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VISUALIZING PRODUCTIVE NETWORKS

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ABSTRACT

Recommending new connections to users is an important tool for productive networks, but users are not always clear about how they are connected to the recommended contacts in the network graph. Providing insight about the arguments used to build a recommendation increases the chances of its acceptance by users. This work is focused on recommendations that rely on an information model that enables recommendation systems, using only the relationships between users, items and keywords. These elements define the productive network graph, which this work represents in a visualization and interaction platform whose goal is twofold: to provide a discovery tool for productive networks, through which users can navigate the graph using different visualization contexts; and to provide insight about indirect relationships, representing which direct relationships are relevant for a particular recommendation. The platform is designed to work with any data that complies with this model. The visualization elements and interaction operations have been evaluated through the implementation of a case study, based on a sample of the Flickr network, producing positive results.

KEYWORDS

Information Visualization, Collaboration, Insight, Perception, Interaction.

1. INTRODUCTION

Most social networks have recommendation mechanisms in place to help the user to find potential contacts or interesting content. Usually, the decision to accept a new contact may be driven by a previous relationship offline, intermediary relationships or similarity of interests. Contact management and relationship suggestion channels on current social networks mimic these circumstances but allow the user to define the network according to a personal determination, even if, from an algorithmic perspective, the new connections chosen are really not recommended.

Allowing the user to analyze, from available data, the circumstances leading to a relationship recommendation, using different perspectives, is an added value to supporting networking decisions.

These principles are not restricted to social networks, and may apply to some computer supported cooperative work networks, therefore this work refers to any suitable network as a *productive network*. Initially presented in (Sabino, Rodrigues, et al. 2014), productive network is defined as any network through which users share content, and are able to annotate that content. The model enables the definition of graphs representing a community's information structure, through the use of three basic concepts: *user*, *item* and *keyword*. Between these concepts, relationships are assumed from evidence taken from the data available in the network. The model allows for the representation of three types of binary relationships between users:

- **Co-authoring**: when two users share the same item;
- **Direct relationship**: when two users are not co-authors but their items are related with a common set of Keywords;
- **Indirect relationship**: when there is no direct relationship between two users but some of the keywords used to categorize their items are related by other users' items.

Section 3 provides a formal description of the productive network model.

From a user's perspective, the complex network of direct and indirect relationship is not easily grasped. To provide insight on the relationship network, this paper presents a web-based graph visualization and interaction platform, which enables the visual identification of relationships in a *productive network*. This work was initially proposed in (Sabino, Gouveia, et al. 2014), and further explored in (Gouveia et al. 2014).

Given that our goal is to provide awareness about relationships on the network, our platform should be able to inform about the context of that relationship and avoid visual cluttering, by selectively show and hide information. The user should be able to navigate through relationships, which may involve changes in the context and require real time decisions to avoid cluttering.

The design goals of the platform are the following:

1. Selectively display the relevant information to understand a particular set of relationships;
2. Provide awareness about the context of any given visualization;
3. Enable changes in the focus of the visualization, between users, items, and keywords;
4. Avoid visual clutter;
5. Enable navigation.

Driven by the model, the platform is based on a graph structure, with nodes representing information elements, and edges as connections between those elements. The information model supports 6 different types of graphs, each with a different combination of basic concepts as nodes and edges. However, not all combinations are useful for a particular network. Therefore, catering for our particular case study (see section 5), the platform enables 3 different perspectives over the network, each tailored to visualize different recommendation approaches: commonly annotated items; users who share keywords; or keywords related with the user's items. The platform is extensible to support the remaining graph representations.

The platform enables the construction of tools that provide insight over the indirect relationship discovery. The platform and its interactive capacities have been evaluated through the implementation of a case study, based on a sample of the Flickr (http://www.flickr.com) network. The case study was evaluated through user studies, and obtained positive results.

Section 2 presents the related work. Section 3 presents the platform user interaction design. Section 0 details the implementation. Section 5 introduces the case study. Section 6 describes the evaluation and presents the results. Section 7 draws some conclusions and discusses future work.

2. RELATED WORK

The visualization platform's main goal is to provide insight on indirect relationships, by enabling the user to navigate the network, while controlling the elements of the view. (Yin et al. 2013; Spence & Press 2000; Gregory 1997) studied the relevancy on enabling users to gain insight, while navigating the system, and how perception is strongly connected to long term memory, thus the importance of using representations that are close to the type of users of the system.

