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ScienceDirect

Procedia Computer Science 149 (2019) 138–150

Procedia Computer Science

www.elsevier.com/locate/procedia

ICTE in Transportation and Logistics 2018 (ICTE 2018)

# Visual analytical dashboards for comparative analytical tasks – a case study on mobility and transportation

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**Abstract**

Mobility, logistics and transportation are emerging fields of research and application. Humans' mobility behavior plays an increasing role for societal challenges. Beside the societal challenges these areas are strongly related to technologies and innovations. Gathering information about emerging technologies plays an increasing role for the entire research in these areas. Humans' information processing can be strongly supported by Visual Analytics that combines automatic modelling and interactive visualizations. The juxtapose orchestration of interactive visualization enables gathering more information in a shorter time. We propose in this paper an approach that goes beyond the established methods of dashboarding and enables visualizing different databases, data-sets and sub-sets of data with juxtaposed visual interfaces. Our approach should be seen as an expandable method. Our main contributions are an in-depth analysis of visual task models and an approach for juxtaposing visual layouts as visual dashboards to enable solving complex tasks. We illustrate our main outcome through a case study that investigates the area of mobility and illustrates how complex analytical tasks can be performed easily by combining different visual interfaces.



*Keywords:* Visual Analytics; Information Visualization; Visual Tasks; Visual Interfaces; Data Analytics; Prediction; Mobility; Transportation

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Peer review under responsibility of the scientific committee of the ICTE in Transportation and Logistics 2018 (ICTE2018).
10.1016/j.procs.2019.01.117

## 1. Introduction

Interaction with visualizations enables the dialog between user and the visual representation of the underlying data. The interactive manipulation of the data, the visual structure or the visual representations provides the ability to solve various tasks and uncover insights. The term “task” in the context of information visualization is often used ambiguously. Often, interactions and tasks are not distinguished for visualization design, whereas the knowledge about the task to be solved with the visualization is of great importance for its design. Commonly visualizations are designed to enable solving a certain task. However, there exist a number of visualization tools that provide different visual layouts for a variety of tasks. These systems and tools show promising results and found their way already to real application scenarios not only in research. The main shortcoming of these systems still remains that they allow just one database or dataset to be visualized. This leads to limitations in those tasks that require higher cognitive processing, such as exploration or analysis. We present in this paper an approach that allows to solve such analytical and exploration tasks by combining different databases with different visual layouts that leads to different visual interfaces. Our approach enables to visualize different databases, datasets, or different sub-sets of the same data and combine different visual interfaces for the different types of tasks. Our main contributions are two-fold: an in-depth analysis of different task models and task classification that should enable users to create such interfaces and a model with different “perspectives” to different or the same data that allows to solve analytical and exploration tasks. This paper starts with the introduction of taxonomies and classifications of tasks in visualization systems. The classifications will enlighten the heterogeneous view on visualization tasks and enable getting an overview of the differences. The classifications will enable to define and differentiate in particular simple search tasks and exploratory analytical tasks that are the main focus of this paper. After classifying tasks, we introduce exploration in context of search with the assumption that analytical tasks are commonly starting with a kind of exploratory search. In this context we differentiate between a bottom-up search paradigm and a top-down search and illustrate that several combinations of these two abstract paradigms exist. Thereafter we introduce our model juxtaposing visual layouts as visual interfaces with the main difference that several databases can be visualized at the same time and enables analytical comparison tasks. In this context we will outline that the following six perspectives give already a good starting point for more complex visual tasks: perspective view, perspective-comparative view, comparative view on level-of-detail, comparative view on data sub-sets, comparative view on data, non-linked view.

Thereafter, we illustrate based on different dashboards the added value of our approach. Thereby, we have chosen the domain of mobility for our case study and illustrate that combining visual interfaces leads to a far easy-to-use and easy-to-understand analytics of mass amount of data.

## 2. Classification of Tasks in Interactive Visualizations

Shneiderman provided one of the most popular task classifications, the “Task by Data Type Taxonomy” [1]. With the assumption that users are viewing collections of data with multiple attributes, he proposed that a basic search task is the selection of items that satisfies the search intents. This classification enhances Shneiderman’s “Visual Information Seeking Mantra” [1] with the tasks relate, history, and extract. The Visual Information Seeking Mantra of Shneiderman proposed a three-stepped task model. Each visualization should start, according to Shneiderman, with an overview followed by zoom and filter and details on demand.

The following Table 1 illustrates the classification of Shneiderman including the seven main visualization tasks.

Table 1: Task by Data Type Taxonomy [1, p. 337]

| Tasks | Description |
|---|---|
| Overview | Gain an overview of the entire collection. |
| Zoom | Zoom in on items of interest. |
| Details-on-Demand | Select an item or group and get details when needed. |
| Relate | View relationships among items |
| History | Keep a history of actions to support undo, replay, and progressive refinement. |
| Extract | Allow extraction of sub-collections and of the query parameters. |

The overall tasks in this classification can be abstracted to the high-level tasks exploration and search and leads to finding (relevant) information.

