comparison

Small multiples is a technique described by Tufte [59], who states that an effective way to facilitate comparisons is to use small multiples of images. Each image contains a different view of the data set, but all the images share a common spatial substrate. As a result, it is easy to visually discover their commonalities and differences. Timelines can easily be stacked and used as small multiples.

Although the compact representation allows more timelines to be visible at once than with flow maps, there is still a limit to physical screen space. Showing all the timelines for the whole network would be too much detail for the analyst. Since we are supporting an investigation task, it is unnecessary to show all the timelines at once. We provide affordances to give the user control over what timelines are visible.

4.2.3 Find related events by pivoting

In an investigation, the goal of the analyst is to reconstruct an event sequence that explains some observed anomalous behavior. The analyst does this by inspecting the traffic of one node to find out who talked to it and when they talked to it. As he finds interesting connections, he traces back the sequence of contacts to different nodes, in order to find the cause of the anomalous behavior. The act of changing focus is called a pivot, because the user is asking for more events where some aspects are fixed and the other aspects are allowed to vary. In Figure 4.3, the user is inspecting the timeline for

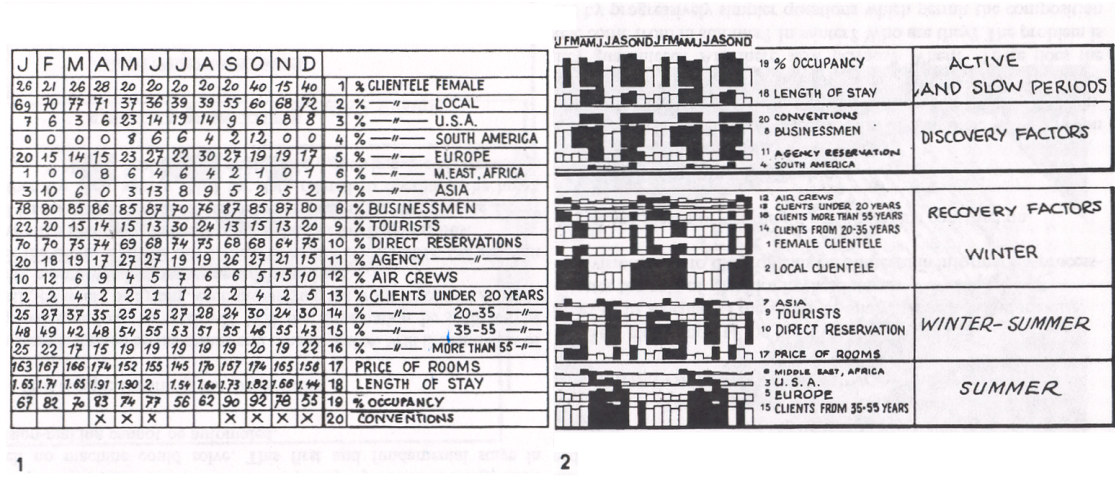
A and sees a connection from A to D that is of interest. By selecting that element in the popup menu, a new timeline for D is created and added below the timeline for A. In this case, the user has constrained that new events contain connections to and from D. The timeline for A only shows events with connections to and from A.

In progressive multiples, the use of popup menus to reveal details on demand is an instance of progressive disclosure [25]. Instead of showing all the timelines at once, the analyst can interact with previous timelines to create new timelines that are relevant to the current investigation focus.

4.2.4 Reorder to reveal structure

Since the investigation process involves many dead ends, it is possible that after many pivots, the display will become cluttered with timelines that do not contribute to a clear understanding of the sequence. Although deletion of timelines can remove clutter, we also allow for reordering of the timelines to allow the analyst to organize the timelines into an understandable sequence.

The idea of reorderable matrices was introduced by Jacques Bertin in his influential books on data graphics [8, 9]. Our design was inspired by his example (Figure



J	F	M	A	M	J	J	A	S	O	N	D		
26	21	26	28	20	20	20	20	20	40	15	40	1	% CLIENTELE FEMALE
69	70	77	71	37	36	39	39	55	60	68	72	2	% —"— LOCAL
7	6	3	6	23	14	19	14	9	6	8	8	3	% —"— U.S.A.
0	0	0	0	8	6	6	4	2	12	0	0	4	% —"— SOUTH AMERICA
20	15	14	15	23	27	22	30	27	19	19	17	5	% —"— EUROPE
1	0	0	8	6	4	6	4	2	1	0	1	6	% —"— M.EAST, AFRICA
3	10	6	0	3	13	8	9	5	2	5	2	7	% —"— ASIA
78	80	85	86	85	87	70	76	87	85	87	80	8	% BUSINESSMEN
22	20	15	14	15	13	30	24	13	15	13	20	9	% TOURISTS
70	70	75	74	69	68	74	75	68	68	64	75	10	% DIRECT RESERVATIONS
20	18	19	17	27	27	19	19	26	27	21	15	11	% AGENCY ——"——
10	12	6	9	4	5	7	6	6	5	15	10	12	% AIR CREWS
2	2	4	2	2	1	1	2	2	4	2	5	13	% CLIENTS UNDER 20 YEARS
25	27	37	35	25	25	27	28	24	30	24	30	14	% —"— 20-35 —"—
48	49	42	48	54	55	53	57	55	46	55	43	15	% —"— 35-55 —"—
25	22	17	15	19	19	19	19	19	20	19	22	16	% —"— MORE THAN 55 —"—
163	167	166	174	152	155	145	176	157	174	165	158	17	PRICE OF ROOMS
1.65	1.71	1.65	1.91	1.90	2.	1.54	1.64	1.73	1.82	1.68	1.44	18	LENGTH OF STAY
67	82	76	83	74	77	56	62	90	92	78	55	19	% OCCUPANCY
			X	X	X			X	X	X	X	20	CONVENTIONS

1 2

Figure 4.4 (1) shows a data table about the guests at a hotel for each month over a two year period. (2) shows the reorderable matrix used to extract patterns of the hotel guests. From Bertin [8].

4.4) which showed how reorderable matrices can be used to discover patterns about the guests of a hotel [8]. The original data table details the guests who stayed at the hotel over a year. Each column represents a month, and each row categorizes the guests by different, possibly overlapping variables, such as country of origin, occupation, and age. The percentages are mapped to vertical bars and colored in black if the value of the cell is above the average for that row. Bertin realized that since the rows have no intrinsic vertical ordering, they could be reordered to reveal temporal structure and similarities among the categorical variables.

4.2.5 Support iterative investigation

Timelines are added sequentially to the display on a new query or pivot, which supports backtracking during an investigation. The vertical order of the timelines should to be a history of what the analyst has done but also allow for reordering of rows. Progressive multiples is a hybrid approach which uses a hierarchical structure with folders. To provide a history of exploration, the vertical order of folders is fixed. Within a folder, however, users can reorder timelines for the purpose of comparison. By default, when users drag-and-drop a timeline from one folder to another, the behavior is to copy a timeline, but not to move it, in order to encourage the preservation of a historical record.

Keeping a record of what the user has interacted with on-screen is a form of external cognition. By keeping the intermediate steps visible as rows, the user does not have to devote limited cognitive resources to remembering what he did. Instead, the user can focus on analyzing the data and looking for comparisons among the rows.

4.3 Timelines

Timelines can show the variation of traffic over time. In addition, the analyst can use a tearoff menu (Figure 3.4) to see the composition of traffic by a dimension other than

time. The menu aggregates the dimension by the same expression used to compute the height of the bars. The user can either inspect the numbers or brush [6] the values to see the temporal distribution of those values in the timelines. When a user hovers over the value, the bins in the timelines containing those values are highlighted in proportion to the percentage of that bin that is taken up by that value. Examples of brushing can be seen in Figure 3.5 and Figure 3.6. Brushing reveals temporal patterns among events which share a common value.

In the display, timelines are organized hierarchically in folders, which also serve as basic units of comparison. Timelines must share a common vertical and horizontal scale in order for juxtaposition to be meaningful. Each folder constrains its timelines to have the same scale, but different folders can have a different scaling. This allows our technique to support investigations for a network which spans a wide range of time and the dynamic range of the data, seen in Figure 3.7.

4.4 Event Plots

Although aggregation makes each timeline compact and useful for overviews of traffic, they are not very useful for sequencing events. Although the raw data is always available to the user in tabular form, this table is hard to interpret. An event plot is an intermediate representation that reveals some visual structure and provides a middle ground between the detail of the event table and the summary view of the timeline.

The horizontal axis of an event plot represents time and the vertical axis of an event plot is mapped to partner IP addresses. Each event table and plot implicitly represents the communication to and from a focus IP. Each row of an event table is mapped to a point in the event plot (Figure 4.5), based on the time and partner IP address. Figure 3.8 shows the first few rows of an event table and Figure 3.9 shows the same data as an event plot. The event table is another instance of Bertin's reorderable matrix, with additional interactive mechanisms that facilitate the sequencing of events.

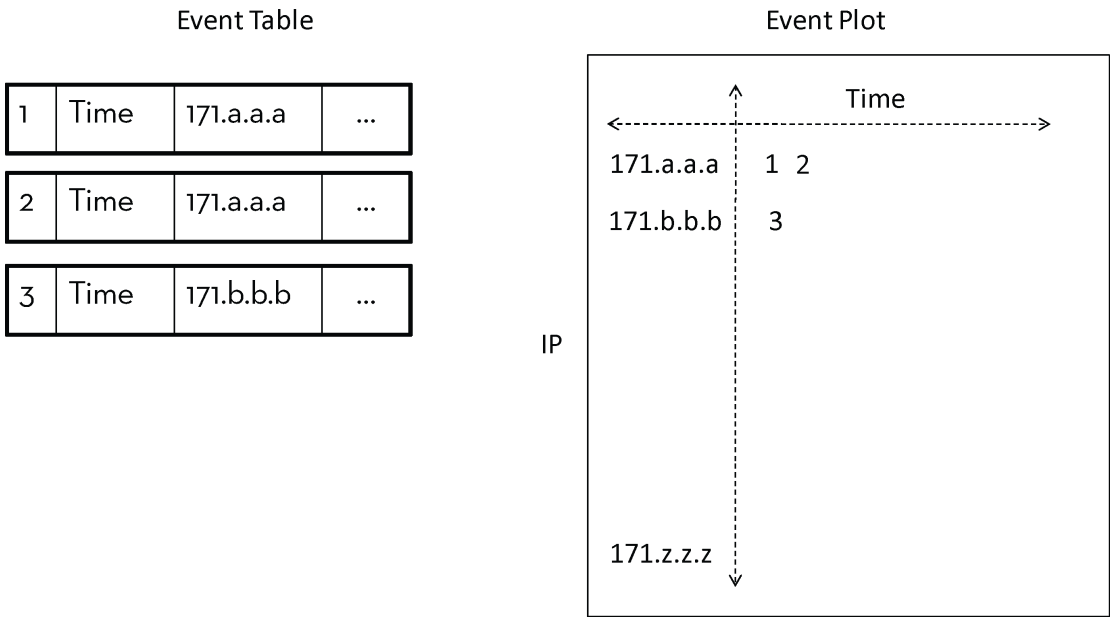


Figure 4.5 An event table is turned into an event plot by mapping each row of an event table to a point in an event plot, determined by the time of the event and the IP of the event. Both event tables and event plots assume a specific focus IP

Each mark is mapped to one of three bin sizes (first quartile, middle quartiles, last quartile) depending upon the total number of packets exchanged between the two IP addresses. From the sidebar, the analyst can adjust the thresholds for the mark size to reduce visual clutter or highlight outliers.

The shape of the mark initially shows the role of the focus IP. If the connection was initiated by the focus IP then it is the client and the mark is a triangle. Otherwise, the focus IP is server and the mark is a circle. Being able to see when a computer switches from being a client to being a server is often a useful heuristic for localizing intrusions. Since too many encodings can interfere with preattentive search, the analyst can choose to view all marks as squares.

The system allows users to brush marks as well as the entries in the sidebar. Hovering over a mark highlights the values in the sidebar that appear in the IP's connections and highlights bins in any timeline containing that IP. For instance, if an IP uses both port 22 and port 80, Isis will highlight those ports when the mouse is over

that row. Hovering over an entry in the sidebar will highlight all the rows that contain that value and the bins in the timeline display that contain that value.

4.4.1 Collecting Brushes

The brushing mechanisms in the timeline displays are also present in the event plot. Instead of a tearoff menu, a sidebar provides a breakdown of the data by different dimensions. A brush of a value will highlight all the rows that contain that value. Due to limited screen space, rows that are brushed may be off-screen and not visible to the user. We address this issue by introducing a new technique that allows users to collect the results of a brush. Since the rows of an event plot have no intrinsic ordering, we can move all the rows that are brushed to the top of the display.