However, the level of complexity must be handled, as too much complexity and the user may not perceive the intended interpretation. (Wong et al. 2003) present different techniques for clutter reduction, demonstrating the relevance of sampling, filtering and clustering in information visualization systems.

The representation of networks using graphs has a long history, and is an approach followed by many research fields that deal with networked datasets (Freeman 2000).

(Heer & Boyd 2005) presented a visualization system for exploration and navigation of large-scale social networks called Vizster. The graph representation and interface layout is similar to ours (central display area, and right panel with detailed information), but instead of our simple/super elements and respective operations (see 0), the system hides information and focus solely on navigation.

The particular problem of representing direct relationships that may lead to indirect relationships requires visual representations of clusters of relationships and users. Several projects deal with similar constraints. Examples are the Discovr (Filter Squad 2011), Health InfoScape (MIT SENSEable City Lab 2011) and Opinion Cloud (Appinions 2011) projects.

Opinion Cloud uses an interesting clustering mechanic for nodes, which is incorporated in super nodes, so that the clutter on the screen would be reduced. It is also a proven concept, since it is in production, being regularly used by The Economist (http://www.economist.com/).

The Health InfoScape is completely designed for a particular health record data type and it is not as generic as our system. It aggregates nodes (representing symptoms) representing most frequent associations between medical conditions. Our platform uses edge thickness to represent frequency of associate.

We represent simple nodes and edge similarly to Discovr, using the same idea of expanding nodes and navigating through the data, instead of a regular search by text, but introduces the notion of super nodes. For the type of data that Discovr uses, which is musical artists as nodes, connected to recommendations, an expandable super node that aggregates several regular nodes could prove useful to represent musical trends or events that can be represented by a collection of artists. To implement this idea, and keep the platform as generic as possible, while being able to tackle large amounts of data, we proposed the use of super nodes. Discovr also does not support different types of visualizations (perspectives). It is important to note that the data from Discovr could be used in our platform leading to a workable case-study, while a sample from Flickr, similar to the one used in our work, could not be loaded into Discovr, as the different visualizations would not work, since the platform is domain dependent.

3. INFORMATION MODEL

This section gives a more precise definition of the productive network model, as presented in (Sabino, Rodrigues, et al. 2014). We extend that definition with a formal representation of the graph visualizations enabled by the platform.

The basic elements of the model are users, *U*, items, *I*, and keywords, *K*. Items are owned by users, and annotated with keywords.

The subscripts used in the definitions serve to distinguish between elements of the same set. We use *i*, *j*, *k* for users; *p*, *q*, *r* for keywords; *t*, *u*, *v* for items; and *m*, *n*, *o*, *u* for set dimensions.

Let us define *U*, *I*, and *K* such as:

$$U = \{U_1, ..., U_n\} \text{ is a finite set of users}, n \geq 1$$
$$I = \{I_1, ..., I_m\} \text{ is a finite set of items}, m \geq 1$$
$$K = \{K_1, ..., K_v\} \text{ is a finite set of keywords}, v \geq 1$$

Definitions 1 and 2 represent the basic item management operations that the network provides to its users.

Definition 1: The ownership by a user, U_i, of an item, I_t, is defined by:

$$O(U_i) = \{I_t \mid I_t \text{ is owned by } U_i, I_t \in I, U_i \in U\}$$
$$Own(U_i, I_t) = \{I_t \in O(U_i)\}$$

Definition 2: The annotation of an item, I_t, by a keyword, K_p, is defined by:

$$T(I_t) = \{K_p \mid K_p \text{ is associated with } I_t, K_p \in K, I_t \in I\}$$
$$Annotate(K_p, I_t) = \{K_p \in T(I_t)\}$$

We refer to keywords that are used in annotations as the user's direct keywords. In definition 3, the set $T(I_t)$ is the set of direct keywords of item I_t.

Definition 3: For a user , U_i, the set of all direct keywords of all of the user's items is defined by:

$$UK(U_i) = \{K_p \mid \forall I_t \in O(U_i), \forall K_p \in T(I_t)\}$$

We now define the relationships that items and keywords enable between users. We begin with the definition of direct relationship, which established a link between users.

Definition 4: A direct relationships, *DR*, between two users, U_i and U_k, is defined by:

$$DR(U_i, U_j) = \{K_p \mid I_t \in I, I_u \in I, \exists K_p \in K : Own(U_i, \mathrm{I}_t), Own(\mathrm{U}_j, I_u), Annotate(I_t, K_p), Annotate(\mathrm{I}_u, K_p)\}$$

It is now possible to describe graphs implicitly defined by the network. Definition 5 presents the graph of users connected by keywords.

