Real-time Intelligent Clustering for Graph Visualization

Lionel Martin[1,2] and Géraldine Bous[2]
[1]*EPFL, Lausanne, Switzerland*
[2]*RTI, SAP Research, Sophia Antipolis, France*

Keywords: Graph Visualization, Social Networks, Graph Clustering, Machine Learning, User Interaction.

Abstract: We present a tool for the interactive exploration and analysis of large clustered graphs. The tool empowers users to control the granularity of the graph, either by direct interaction (collapsing/expanding clusters) or via a slider that automatically computes a clustered graph of the desired size. Moreover, we explore the use of learning algorithms to capture graph exploration preferences based on a history of user interactions. The learned parameters are then used to modify the action of the slider in view of mimicking the natural interaction/exploration behavior of the user.

1 INTRODUCTION

Business Intelligence, (Social) Network Analysis or Biology are just a few examples of domains where graphs are used as data structures to capture the relational structure in the underlying data. To fully take advantage of graphs, i.e. to allow analysts and scientists to gain insight into the data, it is necessary to provide user-friendly graph analysis and visualization tools.

Developing graph visualization tools that are simultaneously simple, intuitive and flexible (i.e. configurable) is a challenge as users have different requirements that translate as constraints in the graph exploration process. For large graphs, displaying the entire dataset leads to clutter and information overload, which impedes the analysis targeted by the end-user; on the other hand, displaying a simplified (filtered or clustered) graph without allowing the user to interactively configure the constraints (e.g. in filters) or the level of detail in the display (e.g. the number of clusters) is simply too restrictive to meet the requirements of most users. Over the years, many authors have proposed approaches and techniques to address the challenge of bringing together simplicity and flexibility in tools for graph analysis and visualization; the reader may refer to (von Landesberger et al., 2011) for a recent review. Some proposals focus on the graph representation itself, showing that node-link diagrams are more convenient for sparse graphs (Ghoniem et al., 2005), while adjacency matrices (Elmqvist et al., 2008) or hybrid representations (Henry and Fekete, 2006; Henry et al., 2007) are more convenient for dense graphs. In parallel, many proposals focus on interactive exploration techniques to address the challenge of visual information overload. Simple techniques like zooming, distortion or panning are helpful in visualizing large graphs (Card et al., 1999). Another possibility is to allow users to interactively reduce the amount of information displayed. Most interactive information reduction techniques belong to two major axes that are clustering, e.g. (Henry and Fekete, 2006; Archanbault et al., 2008; Archanbault et al., 2002), and filtering, e.g. (Heer and Boyd, 2005; Elmqvist and Fekete, 2010). While the latter removes 'uninteresting data' to reduce the amount of information displayed, the former simply aggregates similar entities together into 'visual containers', called clusters. In addition, certain authors also allow to filter according to a degree of interest function (van Ham and Perer, 2009) which reflects the exploration focus of the user.

In this paper, we present a tool for the *interactive exploration and analysis of large clustered graphs*. The tool empowers users to control the granularity of the graph, either by direct interaction (collapsing/expanding clusters) or via a slider that automatically computes a clustered graph of the desired 'size'. More precisely, the slider allows the user to define and control the *visual entity budget* (Elmqvist and Fekete, 2010), which reflects the number of edges and nodes displayed; for a given budget, a clustered graph with a matching number of edges and nodes is calculated and displayed. To ensure continuity and coherence

Martin L. and Bous G..
Real-time Intelligent Clustering for Graph Visualization.
DOI: 10.5220/0004305504710480
In *Proceedings of the International Conference on Computer Graphics Theory and Applications and International Conference on Information Visualization Theory and Applications* (IVAPP-2013), pages 471-480
ISBN: 978-989-8565-46-4

