Innovations in Mobility and Logistics: Assistance of Complex Analytical Processes in Visual Trend Analytics

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***Abstract*— A variety of new technologies and ideas for businesses are arising in the domain of logistics and mobility. It can be differentiated between fundamental new approaches, e.g. central packaging stations or deliveries via drones and minor technological advancements that aim on more ecologically and economic transportation. The need for analytical systems that enable identifying new technologies, innovations, business models etc. and give also the opportunity to rate those in perspective of business relevance is growing. The users' behavior is commonly investigated in adaptive systems, which is considering the induvial preferences of users, but neglecting often the tasks and goals of the analysis. A process-related supports could assist to solve an analytical task in a more efficient and effective way. We introduce in this paper an approach that enables non-professionals to perform visual trend analysis through an advanced process assistance based on process mining and visual adaptation. This allows generating a process model based on events, which is the baseline for process support feature calculation. These features in form of visual adaptations and the process model enable assisting non-experts in complex analytical tasks.**

Keywords—adaptive visualization, visual analytics, trend analytics, process mining, transportation, logistics

I. Introduction

A main challenge that almost any enterprise in the economy has to deal with is the digitalization. Upcoming new technologies together with novel business plans have the potential to revolutionize the market. These changes imperil particularly small and medium sized enterprises (SME), which focus concentrates on their daily business, but not on investigating trends.

Two sectors that are in progress of new technology investigations are the logistics and transportation domain. Especially big players like Amazon and DHL do invest a lot to create novel approaches and trial them soon. A principle challenge is the estimation of which innovation will get important and will be successful on the market [1]. Furthermore, the innovation is not only covering technologies for e.g. economic and ecologic transportation through alternative parcel truck engines. It also covers different approaches such as central packaging stations or drone deliveries. Tools, which enable the identification of new upcoming technologies, ideas and furthermore, give the opportunity to rate them toward (future) relevance, are highly required. The analytical challenges that have to be faced can summarized in three questions [2]:

1) What technologies, business ideas, strategies etc. are coming up?

2) How have these upcoming technologies, business ideas, strategies etc. to be rated in perspective of future relevance?

3) What of these upcoming technologies, business ideas, strategies etc. are relevant for the own market and -more important- the own business?

To react appropriate on market changes, the answering of these narrowed questions early is essential! For these tasks some solutions already exist on the market and are already used in enterprises. But these solutions support only basic search capabilities and -which is more critical- only use patent data. That limits the retrievable insights on IPR protected ones. Non-IPR protected business ideas, technologies or application procedures of novelty could yet not be recognized and identified, which is a significant limitation. Furthermore, for instance in Germany it is not possible to register new business ideas or technological procedures in a patent. Another downside is the age of new recognizable patents. Since the registration of patents requires approx. two years, identified trends are therewith also at least two years old. So, a system that makes use of other more up to date data is needed.

Another challenge is the required expertise of system users of such analytical solutions. To be able to extract trends, users need domain, technical/analysis, and economic knowledge as well as understanding. But the number of users that own these expertise levels are rare on the market and therewith almost not available in SMEs. SMEs therewith demand on intelligent tools that support users in performing beneficial analysis.

Therefore, with this paper we introduce a different approach to handle trend analysis, based on assistance capability. As fundament we use new analytical solution that is based on a modular and scalable processing pipeline for visual trend analysis that supports a variety of data sources. While standard for such applications would be patent data, our system consumes majorly research data coming from

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(open access) digital libraries and web data – e.g. market news from online magazines or enterprise news from their websites. With this data and a highly interactive visual analytical solutions for trend analysis [3][4][5], technology and innovation foresight is possible to identify early market trends.

To address the challenge of the high user expertise requirements, we introduce in this paper a novel graphical assistance feature that supports users via process mining [6][7] in the analysis process. This enables even non-expert users to get assisted in the trend analysis process to observe market changes and upcoming innovations and rate them in perspective of relevance in a sufficient similar quality as full experts can do without assistance. This helps SMEs, in particular from the transportation and logistics domain, to deal with the digitalization and market observation, also if they do not have huge budget for special teams of experts in that field.

The main contribution is a general model for supporting users based on mined processes and the support features. This model is further implemented in a visual trend analytics system to assist users.