Buja, Cook and Swayne [2] proposed a classification concept that investigates the interaction with visualizations (view manipulation) and the tasks that are supported by these interactions. They supposed that the purpose of the view manipulations is to support the search for structures in data. For this search they identified three fundamental tasks for data exploration, namely finding gestalt, posing queries, and making comparisons. Finding certain patterns of interest, e.g. clusters, discreteness or discontinuities, are classified in the task finding gestalt. Posing queries is the next step after gestalt features of interest were found and further information are desired to get a comprehensible view on the chosen parts of the data. For the task making comparisons they distinguish between two types of comparisons. First the comparison of variables or projections and second the comparison of subsets of data. The comparison of variables enables the “view from different sides”, which illustrates the data from different perspectives, whereas the data subset comparison provides a “view of different slices” and thereby of different subset of data [2].

Further they proposed that the identified tasks are optimally related to three manipulation views. For gestalt finding they identified the focusing individual views. Here, focusing provide any operation to manipulate the subset of data or view. The choice of projection, for viewing or the choice of aspect, ratio, and zoom are examples of focusing. For posing queries, they identified linking multiple views. The linking contains view manipulation as brushing or query issuing by highlighting. Making comparisons is related to arranging many views. They propose that the arrangement of large numbers of related plots for simultaneous comparison is a powerful informal technique.

With this tasks and manipulation views they further proposed a set of low-level interaction techniques that are related to each high-level task. Table 2 provides an overview of the proposed tasks, manipulation views and interactions that are related to each other.

Table 2: Task Classification by Buja et al. [2]

| Task | Manipulation View | Interaction |
|---|---|---|
| Finding Gestalt | Focusing individual views | Choice of projection, aspect ratio, zoom, pan, order, scale, scale-aspect ratio, animation, and 3-D rotation |
| Posing Queries | Linking multiple views | Brushing as conditioning / sectioning, database query |
| Making Comparisons | Arranging many views | Arranging scatter plot matrix and conditional plot |

This classification introduces not only a linking of multiple layouts for solving search tasks (query posing), but also arranging many views, which enables performing comparisons and therewith analytical tasks.

Another approach, which correlates low-level interactions with visualization tasks, was proposed by Chuah and Roth [3]. They summarized their “basic visualization interactions” as a set of low-level-interactions with the attributes input, output, and operation and abstracted them to three basic visualization tasks [3, p. 31]. At the lowest level they propose “Data Operations”, which contains interactions affecting the elements within visualizations, e.g. add, delete or derive attributes. The higher level considers “Set Operations”, which refers to operations on sets, which may have group characteristics. The highest level investigates “Graphical Operations”, which are divided into encode-data, set-graphical-value, and manipulate-objects. While the classes encode-data and set-graphical-value change graphical attributes or the mapping between graphical objects and data, the class manipulate objects operates on graphical objects as a unit of manipulation. The investigated tasks in this classification focus on comparison and finding patterns as graphs or in data. The high-level task of this classification can be abstracted as “analysis”. The aspect of analysis was investigated in various works. One early example is the classification of Wehrend and Lewis [4]. They proposed a taxonomy with ten analytical tasks: location, identity, distinguish, categorize, cluster, distribution, rank, compare within entities, associate, and correlate.

Zhou and Feiner proposed an approach by considering not only the interaction and manipulation abilities of visualizations [5]. They investigated the human perception and the intended task of the visual presentation method in their classification to provide a more user centered task-classification.

Based on various existing classifications, they characterized visual tasks along two dimensions. In the dimension Visual Accomplishments, the focus lies on the intention of the visual presentation [5]. They assumed that a presentation intends either to convey the presenter’s message or to help user solving a perceptual task. Based on this assumption, visual tasks are distinguished at the highest level between tasks that inform users by elaborating or summarizing and those, which enables users to perform a visual exploration or computation. Their second dimension Visual Implications considers research outcomes of the human visual perception.

Based on these outcomes they summarize three types of visual perception and cognition principles: (1) the visual organization principle investigates how people organize and perceive a visual presentation, (2) the visual signaling principle investigates the manner how people interpret visual cues and infer meanings and (3) the visual transformation principle explains how people perceive visual cues and switch their attention. This incorporates the outcomes of the pre-attentive visual perception too [6]. Zhou and Feiner use these principles to infer visual tasks and assign them to the first dimension of Visual Accomplishments [5].

A more user-centered approach for classifying task was proposed by Keller and Keller [7]. Their classification considers the goals and intentions of the users and suggest based on these certain visual representations. They classify the user-intended tasks in nine task categories (see Table 3). The main characteristic of their classification is that only analytical aspects play a role for users interacting with visualizations. Previous general tasks like exploration or search does not play any role.