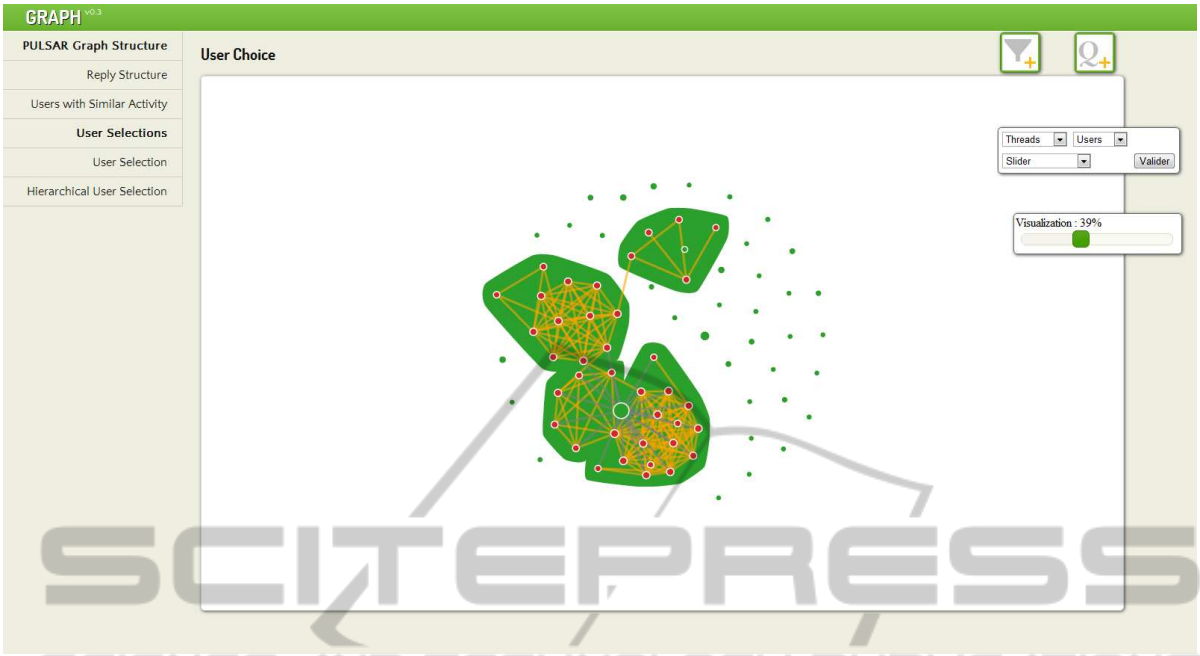


Figure 1: User Interface of our visualization tool.

in the display, i.e. to ensure that the graph displayed with budget y is the graph that would be displayed with budget $x < y$ *plus* a certain number of expanded clusters, we automatically calculate an exploration *sequence* for a hierarchically clustered graph. This sequence is then mapped to the slider; interacting with the latter then allows having a quick overview of the graph at different levels of detail in a user-friendly manner. To further enhance user-experience and enable customization, we explore the use of learning algorithms to capture graph exploration preferences based on a history of user interactions. The tool records user interactions to learn a degree of interest function. This learned function is then used to modify the exploration sequence (and hence the action of the slider) in view of mimicking the natural interaction/exploration behavior of the user.

This paper is structured as follows. After an overview of related work in section 2, we present our tool in more detail in section 3. Section 4 addresses the learning mechanism and details the results. Finally, we conclude in section 5 with challenges for the future.

2 RELATED WORK

During the last decades, graph clustering has been an intensively researched field proposing now a very large choice of methods for various kinds of graphs (the reader may refer to (Fortunato, 2010) for a complete presentation of the different methods). Clustering techniques can be classified into two main categories: structure and attribute-based algorithms. Approaches in the former group use the structural properties of graphs to decide how vertices and edges should be clustered. Examples include methods based on the connectivity of nodes (Kernighan and Lin, 1970; Suaris and Kedem, 1988), the shortest paths between nodes (Wu et al., 2004) and several other measures like e.g. edge-betweenness centrality or modularity (Girvan and Newman, 2002; Radicchi et al., 2004; Newman, 2004; Duch and Arenas, 2005; Blondel et al., 2008). On the other hand, attribute-based clustering algorithms use the attributes of nodes and edges to define clusters (Shneiderman and Aris, 2006; Wattenberg, 2006; Elmqvist et al., 2008). Mixed approaches, taking both the graph structure and its attributes into account, have also been proposed (Archanbault et al., 2008).

Aside from the 'algorithmic aspect' of graph clustering, many contributions propose tools or frameworks for graph analysis and visualization that enable users to interact with the graphs, for example (Henry and Fekete, 2006; Archanbault et al., 2008; Archanbault et al., 2002). More recently, tools allowing users to interactively 'manage' the data itself have been presented. The work of (Heer and Perer, 2011) describes a system for the modeling, transformation and visualization of multidimensional heterogeneous networks.

In parallel, (Liu et al., 2011) propose a tool to extract networks from tabular data which also includes an interactive visual interface supporting operations like aggregation (binning, grouping, etc.) or projection to generate different views of the data at different levels of granularity.

Our work is closest in spirit to (Liu et al., 2011) in that we propose a tool for graph (network) visualization that implements projection and aggregation operations, including clustering with Louvain's algorithm (Blondel et al., 2008). In addition to direct interactive exploration of the graph through expand / collapse operations, our tool also extends the work of (Liu et al., 2011) and other (previously cited) work on interactive graph clustering by allowing the user to manage the visual budget (Elmqvist and Fekete, 2010), i.e. the number of nodes and edges displayed. The visual budget is controlled by a simple slider 'mapped' to a hierarchically clustered graph. Interacting with the slider thus allows to automatically expand/collapse clusters and thereby to quickly gain an overview of the graph with little effort. The most innovative aspect of our proposal lies in the use of machine learning algorithms, which, based on a history of user interactions, learn both how the graph should be (hierarchically) clustered and in what sequence vertices and edges should be expanded / collapsed. Learned parameters are then used to derive a new graph exploration sequence which is mapped back to the slider.

3 TOOL AND USE-CASE DESCRIPTION

Traditional structure-based graph clustering algorithms use predefined measures, like e.g. edge-betweenness centrality, to produce clustered graphs. The disadvantage of such predefined measures is that the clustered graphs they generate may not reflect or meet user preferences and requirements. In an interactive framework, users may however explore the graph and search for the information or subgraphs that they are specifically interested in. Our goal is to provide users with all tools needed to efficiently explore the graph and, in addition, to learn from user interactions to recommend 'views' and 'exploration paths' of the graph that match user interest.