II. General Design and Process Mining based on Events

In recent researches where systems assisting users by guiding them through processes, the system uses a statically define process model as baseline. Wizards, as they are well known from program installation routines under Microsoft Windows, are a very simple representant of this kind of assistant feature. This simple feature gives the user a clear orientation without the risk of confusion and failures, due to straight guidance through each procedural step. While the static process definition for such simple application routines is unproblematic, it gets rather challenging in complex visual analytical systems that provide high numbers of analysis features. To offer a process-based assistance, a smarter way is required.

With the introduction of process mining [6], a fundamental different option is available that could be used for application processes as well. While van der Aalst originally introduced process mining to structure and optimize business processes, it provides the principle properties to use it also on application processes for adaptation capability to assist users based on workflow level.

A. *General Process Support Methodology*

Our process support methodology owns about four major phases [2]:

1. Extracting application events based on user's interaction.
2. The process mining and training phase by analyzing (event-)data.
3. The phase to generate process and support features.
4. The assisted visual trend analytics phase.

The methodology overview is given in Fig. 1. As could be seen in the figure, technically, the first and the last step are performed at the same time.

While the initial system does not own any process information, there is at the beginning in phase one no support available. Anyway, when a user operates with the system at this stage, the application generates events based on the user's interaction. Events are in this perspective actions like mouse clicks, pressed keys on the keyboard, but also internal system states. These events are stored on a server. For the further processing, the collected events are already preprocessed to categorize them in sequences. In this phase the user can use

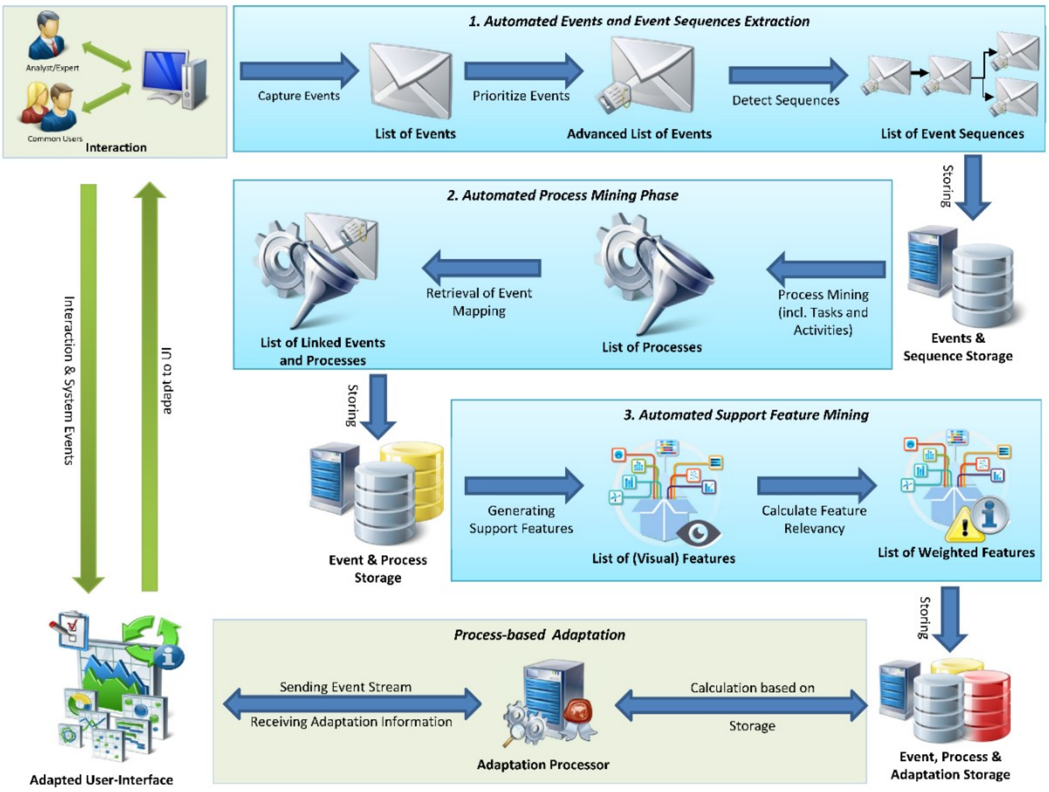

Fig. 1. General concept model to enable process assistance via process mining and user interface adaption

the entire system with all analytical capabilities, but without any support. At this moment, usually exerts are the only users of the system.

In the second phase, the system performs the process mining to generate a process model.