Table 3: Visual task classification by Keller and Keller (adapted from [7])

| Task | Description |
|---|---|
| identify | recognition of objects based on the presented characteristics |
| locate | identification of the position of an object |
| distinguish | determination the difference of objects |
| cluster | grouping of objects based on similarities |
| rank | ordering objects by intended relevance |
| compare | examination of similarities and differences of objects |
| associate | drawing relationships between two or more objects |
| correlate | finding causal or reciprocal relationships between objects |

A comprehensive classification of users' tasks based on user intentions and the interaction role in information visualization was provided by Yi et al. [8]. Their classification attempts to abstract the most used interaction possibilities with users' intentions to provide categories of interaction. They classify the user tasks based on the role of interaction in information visualization in seven categories (see Table 3).

Although the identified categories are abstract views on the interaction roles, the level of abstraction differs enormously. The category "select" for example, can be defined as simple and low-level interaction. Here a user marks an object of interest to be able to follow this object in changed views [8]. In contrast to "select" the category "explore" provide a real abstraction of interaction to a user task. Here the user is able to view on various subset of data to see different characteristics and perform a various number of low-level task e.g., comparing subsets or identifying relevant objects.

Here the first tasks of "identify", "locate", "distinguish" can be ranked as simple search tasks. Thereby the following tasks of "cluster", "rank", "compare", "associate" and "correlate" refer more to more complex analytical tasks that refer to higher cognitive processing.

The introduced approach makes use of different juxtaposed visual views to enable solving more complex analytical tasks. In particular the tasks explore and connect make use of the visual arrangement, whereas the main tasks can be solved with single views.

Pike et al. [9] extended the proposed approach of Yi et al. [8] by differentiating between low-level and high-level interactions intending to meet high- and low-level user tasks and goals and proposed a mutual feedback between user goals and tasks and the affordance of interactive visualizations [9]. They defined seven categories of high-level tasks, which can be achieved by a number of low-level tasks and interactions respectively. Further they relate the representation and interaction intents of interactive visualizations, similar to the proposed classification of Zhou and Feiner [5] to low-level representation and interaction techniques. The proposed approach relates the classifications of user goals and tasks with the abilities and goals of interactive visualization in a "mutual feedback". The relationship of the proposed techniques and the user's goals and tasks is the "analytical discourse", which investigates the low-level interaction and user goals to form a feedback between them [9].

Table 4: Visual task categorization by Yi et al. (adapted from [8, pp. 1226]

| Category | Description |
|---|---|
| select | mark something as interesting to enable the following of the object |
| explore | show something else, e.g., different subset of data |
| reconfigure | provide a different view or arrangement of the underlying data |
| encode | provide a different fundamental view by selecting another visualization technique |
| abstract / elaborate | provide a different level of detail on the data e.g., by details-on-demand techniques |
| filter | provide a view with certain (predefined) criteria |
| connect | provide a visual connection (e.g. by brushing) between the same objects on different views |

The classification of Pike et al. considered the interaction value and user's goal and tasks from both perspectives, information visualization and Visual Analytics and gave a good overview of the high-level tasks intended by users and provided by interactive visualizations. Nevertheless, the differentiation of high- and low-level tasks is not clearly defined. A "compare" task could be a part and therefore a low-level task of "assess" or "analyze", while important tasks like "decision making" [11] are not considered at all.

Fluit et al. proposed a very simple classification of visualization tasks in the special domain of ontology visualizations in the categories Analysis, Query, and Navigation [12]. Therefore, they defined the Analysis task for getting a global view on data, the Query task for finding a narrow set of items, and the Navigation task for graphically navigating through the data. In their revised work [12] the last category Navigation was replaced by "Exploration". They proposed that "Analysis" can be performed within a single domain with various perspectives, in various sets of data, and by monitoring the changes of data over time. The category Query is divided into the processes of query formulation, initiation of actions, and review of results. The task category Exploration is defined as finding information that are loosely of interest for the users. Here a further subdivision is not proposed.

A more recent visual task classification or framework was proposed by Munzner [13]. She proposed based on the main assumption that visualization should enable humans to solve different tasks that leads in best case to a more efficient and effective way of problem solving in two main categories: "Actions" and "Targets". Each task can be described as tuple of actions and targets and leads to a more efficient way of solving tasks. The model of Munzner can be used to create and generate interactive visualization systems that consider the task to be solved as a main attribute of interactive visualizations.

The Actions are subdivided in three main levels of "Analyze", "Search" and "Query". In the analyze category users may want to produce information or consume information, whereas commonly users are consuming information. The analyze category contain six goals, whereas three are assigned to consume and three to produce. The search category is a process that is required for the analysis tasks. The search category contains four goals based on the target location (either known or unknown) and the search target (either known or unknown). This categorization already includes the differentiation between exploration and targeted search as proposed by Marchionini [14, 15] or White and Roth [16]. The last category of actions is "Query" that contains three goals, starting from a single target (identify) to a set of multiple targets (compare) and the full set of possible targets (summarize) [13, pp. 43-55]. The following table illustrates the "Actions" according to Munzner [13].

As Actions are defined by Munzner as verbs, targets are the nouns. Each target refers to some aspects of data that is of interest for the user. Munzner proposes three high-level of targets are of great interest for the user: trends, outliers and features. 'These three targets can be derived from any kind of data. Further targets are prosed that may rely on the number of attributes: "distribution", "dependencies", "correlation", "similarity" and "extremes", or to the type of data: "topology", "paths" and "shape".