3.1 Overview

In this section we focus on the graph exploration alone (learning is addressed later). Our prototype for graph analysis is shown in figure 1. It is composed of an interactive graph visualization panel, a menu for selecting data aggregation operators (clustering, filtering, grouping and projection) in the top right corner and a slider to control the visual budget just below.

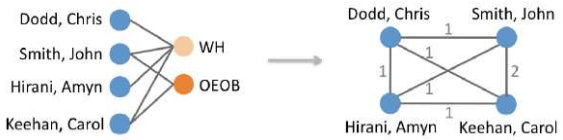


Figure 2: Projection (Liu et al., 2011).

The use case considered in this paper is a social network extracted from an online forum (the SAP Community Network). More precisely, we analyze the graph that arises from the reply-structure between messages. Forums have a natural hierarchical structure, as every forum contains threads, which in turn contain the messages; messages in turn have a unique author. Hence, two distinct hierarchical structures (forum-thread-message and author-message) are linked together by the replies between messages. From the author-message perspective, the reply structure induces a bipartite graph. It is therefore convenient to calculate projections (Latapy et al., 2008) of one set (i.e. hierarchy) over the other. The projection of a bipartite graph is a graph whose vertices belong to one set and are connected by edges if and only if they shared a neighbor in the original bipartite graph (see figure 2). This can expose correlations in the data (e.g. author-author connectivity). In addition, it also is of interest to exploit the natural hierarchies contained in the data to group nodes in a semantically meaningful way. Both approaches are implemented in our tool.

The disadvantage of semantic grouping and projection is that the graphs they generate are usually highly connected graphs, which are difficult to visualize due to the high number of edges. Therefore, the tool also offers the possibility to cluster the graph. Our tool implements Louvain's clustering method (Blondel et al., 2008), which is based on the graph modularity measure (Newman and Girvan, 2004), as it is a fast and efficient algorithm. This method has the advantage of producing hierarchically clustered graphs, which can be used for interactive exploration by expanding/collapsing clusters, a feature which is also offered in our graph analysis tool.

3.2 Entity Budget Interactions

Interactive graph exploration as described above can be a tedious and time-consuming process. It is therefore convenient to provide users with a simple way to visualize a hierarchically clustered graph at different levels of granularity. With this goal in mind, our tool offers the possibility to use a slider to con-

trol the amount of information displayed using a precise *measure*. The maximum of information that can be displayed is the entire graph; the minimum is a maximally clustered graph, i.e. a single cluster node (the root node of the hierarchically clustered graph) for each connected component of the graph. Consider a graph G containing a total of $|E|$ edges and $|V|$ vertices. For a clustered graph G_i, $|E_i|$ and $|V_i|$ denote the number of visible edges and nodes, respectively. The measure that reflects the amount of entities in graph G_i is calculated as

$$I_i = \frac{|E_i| + \beta|V_i|}{|E| + \beta|V|}, \quad (1)$$

where $\beta = \frac{N_{\max}(N_{\max}-1)}{2}$ and $N_{\max}$ denotes the maximum number of neighbors in the graph. Now that the measure and the notion of 'maximum' and 'minimum' graphs have been defined, the intermediate steps must be considered: which graph should be associated to the measure I_i? Indeed, the slider will simply help the user to choose the proportion of information to display given the measure associated to it; however, there may be more than one way to partially expand a hierarchically clustered graph to match the measure I_i. It is thus necessary to define how this measure should be interpreted, both in terms of which entities should be displayed and also concerning the proportion of nodes and edges.

'Navigating' from the minimal to the maximal graph with expand operations can be done in several ways. For example, it is possible to expand clusters in either a purely 'depth-first' or 'breadth-first' fashion, but anything in between is also possible. Moreover there are distinct partially expanded graphs that may have the same number of entities. Since there are several ways to reach a given quantity of information, there are also potentially different intermediate steps leading to the same configuration (see figure 3). Hence, there are many distinct *sequences* of expand operations that can lead from the minimum to the maximum graph. The slider should however only be mapped to *one* sequence, which we call the *default sequence*. Many parameters can be considered to determine the order in which the different elements are displayed using the slider. For example, parameters related to the size of the nodes, the strength of the links, the number of neighbors, and so on.

With a default exploration sequence defined, increasing the proportion of information is the same as applying several (or sometimes just one) expand operations on the minimal graph. The *continuity* of the measure mapped to the slider is thus an important consideration: the measure is a continuous scale, but expand operations may cause large 'jumps' in the

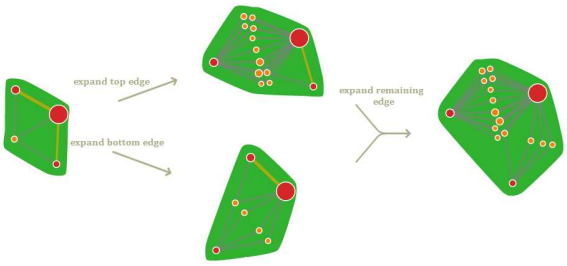


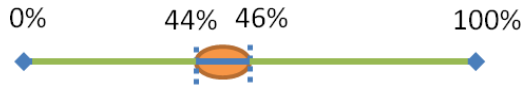
Figure 3: Two different sequences leading to the same configuration.