Definition 5: The graph that relates users in the network is defined by $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$, such that:

$$\mathcal{V} = \{U_i \mid \exists U_j \in U : DR(U_i, U_j) \neq \{\varnothing\}\}$$
$$\mathcal{E} = \{K_p \mid \exists U_i, U_j \in U : \mathrm{U}_i \neq U_j, K_p \in DR(U_i, U_j)\}$$

Note that the definition excludes isolated users, which cannot be related with any other users through any keyword. Our model does not consider users in isolation.

In (Sabino, Rodrigues, et al. 2014; Sabino & Rodrigues 2014), the productive network model is presented with a single graph inferred from the network, which relates users through keywords. The graph in definition 5 is that same graph, but in fact, it is only one of six different graphs that can be defined using the three basic concepts of our model. Each graph uses a different combination of node and edge.

For the task of enabling changes in the focus of the visualization (task 3, in section 1), we must take into account additional combinations of basic concepts. Furthermore, to avoid visual clutter (task 4), we propose to restrict the graph nodes to a set of related elements. A particular visualization is seeded by a particular node, and the complete set of nodes and edges are defined by the relationships that other elements have with the seed element.

Table 1 presents all possible combinations. The graphs in the table provide several structured representation for enabling different visualizations of the information in the network.

To build a graph in Table 1, we begin with a random or user selected node. The content of this initial restricts the type of content available for the node set. The type of edge is selected by the user.

The set of edges contains all the relevant edges for each node in the set of nodes, according to the specifications in Table 1. Each element in the set of nodes is queried in the network to obtain all its relevant edges. When an element that is not in the set of nodes would enable an edge with an existing node, this element is included as a node, and is then queried in the network for edges.

This approach will eventually include all the nodes and edges in the network, leading to the visual clutter we are set to avoid.

To deal with the clutter, we propose two special types of node and edge, in order to represent sets instead of single elements: the super node and super vertex.

We select every initial element as a single node. Furthermore, each element that uniquely uses an edge to connect to a single node, is also a single node. All other elements are grouped in a super node. Similarly, each edge that connects to an edge (single or super), is represented as a single edge if there are no more edges that could connect the nodes. Otherwise, it is represented as part of a super edge. A further description of single and super nodes and edges is presented in Section 0, and in Table 2. Operations available to the different element types

Table 1. All possibilities of productive network graphs.

Nodes - $\mathcal{V}$	Edges - $\mathcal{E}$	Graphs - $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$
Users	Items	$\mathcal{V} = \{U_i \in U \mid \exists U_j \in U : DR(U_i, U_j) \neq \{\emptyset\}\}$ $\mathcal{E} = \{I_t \in I \mid \exists U_i, U_k \in \mathcal{V} : U_i \neq U_j, Own(U_i, I_t), Own(U_k, I_t)\}$
	Keywords	$\mathcal{V} = \{U_i \in U \mid \exists U_j \in U : DR(U_i, U_j) \neq \{\emptyset\}\}$ $\mathcal{E} = \{K_p \in K \mid \left\{ \begin{matrix} \exists U_k \in \mathcal{V} \mid \exists I_t \in O(U_k) : Annotate(K_p, I_t) \\ \exists U_j \in U : K_p \in DR(U_i, U_j) \end{matrix} \right\} \}$
Items	Users	$\mathcal{V} = \{I_t \in I \mid \left\{ \begin{matrix} \exists U_i \in U, \exists U_j \in U : Own(U_i, I_t), Own(U_j, I_t) \\ \exists K_p \in K : Annotate(K_p, I_t) \end{matrix} \right\} \}$ $\mathcal{E} = \{U_i \in U \mid \left\{ \begin{matrix} \exists I_u \in \mathcal{V} : Own(U_i, I_u) \\ \exists U_j \in U : DR(U_i, U_j) \neq \{\emptyset\} \end{matrix} \right\} \}$
	Keywords	$\mathcal{V} = \{I_t \in I \mid \left\{ \begin{matrix} \exists U_i \in U, \exists U_j \in U : Own(U_i, I_t), Own(U_j, I_t) \\ \exists K_p \in K : Annotate(K_p, I_t) \end{matrix} \right\} \}$ $\mathcal{E} = \{K_p \in K \mid \left\{ \begin{matrix} \exists I_u \in \mathcal{V} \mid Annotate(K_p, I_u) \\ \exists U_j \in U : K_p \in DR(U_i, U_j) \end{matrix} \right\} \}$