One main aspect of Munzner's work is that she addresses that a visualization idiom can be constructed out of a set of design choices. These design choices also include juxtaposing visualizations, partitioning and superimposing visualizations. [11] We investigate in this work in particular the juxtaposing design to enable solving analytical tasks that commonly start with a search task as Munzner proposed.

Table 5: Actions according to Munzner [13]

| Actions | | |
|---|---|---|
| **Analyze** | | |
| *Consume* | | |
| Discover | Present | Enjoy |
| *Produce* | | |
| Annotate | Record | Derive |
| **Search** | | |
| | *Target known* | *Target unknown* |
| *Location known* | Lookup | Browse |
| *Location unknown* | Locate | Explore |
| **Query** | | |
| Identify | Compare | Summarize |

## 3. Exploratory Search

Commonly analytical tasks start with a search task [13]. The main intention is to reduce the amount of visualized data or to focus only on targets of interest. We consider in this paper only exploratory tasks based on the assumption of Marchionini [14, 15]. Locating outliers or identifying certain items are not considered, thus these commonly leads to faster interpretation, where the analytical tasks are rarely needed.

Exploratory search [14, 15, 16] enables with the different stages of exploration the acquisition of in particular implicit knowledge or information. Implicit in this context refers to that kind of knowledge or information that is not explicitly known or may not be formulated by the user explicitly, e.g. due to lack of knowledge. From the visualization point of view, implicit knowledge or information refer to that knowledge that is not explicitly modeled in the data but can be enlightened through the visualization of the modeled data [17].

Different disciplines provide technologies, systems, and approaches to enable the acquisition of implicit knowledge or information. For simplifying the investigation of these approaches, we classify the methods into bottom-up and top-down approaches. The standard search process [18], e.g. is a simplification of a bottom-up approach. The approach attempts to formalize the iterative search process a three-stepped model of Query Formulation, Query Refinement and Result Processing. This model assumes that the search begins with the formulation of query of known knowledge. During the search process the subject gets more knowledge about a certain topic to refine his query and gather more knowledge about the certain topic. The main aspect of this model is that the search process starts with the ability to formulate a query and to reformulate the query during the search. During the search process new knowledge is adopted, which leads to a reformulation of the query. A more complex example for a bottom-up information gathering and search process is the information-seeking process Marchionini [14, 15]. This process includes eight phases and encloses the internalized problem solving of subjects too. Marchionini's model consists of eight phases in information seeking: Recognize and accept an information problem, Define and understand the problem, Choose a search system, Formulate a query, Execute search, Examine results, Extract information and Reflect/iterate/stop [14, pp. 49-58], [17].

The exploratory search approaches are commonly bottom-up approaches that start with a search term and enable in different stages the investigation, reformulation, learning, and refining. The process of information exploration in information visualization is contrary to the bottom-up approaches of search interface. Commonly in this context a top-down approach is proposed [1]. The most famous example for a top-down information exploration or gathering model is the already introduced Visual Information Seeking Mantra [1]. This model proposes the opposite of the bottom-up approach and is designed for the visual information seeking. The three-stepped model propagates to Overview the data first, then Zoom and Filter the relevant parts and finally gather Details on Demand. Beginning with the overview of data, this model premises not the verbalization ability, here the focus is on the recognition ability. If a subject detects in the overview step an area-of-interest, he can zoom into the area or filter this information out. After he gets enough information to recognize a seeking problem, details about the information can be fetched. The top-down model of search and information acquisition based on Shneiderman's work is applied to many visualization environments and is the main approach for gathering information in visual environments [17].

The investigation of the search process in a bottom-up manner plays an increasing role in visualizations. van Ham and Perer [19] for instance proposed a bottom-up search approach in visual environments that starts with search, by means of querying the data-set followed by show context that enables the contextual view on data and expand on demand that provides a detailed view on demand.

The described seeking approaches require different human abilities required for solving a seeking problem. In a bottom-up approach the formulation of the searched topic is important, whereas the recognition ability plays an important role in the top-down approaches. The mentioned top-down approaches are primary information visualization approaches thus, the overview of information and recognition of area-of-interest can be more supported with visualization systems.

## 4. Model for Visual Analytics Dashboards

Most of the visual layouts specialize upon one feature of data. This is because the visual layouts have advantages for a special data type, but disadvantages for others. We can easily show the relations between instances in an arbitrary graph-layout, which provides interaction methods for expanding or collapsing a node to gain a better overview, but we can hardly display a textual article, a picture or properties like geographical or temporal data in arbitrary graphs. On the other hand, geographical visual layouts support the view and search for geo-related properties, but their enhancement with relational or hierarchical layouts may lead to overcharging users and non-comprehensible visualizations. To face on the one hand the visual overflow and support on the other hand the solving of analytical tasks, we introduce a model that reduces the information overload by separating the visualized information in a visual interface of juxtaposed visual layouts.