number of items displayed. Indeed, if a step in the sequence corresponds to expanding a large cluster containing ΔI entities, the measure will increase drastically at once. However, when the user interacts with the slider, she may very well move it from value I_i to $I_{i+1} = I_i + \delta \cdot \Delta I$, with $0 < \delta < 1$, i.e. within the gap of the graph corresponding to value I_i and the one corresponding to value $I_i + \Delta I$. When this occurs, our exploration algorithm shows only part of the information contained in a cluster with respect to the value δ. Overall, the process to expand the graph with a change in the slider from position I_i to an entity budget EB (with $EB > I_i$) is the following:

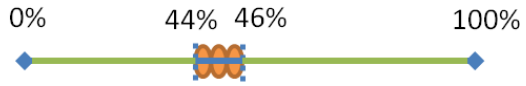
- clusters are opened according to the default sequence $G_i, G_{i+1}, \ldots$ as long as EB is not exceeded. In other words, if the k^{th} graph of the sequence satisfies $I_k < EB < I_{k+1}$, then graph G_k is displayed entirely.
- to allocate the missing part of the entity budget $EB - I_k$, part of the $(k+1)^{th}$ graph is shown as well. This is achieved by expanding the next cluster (which differentiates G_{k+1} from G_k) partially, i.e. showing as many entities as necessary to reach EB and leaving the rest hidden within the cluster.

On the other hand, when the slider is placed at a value $EB < I_i$, the opposite is done: clusters are closed following the sequence in reverse order until reaching graph G_{k+1} satisfying $I_k < EB < I_{k+1}$ with $k+1 \leq i$; the expanded cluster that differentiates G_{k+1} from G_k is then partially closed to match EB.

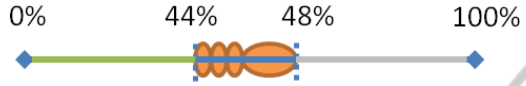
The challenge is that the user can also interact directly with the graph to expand and collapse nodes. If the user first uses the slider to partially expand the graph and then starts interacting directly with the graph (performing expand / collapse operations) the default sequence may not be further applicable, as, through her interactions, the user is likely to define sequence different from the default one. For example, assume that she uses the slider to display 44% of the information and then expands the three smallest node clusters displayed, C_1, C_2, and C_3. The new amount of information displayed is 46% (see figure



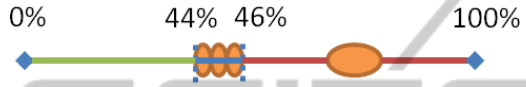
(a) Default sequence before interaction, next action after 44% is opening C_0.



(b) Alternative sequence defined by the user after the expansion of C_1, C_2 and C_3.



(c) Smallest modifications to be consistent with user interactions. The part in gray can be or not be identical to the one of the old default sequence.



(d) Modifications of everything beyond 46% to improve the next explorations for the user.

Figure 4: Modifications of the default sequence according to user interactions.

4(b)). Assume the default sequence's next operation after reaching 44% was to expand another cluster, C_0, than the ones interactively expanded, modifying the measure to 46% as well (see figure 4(a)). If the user now moves the slider to 48%, the heuristic that defines the order of the operations cannot 'know' that the cluster C_0 is not expanded and that it cannot expand C_1, C_2 or C_3 anymore. We thus need to define a way to smoothly go from the configuration before and the configuration after user interactions. In this example, we need at least to redefine the default sequence between 44% and 48% (see figure 4(c)). But even if it seems still valid to consider the old part of the sequence between 0% and 44% and beyond 48%, nothing forbids changing it as well (see figure 4(d)).

Our solution to this problem is the following. When the user explores graph G_i in a different order from that defined in the default sequence, the latter is reordered such that the partial sequence defined by the user is 'inserted' after G_i. More precisely, if the sequence is $...,G_i,G_{i+1},...,G_k,...,G_l,...$ with $i+1<k<l$ and at G_i the user expands the clusters that lead to G_k and then G_l, the default sequence becomes $...,G_i,G_k,G_l,G_{i+1},...$. Note that this does not pose inconsistency problems: the sequence in which clusters are opened is arbitrary *provided* no cluster is opened before any of its parent vertices, i.e. before any of the clusters in which a cluster is itself contained. Since this principle cannot be violated by manual exploration, redefining the default sequence by capturing user interaction is perfectly consistent with the hierarchically clustered graph.

4 INTERACTIVE LEARNING

As we have just shown, a hierarchically clustered graph can be explored in many distinct ways. To map one exploration sequence among the many possible to the 'exploration slider' thus involves a default choice which can be based on several criteria. In the previous section, this choice was made on the basis of two considerations: first, the exploration sequence must be sufficiently fine-grained to be mapped to an (approximately) continuous measure; second, it must be possible to modify subsequences of the default sequence in case the user interacts directly with the graph. Nevertheless, the choice of the default sequence is still highly arbitrary and it is thus convenient to introduce more criteria (i.e. constraints) to further reduce the set of feasible sequences. Most importantly, it is possible to introduce constraints that reflect user preferences or patterns in the graph exploration behavior. By keeping track of user interactions with the graph, it is possible to 'learn' the exploration behavior of the user with machine learning algorithms. The rules acquired through learning can then be used to update the default exploration sequence in such a way that it infers the natural behavior of the user.