In the third phase, the support feature mining is performed. At this phase, the assistance features, such as recommendation and interface adaptations to certain databases, visualizations or filter criteria while performing a specific process task were extracted in behalf of the specific process stage.

In phase four, the system owns now about all assistance features, which allows now also non-expert users to perform trend analysis in which the system enables assistance in any step.

B. *General Event Taxonomy Definition*

The conceptualized and implemented processing mining approach majorly follows the definition of van der Aalst [6] with just some minor modification, which are explained in detail in a previous work [2]. The fundament for the process mining is the definition of the events. Our event log consists of a variety of structured events of the system, such as:

- System state events about internal states such as file reads, context switches, exceptions etc.
- Interaction events of users cover usually any kind of visual interaction with the corresponding devices.
- Data events belong to the effect on the data model in the system. The actions that this event type covers are data source changes, data reloads or set filter criteria.
- Visualization events relate to changes on active visualizations on the screen. In particular parameter changes, such as modifications on the layout and visual representation are addressed by this event.
- Explicit task and activity events, are representing the use case, so the broader analytical goal the user has in mind. This can be something like a certain competitor analysis or a specific scenario analysis.
- Adaptation events are not directly user interaction events, they reflect more hints of the system. Here the system logs if hints were used or neglected by a user.

C. *Explicit versus Implicit Task Selection*

The idea is majorly based on a passive system that most of time only observes the user's interaction and system status and presents support wherever it may help the user. However, for major task, particularly at the very beginning of the analysis, it is almost impossible to detect the analysis purpose automatically or gather the information implicitly. And therewith a guidance is almost impossible at this stage. To solve this beginning uncertainty, an explicit task selection can be provided. The interface to select an explicit task is illustrated in Fig. 2. This task selection is shown at the very beginning. But also, during the analysis the system can request explicitly what activity is more likely of interest of the user.

Since these explicit tasks in our approach represent the cases in process mining (see [6]), it is to mention that they are not always been given. For this restriction we had to modify our algorithm. So, we finally use the explicit task as case when given, and if we don't own the information, we use random case numbers. However, the quality of the process model increases the more often the explicit task is named by the user.

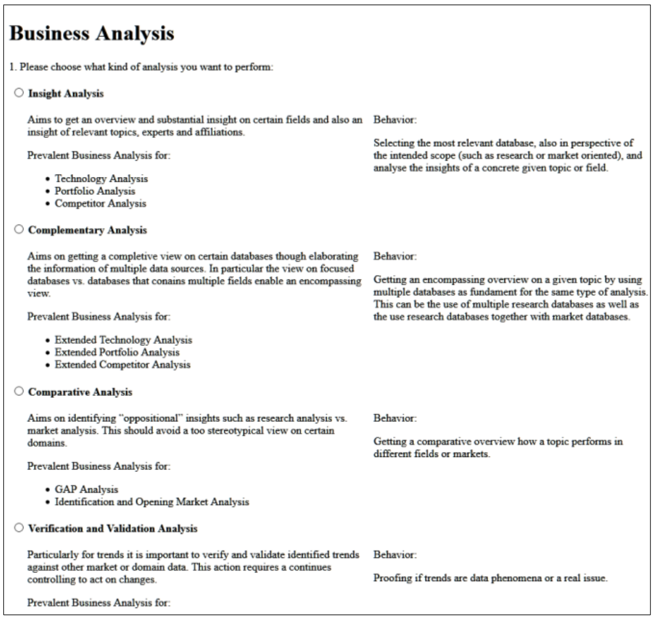

Fig. 2. Initial explicit task selection screen where the user can choose the main purpose of his following analyzes

D. *Event Taxonomy Definition*

To be able to later perform a process mining the event definition is essential to gain insights. Therewith the event names follow a taxonomy structure (see Fig. 3) from very abstract to a concrete meaning. Thereby we distinguish the events for our trend analytics software fundamentally in data, interaction and status events.

Data events cover the basic action on given data or the Application Programming Interface (API). It includes actions such as search, open and changing parameters e.g. which meta-data properties should be considered in a search.

Interaction events are strongly orienting on the user's interaction with the system. Here, the raw actions such as mouse-clicks on a specific data element or in general on the screen is being traced. It is important to mention that the interaction event do not have a semantic or interaction design meaning – so it cannot be interpreted if the interaction means a selection or is a click on a white space. The current considered events are related to the used interaction device for keyboard, mouse and touch displays.