Our model separates data models with their attributes and visualizes this information in separate visual layout without losing any information and without overcharging the user by complex visualizations. The advantage of the separation of complex information units is obvious; the user of is able to perceive the same information from several perspectives by the placed juxtaposed visual layouts. With this approach both, bottom-up and top-down approaches are supported. A bottom approach starts with the query formulation. If the formulated query is precise enough, a data instance and the modelled neighborhood is presented. Otherwise, if the query is not specific or the user wants to have an overview, the abstracted schema of the data is presented. The different perspectives on data enable more comprehensible view.

Thereby the visual layouts are linked with each other and make use of a brushing and linking metaphor to support the comprehensible view and changes on users' interactions.

The visual layouts can be integrated in the visual interface to provide different perspectives on the same information in abstracted and different ways. Users are able to rearrange or add visual layouts on the screen or dismiss the placed visual layouts. The view on different perspective or aspects on the same data and data-set with different visual layouts allows to arrange different visual interfaces and solve analytical tasks. The main purpose remains the support of exploratory search. In order to support this search, we identify following styles for our model:

- Perspective view: Visualization of the same data with different visual layouts.
- Perspective-comparative view: Visualization of different sub-set of data from the same data-base with different visual layouts.
- Comparative view on level-of-details: Visualization of the same data using the same visual layouts with different parameters.
- Comparative view on data sub-sets: Visualization of different data sub-sets from the same data-base with the same visual layouts.
- Comparative view on data: Visualization of different data-bases with the same visual layouts.
- Non-linked view: Visualization of different data-bases with different visual layouts.
-

With the different adjustments of the visualization interface, different goals can be achieved and different requirements fulfilled. As introduced, the perspective view enables the exploration of a queried sub-set of data from different perspectives with different visual layouts. The layouts are linked with each other and the user is able to navigate through the different visual layouts and gather required information from other visual layouts. The perspective-comparative view allows solving comparative tasks by providing the free choice of visual layouts for different data-subset form the same data base. Here only one data-base is queried, e.g. by different search terms. The results for each sub-set of data are linked with each other, whereas the visual layouts are just linked through the data. If a user interacts within a visual layout, only those visual layouts react to the interaction that visualize the same data-subsets. Adding a visual layout leads to a coupling of this with the data sub-set of the last user interaction. The user is able to change the linking each visual layout.

The perspective-comparative view enables to compare tasks with the freedom to choose the visual layout for each data-subset. This view is in particular efficient if the data sub-set has different characteristics. Thus, this view is not providing at each level the same visual layout, it goes beyond comparison tasks and enables a more investigative view on various topics of the same data-set. A comparative view on a low-level is provided by the comparative view on level-of-detail. This view enables the visualization of the same data with the same visual layouts, but different parameterization for gathering on the one hand an overview and on the other hand a detailed view on the data.

The parameterization of certain visual layouts allows controlling the level of detail as part of the zooming. The zoom levels may vary from visual zoom, to semantic zoom with semantics-based filtering. For example, the level of detail can on the one hand be used to show a greater part of the semantics or information space for showing the structure of the information and on the other hand with small numbers of elements of interest to show detailed information.

There are two main ways to combine the same visualization technique duplicated in a cockpit for providing more information. First the level of details can be provided as a zoom on a specific area of the semantics while the entire search results is displayed too and second the semantic neighbors of a particular focused elements can be enhanced and reduced due to enabling an overview and detailed view. A reduction of the numbers of entities can be achieved by filtering the information, e.g. based on relevance metrics.

With this kind of information visualization, a similar effect can be achieved. Many information elements give an overview about the whole structure of the data and the information about the focused element can be revealed with a visual layout that visualizes a small number of elements.

A similar approach with a more focus on comparative tasks is provided by the comparative view on data sub-sets. This view enables the visualization of different search or interaction results with the same visual layouts that are commonly placed upon each other. The usage of same visual layout supports the comparison and analysis process thus, a direct visual correlation is built. Visual layouts visualizing the same content or query result are linked with each other, while visual layouts that visualize another subset are not affected. The interaction coupling of visual layouts is depending on the data that are visualized. If a user interacts with the visual layout that visualizes a certain data-set, only those are changed by users' interactions that are visualizing the same content. With this procedure and the visualization through the same layouts, the users are able to navigate independently through the different sets of data and get insights, compare results, and investigate deeper search tasks on each data base.

The comparative view on data sub-sets enables solving comparative and analysis tasks in one domain of data. With the growing data sources on Web, the combined search on different data sources gets more and more relevant. We mean with the combined search, a simultaneous search in different data bases on Web with the same search term. This enables a deeper search and investigation of certain entities or information of interest by considering not only one data base. One main side effect of this search is that the visualization of the results enables to validate and proof the quality and information value of a data-base.

One main goal remains the support of exploratory search and analytical tasks by providing appropriate visualizations that enables an adequate and comprehensible result retrievement. Our comparative views on data enable the simultaneous search and visualization of search results from different data sources. Thereby the search results from each data base are visualized with the same visual layouts to enable a more comprehensible view on data. The visual layouts that are visualizing data from the same data base are linked with each other and enable the independent navigation in various data sources.