4.1 Learning Framework

(Clustered) vertices and edges in a graph have different characteristics that can be integrated as parameters in an *interest* (or preference) *function*. The characteristics (i.e. criteria) we consider are structural:

- the number of neighbors of a vertex;
- the number of entities in a cluster (which reflects the size of a node in the clustered graph);
- the depth of the hierarchy in a clustered node and
- 'edge width' (which reflects its weight).

From a record of user interactions (which evolves in real-time as the user explores the graph), it is possible to deduce and quantify which (combination of) criteria best reflect user behavior. In what follows, we detail the model and the learning framework.

We denote the set of possible actions as $\mathcal{A} = \{a_0, a_1, \ldots, a_n\}$. Each of these actions corresponds to collapsing or expanding a specific node. When the user chooses to perform action e.g. a_0, we can deduce that action a_0 is preferred to all the other available actions, i.e. $a_0 \succ a_i$, where $i = 1,\ldots,n$ and $\succ$ is the notation for 'preferred to'. Since action a_0 is performed on a specific node, we can deduce that the specific characteristics of the node are what made this node relevant for the user. The interest function (also known as 'utility' or 'value function' in the decision

theoretic contexts) is a function $u : \mathcal{A} \to \mathbb{R}$ that satisfies $a_i \succ a_k \Leftrightarrow u(a_i) \geq u(a_k)$ for all $a_i, a_k \in \mathcal{A}, i \neq k$ (Mehta, 1998; Aleskerov et al., 2007). In other terms, $u(a_i)$ is the 'value' of action a_i as *perceived* by the user (Keeney and Raiffa, 1976). The utility function is a parametric function that aggregates (i.e. takes into account) all the criteria listed above. More precisely, $u(a_i)$ is a function of the marginal utilities $u_j(a_i)$, which model the value of action a_i on criterion j. The most frequently used aggregation model is the *additive model*, which leads to

$$u(a_i) = \sum_{j=1}^{J} u_j(a_i) \quad \forall a_i \in \mathcal{A}, \tag{2}$$

where J is the total number of criteria. With this model, the utility of an action is thus the sum of its marginal utilities. To define the marginal utilities, we use a simple linear model. Before we detail the equations, we must first take into account the fact that some criteria should be minimized (i.e. the smaller, the better for the user) or maximized (the larger, the better). Let

$$s_j = \begin{cases} -1 & \text{if criterion } j \text{ is minimized and} \\ 1 & \text{otherwise.} \end{cases} \tag{3}$$

Marginal utility functions are then defined as

$$u_j(a_i) = w_j \left(\frac{1 - s_j}{2} + s_j \frac{a_{ij} - \min_j}{\max_j - \min_j} \right), \tag{4}$$

where w_j is the weight of criterion j, a_{ij} is the actual (non-subjective) value of action i on criterion j and $[\min_j, \max_j]$ is the domain of criterion j (i.e. $a_{ij} \in [\min_j, \max_j], \forall i, j$). For example, for the criterion 'number of entities in a cluster' and a cluster i containing 20 entities, we would have $a_{ij} = 20$.

The weights are the parameters that we seek to estimate. Every interaction of the user can be translated into a constraint $a_i \succ a_k \Leftrightarrow u(a_i) \geq u(a_k)$ using the model described above; the goal of the learning procedure is to determine the weights in such manner that as many constraints as possible are satisfied. To learn the weights, we apply the UTA method (Jacquet-Lagrèze and Siskos, 1982; Siskos and Yannacopoulos, 1985) which consists in solving the following linear optimization problem:

$$\begin{cases} \min \sum_{a_i \in \mathcal{A}} \sigma(a_i) \\ \text{s.t. } u(a_i) + \sigma(a_i) \geq u(a_k) + \sigma(a_k) \text{ if } a_i \succ a_k \\ \quad \sum_j w_j = 1 \\ \quad w_j \geq 0 \quad \forall j \\ \quad \sigma(a_i) \geq 0 \quad \forall a_i \in \mathcal{A}, \end{cases} \tag{5}$$

where the $\sigma(a_i)$ are error-variables assigned to each action $a_i \in \mathcal{A}$. By minimizing the sum of the error variables, this linear program determines the weights that allow most closely matching the preference constraints derived from user interactions. For more details on this and other topics in UTA and other related methods, the reader may refer to (Siskos et al., 2005; Bous et al., 2010).

A final remark is due. In decision theoretic contexts, it is known in advance whether a criterion should be maximized or minimized, i.e. the value of s_j is given (the decision maker provides this information 'orally' to the analyst). In our context, however, this information must be interpreted from user interactions directly. To estimate the signs, we define a set of points in the neighborhood of the origin (in utility-function space) and compute the distance to the constraints for those points. Then we take the signs of the point in the set that minimizes the total error (sum of the errors).

In the following section, we describe the 'learning procedure', i.e. how user interactions are recorded and interpreted in view of applying the learning algorithm.

4.2 Learning Process

Learning from user interactions implies storing the preference constraints and solving the optimization problem discussed in the previous section. Figure 5 gives an overview of the different steps of the real-time learning process: first, every interaction is translated into preference constraints (on the basis of the criteria defined in the previous section), which must be stored. The set of constraints is then used to determine whether criteria should be minimized or maximized (sign detection); next, both the constraints and the signs are used to calculate the weights of the interest function by the resolution of (5). Once the interest function has been 'learned', it is used to define the default sequence for the exploration of the graph with the slider.