Brushing allows the analyst to visually discover non-temporal structure in the data. The advantage of collecting a brush is that the analyst can spatially group related rows together and interactively organize the event plot into a structure that is relevant to his investigation. Figure 3.13 illustrates an example of collecting a brush by shared ports, which creates an image that can be read top-to-bottom and left-to-right.

4.4.2 Continuous and Ordinal Time

To make sequencing events easier, users can change the view of the event plot (Figure 4.6) between continuous and ordinal time. In *continuous time*, events are placed on the horizontal axis such that the distance between the events is proportional to the amount of time between the events. Although using continuous time allows users to see the distribution of events in time, sometimes users may only care about the order of the events and not about when they occurred. Continuous time is useful for an initial view of the data. *Ordinal time* equally distributes the events on the horizontal axis, regardless of their timestamp. The advantage of ordinal time is that gaps in the event plot (Figure 3.14) indicate to the analyst that there is information that is not visible on-

screen. However, the disadvantage of ordinal time is that large bursts of activity may overwhelm the event plot and allocate too much space to a small period of time.

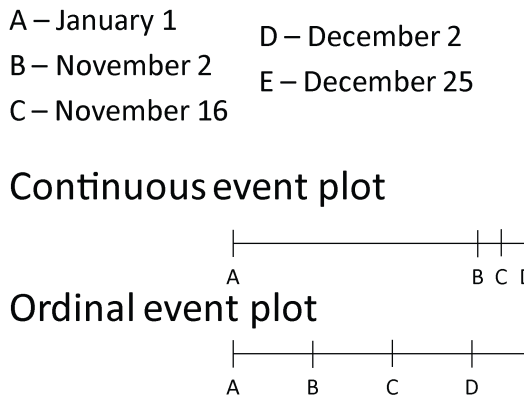


Figure 4.6 Continuous time places events on the horizontal axis to show the distribution of the events in time. Ordinal time equally distributes events on the horizontal axis.

To control the spacing of events, users may also manipulate gridlines. A gridline is associated with a mark on the event plot. The gridlines fix the positions of events in the plot. Gridlines may be interactively dragged to compress periods of time that are unimportant and expand periods where precise sequencing of events is necessary for readability. Figure 3.16 shows an example of manipulated gridlines.

5 Evaluation

Our evaluation addresses the following questions:

1) How well do progressive multiples support network investigation?

2) Is Isis useful to network analysts, and if so, in what way?

To answer the first question, we conducted a task analysis of the investigation process. We use this task analysis to distinguish which parts of the investigation process are accelerated by the use of progressive multiples. We also applied progressive multiples to the investigation of a simulated epidemic and ran a study with novice users. As we had access to only a small number of expert users, this allowed us to evaluate interaction techniques for investigation with a larger group of users.

To answer the second question, we conducted analyses of historical intrusions to make sure Isis was able to investigate these older intrusions. We also deployed Isis with existing analysts to evaluate its performance with live intrusions. The intrusions were later verified by inspecting the system logs of the identified systems.

5.1 Task Analysis of Isis

We conducted a task analysis of the investigation process both before and after Isis was introduced, which can be found in Appendix A: Investigation Task Analysis. We use this task analysis to argue that the main acceleration comes from using visualization for *(Step 11) Action: Get Traffic Overview and Inspect Connections*. The analyst repeats this action constantly throughout his or her analysis. Making this inner loop faster will improve his or her ability to investigate an intrusion.

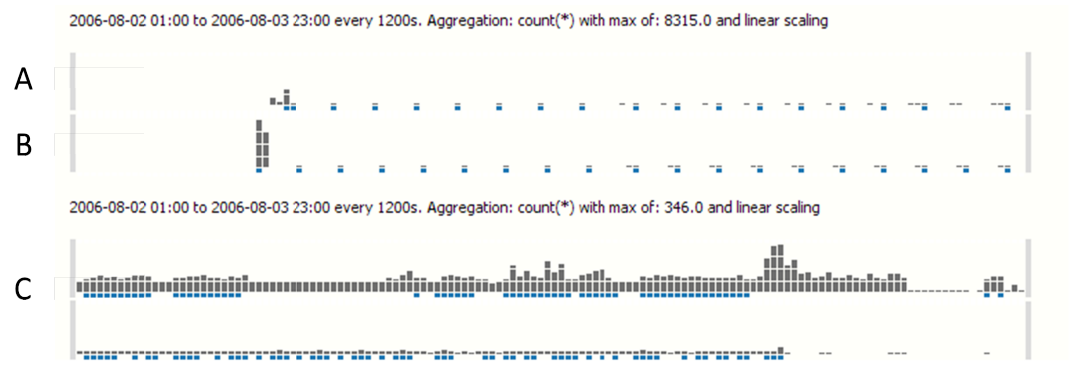


Figure 5.1 Timelines showing a periodic connection from remote computers A and B on the X-Windows port. The blue marks indicate the presence of the keylogged machine. The keylogged machine is also connected to C, which indicates how the attackers were able to break into C.

Before Isis was available, the analyst would have to *(Step 18) Interpret Query Results by looking at raw text*. Although the raw text contains all the information of the visual representation, the discovery of patterns is made much easier with the use of graphics. Here is the simplified investigation process, repeated from 3.2:

For each IP to investigate

a. Inspect its traffic to determine it is related to the intrusion
b. Compare its traffic to others for correlations in time and attributes
c. Refine the query by adding filters if necessary
d. Pivot to see related traffic if necessary

The next sections describe how Isis accelerates the process of inspection and comparison. Isis also makes it easier to refine a query and to pivot. These are the result of the automatic query construction, rather than the difference between text and graphics.

5.1.1 Accelerating Inspection

Timelines accelerate inspection because they provide traffic overviews which make it easy to see periodicity, spikes, or bursts of activity. Figure 5.1 shows a set of timelines

that reveal a periodic connection from a remote machine to a computer at Stanford. It would be difficult to extract the periodicity, spikes, or bursts from raw text.

Brushing accelerates inspection because it makes the temporal distribution of different dimensions in a timeline visible. These dimensions were chosen by the analyst as the ones most useful for an investigation:

- *IP addresses* are the unit of investigation.
- *Port* often indicates the traffic type of a connection.
- *Role* indicates if the computer is primarily acting as a client or a server, useful for spotting if a system is changing roles. Since most systems used as clients to fetch web pages or email, a switch to a different role usually suggests that a system has been compromised.
- *Virtual LANs* are units of administrative control at Stanford. Different administrators control different subnets, and making it easy to differentiate subnets can aid the investigator in locating the appropriate administrator.
- *ASNs* represent blocks of remote IP addresses controlled by the same administrative unit. Seeing the distribution of traffic by ASN can reveal the presence of multiple IP addresses controlled by the same attacker.

5.1.2 Accelerating Comparisons

To illustrate how comparisons are accelerated with Isis, we use the investigation case study described in 3.3. To understand the results of a query, the analyst has three visual representations available: an event table, an event plot, and a timeline. Figure 5.2 shows the same data viewed with an event table and an event plot. Both images are 1920 pixels high, yet only 8% of the event table is visible, while the event plot is completely visible.

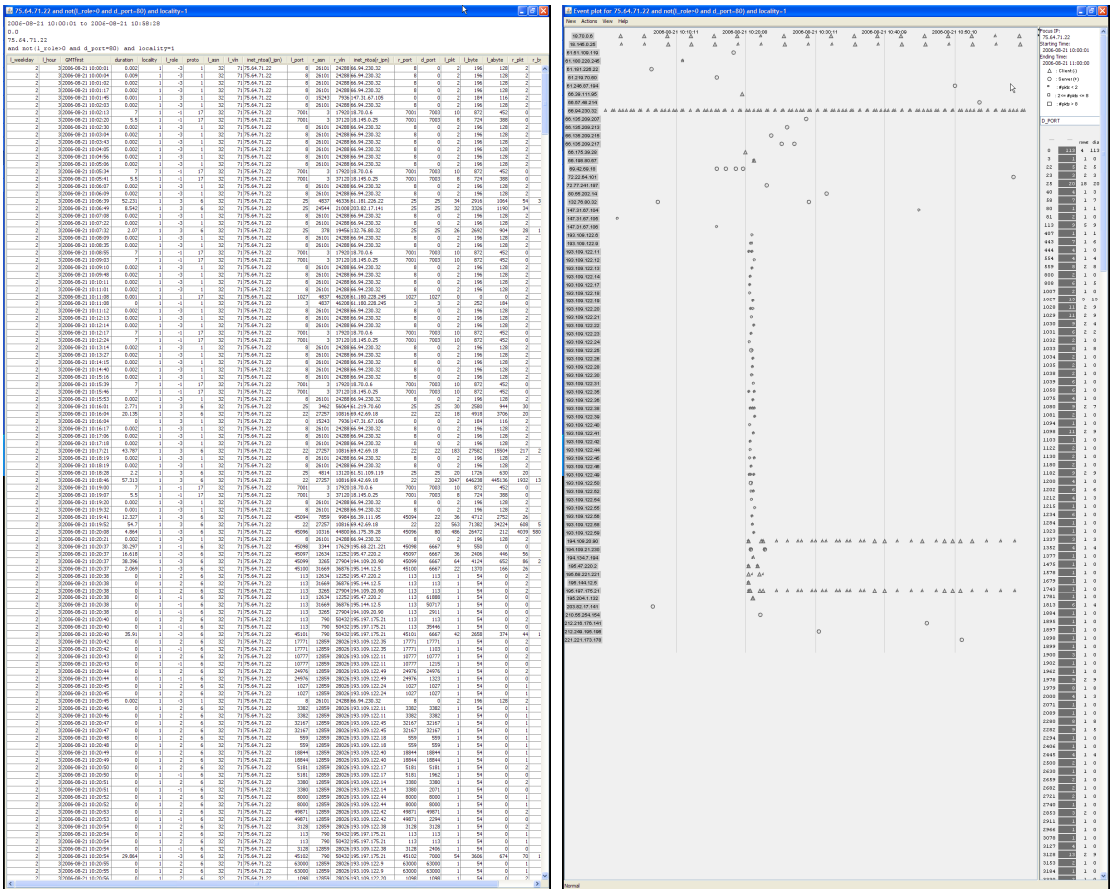


Figure 5.2 *(left)* An Event Table showing 1432 connections that occurred in one hour. The original image is 1920 pixels high and only shows 8% of the rows. *(right)* An Event Plot showing the same data, which is completely visible. The Event Plot may use less space than the event table because each row is mapped to a mark and overplotting is allowed.

The event plot accelerates comparisons as compared to the event table because it changes the focus of the representation to be at the level of an IP rather than an individual communication. The event plot hides the extra detail from an event table through the use of tooltips. This allows the analyst to focus on sequencing events by comparing the position of the marks on each row with one another.