Keywords	Users	$\mathcal{V} = \{K_p \in K \mid \exists I_t \in I : Annotate(K_p, I_t)\}$ $\mathcal{E} = \{U_i \in U \mid \begin{Bmatrix} \exists K_q \in \mathcal{V} \mid \exists I_t \in O(U_i) : Annotate(K_q, I_t) \\ \exists U_j \in U : DR(U_i, U_j) \neq \{\varnothing\} \end{Bmatrix}\}$
	Items	$\mathcal{V} = \{K_p \in K \mid \exists I_t \in I : Annotate(K_p, I_t)\}$ $\mathcal{E} = \{I_t \in I \mid \begin{Bmatrix} \exists K_q \in \mathcal{V} \mid Annotate(K_q, I_t) \\ \exists K_p \in K \mid K_p \notin \mathcal{V} : Annotate(K_p, I_t) \end{Bmatrix}\}$

The next section presents the visualization and interaction framework which enables a visual representation of the graphs in Table 1, and a set of operations that enable the user to change from one graph to another.

4. PLATFORM DESIGN

The representation of the graph is based on visual elements, described below, which are identified by labels. Each label may be a name, an image, or both. It also uses the notion of super elements, which are collections of single elements, to deal with visual cluttering. The platform enables visualizations using any combination between two of the three productive network concepts (users, items and keywords) as a relationship. An example of a visualization is items, e.g. photos (as nodes), connected through common keywords (as edges).

4.1 Platform Description

The platform’s web-interface has three main areas, presented in Figure 1. The central area displays the interactive graph. On the top panel, the user can choose the type of visualization he wants to use and check which is the current one. Finally, the right panel provides access to all the information relative to the currently selected graph element. All areas are interconnected and the interaction in one of them could trigger a change in another (e.g. the selection of a graph element triggers a change of information on the right panel).

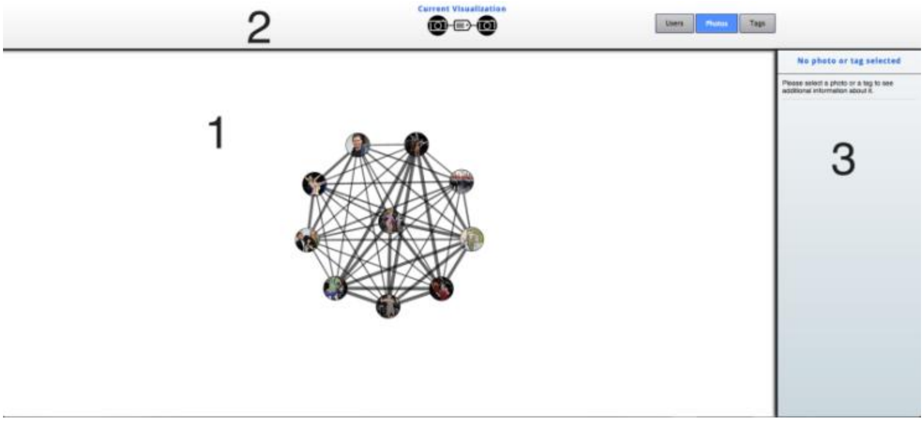

Figure 1. Main area: 1 - Graph area; 2 - Top panel; 3 - Right panel.

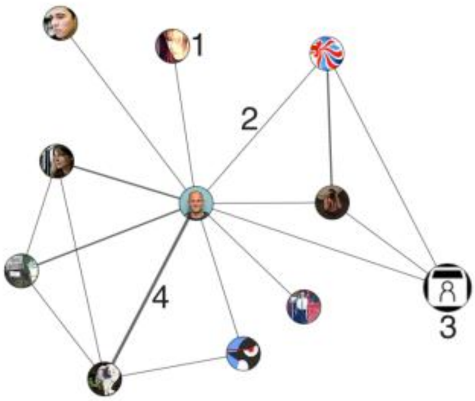

Figure 2. Visualization elements: 1 - Single Node; 2 - Single Edge; 3 - Super Node; 4 - Super Edge.

The graph area enables visualization and interaction with information and connection elements (see Figure 2), providing browsing and searching tools on the collaborative potential information.