In addition to these steps, we emphasize that learning and updating the 'interest function' of the user in real-time raises several questions. For instance, how frequently should the interest function be updated? And, how should the record of user interactions (i.e. the set of constraints) be managed and updated?

With respect to the record of user interactions, there are several possible solutions. The first and simplest one is to keep all constraints generated, but this has the disadvantage to lead to a very high number of constraints, which may pose storage problems. Al-

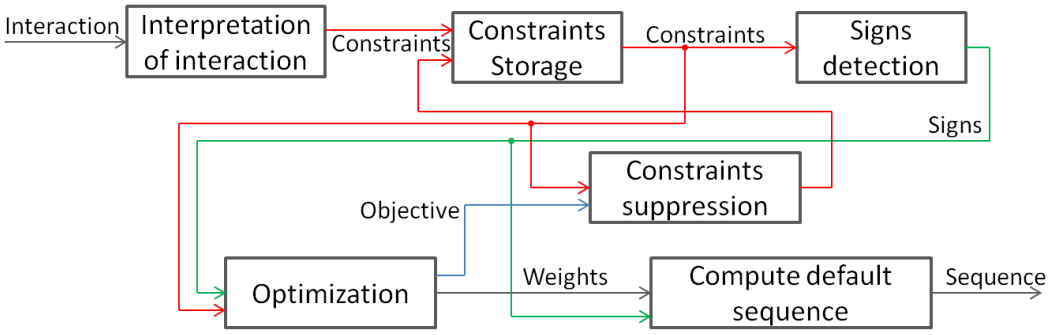


Figure 5: Diagram of the real-time learning process.

ternatively, it is possible to reinitialize the set of constraints on a regular basis, e.g. for each graph explored or each use of the software. More advanced update procedures are possible, but, for testing and experimentation purposes, we chose to reinitialize the history at each use of the software.

For a given record of user interactions, the next challenge is to decide which constraints should be used in the optimization problem (i.e. we here distinguish between storage and optimization issues). As the number of constraints grows, the error variables in the optimization problem may increase. This is typically the case if the interaction pattern changes over time. For example, the user may start exploring a graph with a few 'random' actions before starting to show a consistent exploration behavior. Large error variables can thus be considered as indicators reflecting that the set of preference constraints may no longer be relevant and require an update. However, determining which constraint needs to be removed from the record in order to maximally reduce the objective function of (5) is a combinatorial problem and its exact resolution is difficult to implement in a real-time learning environment. To solve this problem, we therefore implemented and tested several heuristic methods.

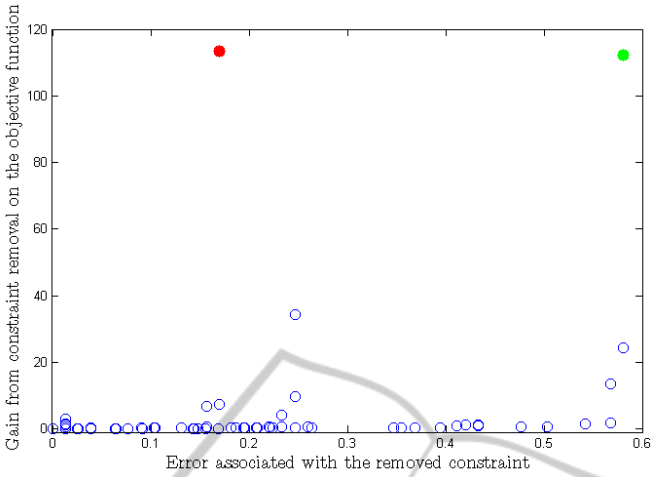
A fast and simple heuristic to address the problem is to simply remove the constraints that trigger the highest error variables. Our experiments show that this heuristic approach yields good results (see figure 6(a)) compared to the optimal solution (computed by exhaustive enumeration). In our implementation, as soon the objective function of (5) exceeds a certain threshold, the heuristic method is applied (one or several times) to bring the value of the objective function below the threshold.

A second heuristic method tested was to remove the oldest constraints. The idea here is that, if the interaction pattern has changed, then old constraints are obsolete and should thus be removed. However, this technique does not work well as it does not significantly reduce the objective function. The reason for this is that, when the change in the interaction pattern occurs, it may take many more constraints to exceed the threshold of the objective function. In our experiments, this method required removing more than half of the constraints for a given threshold in order to reduce the value of the objective function significantly (see figure 6(b)).