The event plot can use less space than the event table because each row in the event table is mapped to a single mark and overplotting is allowed. The compression by the event plot depends upon the number of partner IPs in the data set. The most efficient use of space occurs if there is only one partner IP. In that case, the event plot

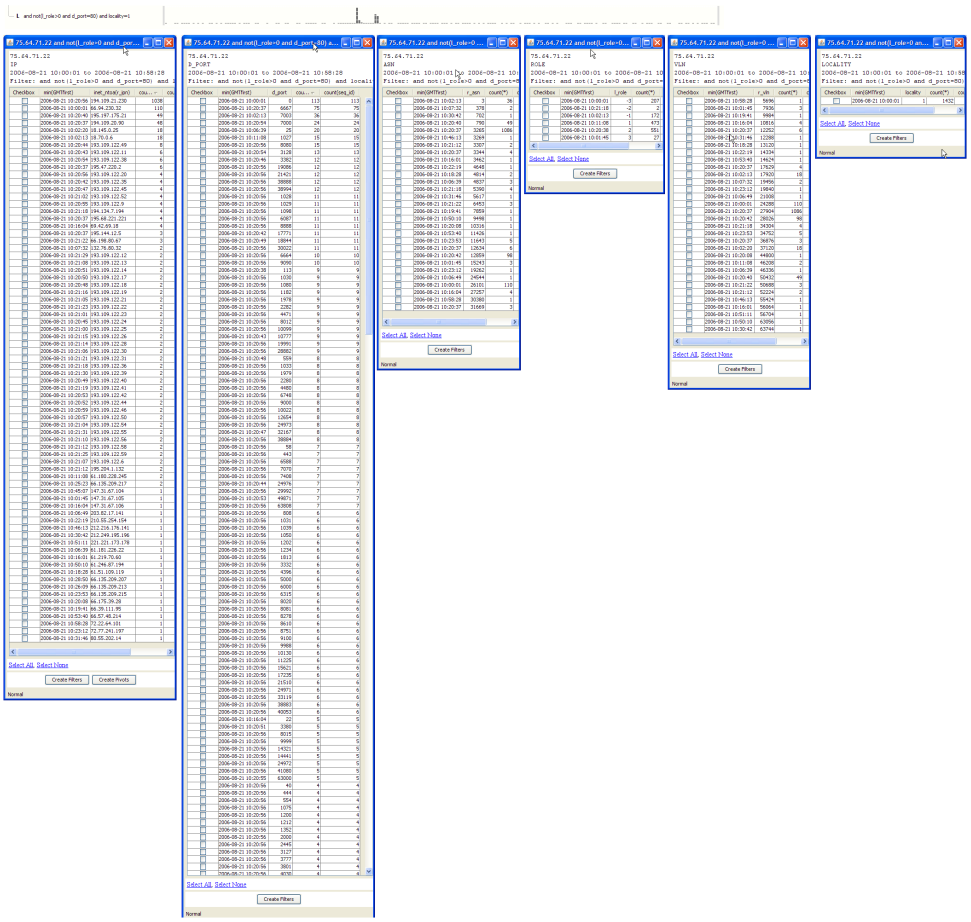


Figure 5.3 Shows the same data and scaling as Figure 5.2 as a timeline with all of its tearoffs to compare the amount of space used by different representations. Timelines accelerate comparison because they use much less vertical space than an Event Table. Although this aggregation hides certain details it allows administrators to understand high level patterns of traffic for multiple IP addresses since more timelines are visible on screen at once.

will only have one row. The least efficient use of space occurs if each partner IP makes one connection. In that case, the number of rows taken up in the event plot will be equivalent to the number of rows in the event table and no compression will occur.

Although the efficient use of vertical space in an event plot contributes to its improvement over an event table, even in the least efficient case, the event plot makes temporal comparison easier. In this case, each row would have a single mark. The position of the mark still encodes when this connection occurred, which is still more useful for sequencing than the raw text.

Figure 5.3 shows a timeline and its tearoff menus using the same vertical scale as Figure 5.2. Timelines display the information for an IP address in a small vertical area, which allows more timelines to be on screen. The presence of multiple timelines makes comparisons among different IPs easier than with an event table or an event plot, which use the whole screen to display a single instance. Timelines use less space because they use more aggregation than the other techniques. The use of tearoff menus allows the user to get additional details on demand for the dimension that he is interested in, instead of showing all the detail at once.

5.2 Epidemic Case Study

To get more feedback about specific interface elements of progressive multiples and extend the technique to the visualization of other kinds of event data, we turned to epidemiology, which also required the forensic analysis of event data. For this domain, we constructed a simulation, not intended to be a realistic infection model, but designed to create temporal data that could be analyzed by a broad range of users. For the domain of network security, it was difficult to get experimental time from experts. An advantage of choosing the epidemic domain was that we were able to have more people give feedback on the interface because it did not require expert knowledge to interpret the visualizations.

The scenario presented to subjects was that they were analysts for the CDC during an epidemic. Subjects were told there was a single carrier and that the length of the incubation period of the disease was fixed, but unknown. The subject's goal was to determine the identity of the carrier by using the interface. Subjects had the ability to "test" a person, which represented sending a CDC team out into the field to verify if the person carried the virus or not. A cost was associated with the test to encourage

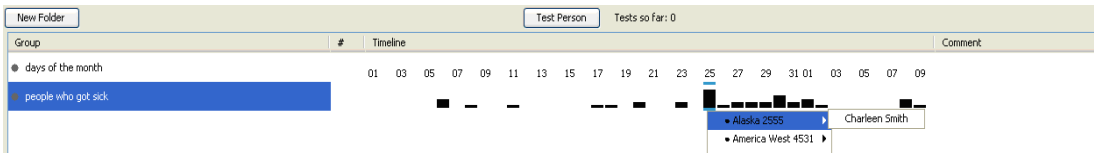


Figure 5.4 The initial view of the epidemic visualization. The first row shows the days of the month and the second row counts the number of people who got sick on each day. Clicking on a bar shows a list of people who got sick on that day, grouped by location. In this image, Charleen Smith got sick on the 25th, but was infected some number of days before taking that flight. Selecting a name creates a timeline of that person's movement.

subjects to use the interface to accumulate enough visual evidence to decide if someone was a carrier, instead of "solving" the problem by testing everyone.

Eight subjects used the prototype on two data sets. Seven subjects were engineering graduate students and the eighth was a researcher in computer science. Subjects were asked to follow a talk-aloud protocol as they worked. Each study took between 60 and 90 minutes. The last 30 minutes were reserved for questions to ask about their reactions to different interface components, such as the pivoting interface and the use of folders.

During the study we took notes and asked questions of the subjects about their analysis process. By having subjects talk aloud as they worked, we were able to judge which features of the interface were useful to their analysis. We asked them to justify why they were pivoting on certain people and to explain why they wanted to "test" a particular person as the carrier. We were also able to see if subjects referred to the visualization history to explain their reasoning.

Before we present the results of the study, we discuss the specifics of the simulation and the prototype.

5.2.1 Simulation Data

The simulation has 14 cities. Each day, some of the people in each city travel to another city on a flight. A single carrier is chosen at random from the population. If the carrier shares a flight with a person, that person is infected with a fixed probability.

After becoming infected, people continue to travel and spread the virus with the same probability as the carrier. Once a fixed incubation period passes, infected people manifest symptoms, become sick, and stop traveling. The carrier never gets sick and continues taking flights. The first 40 days of two epidemics were simulated, with different incubation periods and initial populations. The first set had 200 people per city and the second had 300 people per city.

5.2.2 Visualization Prototype

The prototype that was developed for the user study also uses timelines, but is not the same system as Isis. It is an earlier version of the Isis code modified for this scenario. The epidemic prototype shares the same interaction techniques, including the ability to brush related events, pivot, and to reorder rows. In the epidemic prototype the investigative focus is on a single person, as opposed to an IP address, as it was with Isis. In the network security domain each event represents a communication between two IP addresses.

In the epidemic domain, each event in the system is a record of each person's apparent health and location for every day. This information is presented in two ways. First, there is an overview timeline which shows when people got sick, as seen in Figure 5.4. Users may also create the timeline of a person who got sick on a given day, which can be seen in Figure 5.5. Users can interact with existing timelines to produce new ones. These interactions are the same as in Isis, although they have been modified to be relevant for the investigation of an epidemic.

Brushing to expose structure in the data. We provide brushing to reveal underlying structure in the data. For the epidemic task, events are linked if their location is the same. Moving a cursor over a bar will highlight that bar in blue-green. If the cursor is over a person's timeline, the system highlights other bars in other rows with

the same location as the current bar. For example, in Figure 5.4, if any other bars contained American Eagle 5992, they would be highlighted.

Managing rows. We use a hierarchical folder representation similar to that of Windows Explorer. We chose not to allow folders within other folders as we wanted to keep the grouping mechanism simple. Timelines created by the same interaction appear in the same folder so that they are meaningfully grouped. Within folders, users can reorder timelines to facilitate comparisons. Users manage space by deleting rows or expanding and collapsing folders.

History and narrative. Folders are added sequentially to the display in the order of their creation. Their position is fixed to provide users with a history of exploration. Comments can be added to any row. Users may create empty folders and populate them by dragging timelines from other folders.

5.2.3 Results of User Observation

Seven of our eight subjects were able to find the carrier with one or two tests. Each subject worked with two data sets. Of the subjects who found the carrier, the first

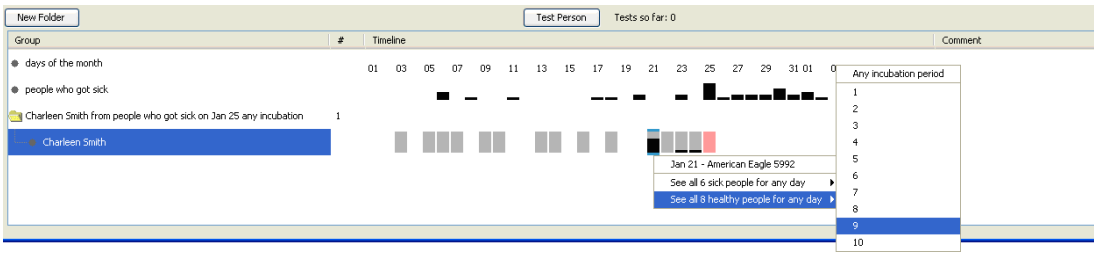


Figure 5.5 Timeline for Charleen Smith's Travel on Airplanes. The 14 gray boxes indicate the days she took a flight and the red box on the 25th of the month indicates when she got sick. The height of the black bar counts the number of people who traveled with Charleen who later got sick at *any time*. Clicking on a gray box shows the timelines for the other people on the flight who are sick or healthy at the end of the simulation. The lack of black bars until January 21st means that until then, Charleen never traveled with anyone who later got sick. On the 21st, 6 other people got sick after being on a flight with her. Here the user is creating a folder containing timelines for healthy people who traveled with Charleen on American Eagle 5992. Selecting #9 means the black bars of the new timelines will only count the other people who got sick *exactly 9 days* after traveling with the healthy people from American Eagle 5992.

time it often took 30 to 50 minutes to understand the strategy necessary to find the carrier. However, once they understood the strategy, they were able to use the visualization to quickly find the carrier, often on the order of 5 minutes. In and of itself, this does not prove the utility of our interface. However, our observation of users' interactions with a set of timelines allowed us to identify issues for improving the design of future systems.

A successful investigation depended upon understanding that the fixed incubation period could limit the number of potential pivots. When a user selects a bar on a timeline for one passenger, he can pivot to see the timelines of the other passengers on the same flight. He can see all people who are sick at the end of the simulation or all the people who are healthy. The height of the bars in a person's timeline represents the number of people on that flight who got sick *N* days after taking that flight. N can be a specific number of days or count people who got sick at any point after taking the flight. Once the user finds the incubation period, he can create timelines for the incubation period. This makes the height of the black bars more useful, because only users who are infected will have black bars.

Finding the incubation period has no exact analog in the network security domain, because there is no constraint on when a hacker can start using a compromised machine. We included the incubation period as a simplified proxy for the filtering of traffic in the network domain by a port or by a packet threshold to remove irrelevant communication. Our purpose was to simulate the information overload faced by an administrator when beginning an investigation.

Narrative and History Management

We observed that the user's ability to construct a narrative often depended on their search strategy. Some users were disciplined about their exploration and used a depth-first approach. They would pivot to create a new set of timelines, and then recursively explore those timelines before coming back to the first level.

In the post-task interview, these users explicitly referred to the row history to recall how they had analyzed the epidemic. Figure 5.6 is an example of a visualization created by a participant who had successfully found the carrier. Donny Jacobson was the first person to become sick. The user concluded that the incubation period was 5 days by intersecting the possible set of incubation periods for Pedro, Della, and Harriet. Five days before Donny became sick, he traveled on JetBlue 2181, on January 3rd. The second folder shows the healthy people from that flight. The height of the black bars only counts people who got sick exactly 5 days after traveling with this group. By looking at the black bars and gray boxes for Bill Bilodeau, the user observed that many people became sick 5 days after traveling with him. Other passengers, such as Greg

Figure 5.6 An example of an analysis performed by a user to locate the carrier, Bill Biloudeau. Donny Jacobson was the first person to become sick. During the interview, the user created a new folder labeled "Story" to explain his reasoning to the interviewer.

Baron, never flew with anyone who got sick 5 days later. The user verified that Donny had infected Chadwick, but Bill had infected Donny and the other passengers. During the interview, the user created a new folder labeled "Story" to explain his reasoning to the interviewer.

The folder labeled "Story" shows the carrier, Bill Bilodeau's pattern of movement, followed by the first several people he infected. In particular, 5 days before Donny Jacobsen became sick, he took a plane flight, JetBlue 2181 with Bilodeau.

However, other users employed a breadth-first approach. These users would pivot on multiple events on a single timeline before looking at the results of their pivots. This would add multiple folders of results to the interface. When the user encountered that pivot result much later, he was unable to remember why he had created it. This was exacerbated because users did not usually add comments to the row. Users stated that they had forgotten which object they had interacted with to generate a row. We describe this problem as being unable to determine a row's lineage.