Users are able to add, rearrange or dismiss certain visual layouts. This effects the entire visual interface, e.g. if a user adds a new visual layout on the screen, the same visual layout appears twice for two data bases.

The model is not limited to certain number of data bases. Therewith the user is able to view retrieved results from various data bases simultaneously. Although the number of the data bases is not limited, the system limits the number of visual layouts based on the user model to not overcharge the user with visual information. The comparative view on data enables analysis tasks without querying different data-bases and changes the view. The results are presented in the same way, so that the process of investigation in analytical tasks and exploratory search can be supported in one visual interface.

The comparative view on data has the advantage that all results from all data-bases are visualized in the same way and enable therewith an easy comparison. The view is limited to the fact that only the same visualization can be used in this context for the various resulted data. These resulted data may have different attributes that cannot be visualized with the certain chosen layouts. In these cases, information about the results are lost. To face this aspect, we introduce the non-linked view that has no limitations at all. It enables the visualization of data from different data-bases with various visual layouts. The main idea is to provide a nonlimited view for the deeper exploratory search steps as proposed by Marchionini [10]. Thereby we use the visual layout linking for the data-bases too, as in other views, but the user is able to disable this linking even for the same data-base. This procedure enables the freedom of retrieving the search results from different perspectives and different data-bases according to the assumption and theories of constructivism. The user gets guidance for the visual layout when he selects a data-base.

The visualization interface arrangements enable to view data from different data-bases or different sub-sets of the same data with the same or various visual layouts. With the juxtaposed arrangement and linking of visual layouts the approach supports the entire process of exploratory search. We introduced six different styles or views how the visualization interface can be used for the different stages of exploratory search or the given tasks. These six views should be seen as examples how the visual layouts can be arranged and what kind of tasks and in which process they support the user. Although the juxtaposed arrangement of visualization can be performed manually and provide therewith a more 'adaptable' character, we focus on automatic adaptation that generates the adequate visual interface through machine learning methods. Previous works on visual interface arrangements allowed us to enhance the model and provide a sufficient interface collection that is based on industrial requirements and tested in real situations.

## 5. Application to Analytical Tasks in Mobility and Transportation

Mobility, transportation and logistics gain recently rapid changes. These changes include both, technological innovation that are applied in particular to mobility and societal changes with regards to mobility behavior. Visual Analytics systems enable to gather information about both to react to these changes rapidly and be competitive. To illustrate this issue, we introduce a case study where Visual Analytics dashboards in particular for the early awareness of technologies can be used. The early awareness of technologies enables a more goal-directed and efficient way for deciding future strategic directions in mobility and transportation. Possible sources for this valuable information are ubiquitously and freely available in the Web, e.g. news services, companies' reports, or social media platforms and blog infrastructures. To support users in handling these information sources and to keep track of the newest developments, current information systems make intensively use of information retrieval methods that reduce the amounts of documents according to a given query. The commonly used search mechanisms are primarily focused on providing the users with easy access to information of their interest and deal with the access to information items and resources [20], but neither provide an overview of the content nor enable the exploration of emerging or disappearing technological changes. [21]

This case study builds upon our previous work on visual trend analytics [21] and enhances the approach with dashboarding to allow the analysis of early signals and technologies in mobility and transportation. The main questions that should be answered here are the following (1) *when* have technologies in mobility emerged and *when* established? (2) *where* are the key-players and key-locations of those technologies, (3) *who* are the key-players, (4) *what* are the core-topics related to those technologies (4) *how* will the technologies probably evolve, and (5) *which* technologies or topics are relevant for an enterprise? [21]

The integrated dashboards should allow to view and interact with the different aspects of data gathered through unsupervised machine-learning methods. The underlying data in our case study come from the DBLP-data base and are enriched with further information and information extraction methods. For a review of the used methods, we refer to our previous work [21].

Let us assume that an analyst from the area of mobility is interested in emerging technologies in the area of mobility.

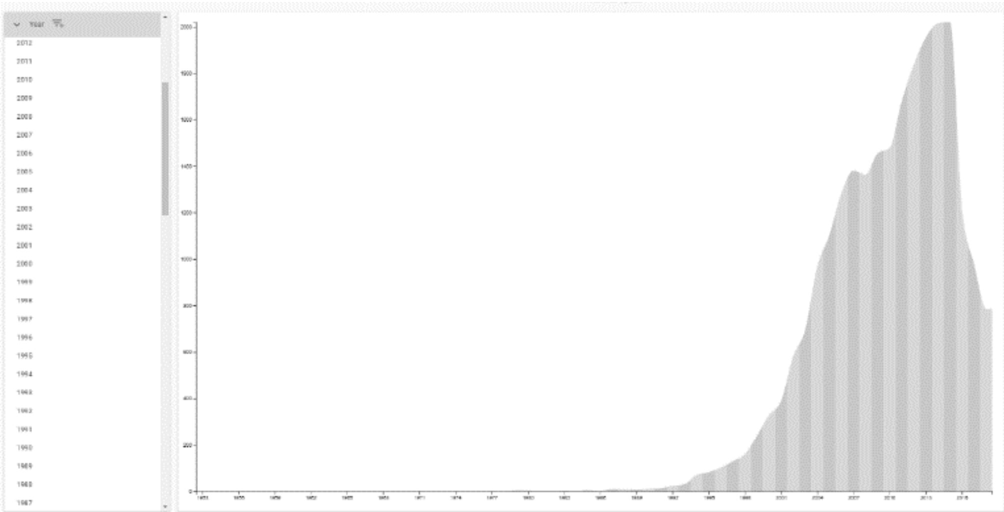

Fig. 1. Temporal overview of the frequency of documents containing the term “mobility”