The most meaningful event types are the **status events**. They represent the most specific conditions of the system, which are mostly related to meaning of interactions or performed parameter changes on the system. These events are usually individually triggered by specific visual components of the software in behalf of previous interaction events. So, in most cases it is the interpretation of a specific interaction of a user. Examples are data elements selection, set filter settings or opened visualizations.

E. *Process Mining Implementation*

Via the implementation of the α-algorithm or the use of an existing software, such as PM4PY (see https://pm4py.fit.fraunhofer.de), the process mining can be performed on the collected events that make use of the introduced event taxonomy. Therefore, the software must be used by confident analysts and domain experts first, while during their usage any action is logged. The logs are the fundament to mine processes that represents specific analysis and particularly the different analysis strategies to find insights in the data.

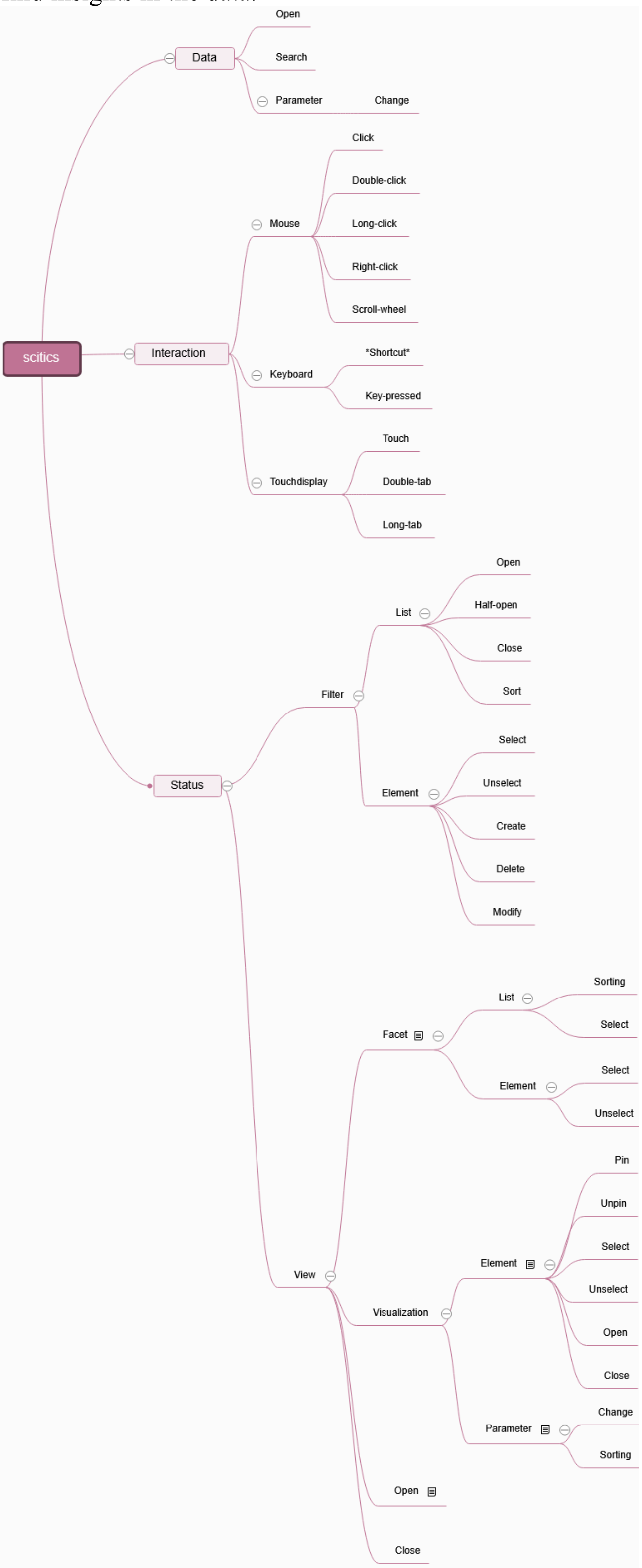

Fig. 3. Taxonomy of the events that are integrated in our trend analytics software on which bases the process mining is working

As result a big process will be generated based on linked events. Due to the taxonomy and especially the *status*-events, specific interactions are named that later a non-expert will help in advancing his analysis. The process model can look like Fig. 4, which should show the model as basic example.