To support investigation for both search strategies, it is important to develop interaction techniques for making lineage more visible. The network administrators that we have worked with have not needed these row lineage tools. However, we believe that this is primarily due to a lack of complexity in the intrusions that we have faced, as they only involve in the tens of computers, whereas this investigation spanned hundreds of different passengers.

When there were a large number of rows, users did not remember having already seen a timeline for a specific person's movements, which led them to repeat pivots and create the same row twice. Users wanted to be able to mark a person with an icon, such as a star, and then have the system "star" other occurrences of that person.

However, users generally liked the row history and the organization imposed by collecting timelines in the same folder. Most users were careful about deleting

unnecessary rows and did not run into as many problems as users who expanded many rows. Users found brushing of similar rows to be helpful, although sometimes there were so many rows that the highlighted ones were off-screen.

Brushing

As we have mentioned, although timelines are useful when looking for temporal patterns, it is difficult to see non-temporal structure in event data. By implementing different kinds of brushing, it is possible to reveal non-temporal information

The advantage of using brushing is that it is transient in nature and does not clutter the display. On the other hand, sometimes brushing may reveal an interesting pattern, but there is no way to record that in the history. One way to combine the advantage of transient and permanent display would be to have a brush-to-folders, which allows users to save highlighted rows into a folder. This is similar to the collect-brushed-rows that was implemented in the event plot.

Other Feature Requests

Users wanted to sort the timelines in a folder by one of their attributes. For example, some users wanted to sort the rows by location to see who had traveled together, or by the height of the black bars, which counted how many people got sick after being in a particular location.

Users also wanted to operate on sets of folders. For example, they wanted to intersect two folders and store the result as a new folder. A common strategy was to find two flights the carrier must have taken. Users would expand the set of healthy people for each flight, and then manually intersect the contents of the two folders. For folders with 10-20 people, this was tractable, but for larger numbers of people this was impossible.

5.3 Historical Intrusions

To assess the usefulness of Isis, we evaluated its performance on historical intrusions from September 2005 to November 2007. We compiled the list in Table 2 by inspecting the archives of a security mailing list for the administrators in the EE and CS buildings at Stanford, which is used to notify other administrators about an ongoing intrusion where action needs to be taken or to report upon the results of an investigation. For each type of intrusion, we used Isis on a representative intrusion to see how handle that case.

Scanning Others, DOS, Spam. When we began working with network administrators, intrusions that caused high volumes of traffic were the most common kind of problem. Since a large volume of traffic produced by a single computer is not difficult to notice, it served as a good test case for Isis. The different traffic volumes required the ability to display different traffic with high dynamic range and spurred the development of different vertical scaling across folders.

IRC Usage and Open FTP. More recently, the most common intrusion type is caused by a SSH troll that guesses a weak password and then starts up a connection to an IRC server. An investigation of this type of intrusion is detailed in 3.3. Intrusions that use well-known ports like IRC or FTP can be isolated with the text filters in SQL.

Count	Symptom
24	IRC usage
12	Scanning Others
2	Open FTP
2	DOS or Spam
2	User noticed odd behavior
1	Not reported

Table 2 A list of the 43 historical intrusions from 9/2005 – 11/2007 on the EE and CS networks and the symptoms that triggered an investigation

Unlike the earlier intrusions which identified IPs by traffic volume, these intrusions required understanding the composition of traffic. Early designs of Isis only allowed users to brush the partner IP addresses, but to handle the IRC and FTP intrusions, it was important to allow users to brush attributes to see their temporal distribution. As can be seen in the investigation of 3.3, being able to see when traffic on different ports began is important for localizing an intrusion.

Another challenge was that the sequence of events posed by the IRC and FTP intrusions was more complicated than the ones posed by denial of service or spam attacks. Those attacks were usually caused by a computer getting infected and then immediately flooding the network with traffic. There were only two steps: the activation of the virus and the start of malicious behavior. The stages of an IRC or FTP Intrusion were separated by longer stretches of time.

The timeline display by itself was not useful for sequencing an intrusion. Each timeline showed all the traffic to and from a single focus IP. The problem was that the high level of aggregation obscured detail about individual events. Filtering a timeline using SQL would reduce the number of events, but could not pick out individual events. The other problem was that the event table view which showed the raw detail was similarly too detailed, and so it was not until we experimented with the event plot that we were able to easily sequence these events.

Odd Behavior. The most challenging historical intrusion consisted of a break-in on a low-traffic machine that survived a reformat and reinstall of the client machine over a week. After some investigation, the administrators realized that one of the users of the machine used an X-Windows program that allowed anyone in the world to connect to it by default. This allowed hackers to remotely connect to his system and use a keylogger to steal his password, which granted them access to the system. Figure 5.1 shows part of the investigation that was recreated using Isis.

This intrusion was challenging because the development of Isis had assumed a model where the analyst always had a focus IP in mind. In earlier investigations, the analyst would receive a report that notified them about the suspicious behavior of a specific computer. Although the investigation began in the same way in this instance, we soon realized that sometimes the analyst would identify a suspicious traffic pattern but not have a specific focus IP in mind. The analyst knew that the attackers were scanning computers at Stanford on port 6000 to look for open X-servers, but he did not know the identity of those computers.

Prior to this case, Isis only allowed the analyst to pivot on an IP address, but we added the ability to do a pivot-by-attribute. Using this feature, the analyst can pivot on other dimensions than just IP address. He can specify a traffic pattern to look for, such as "all IPs with traffic on port 6000" or "all IPs with traffic above a certain number of bytes."

5.4 Deployment with Analysts

Since the beginning of this project we have deployed early versions of Isis with the principal network analyst of the EE and CS department in order to get immediate feedback on different design ideas. Since July 2007, we have been able to deploy a fully-functional version of Isis that has been used to investigate 5 intrusions of the 43 used to generate Table 2. This section describes the lessons we have learned from this deployment.

After the deployment, the analyst estimates that 2/3 of the time in an investigation is now spent inspecting system logs, whereas only 1/3 of the time is spent looking at flow records. Isis has accelerated the process of interacting with the database so that now the majority of the time is spent inspecting system logs. The reason that system logs must be used is that flow records only indicate that two computers communicated with one another but do not contain any confirmatory evidence. System logs must be

looked at for traces of activity at the times indicated by the flow records. We chose to focus on accelerating flow analysis because locating the appropriate system logs to inspect can only be done after completing a flow analysis. Without the system, the process of inspecting flow records would take much longer.

Although the system was developed in consultation with a single analyst over a long period of time, we have been able to demonstrate our system to other analysts as well, to get their feedback. In particular, we have presented the system to experts at US-CERT (the Department of Homeland Security's United States Computer Emergency Readiness Team) who have expressed interest in participating in a pilot deployment.

5.4.1 Useful features

Analysts liked the use of timelines in the system, the facilitation of pivoting and filtering, and the brushing of related events. However, there were three other novel features that we would like to discuss in more detail.

Collecting Brushed Events. Our analyst, the response from attendees at the 2007 Workshop of Visualization for Computer Security, and from the demonstration to analysts at US-CERT indicated that this was one of the most interesting techniques. The ability to use dynamic brushing to affect the static layout of the visualization is very powerful because it allows users to impose structure that reflects the connections that they have discovered in the data.

Ordinal Time in Event Plots. The ability to change the representation of time provided the analyst with multiple views of the sequence of the data. A continuous representation presents the analyst with an accurate idea of the temporal pattern of events. However, the ordinal representation allows the analyst to understand the sequence and to notice if there are gaps in the sequence of events that he has assembled.

Filtering and Aggregation in SQL. The initial decision to allow the analyst to directly alter the WHERE clause of the SQL query was thought to be a temporary scaffolding to enable rapid prototyping of interface elements. However, we soon realized that selectively exposing SQL in parts of the interface provided flexibility for expert users.

Pivoting by Attribute. We assumed that the analyst would always have an IP to focus on during the investigation. However, some investigations required a more general pivoting mechanism. Instead of focusing on a single IP, the analyst might need to look for "any IP using port 6000" or "any IP from ASN 32" which was not supported under a simple pivoting model. The introduction of the pivot by attribute feature allowed the analyst to pose more open-ended questions to the system which supported more kinds of investigation.

5.4.2 Unused features

Row Lineage. Our experience with the epidemic case study suggested that the analyst could get lost if the investigation spanned too many levels, despite the fact that the ordering of the rows provided them with a simple exploration history. We included a mechanism that would highlight the 'parent' timeline of the timeline hovered over by the mouse. However, the investigations we observed for network security did not create as many rows as the epidemic case study did. As a result the analyst did not use the row lineage brushing as much as we had thought.

5.5 Conclusion

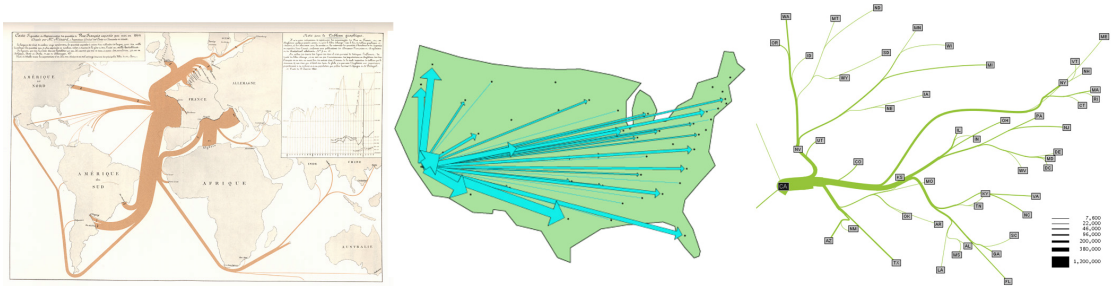
This chapter shows that the progressive multiples technique supports the intrusion process. We did this by describing the investigation of a single IP address as a four-step loop: inspection, comparison, refining, and pivoting. The inspection and comparison steps are accelerated by Isis through the use of visual representations. We

described the results of an epidemic case study which allowed us to test some interactive techniques such as brushing and reordering with a larger group of users. We found that the search strategy employed by the users could affect how well they were able to use the interface to identify the cause of the epidemic.

We then evaluated the system we had built based on progressive multiples. First, we categorized the intrusions analysts had observed over the last two years. We then used Isis to investigate these intrusions and to ensure that our design was able to deal with the differences among known intrusion types. Second, we used Isis to investigate new intrusions during a four-month deployment. This experience suggests that some features were useful: collecting of brushed events, ordinal time, the use of SQL, and pivoting by attribute. Row lineage was not used. The results indicated that Isis was a useful complement for the analysis of intrusions.

6 Flow Map Layout

Cartographers have long used flow maps to illustrate the movement of objects among locations. A flow map shows the spatial distribution of univariate geographic phenomena [53]. Lines of varying width which represent the number of objects being transferred are overlaid on the map. Visual clutter is reduced by merging edges that share destinations. The first flow maps illustrated rail ridership in Ireland and since then, cartographers have used flow maps to depict migrations, trade, and any data set with a from-to relationship [16]. A well-drawn flow map allows a user to see the differences in magnitude among the flows with a minimum of clutter. Figure 6.1a is a hand drawn map by Minard illustrating the export of wine from France. Figure 6.1b shows a computer generated flow map by Tobler [56], which is cluttered because it does not take advantage of the techniques of hand-drawn maps.



(a) (b) (c)

Figure 6.1 Flow Maps. (a) Minard's 1864 flow map of wine exports from France [59] (b) Tobler's computer generated flow map of migration from California from 1995 - 2000. [56] (c) A flow map produced by our system with the same migration data.

This chapter describes a technique used to automatically generate flow maps using hierarchical clustering. Its focus is the generation of geographic flow maps. We applied a variant of this technique to the visualization of network intrusions, and section 4.1 describes this effort in more detail. The network intrusion flow maps used an alternate layout that emphasized time. The results suggest that flow maps are good for presenting summaries of events on a network at a higher level of aggregation than event plots and timelines. Unfortunately, they do not support the process of forensic analysis very well, which resulted in the use of timelines and event plots in Isis.

6.1 Introduction

Our initial goal was to see if it was possible to automatically generate a flow map. Figure 6.1c illustrates a flow map generated automatically by our system. Hierarchical clustering creates a flow tree that connects a source (the root) to a set of destinations (the leaves). The algorithm attempts to minimize edge crossings and supports the layering of single-source flow maps to create multiple-source flow maps. The algorithm preserves branching substructure across flow maps with different roots that share a common set of nodes.

This technique supports the production of flow maps for a variety of data sets. Using data from the US Census and the local network, we were able to produce geographic maps of migration and computer traffic. This technique was adopted by other users to illustrate the flow of ecological resources [39, 40] or the flow of documents in an organization.