He is aware about the topics that are emerging, due to their appearance and discussions in news-feeds and social media and maybe he is an expert and knows already some of emerging technologies. However, even if he is an expert, he may not be aware of weak signals that are now emerging in science and could be potential technologies in future. Further he may not be aware about the topics that relevant in other countries. To get a first overview, he starts a search with the very fuzzy term of “mobility”. He gets a temporal overview of the frequency of the papers mentioning “mobility” (see Figure 1).

The temporal overview gives two main information, first the year where the term appeared first (in our example 1987 and second the temporal overview over the entire years. The main information consists of the facts that there are 24394 documents related to the term mobility. The climax of this term was in the year 2015 and after 2015 the term lost on frequency, which may lead to the assumption that this topic loses interest in the research community.

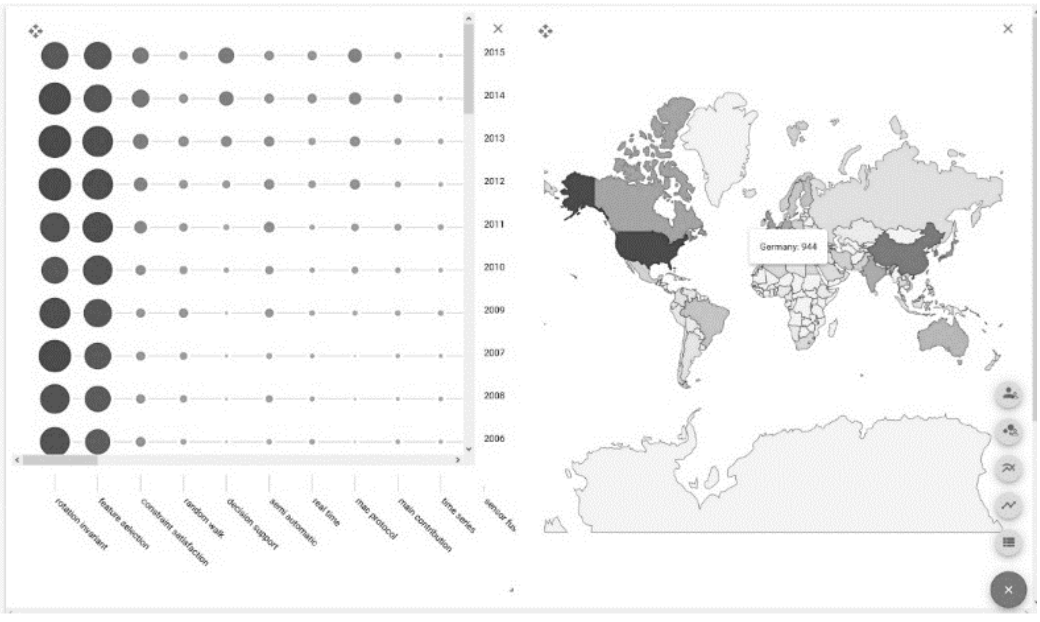


Fig. 2. topic frequency per year and document frequency by country for the term "mobility"

By combining the visualizations as a dashboard, the user is able to much more information and perform analysis and comparison tasks. Let us assume that the analyst wants to know which technologies are or were of interest in context of mobility and which countries worked on this topic in the last years. The analyst is able to create a dashboard that gives him extracted information (though text mining) of the most relevant topics in context of mobility and a geographical visualization that enables him to see the frequency distribution of the documents based on countries. This distribution is visualized by saturation, that enables a fast information gathering (see Figure 2).

The analyst is able to gather several information from this quite simple dashboard. First, he sees that there are two dominant topics in context of mobility, namely “rotation invariant” and “feature selection” and further several topics like “constraint satisfaction” and “random walk” that are of research-interest in context of mobility. But it can be easily seen that “decision support” in context of mobility were ten year ago not of interest but gained emerging interest in the searched area. So, an assumption could be that decision support plays now a higher role in this context. The geographical visualization refers to the key-locations or key-countries working on this topic. The saturation clearly shows that the United States and China are leading the research in this area. The user is able to hover over each country and gather the real numbers of documents of each country related to a search phrase.

We further proposed that key-players and their topics play an important role for the analysis. Let us assume that the analyst wants to get information about key-players in the area of mobility, their main sub-research topics and the correlations between him and other authors. The analyst is able to create a dashboard that enables him to gather the most relevant key-researchers in the area and their sub-topics (see Figure 3).