4.2 Elements and Operations

The visualization elements can be divided into two groups:

- Information elements to be analyzed, either represented by a single node in the graph or by a super node (group of single nodes);
- Connecting elements, represented by a single edge, or a super edge (group of edges). Super elements represent a collection of nodes or edges, respectively.

Combinations of these four elements (simple and super nodes, and simples and super edges) together form a visualization graph.

Each element enables two different types of inter-dependent operations, i.e., the second type can only be applied after the first.

Table 2 presents a description of every operation available to each type of element.

Table 2. Operations available to the different element types

Element	Operations	
Single Node	**Selection** Access to the node's information.	**Expansion** Access to nodes related through a chosen edge. If the results include more than one node, the nodes are grouped in a super node.
Super Node	**Selection** Access to every single node that belongs to the super node.	**Extraction** Moves interior node from the group into the graph area. If every node is extracted, the super node disappears.
Single Edge	**Selection** Access to the edge's information.	**Addition of a single node** Chooses one related node and adds it to the graph as a single node.
Super Edge	**Selection** Access to every single edge contained in the super edge.	**Expansion** Moves nodes reachable from an interior edge of the group into the graph area. If the results include more than one node, these are grouped in a super node.

Table 2, Figure 2 shows sample node representations using the Flickr case study (see section 5).

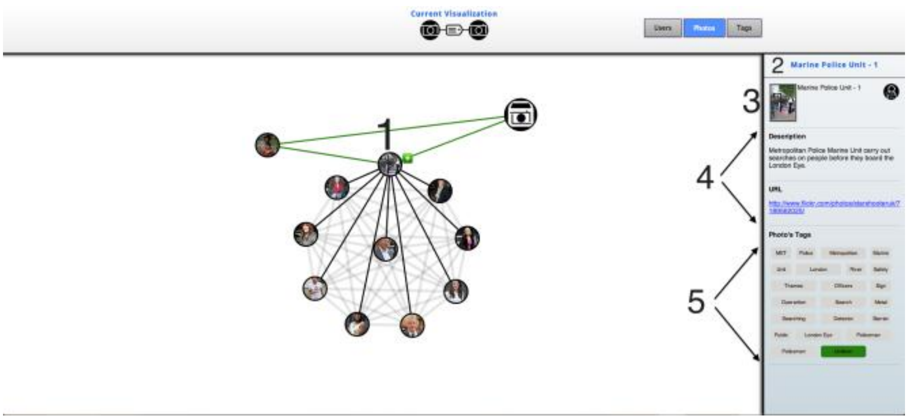

Figure 3. Representation and operations of simple nodes: 1 - Selected node; 2 - Text label; 3 - Image label; 4 - Additional information; 5 - Node's edges that can be expanded (nodes already visible are highlighted).

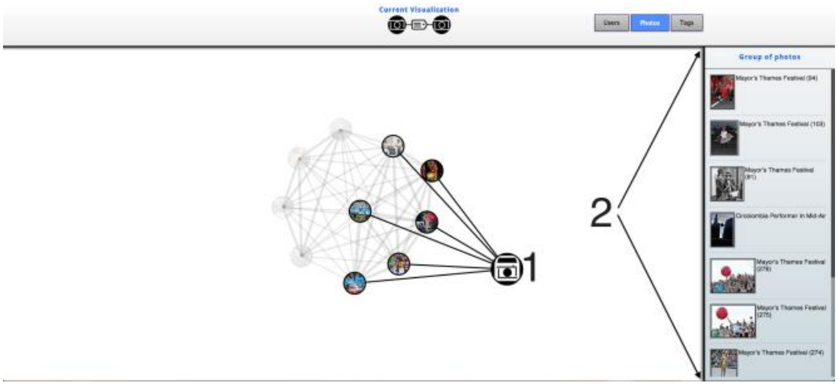

Figure 4. Representation and operations of super nodes: 1 - Selected super node; 2 - Group's single nodes. Each can be added to the graph by the extraction operation.