6.2 System Design

Good, hand-drawn flow maps share three common characteristics: intelligent distortion of positions, merging of edges that share destinations, and intelligent edge routing. The technique attempts to produce flow maps with the same characteristics as

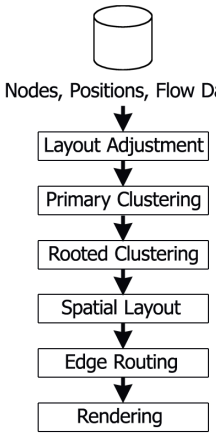


Figure 6.2 System Diagram

these hand-drawn exemplars. Minard's map of wine exports (Figure 6.1) illustrates these characteristics. The Strait of Gibraltar has been widened and the UK has been shifted away from France to make room for the flow lines. However, these distortions preserve the relative positions of countries with respect to one another. Edges going to different regions of the world are merged and in this map, edge crossings are minimized.

Other characteristics of flow maps described by cartographers concern their visual appearance [43]. Flow lines should be the dominant visual element and should be easily distinguishable from other map symbols. A linear mapping should be used to transform data values to line thickness. The map legend must be clear and provide key values for line widths. If edges cross, smaller lines should rest on top of larger lines. To our knowledge, there are no published guidelines describing automatic layout of a flow map that looks hand-drawn.

A layout adjustment algorithm achieves intelligent distortion of positions by ensuring that the separation distance between nodes is greater than the maximum thickness of the flow lines. This algorithm guarantees that nodes maintain their left-right and up-down positions relative to one another [38].

Merging edges that share destinations is done by using hierarchical clustering to find nodes that are close together. The tree formed by the hierarchical clustering is the basis for the branching structure of the flow map. The clustering is generated such that the root of the flow map is the root of the tree. Binary hierarchical clustering allows a layout formulation in a simple and recursive manner. A non-binary approach would result in a better visual layout and is an area for future work.

Edge drawing and routing also uses hierarchical clustering. The recursive procedure to layout node positions uses the fact that all branches are binary. Clusters

are modeled as rectangular bounding boxes enclosing their nodes. The edges check for intersections with the bounding boxes of their siblings. If an intersection exists, the node is placed such that edges connected to that node are routed around the bounding box.

To visualize more general networks using flow maps, it is necessary to support maps with more than one root. Multiple-source maps can be created by layering single-source maps that have been generated by the algorithm. To make layering more effective, node position and branching structure is preserved across flow maps, which makes it easier to compare and contrast flow patterns across different layers. This is done by generating a primary hierarchical clustering that relies on the positions of the input set of nodes. The rooted clustering tree used to lay out each flow map is a modification of the primary hierarchical clustering tree.

Figure 6.2 presents an overview of the system. The input consists of a set of nodes, positions, and flow data among the nodes. There are layout phases and a rendering phase.

Layout phases ensure that nodes are adequately spaced, generate a topological layout tree, choose the positions of the branching points, and route edges around obstacles. The rendering phase converts the given spatial layout tree into a set of thick splines for each edge and generates a legend for the flow map.

6.3 Layout

Sections 6.3.1 to 6.3.5 describe the steps of the algorithm for generating a single-source flow map. In 6.3.6 we describe the additional considerations that arise from having multiple layers.

6.3.1 Layout Adjustment

The layout adjustment step enforces a minimum separation distance among the nodes in the horizontal and vertical directions and preserves their relative positions to one another. The minimum separation distance is the maximum width of a flow line in pixels. We use Misue et al.'s force scan algorithm [38] which runs in $O(n^2)$. We have observed that good flow maps contain a moderate number of nodes (less than 100), so the efficiency of the algorithm is not an issue for static maps. Nodes are sorted into two lists, one ordered by x-coordinate and the other ordered by y-coordinate. The algorithm consists of a horizontal scan followed by a vertical scan to enforce minimum separation distances.

We also experimented with a force directed scheme from the graph drawing literature [57]. Force directed methods often included randomness in the system to avoid local minima in layout. However, we were interested in generating flow maps with stable node positions for a given set of nodes. The force directed technique resulted in slightly different layouts each time and the algorithm of Misue et al. [38] remains stable. The stability of node positions allows layering of flow maps on top of one another. Without this constraint, there might have been a better way to create a flow map by adjusting positions.

6.3.2 Primary Hierarchical Clustering

The primary hierarchical clustering captures information about the spatial distribution of the input nodes. An agglomerative hierarchical clustering [24] creates a binary tree from the input set of nodes. The input nodes are at the leaves of the primary hierarchical clustering. The distance between two clusters is the Euclidean distance between the centers of their rectangular bounding boxes. Figure 6.3 gives an example of how a primary clustering is generated.

6.3.3 Rooted Hierarchical Clustering

The goal is to generate a flow map with a given node *r* at the root. The tree produced by the primary hierarchical clustering is not suitable because its root is a combination of clusters of input nodes. The tree produced by the primary clustering is modified to generate a tree where node *r* is the root and connects to the other input nodes. For a given root node *r*, nodes to be reclustered are accumulated by following parent pointers from node *r* to the root of the primary clustering tree. Clusters hanging off this path are added to the set to be reclustered, including the cluster with node *r*. Figure 6.3 demonstrates how rooted clustering modifies a primary clustering.

Following these parent pointers takes *O(lg m)* time in the average case since the height of a balanced tree is *O(lg m)*. Clustering the accumulated set takes $O(lg\ m)^2$ time, where *m* is the total number of nodes in the system, including nodes generated by the primary clustering as well as the input nodes. This is *O(n)* nodes, where *n* is the number of input nodes in the system. Without reuse of substructure from the primary clustering, the rooted clustering would take $O(m^2)$. The existing system implements

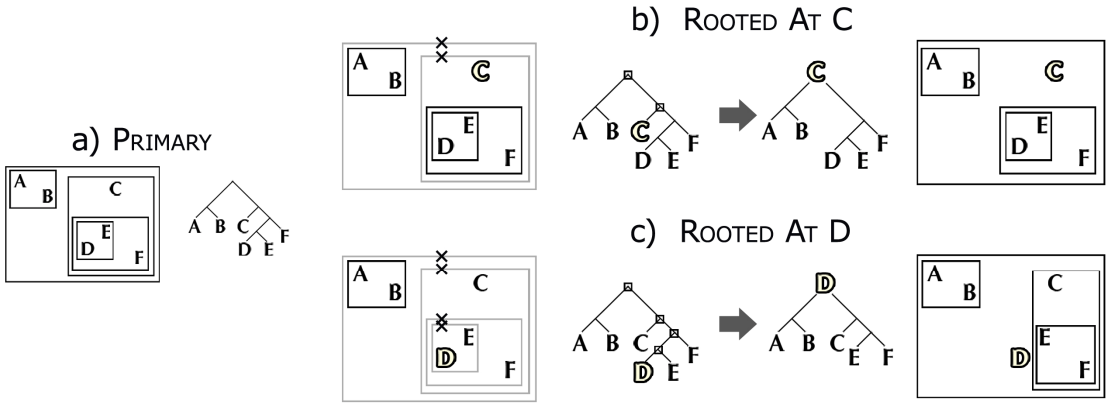


Figure 6.3 Hierarchical Clustering. A flow map tree is generated by clustering a set of nodes. (a) We show a spatial representation of the primary hierarchical clustering (PHC) and its equivalent tree. Rooted hierarchical clustering (RHC) modifies the PHC to produce a flow map for a particular root. The x's on the bounding boxes indicate the clusters that are not reused. (b) The RHC for a flow map from C. The (A,B) and the ((D,E),F) clusters are kept. (c) The RHC for a flow map from D. Only the (A,B) cluster is preserved.

this simplified version of the algorithm that takes $O(m^2)$.

Rooted hierarchical clustering merges nodes differently from standard hierarchical clustering. Suppose the algorithm wants to merge clusters C1 and C2 because they are the closest in the system. Before it does so, it checks to see if C1 or C2 contains the root node *r*. Suppose C1 contains *r*. C2 is marked for attempting to merge with the root. The algorithm looks for another cluster C3 to merge with C2. C3 must be unmarked and distance(C2,C3) ≤ distance(C2, root). If only the C2 cluster was marked without looking for C3, the algorithm might miss an opportunity to merge clusters on the same side of the root. The distance check ensures nodes are not merged on opposite sides of the root. It terminates if it cannot find an unmarked cluster C3.

When the reclustering terminates due to the algorithm being unable to find any unmarked clusters, the remaining clusters in the system become the children of the source cluster. All the nodes except for the root of a rooted clustering have two children. Since reclustering may terminate with more than two marked clusters, a rooted hierarchical clustering is not always a binary tree, in contrast to a primary clustering, which is always binary.

The last step in the rooted clustering computes the weights of the clusters. Given the flow data among the nodes, it is possible to compute the amount of flow from the root *r* to the destination nodes. This is recorded as the weight of a node. The weight for each cluster is computed bottom-up, in $O(m)$ time.

6.3.4 Spatial Layout

The next step is to recursively lay out the tree of flows rooted at the source. Each node creates a branching structure from the parent to its two children. The challenge is to minimize edge crossings. The algorithm assumes the bounding boxes of the children do not overlap. If the layout of the subtrees corresponding to each child is contained

within its bounding box, then the branch between the parent and the child will not intersect the tree corresponding to the child.

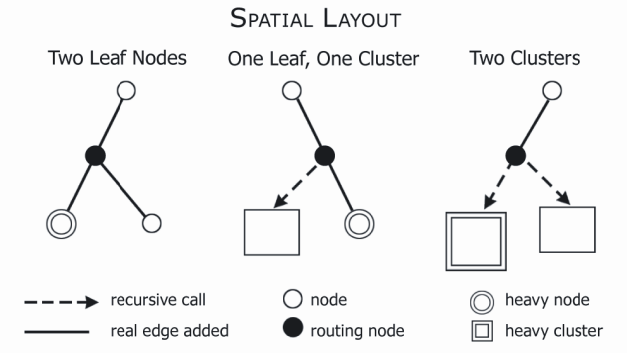


Figure 6.4 Spatial Layout. The binary structure of the rooted clustering allows to us generate the layout recursively. Branching points are always placed on the line between the start node and the destination that has more weight (or flow).

A branching node is created between the root and each of its immediate child clusters. The position of that node is chosen by computing the line *l* from the root's position *a*, to the center of the cluster *c*. The closest intersection of *l* with *c*'s bounding box is called *b*. The position of the branching node is the average position of *a* and *b*, or *(a+b)/2*. The algorithm recurses on the grand children of the root nodes.

Figure 6.4 illustrates the placement of a binary branching point for the three cases: a split between two leaf nodes, one leaf node and a cluster, or two clusters. Branching nodes *n* are placed halfway between the position of the start node, *a,* and another point *b*. For two leaf clusters, *b* is the location of the heavier node. For the other cases, let *l* be a line between *a* and the center of the heavier cluster. *b* is the closest point to *a*, on the line *l*, that intersects the bounding box of either child cluster. In both cases the position of the branching node *n* is set to be *(a+b)/2*.

An edge is always added from the starting node to the branching node *n*, and an edge from *n* to the leaf nodes. The algorithm always recurses on clusters. Note the branching point may be placed where an outgoing edge intersects the bounding box of one of its children. We describe how the algorithm avoids these intersections in the next section.

6.3.5 Edge Routing

Edges are routed around the bounding boxes within the same hierarchical cluster. A consequence of this is that the edges from the root node to its immediate children are not routed, because they are not in a cluster with one another. We will discuss this issue in more detail in 6.5. We illustrate how the algorithm routes edges around sibling clusters for the case of two clusters in Figure 6.5. Step 1 illustrates for each branching point *b1*, the algorithm checks if the edge *b1-b2* or the edge *b1-b3* intersects its sibling's bounding box. *b1-b3* intersects the bounding box of cluster *c1*, so *c1* occludes *c2*. Step 2 shows how to find the closest corner on the bounding box *c1* to the line *b1-b3* and how to create a new node at that corner to route the edge around the bounding box. Step 3 checks the line from the new node to *b3* to see if it intersects *c1*. If an intersection exists, the point *b3* is moved to just outside the corner of the bounding box of *c1*.

Figure 6.5 also illustrates how the algorithm decides which corner to position nodes. If an edge that intersects a bounding box, it splits it into two parts. The algorithm computes each area of each part of the box split by the edge. It chooses the corner on the side of the edge with less area.

6.3.6 Multiple Layers

Previous sections described how the layout works for a single layer, which is created to depict data from an initial query. Here we describe the modifications to the algorithm when users generate further queries to get a combined visualization.