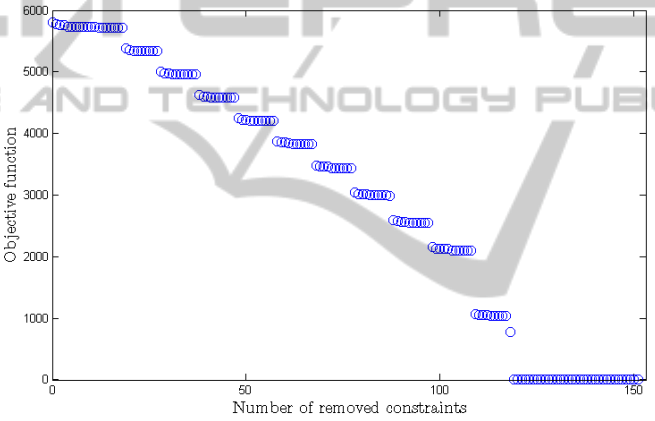
A third approach is to define a lifetime for each constraint. As soon as a constraint is generated, it is included in the optimization problem for a limited number of steps (counted in user interactions) only. The intuition behind this technique is that, if the user is consistent and continues to explore the graph with the same goals, then similar constraints should 'naturally' reappear regularly. This method not only produces good results (see figure 6(c)), but it also allows to solve the storage and memory problem evoked earlier in this section. While this solution is the most technically and conceptually satisfying, 'preference constraint management' is an important component of systems which learn from user interaction; therefore it is important to test this and other methods with a larger pool of users to evaluate which approaches are most 'natural' to users. We leave this question open for further research.

5 DISCUSSION

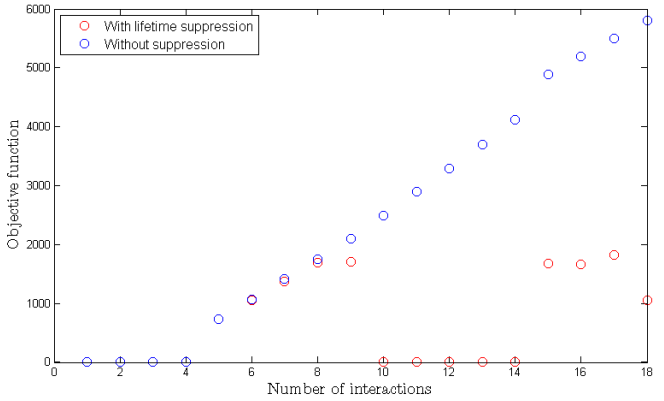
Our main goal in this investigation was to analyze the feasibility and technical requirements of an 'intelligent visual analysis system' for complex data structures on the basis of 'simple' controls. The combination of fields like Visual Analytics and Artificial Intelligence are still at a pioneering stage and the challenges left to address and topics that still have to be investigated are many. The *model*, the *learning set* and the *interpretation* of man-machine interactions are the three ingredients that ultimately define the 'behavior' and quality of a learning-based system. Therefore, it



(a) Test on constraint suppression that shows that the removal of the constraint with the largest slack variable (in green) is one of the best solutions to minimize the objective function (optimum is in red).



(b) Evolution of the objective function when removing the constraints one by one from the oldest to the most recent.



(c) Evolution of the objective function when constraints are taken into account only in the 5 steps that follow their apparition.

Figure 6: Experimental results of constraint management heuristics.

is necessary to experiment with several models and 'constraint management techniques' in order to understand how real-time learning systems for visual analytics should be designed to better reflect user behav-

ior and maximize user satisfaction.

In addition to the 'conceptual' and system-design oriented challenges, it is worthwhile to address the 'behavioral aspects' of graph exploration, which also play a key role in a system designed to learn from man-machine interactions. For instance, it is worth investigating whether preferred interactions differ from graph to graph or application area or whether they are particular to a user. Moreover, in depth experimental evaluations would allow to analyze the efficiency of exploration strategies, as well as to determine how and when 'good strategies' should be recommended to users in view of avoiding confinement to systematic routine exploration mechanisms.

Finally, many technical challenges have to be addresses as well. In addition to a formalization of the methods and techniques we presented here, many directions for future research exist. To name a few, we cite the interest function described used in our investigation, which is only based on criteria related to the structure of the graph; a relevant extension is to introduce attribute-based criteria as well. In addition, it is worthwhile to further analyze how sequences of interactions should be interpreted for real-time machine learning algorithms. Indeed, a single action on a graph may not necessarily reflect user intention. In other terms, certain goals of the user may require a sequence of actions to be met. The challenge is then not only to define a model capable of modeling preferences on such sequences, but ultimately also to detect or interpret them in what is otherwise nothing but a long list of interaction events.

6 CONCLUSIONS

In this paper we presented a new tool developed to understand and improve user experience in the exploration of graphs. The tool empowers users to control the granularity of the graph, either by direct interaction (collapsing/expanding clusters) or via a slider that automatically computes a clustered graph of the desired size. Moreover, we explored the use of learning algorithms to capture graph exploration preferences based on a history of user interactions. The learned parameters are then used to modify the action of the slider in view of mimicking the natural interaction/exploration behavior of the user.

Our work is a first step toward the use of machine learning algorithms to define the actions associated to simple interactive controls, like sliders, for the exploration of complex data structures like graphs. We show that such an approach is technically feasible and encourage further research in this direction in view of bringing graphs and graph analysis closer to users. In general, visual analysis systems designed to learn from user interactions with the goal of enhancing user experience deserve more attention and have many fascinating research challenges to offer.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the valuable comments of the anonymous referees, which helped to improve the initial version of this manuscript.

REFERENCES

Aleskerov, F., Bouyssou, D., and Monjardet, B. (2007). *Utility Maximization, Choice and Preference*. Springer, Berlin.