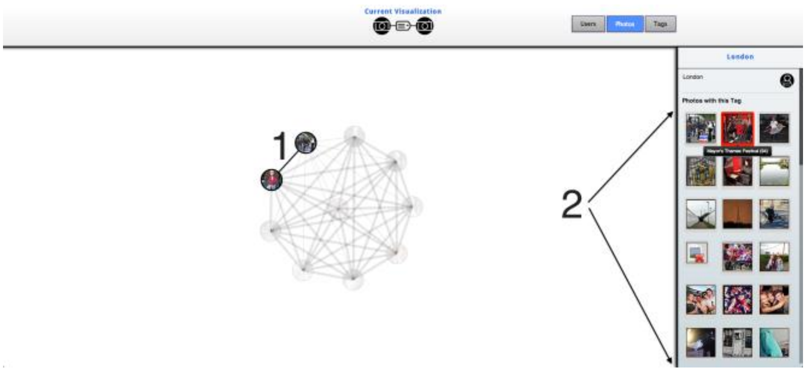

Figure 5. Representation and operations of simple edges: 1 - Selected edge; 2 - Edge's nodes that can be added to the graph (addition operation). The red color on the node means that it still does not exist on the graph.

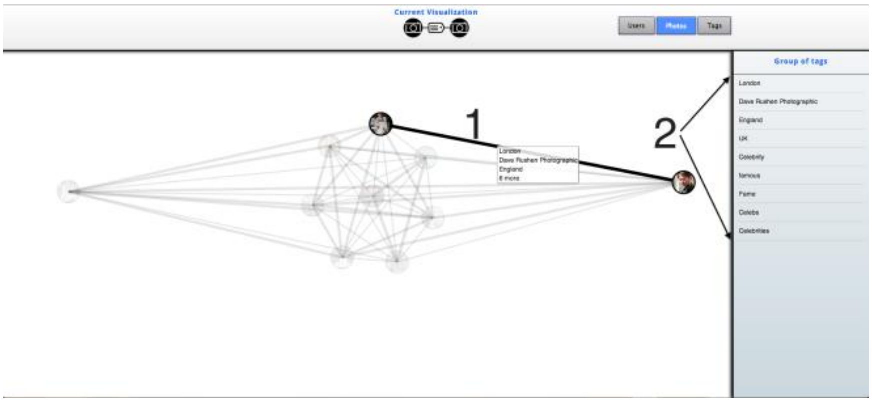

Figure 6. Representation and operations of super edges: 1 - Selected super edge; 2 - Single edges. Each one of them can be added to the graph by the expansion operation.

Navigating the information elements through their connections, by expanding, adding and extracting elements, enables the user to interactively add wanted elements to the visualization. Moreover, the user is allowed to manage the level of clutter on the interface, e.g. by choosing which edges to expand and moving nodes around.

4.3 Graph Interaction

Interaction is enabled by dragging nodes, selecting elements (node or edge), zooming (mouse scroll), or dragging the whole graph (panning, click and drag on an empty space). Each element can be subject of two types of operations (see section 0). The selection operation is triggered by a mouse click on the element, showing the element's information. Context operations like expansion, extraction and addition, available after a selection, are accomplished through drag and drop. For example, when a single node is selected, the edge expansion operation for the node is accomplished by dragging the edge label from the right panel to the graph area.

Element information is presented on the right panel. It includes the element's title and, when available, a text label. If applicable, it also includes the image label and any additional information. The right panel may also shows listings: if the selected element is a single node, then the panel lists every edge that the node uses as a connection; if it is a single edge, the panel will list every node related to another node through the selected edge.

Expansion and addition operations can be triggered on selected elements (see section 0). When an element is selected, the elements that are not directly connected to it become faded, to eliminate clutter on screen (Ellis & Dix 2007).

A super node representation is larger than a single node's, varying with the number of nodes that the group contains. A super edge is thicker than a single edge, with the thickness also varying with the number of single edges that it represents. When a super element is selected, the single elements that belong to it are listed on the right panel. Extraction (super node) and expansion (super edge) operations can be applied on the group's single elements through their drag and drop movement into the graph area (see section 0).

4.3.1 Switching Visualizations

Switching between visualizations is enabled by buttons at the top panel, and by the context of the selected element, e.g., when visualizing items connected by keywords, and an item is selected, the interface provides a switch button at the right panel to a graph of the users related with the item (see Figure 7 for an example). The operation is also possible when selecting an edge, e.g., selecting a keyword enables a switch button to a graph of users related with the tag.

Figure 7. 1 - Switch button; 2 - Available nodes, related to the selected element, for the new (changing context) graph visualization.

4.4 Implementation

The web interface was developed with the support of the D3 (Data-Driven Documents – http://d3js.org/) Javascript framework, which automatically arranges the nodes and edges, while trying to avoid overlaps between them.