Each additional query might introduce new nodes that did not exist in the previous query. As a result, the layout adjustment step must be re-run for each new query, which may take $O(m^2)$ where m is the total number of unique nodes accumulated over all the queries. The positions of all the nodes are reset to their initial locations, and the

layout adjustment step is run as described in 6.3.1. When the algorithm gets new nodes, it also runs the primary hierarchical clustering step again, which takes $O(m^2)$.

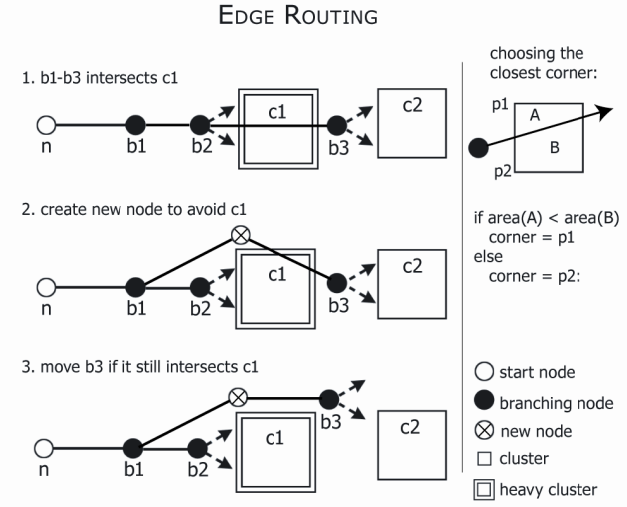


Figure 6.5 Edge Routing. Spatial layout may cause an intersection by placing b3 in a way that intersects c1. The algorithm finds the intersection of b1-b3 with c1, and adds a new node and adjusts the position of b3 to avoid c1 if necessary.

The hierarchical clustering steps in the system must be modified to account for the fact that not every cluster belongs to every layer. Every cluster has a list of the layers with which it is associated. Clusters also store a mapping from layers to a list of their subclusters which appear in that layer. The current implementation of rooted clustering runs in $O(m^2)$. This is because we do not propagate the layer information up the tree when constructing the primary hierarchical clustering, so we have to inspect the subtree to find which subclusters appear in which layer. However, by storing subclusters' information at each level, this would improve the running time of rooted clustering $O(\lg m)$ to accumulate nodes and $O(\lg m)^2$ to recluster the set.

The edge routing is done on a per-layer basis, which will cause many edge crossings if too many maps are layered on top of one another.

6.4 Rendering

To make the flow map visually appealing, each edge is rendered as a Catmull-Rom spline which interpolates between the nodes of the spatial layout tree that we produced. The splines are rendered such that they have width proportional to the weight of the edge and the widths are constrained by a minimum and a maximum display

width. The data is mapped to this interval using a linear or a logarithmic function. The splines are adjusted so that edge widths add up visually. For each binary branch, the starting point of the child splines is shifted by a distance proportional to the width of the child, in a direction perpendicular to the vector that represents the edge.

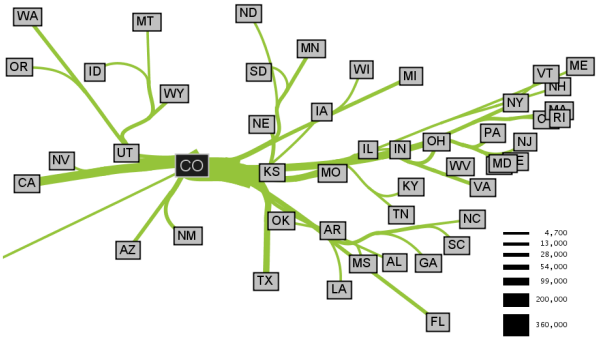


Figure 6.6 Outgoing migration map from Colorado from 1995-2000, generated by our algorithm without layout adjustment or edge routing. Note how the spatial structure imposed by our hierarchical clustering still merges edges in a way that produces a clean map despite the lack of edge routing.

A legend for the map is generated by running k-means clustering [24] on all the edge widths that appear in the map. We chose to generate 7 categories for the legend. Since the algorithm does not enforce that a bin in the k-means should not contain 0, some legends may have less than 7 categories. The location of the legend on the map is set manually. A unique color is set for each layer as to distinguish them.

6.5 Results

We used several data sets to test our algorithm. The US Census data for 1995-2000 [12] records all of the county to county migrations. Network traffic data was recorded from our lab's router over a period of several months. The ecological footprint data is courtesy of the Footprint Network [39]. All the node positions were specified in latitude and longitude, and converted to screen space via a Mercator projection. The maps produced by our system were produced in a few seconds of time on a 1.4GHz laptop. The system is written in Java using Heer's prefuse visualization toolkit [21].

The technique produces aesthetically pleasing flow maps for a variety of data sets. However, there are still cases where the flow maps do not look as good as ex-

pected. To understand these failure cases, we analyzed the technique in terms of the three characteristics of good flow maps.

Intelligent Distortion. The force scan algorithm [38] used for layout adjustment separates the nodes and guarantees that the relative positions of the nodes are not changing with respect to one another. The problem with this method can be seen by comparing Figure 6.1c with Figure 6.6. While Figure 6.6 is clearly recognizable as the outline of the United States, Figure 6.1c has been vertically distorted so that the states on the East Coast are spread apart. This stretches out the West Coast too much.

Merging of edges that share destinations. The implementation of hierarchical clustering is able to find spatial clusters in the data sets we use. The biggest drawback to the algorithm in this regard is that all splits are binary. If there are too many destination nodes in a small area, forcing binary splits introduces too many extra routing nodes and leads to clutter. In addition, with too many nodes, continuity constraints for splines cause them to loop.

Intelligent edge routing. The heuristic works well for simpler cases and sometimes does not work well for larger cases. One problem is that there is no routing on the edges leaving the root. Branches in these separate binary trees don't know about each other and may overlap. In Figure 6.8, the reason why there are so many edge crossings is that our method assumes bounding boxes created by our spatial clustering are disjoint.

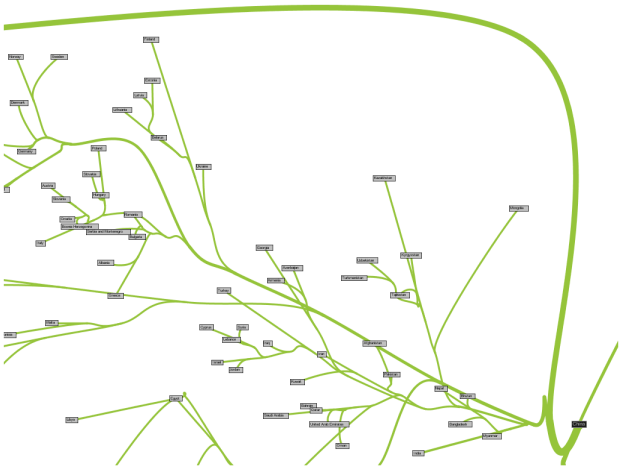


Figure 6.7 Imports to China. A part of a flow map showing the top 200 countries from which China receives imports. The thick line curving around the top are the imports from the USA (not shown), which without edge routing would have gone straight through the middle of the image. Edge crossings still occur in some parts of the map, illustrating cases where our routing does not work. For more information see the discussion.

However, our clustering does not always produce disjoint boxes, so we cannot always apply our heuristic. A better solution would be to use a clustering technique where the bounding regions are polygons.

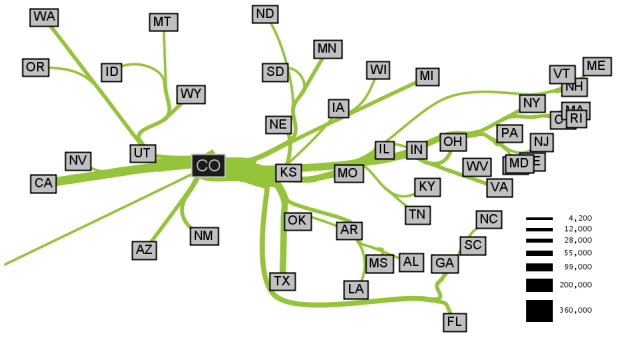


Figure 6.8 Outgoing migration map from Colorado for 1995-2000 generated using edge routing but no layout adjustment.

Layering and branching structure. We have found that the method for sharing substructure across flow maps that share a common set of nodes works quite well. Figure 6.9 has an example where two flow maps layered together share branching structure to several nodes.

Linear or logarithmic display widths. In our initial maps we used logarithms to map our data to a display width, because we were working with network data where there were many orders of magnitude in the data that we were plotting. However, for data sets not dominated by a few high magnitude values, we find that linear mappings draw the eye more. All the maps we demonstrated in this chapter use linear mappings.

6.6 Related Work

A survey of American flow mapping history and techniques is described in [43]. Flow map design is discussed in various geography textbooks [16, 53]. Guidelines are given on legend design and the use of a visual hierarchy to emphasize flow lines over region boundaries. However, there are no guidelines that are given on how to create a flow map. Ruggles and Armstrong [49] discuss a framework for the cartographic visualization of networks. More generally, map design is discussed in [34].

An alternative method of layout adjustment is described by Lyons [33], who improves the distribution of nodes in a graph and uses measures for graph similarity

and distribution to decide if too much distortion has occurred. Since this method tends to more evenly distribute the nodes, it tends to blur out geographic features, which is not as useful for flow maps.

Our edge routing technique is related to the ones found in the graph drawing literature. Dobkin et al. [17] describes how to route individual edges through a set of obstacles represented by polygons. Unfortunately, they leave the question how to do this for multiple edges open.

Our work is related to Agrawala and Stolte [2], who studied hand-drawn route maps to understand the principles that made them effective. They made use of intelligent distortion to produce computer generated route maps.

6.7 Discussion

There are many areas of future work suggested by this project. Global enforcement of horizontal and vertical ordering seems too strict for flow maps. A better layout adjustment algorithm might only enforce horizontal and vertical ordering within some 2D local window of each node, so that things may be globally distorted but locally consistent.

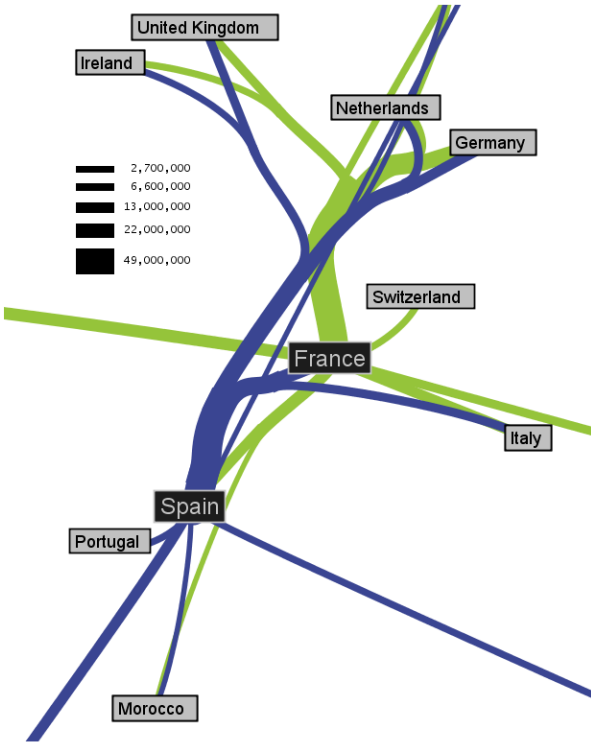


Figure 6.9 Branching Structure. A close-up of top 15 imports to Spain and France. Notice the branching structure is shared across different nodes, for example Spain, and France branch to the Netherlands, Germany and the UK in the same way. Arrows are not rendered by the system.

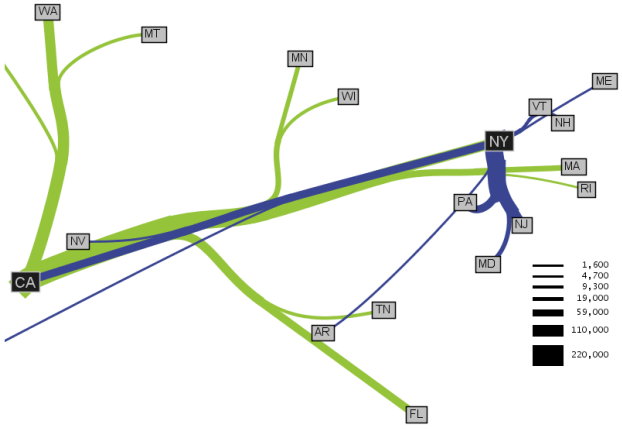


Figure 6.10 California and New York migration. Another example of how layering can be used in our system. The map shows the top 10 states that migrate to California and New York. Flow maps make it easy to spot an interesting spatial pattern, namely that New York tends to attract people from the East Coast, while California residents come from more geographic regions in the United States.