Archanbault, D., Munzner, T., and Auber, D. (2002). Tuggraph: path-preserving hierarchies for browsing proximity and paths in graphs. In *Proceedings of IEEE Pacific Visualization Symposium*, page 113120.

Archanbault, D., Munzner, T., and Auber, D. (2008). Grouseflocks: Steerable exploration of graph hierarchy space. *IEEE Transactions on Visualization and Computer Graphics*, 14:900913.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., and Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008:P10008.

Bous, G., Fortemps, P., Glineur, F., and Pirlot, M. (2010). ACUTA: A novel method for eliciting additive value functions on the basis of holistic preference statements. *European Journal of Operational Research*, 206:435–444.

Card, S., MacKinlay, J., and Schneiderman, B. (1999). *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann, Burlington.

Duch, J. and Arenas, A. (2005). Community detection in complex networks using extremal optimization. *Physical Review E*, 72:027104.

Elmqvist, N., Do, T.-N., Goodell, H., Henry, N., and Fekete, J.-D. (2008). Zame: Interactive large-scale graph visualization. In *Proceedings of the IEEE Pacific Visualization Symposium*, pages 215 –222.

Elmqvist, N. and Fekete, J.-D. (2010). Hierarchical aggregation for information visualization: Overview, techniques and design guidelines. *IEEE Transactions on Visualization and Computer Graphics*, 16:439–454.

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, 486:75 – 174.

Ghoniem, M., Fekete, J.-D., and Castagliola, P. (2005). On the readability of graphs using node-link and matrix-based representations: A controlled experiment and statistical analysis. *Information Visualization*, 4:114–135.

Girvan, M. and Newman, M. E. J. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, 99:78217826.

Heer, J. and Boyd, D. (2005). Vizster: visualizing online social networks. In *Proceedings of the IEEE Symposium on Information Visualization*, page 3239.

Heer, J. and Perer, A. (2011). Orion: A system for modeling, transformation and visualization of multidimensional heterogeneous networks. In *Proceedings of the 2011 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 51 –60.

Henry, N. and Fekete, J.-D. (2006). Matrixexplorer: a dual-representation system to explore social networks. *IEEE Transactions on Visualization and Computer Graphics*, 12:677–684.

Henry, N., Fekete, J.-D., and McGuffin, M. (2007). Nodetrix: a hybrid visualization of social networks. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1302 –1309.

Jacquet-Lagrèze, E. and Siskos, Y. (1982). Assessing a set of additive utility functions to multicriteria decision-making: the UTA method. *European Journal of Operational Research*, 10:151–164.

Keeney, R. L. and Raiffa, H. (1976). *Decisions with multiple objectives: Preferences and value tradeoffs*. Wiley, New York.

Kernighan, B. W. and Lin, S. (1970). An efficient heuristic procedure for partitioning graphs. *Bell System Technical Journal*, 49:291307.

Latapy, M., Magnien, C., and Vecchio, N. D. (2008). Basic notions for the analysis of large two-mode networks. *Social Networks*, 30:31 – 48.

Liu, Z., Navathe, S., and Stasko, J. (2011). Network-based visual analysis of tabular data. In *Proceedings of the 2011 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 41 –50.

Mehta, G. B. (1998). Preference and utility. In Barberà, S., Hammond, P. J., and Seidl, C., editors, *Handbook of Utility Theory*, volume 1, pages 1–47. Kluwer, Dordrecht.

Newman, M. (2004). Detecting community structure in networks. *The European Physical Journal B - Condensed Matter and Complex Systems*, 38:321–330.

Newman, M. E. J. and Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, 69:026113.

Radicchi, F., Castellano, C., Cecconi, F., Loreto, V., and Parisi, D. (2004). Defining and identifying communities in networks. *Proceedings of the National Academy of Sciences*, 101:2658–2663.

Shneiderman, B. and Aris, A. (2006). Network visualization by semantic substrates. *IEEE Transactions on Visualization and Computer Graphics*, 12:733 –740.

Siskos, Y., Grigoroudis, E., and Matsatsinis, N. (2005). UTA methods. In Figueira, J., Greco, S., and Ehrgott, M., editors, *Multiple Criteria Decision Analysis: State of the Art Surveys*, pages 297–344. Springer, Berlin.

Siskos, Y. and Yannacopoulos, D. (1985). UTASTAR: an ordinal regression method for building additive value functions. *Investigaao Operacional*, 5:39–53.

Suaris, P. R. and Kedem, G. (1988). An algorithm for quadrisection and its application to standard cell placement. *IEEE Transactions on Circuits and Systems*, 35:294–303.

van Ham, F. and Perer, A. (2009). Search, show context, expand on demand: supporting large graph exploration with degree-of-interest. *IEEE Transactions on Visualization and Computer Graphics*, 15:953960.

von Landesberger, T., Kuijper, A., Schreck, T., Kohlhammer, J., van Wijk, J. J., Fekete, J.-D., and Fellner, D. W. (2011). Visual analysis of large graphs: State-of-the-art and future research challenges. *Computer Graphics Forum*, 30:17191749.

Wattenberg, M. (2006). Visual exploration of multivariate graphs. In *Proceedings of the SIGCHI conference on Human Factors in computing systems*, pages 811–819.

Wu, A. Y., Garland, M., and Han, J. (2004). Mining scale-free networks using geodesic clustering. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 719–724.