The algorithm uses the Vertlet integration (Verlet 1967) to allow for simple constraints (Dwyer 2009). The nodes are given a repulsive force to prevent overlap between them and the center of the screen holds a pseudo-gravity force, in order to maintain the elements on the center of the screen and to prevent disconnected sub-graphs to leave the screen. This pseudo-gravity force becomes stronger the farther an element is from the screen, contrary to the normal gravity force. The algorithm also has a friction value which reduces the velocity of the animation through time until it reaches zero, in order to stop the graph elements from moving for too long.

Although the algorithm tries to prevent every element from overlapping, the increase of elements on screen will make this harder for the edges. The user is able to drag and drop the nodes in order to manually adjust the layout.

5. CASE STUDY

The example used for the development and testing of the platform was Flickr, a Yahoo platform where users can share photos. Flickr's data model is easily adapted to the platform's model: Flickr users, photos and tags are modeled into the (Sabino, Rodrigues, et al. 2014) model of users, items and keywords, respectively. In Flickr, users submit their photos and associate tags with them, thus also becoming individually associated with the tags. These associations enable several perspectives over the network, possible to be visualized in the platform: users connected by tags, photos connected by tags and tags connected by photos.

5.1 Case Study Limitations

This work focused on a Flickr dataset, mainly because the relationship model in (Sabino, Rodrigues, et al. 2014) was initially validated using the same dataset. However, Flickr does not enable users to be connected by common photos. This happens because photos are singularly authored. This fact limits the model, since it is not possible to identify current relationships with items (photos) as a connection, on this particular dataset.

Moreover, Flickr does not supervise the quality of the annotation process, leading to duplicated keywords and empty values.

6. EVALUATION

The platform was evaluated by 15 users. Two types of questionnaires were presented. The first questionnaire was designed by the project's team and divided into two parts. The first part consisted of a general appreciation, based on pair-valued adjectives. In the second part, users were asked about the different features in the platform, related to usefulness and easiness of use.

The second questionnaire was made on Attrakdiff (http://attrakdiff.de/sience-en.html) and consisted of pair-valued adjectives to evaluate the general appreciation of the tool.

6.1 First Questionnaire Results

The general appreciation results, as seen in Figure 8, are positive, with most users considering the platform intuitive, pleasant, creative, useful, captivating and clear. Although the radial plot in Figure 8 shows the normalized results, to avoid routine responses by the users the choices were not always positively growing i.e., the value of 5 was not always associated with the most positive adjective and the value of 1 was not always associated with the most negative result.

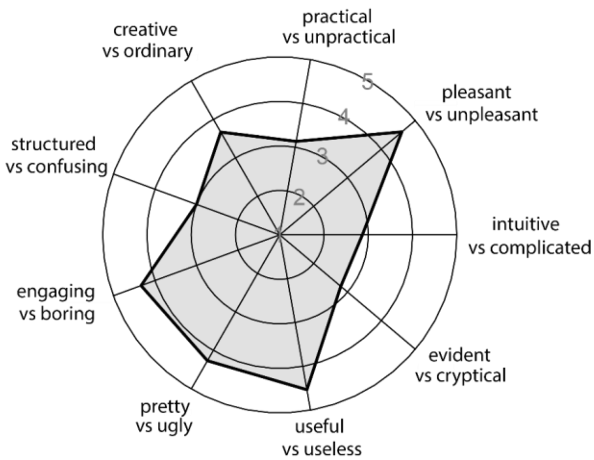

Figure 8. Summary of the results about the general appreciation of the platform. Paired adjectives were associated values between 1 and 5. Highest values are associated with the first (positive) adjective.

Table 3 summarizes the results of the second part of the questionnaire. It shows query by navigation was successful in enabling the exploration of new information, which partially validates our goal of providing awareness about the context and confirms the navigation as well suited interaction approach to switch between different network visualizations.

Users reacted positively to the amount of data that is generated (i.e., a single node or a super node) and understood the importance of hiding unwanted information and that the platform was successful in implementing this aspect. We successfully achieved our goal of avoiding visual clutter, while assuring that the user remains aware about the current visualization context.

Showing two components connected to each other is not always enough, and users felt the need to switch to other types of connections under the context of a specific element to learn more about the data, which validates the goal of enabling changes in the focus of the visualization. However, the users pointed out that the switch button was not immediately seen and could be better highlighted.