Although using binary clustering makes our spatial layout step simpler, having non-binary splits could eliminate some clutter and some loopy edges. Also, instead of our heuristic-based method for edge routing, it may be possible to use simulated annealing to adjust the edge positions.

We are also interested in the layout and display of data that does not explicitly have a location. Although all of our work has been on data sets with geographic locations, it may be interesting to generate flow maps for more abstract sets of objects that have no predefined positions but that can be grouped in other ways.

6.8 Conclusion

This chapter presents a method to automatically generate flow maps. Distortion is used to ensure that our nodes are well spaced but still preserve their relative positions to one another. Edges are merged based on their destinations using hierarchical clustering. This allows flow maps with the same

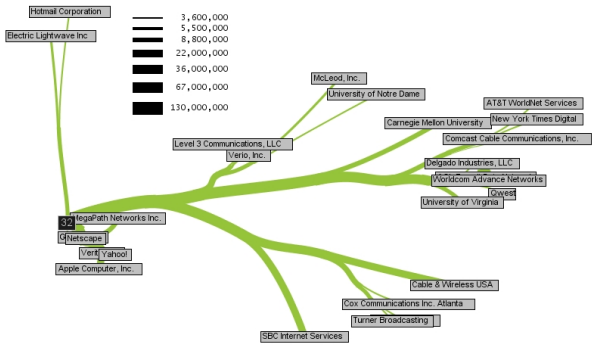


Figure 6.11 An example of the top ASN (Autonomous Systems) that a computer from our lab communicated with in one day. The latitudes and longitudes for the ASNs were obtained by manually looking for the city or state in which the ASN was registered.

input nodes to share branching structures. Finally, the spatial information from the hierarchical clustering is used to do edge routing to avoid edge crossings.

7 Conclusions and Future Work

This dissertation has demonstrated that interactive visualizations consisting of progressive multiples of timelines and event plots can support the forensic analysis of network events. It has also demonstrated that flow maps are useful for presenting summaries of network behavior and provides a technique for automatically generating a geographic flow map.

Progressive multiples of timelines and event plots were designed in collaboration with the principal network security analyst of the EE and CS departments at Stanford. We developed a system, Isis, for network security analysts, which has been used to successfully investigate intrusions in a long-term deployment. Based on our observations of usage, we have formulated several design guidelines for future systems that visualize network events or conduct forensic analysis.

7.1 Design Guidelines

Use timelines instead of node-link diagrams to sequence network events for forensic analysis

Our experience with the flow map prototype suggested that using node-link diagrams to sequence network events was difficult for users to understand. The flow map prototype used a radial layout, where time increased clockwise around a focus node. The primary task is to sequence events, which requires comparisons of multiple focus nodes. The problem is that the same position on the circle around a focus node might mean different things across different node-link diagrams, since the radial flow

map uses an ordinal view of time. Using a continuous view of time to facilitate comparisons across node-link diagrams yields space-inefficient timelines that are curved. As a result, it makes more sense to directly use a normal timeline, which can be easily stacked for the purposes of comparison and sequencing.

Provide dynamic previews to make an exploration history more meaningful

Brushing's primary purpose is to allow the user to quickly understand the temporal distribution of other dimensions of the data. Brushing has been used in prior work for dynamic previews [6]. However, this dissertation suggests that brushing also improves the quality of an exploration history. Without brushing, users would have to create new rows in order to understand different traffic patterns, which is an inefficient use of space. Brushing makes an exploration history more meaningful because it allows users to preview the effects of their actions. As a result, they only create timelines for states which they want to refer back to as they continue with their investigation.

Allow users to save the results of a dynamic preview in a static form

Brushing reveals objects that share common attributes, but the result is often transient, which can make it hard for users to remember what they have just brushed. We allow users to save the results of a brush by restructuring the display. In our system, the user may collect the rows that have been brushed and move them to the top of the display. This makes off-screen rows visible to the user. The novel idea is that this allows the display to be reorganized by first brushing related events and then grouping them together. We believe that the idea of restructuring displays based on brushing can be applied to other exploratory visualization systems.

Support interactive views of time

The event plot also supports continuous and ordinal views of time. Both views support the sequencing of events. A continuous view of time allows users to understand the distribution of events in time. However, since an intrusion may take place over a very short amount of time, a continuous view of time may only allocate a small amount of space to the relevant time period. An ordinal view of time allocates space more equitably and allows users to see any missing gaps in the event sequence. However, an ordinal view of time can allocate too much space to large numbers of events that are concentrated in a small period of time, such as a denial-of-service attack. As a result, we allow users to use both views of time and to control the space allocated to time periods with interactive gridlines.

7.2 Limitations

The size of the datasets being visualized is constantly growing. For example, the traffic at the university's border is an order of magnitude larger than the traffic seen in the EE and CS departments. Given the volume of data, the visualization that runs on the analyst's workstation should offload calculation to a remote database. We have been able to conduct analyses spanning a few days, using queries that run over tens of millions of events and select tens of thousands for display. If an analyst needed to search a few billion rows, our preliminary evidence suggests that this could be done by distributing a query across a clustered database server. However, even if the query eliminated 99.99% of the rows, it might still generate a result set of several hundred thousand events and a degree of overplotting that could easily overwhelm event plots with ordinal time. Incorporating methods that abstract flows into larger behaviors by Kannan [26], Xiao [64], or Karagiannis [27] holds promise for reducing clutter as well as adding useful information for the analyst.

Designing tools for expert users that leverage their domain knowledge remains a difficult problem. Expert users are often reluctant to adopt new tools unless they provide a significant improvement over existing tools. Since these tools tend to have a significant learning curve, it can be difficult to engage expert users who will take the time to evaluate and use the design prototypes. Practices that work well for novices or for tools used occasionally can be inefficient and even annoying for those who must use them every day. The *ad hoc* nature of incident analysis suggests we should design each tool to do one task well, knowing that the analyst will combine it with other tools. It is important to provide import and export mechanisms to make it easier to move among different tools. Network incident response is still more art than science and likely to remain that way for some time to come.

7.3 Closing Remarks

This dissertation integrates the user-centered iterative design practices of human-computer interaction with the development and evaluation of visualization techniques. The goal of this work has been to create visualizations that are useful for solving real problems that are faced by real users. A long-term engagement with a small user population can inspire the creation of visualizations that are useful to a broader group of users. We hope that the user-focused process of design and evaluation described in this dissertation can inspire further research into the development of aesthetic and effective visualization systems.

Appendix A: Investigation Task Analysis

This appendix contains a task analysis of the process of network intrusion investigation based on our observations of investigations conducted by the principal network analyst, John Gerth, of the EE and CS departments at Stanford University. This task analysis is inspired by the GOMS methodology [11] presented by Card, Moran, and Newell. The task analysis motivated the development of our technique to support the investigation process.

Our task analysis is a high-level description of the investigation process using the old technique (indicated by SQL) and our new system (indicated by ISIS). It consists of goals, which refer to what the user is trying to accomplish, and actions, which refer to how the user can move closer to a goal in our system. Goals and Actions can have subgoals or subactions.

Goals (marked with G:) and Actions (marked with A:) are numbered so that they may be referenced in the text. SQL or ISIS indicates the differences in actions depending on the tool used. If the description of the Action is brief, the action is described inline with the goal it supports. If the Action is more complicated, it can be found in a separate description and a reference number is provided.

The difference between Goals and Actions is that Goals are not specific to the system. For instance, (*Step 8) Find Connections of Intruders* is a goal and the only action that is listed is *(Step 11) Get Traffic Overview and Inspect Connections*. In our system, the only way to find connections is by looking at traffic overviews, but there are many other ways of achieving this goal. For example, the administrator might run an automated data mining algorithm to extract possible connections.

1. Investigate Intrusion. *Once an analyst is notified a computer may be compromised, he or she begins with this high level goal.*
    a. G: Find Compromise on Machine (2)
    b. G: Find Connections of Intruder (8)
    c. G: Find Other Compromised Machines (9)
    d. G: Create Report (10)

2. Find Compromise on Machine. *Log onto a computer to inspect it*
    a. G: Inspect ports (3)
    b. G: Inspect binaries for tampering (7)

3. Inspect Ports. *One way to discover if a computer is compromised is to look at its open ports to see if it is running a non-standard service.*
    a. G: Find Open Ports (4)
    b. G: Determine if port is suspicious (5)
    c. G: Find users associated with open ports (6)

4. Find Open Ports. *Open ports on a system are a symptom of a compromised computer, and may indicate that it is running an unauthorized service*
    a. Run nmap against the system to find the current set of open ports

5. Determine if Port is Suspicious. *Given a list of open ports, the analyst needs to determine if any of those ports are suspicious*
    a. Use domain knowledge of ports
    b. Connect to a port with telnet to see if it is running an interesting service

6. Find Users Associated with Open Ports. *If a suspicious port is running, find the users associated with the open ports.*
    a. Logon to system and look at running processes
    b. Associate the start time of process with user logins by scanning text logs

7. Inspect binaries for tampering. *Another way to discover a compromise is to inspect system binaries to make sure they are legitimate. For example, an intruder may have modified the programs running on the machine to log keystrokes to steal passwords.*
    a. Hash the system binaries and compare to known-good copies

8. Find Connections of Intruders
    a. A: Get Traffic Overview and Inspect Connections (11)

9. Find Other Compromised Machines. *Given the set of machines involved in the initial intrusion, look for other local machines contacted by those intruders and repeat the process of 'Investigate Intrusion' for those local machines.*

10. Create Report. *The analyst usually writes an email to summarize the investigation. The email provides a list of compromised computers and is sent to other analysts so that he or she can take action. The email may contain different types of evidence:*
    a. System logs that show the time of the connection made by the intruder
    b. A list of running processes on the system and the time they were started
    c. An image from Tableau that shows timelines of connections made to/from remote computers, color coded by port

11. A: Get Traffic Overview and Inspect Connections (IPs, Time Interval)
    a. For each IP
        i. A: Formulate Query [SQL, ISIS] (12)
        ii. A: Interpret Query Results[SQL, ISIS] (18)
        iii. A: Compare Query Results to Others[SQL, ISIS] (31)
        iv. A: Refine Query [SQL, ISIS] if necessary (33)
        v. A: Pivot to See Related Traffic if necessary (26)

12. A: Formulate Query
    a. A: Choose Time Range (13)
    b. A: Choose Measure and Aggregation (14)
    c. A: Choose Filter Statement (15)
    d. A: Construct Query [SQL, ISIS] (16)
    e. A: Run SQL(Query, [SQL, ISIS]) (17)

13. A: Choose Time Range. *Intruders tend to be impatient, and start using the computer immediately after they break into the system. As a result, 24 hours is the usual time range that is chosen. However, there have been instances where the compromised computer was compromised long before it was used by the attacker.*

14. A: Choose Measure and Aggregation. *The traffic measures are determined by the available event data and the aggregation expressions are provided by MySQL.*
    a. Select Measure
        i. # of total flows, # of incoming or outgoing flows
        ii. # of total bytes, # of incoming or outgoing bytes

iii. # of total packets, # of incoming or outgoing packets
iv. # of application bytes (excludes bytes for communication overload), # of incoming / outgoing application bytes

b. Select Aggregation Statement
i. Minimum
ii. Maximum
iii. Average
iv. Count, or Count Distinct
v. Sum

15. A: Choose Filter Statement. *A filter determines what traffic to include or exclude, through SQL expressions. Select from:*
a. IP
b. ASN
i. Include or exclude results to computers from similar ASNs. Can filter a block of IPs from ASNs that are known scanners
c. Ports
i. Include traffic using a specific port of interest (IRC or SSH)
ii. Exclude traffic on benign ports such as web traffic, DNS, or mail
d. Role
i. Distinguishes when a computer is a client or a server. Useful for seeing when a computer switches from being a server (an intruder logs onto it) to being a client (the compromised computer connects to remote IRC servers).
e. Locality
i. Exclude traffic local to Stanford to look for remote attackers
ii. Virtual Lan (Subnet)

iii. Different administrators control different subnets at Stanford, so can be useful to limit queries by the Virtual Lan

f. Measures. Some examples are:

i. Packets. Exclude connections with less than 30 total packets. It takes at least that many packets to be exchanged for connection to be established.

ii. Bytes. Exclude connections where number of bytes transferred is below 10,000 bytes. The more bytes transferred, the more likely a significant download took place.