The visualization illustrates clearly that “Mario Gerla” and “Leonardi Barolli” published the most papers related to mobility. It further shows that both are working on ad hoc systems, routing protocols and traffic flow. Further the co-author graph illustrates with whom they are working. In Figure 3 Mario Gerla is highlighted with his co-authors. If the analyst is more interested in mobility management, he can easily identify the researchers working on this topic. We see that the most publications in the area of mobility management with regards to “mobility” was written by “Hangke Zhang”, followed by “Susana Sargento” and “Sajal Das”. With this dashboard the identification of key-players in a certain area is possible. Thereby the core research topics can be gathered and the co-author graph illustrates the collaboration of the researchers. Further the left facet list illustrates the institutions that are working in this area.

The short case study aimed to give a possible application scenario for identifying several aspects. These aspects can be used to find collaboration partners, core- and emerging topics, competitors and market-relevance of technologies and innovations. However, the human intelligence is still required to gather substantial information out of the data.

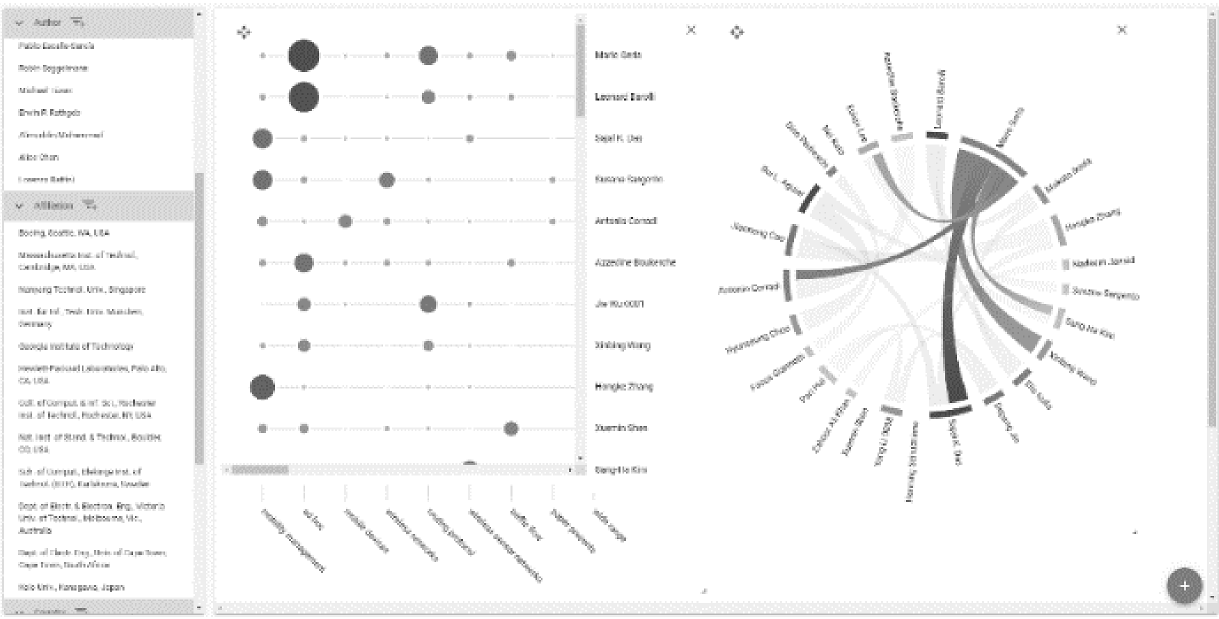

Fig.3. key-players and their research topics in the area of mobility

## 6. Conclusion

We introduced in this paper our model for arranging visual layouts and combining them with different databases, datasets and sub-set of data to enable solving exploratory analytical tasks. We first introduced different classifications, taxonomies and models for visualization tasks. This should enable identifying the most relevant analytical and exploratory tasks. In context of exploration, we will introduce two different views on the search process, the bottom-up search that starts with the formulation of a query and provide the result processing in an iterative manner of query refinement. In contrast to that the top-down search process starts with an overview on a knowledge domain and provides various interaction abilities to process the required detailed information. It is important in context of visualization to differentiate between these two search processes, thus the bottom-up search requires formulation ability and the top-down search relies more on the human recognition ability. Based on these assumptions, we introduced our visual interface model that makes use of the visual layout arrangement to provide various views on the same or different data for exploratory and analytical tasks. Overall, we identified six different views that interconnect visual layouts and data with each other or disconnect them. The approach enables different perspectives or the same view on different data or the same data. We thereby differentiated in our model 'data' as a data-set of the same data-source and from different data-sources. The identified six views on data as visual interfaces were described and illustrated exemplary. Thereafter, we applied our model to a case study in the area of mobility and illustrated clearly that the combination of visual interfaces with different aspects leads to a better gathering of mass information.

## Acknowledgements

This work has been carried out within the Research Group on Human-Computer Interaction and Visual Analytics of the Darmstadt University of Applied Sciences (https://vis.h-da.de). The paper is a revised version of a previously published work.

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