Some users had difficulties in identifying the navigation context, which could be related with inconsistencies in the Flickr data, as presented in section 0.

Table 3. Platform features evaluation results

Dimension	Evaluation: [ordinal] – count (percentage)				
Usefulness in expanding a tag.	Not Useful [1] 0 (0%)	[2] 1 (7%)	[3] 1 (7%)	[4] 8 (53%)	Very Useful [5] 5 (33%)
Usefulness of the clustering of nodes.	Not Useful [1] 0 (0%)	[2] 0 (0%)	[3] 0 (0%)	[4] 3 (20%)	Very Useful [5] 12 (80%)

Usefulness of the visualization switch.	Not Useful [1]	[2]	[3]	[4]	Very Useful [5]
	0 (0%)	0 (0%)	0 (0%)	5 (33%)	10 (66%)
Easiness in using the visualization switch and identifying the current context.	Hard [1]	[2]	[3]	[4]	Easy [5]
	0 (0%)	1 (7%)	2(13%)	8 (53%)	4 (26%)
Easiness in defining the meaning of the graph elements and in navigating to the wanted context.	Hard [1]	[2]	[3]	[4]	Easy [5]
	0 (0%)	1 (7%)	1 (7%)	8 (53%)	5 (33%)

6.2 Attrakdiff Results

The results of the Attrakdiff questionnaire are summarized in Figure 9. The user interface was rated as desired. In terms of hedonic quality, the results indicated that the users identified with the product and were motivated and stimulated by it.

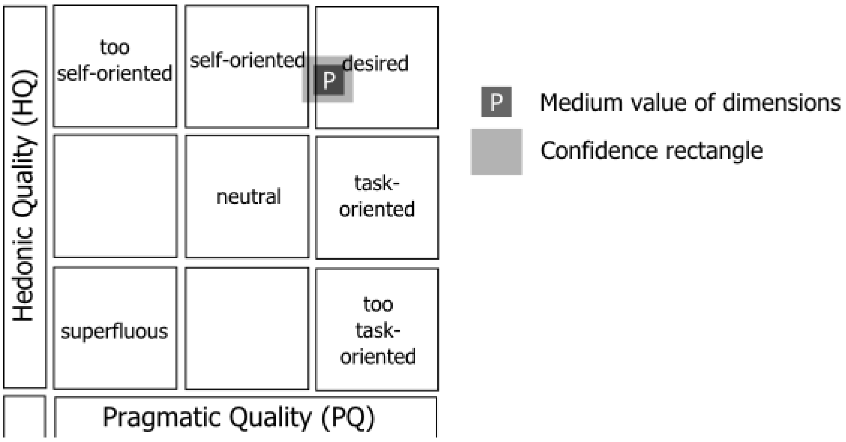

Figure 9. Attrakdiff results.

6.3 Evaluation Threats

Although two different questionnaires were submitted to the testers - a time period passed between the filling of the two - both produced similar results, giving more support to our results. However, we believe that their impact could be greater if two different groups of testers were used. This would be a more viable way of backing the results.

The questionnaires' answer scales are semantic differential scales, which are analyzed as interval scales, although it is only possible to guarantee a consensus on their validity if they were interpreted as ordinary scales. This lack of consensus exists because some researchers defend that the scale has, in itself, a problem which relates with the interpretation of intervals (Tullis & Albert 2008). Each user can have a different interpretation of the distances between the values, qualifying them in different ways.

7. CONCLUSIONS AND FUTURE WORK

This work presented a visualization and interaction platform for productive networks, where users are able to discover potential relationships through related data.

From the model of productive networks, we derived the formal definition of the content of all relevant visualizations, in an information discovery perspective.

The platform is designed to be used with different types of data, giving the possibility of finding relationships in many different fields, like music, cinema, literature, etc. The evaluation made to the system showed that it is successful in providing users with the information they look for, based on existing and potential connections in the data, when searching for collaboration potential while maintaining an uncluttered screen. The overall evaluation was positive.

Plans for future work on the platform are focused on interface elements like save and undo buttons, to enable users to go back to previous searched information. Although the aim of the platform was to enable exploration through the information, a way to search information by text is also planned. Finally, a feature to collapse or delete nodes was suggested by users during evaluation. This function would facilitate cleaning the screen when too much information is visible. Future work also includes experiments with different productive networks, specifically those where items can be related to several users, e.g., scientific articles indexing networks, and movie, music, art, or literature databases.

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