16. A: Construct Query. *Done by hand in SQL, but Isis will construct this automatically. This provides a minor speedup to the analyst.*

17. A: Run SQL (Query, SQL or ISIS). *Wait for query to return results, which may appear textually or graphically.*

SQL (Returns a textual list of results)

ISIS (Returns a graphical timeline)

i. A: Make Folder(Label: Use IP) (27)

ii. A: Make Timeline(Query, Folder: Use the one just created) (28)

18. A: Interpret Query Results. *Look at query results for one of the following things which might suggest a suspicious connection. Select from:*

a. Spikes, bursts, or periodic patterns of activity

b. Volume above/below a threshold of bytes, packets, or flows transferred

c. Traffic using a suspicious port

d. Traffic from a suspicious IP or ASN

SQL

i. A: Look at Text

ISIS

i. A: Look at Visual Timeline

ii. A: Interact with Timeline

19. A: Look at Text. *Inspect a text list of results for one of the items described under (18). This provides detail but makes it hard to understand temporal distribution of the traffic. See the discussion in 5.1.*

20. A: Look at Visual Timeline. *The timeline provides an overview of traffic and can find spikes, bursts, or periodic patterns of activity. See the discussion in 5.1.*

21. A: Interact with Timeline. *Obtain additional information by getting more detail, breaking down traffic by other dimensions, or viewing traffic in different visual representations. Select from:*

    a. Get menu for the whole timeline or a subset of the bins

        i. A: Create Tearoff (Query, Bin, Dimension) (22)

        ii. A: Make Event Plot(Bin) (34)

        iii. A: See Underlying Data as Text Table (32)

        iv. A: Adjust Vertical Scaling (29)

    b. A: See Tooltip for Bin (30)

    c. A: Compare Timeline (31)

    d. Delete Timeline

22. A: Create Tearoff (Query, Bin, Dimension). *Creates a tearoff menu that displays a table that shows the distribution of traffic in the bin by one of the following dimensions: ip, port, vlan, asn, locality, and role. Select from:*
    a. Sort by increasing or decreasing aggregate value or by name
    b. A: Brush(Current Item, Dimension) (23)
    c. A: Scan highlighted bins (24)
    d. A: Subdivide Timeline(Bin, Dimension) (25)
    e. A: Pivot(Bin, IP of current item) only if Dimension = IP (26)

23. Brush(Item, Dimension). *Highlights all other bins in all other timelines that contain an event with same name and dimension*

24. Scan Highlighted Bins. *Highlights show the temporal distribution of the brushed non-temporal dimensions: ip, port, vlan, asn, locality, and role*

25. Subdivide Timeline(Bin, Dimension). C*reate a new folder that contains a timeline for each value of the dimension in the given bin. For example, subdividing a timeline T on port would result in a new folder where each timeline T' would show the traffic of T filtered on a single port.*

    a. Make Folder(Label: Focus IP)
    b. For each value of dimension in the given bin that was selected
        ii. A: Filter(Query, Folder) (33)

26. Pivot(Query, New IP)
    a. A: Update Query so that the New IP is the focus
    b. A: Run SQL (17)

27. Make Folder(Label). *Add a new folder to the display with the provided label*

28. Make Timeline(Query, Folder)
    a. Run SQL(Query) (17)
    b. Add timeline of the query results to the given folder

29. Adjust Vertical Scaling(Folder, Log or Linear). *Timelines are scaled in relation to the maximum value of the aggregate in the current folder. Linear or logarithmic scaling can be used.*

30. See Tooltip for Bin. *Hovering over a bin shows the time range spanned by the bin and displays the value for the aggregate.*

31. Compare Timeline. *The analyst can reorder timelines within a folder to make comparisons easier. If timelines are in different folders, an analyst can copy a timeline from one folder to another.*

32. See Underlying Data(Bin). *Creates a table that shows the raw data for the bin*
    a. Sort table by column (local/remote packets/bytes/flows, local/remote port, local/remote IP, local/remote ASN, time, role, locality, vlan)

33. Filter (Query, Filter String, Folder)
    a. Update query with the newly provided filter string
    b. A: Run SQL(Query) (17)
    c. A: Make Timeline(Updated Query, Folder) (28)

34. A: Make Event Plot(Bin). *View the traffic contained in the bin as an event plot for the focus IP. Each partner IP is a row on the vertical axis and time is mapped to the horizontal. Each mark represents a connection between the focus IP and the partner IP. Select from:*
    a. A: Switch View of Time ([Continuous or Ordinal]) (35)
    b. A: See Tooltip for Mark (36)
    c. A: Map Size of Mark (37)
    d. A: Map Shape of Mark (38)
    e. A: Manipulate Gridline (39)
    f. A: Brush Dimension (23)
    g. A: Mark Dimension with Color (40)
    h. A: Collect by Brushing (41)

35. Switch View of Time([Continuous, Ordinal]). *Events are either plotted on the x-axis in continuous or in ordinal space. In continuous space the distance between events on the x-axis is proportional to the amount of time between the two events. In ordinal space the distance between events on the x-axis only indicate that an event came before or after another.*

36. See Tooltip for Event Plot Mark. *Displays additional information about the connection in a popup window: time, # of packets, role, ASN*

37. Map Size of Mark. *Make the mark size into small, medium, or large, based on the # of packets. Marks are ordered by # of packets. If the mark is below the 25% percentile, it is shown in a small size. If the mark is above the 75% percentile, it is show in a large size. Otherwise it is shown in a medium size. The thresholds are adjustable by the analyst.*

38. Map Shape of Mark. *A user may choose to map client connections to a triangle and server connections to a circle to disambiguate between outgoing and incoming connections.*

39. Interact with Gridlines. *Gridlines are added to the event plot at reasonable time intervals (every 5, 10, 15, 20, etc… minutes), depending on the time span of the data. Port scanning and other kinds of network activity far outweigh the few connections that make up the SSH connection that is the intrusion. This may cause salient events to be spaced too closely to be read. Adjusting the gridlines allows users to change the spacing allocated to each mark. Select from:*
    a. Add Gridline
    b. Remove Gridline
    c. Adjust Gridline (drag it to the right or to the left)

40. Mark Dimension with Color. *If an analyst is interested in a particular value for a dimension, he or she can pick a color for the marks that with that value. This color is reflected across all other event plots for that dimension. Each dimension has a unique set of colors, but different dimensions may share the same color. To avoid confusion, only one dimension is colored at a time.*

41. Collect Brushing. *Moves all the rows that are brushed to the top of the display. This allows the analyst to organize an event plot to more clearly show a sequence of events.*

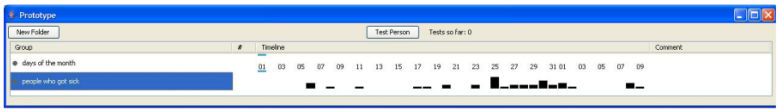
Appendix B: Epidemic User Study Materials

INSTRUCTIONS

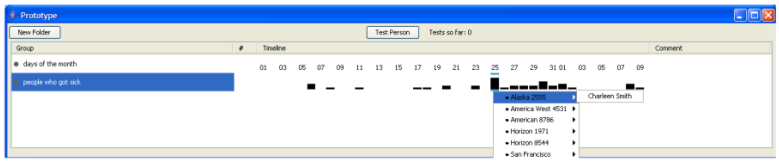
In this scenario, you are an analyst with the Centers for Disease Control. Over the last few weeks, people traveling on flights have been getting sick. You know the following:

- There is a single carrier of the disease. They infect other people on flights but they never become sick themselves.
- When people get infected, there is a fixed incubation period of a constant number of days until they get sick and show symptoms. During that time they continue to move around and may infect other people. Eventually they become sick, at which point they stop taking flights and go to the hospital.

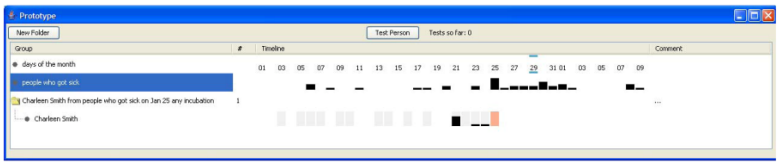
Your task is to use the visualization to determine who might be a carrier, so you can send a CDC team to test them for the virus. Unfortunately, it's expensive in terms of time and money to send a team out to test the person, so they want you to test as few people as possible.



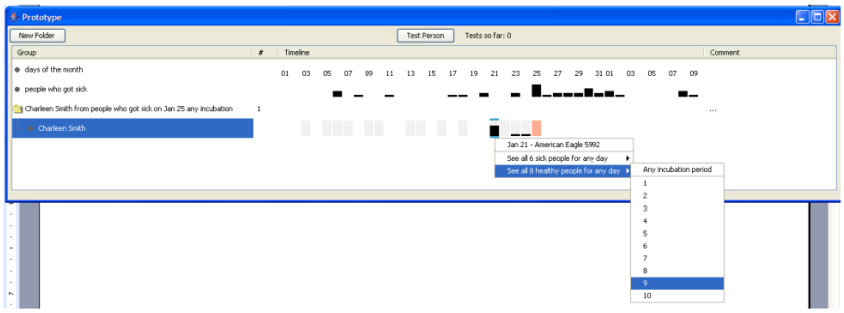
The initial view consists of two rows, which show a calendar with days of the month, and a bar graph where the x-axis is days, and the height of the bars encode how many people got sick.



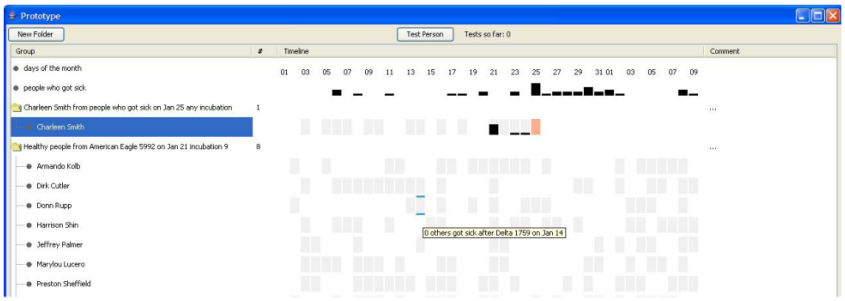
Clicking on a bar gives you a menu where the entries list the locations where people got sick. Submenus show the names of the people themselves.



Clicking on a person's name gets you a timeline that shows a person's movements. Gray boxes indicate flights the person took. The height of the bar (in black) indicates the number of people who were also on that flight with that person, and who later got sick at **ANY** time. Gray boxes without black indicate no one on that flight later got sick. Red boxes indicate when people got sick.



When you click on a bar, you can choose to see the travel timelines of all the people on the flight who eventually got sick, or all the people on the flight who are still healthy. When selecting timelines this way you can choose to request that the bars of those timelines show people who got sick after **any number of days** after the flight, or after a **specific number of days.** In the screenshot above, we are choosing to see timelines for all the healthy people who were on American Eagle 5992. We are choosing the height of the bars to be mapped to the "number of people who got sick 9 days after traveling on that flight"



Above, there are 7 people who are still healthy after being on that flight. Since there are only grey boxes, they also never traveled on any flights where anyone got sick 9 days after traveling with them.

To **test** a person, simply select a row with that person and click the test button. That will tell you if that person is the carrier, but remember that you don't want to spend your tests recklessly.

Rows may also be **deleted** with the Delete key, and you can undo a single delete with Control+Z. You can **create a folder** by using the New Folder button. Rows may be dragged between folders or reordered within a folder by double-clicking a row and dragging to your desired destination. **Rows may be renamed** by double clicking on them. **Comments** may also be added in the same way, by double-clicking the comment column.

Epidemic Visualization Questionnaire

1. Name:
2. Gender: M / F
3. How much experience have you had working with visualizations?

4. What was your strategy in looking for the carrier?

5. What did you think about the use of bars? Were they confusing?

6. Did you ever delete a row by accident? Was the undo helpful or not?

7. Was it easy to keep track of the rows you had created?

8. Were the tooltips informative or uninformative?

9. Did you notice the highlighting of rows? Was that useful or not to you?

10. Was the incubation period helpful in your investigation?

11. Did you ever create new folders?

12. Did you ever move rows around within a folder? Was this useful or not?

13. Did you ever copy rows to a new folder? Was this useful or not to you?

14. Did you ever add comments to rows? Was this useful or not to you?

15. Was there anything in the interface that you particularly liked?

16. Was there anything in the interface that was confusing?

17. Do you have any other comments or suggestions?

Thanks for your time!

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