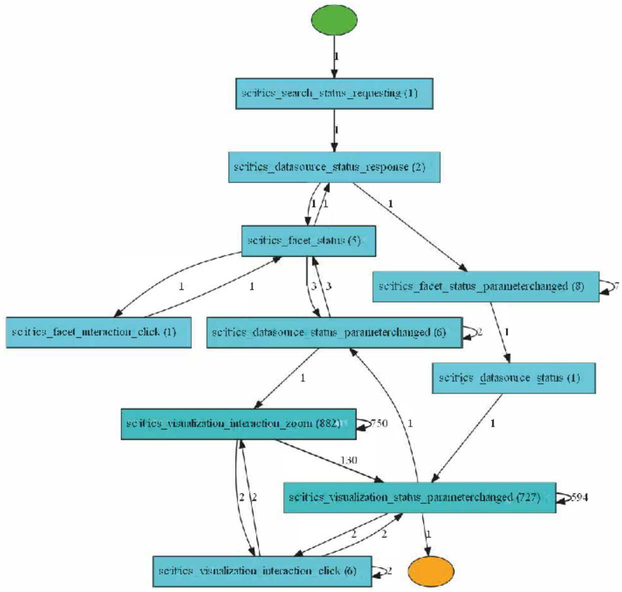

Fig. 4. Example process model, generated based on events from our trend analytics software

III. Assistence Model and Process Assitance in Visual Trend Analytics

The previous section aimed on introducing the very first step: How to integrate a logging based on specified events and furthermore, to generate a process model that covers all activities of a performed trend analysis. Since a further goal is to enable assistance in trend analytics, the process model is a major fundament to be able to track actions of a user and knowing in which process stage he might be and what step could be next or what feature/UI-change might be useful too. The idea is now to combine the process model with recommender systems to adapt the interface. To achieve that, three further steps are needed:

- Extraction of support features and creation of an assistance model.
- Application of the assistance model while a user is using the system.
- Performing the adaptation.

A. *Extraction of Support Features and Generating an Assistance Model on Top of the Process Model*

In particularly while storing the status events, further parameters such as set filter, changed parameters (e.g. on searching data), selected data sources or elements and opened visualization are stored as well. In the process mining we only considered the basic events (better to say the event types) without all the given further technical information, because just the process itself is in focus. However, we also stored the transitions, particularly which events are subsumed to which generated specific process stage. In fact, for any process stage, we assume which events lead to these step, and furthermore which technical support feature was the user using. As a result, we can generate a feature support list for any process stage, consisting among other of all selected visualizations, used filters etc. Via simple weighting algorithms we are now able to rank the support features in perspective of relevance.

As a result, we get an assistance model that advances the previously generated process model. On the basis of the assistance model together with the process model, we can now integrate adaptation capabilities.

B. *Application of the Assistance Model*

The API for the event logging is designed to primary store any event occurred meanwhile user's interaction. However, we also considered a feedback, which can be empty or gives specific assistance command to the frontend.

These commands can enable a **guidance** through the entire analysis task. While at the beginning of the analysis rare atomized recommendations can be given due to high amount of uncertainty about the task, the more and more precisely the recommendations become the more the user is progressing in the analysis. To compensate the uncertainty lack at the beginning, we offer the users a principal task selection in which behalf general adaptations can be performed, such as a comparative user-interface to analyze multiple objectives parallel or a single view that enables a very encompassing and detailed view on the data.

In contrast, the recommendation and assistance features in the mid of analysis task differ in its more data and task driven actions. Since at this stage the identification of the current activity is better to realize, the assistance is significantly more detailed with recommendations such as specific as selected data sources (IEEE), visualization layout (e.g. slice chart), filter criteria (e.g. by country Germany). If a concrete support feature could be identified toward the current user activity, a hint is shown to the user as suggestion – here the user can accept or decline it (see Fig. 4). If a feature has a high probability, the system automatically performs the change directly without prompting – but, this is very restrictively used, since it can confuse the user if e.g. visualization changes within a session without any notice.

The process mining replaces in our implementation traditional workflow-based adaptation approaches, which were usually hard to define – especially in an atomized manner. However, the main goal is similar, in particular in perspective of BPMN [8][9], to guide the user through given business processes. Even the here mined process model does not represent a BPMN, it addresses the business process from the application usage side.

But the support via **adaptation** capabilities goes beyond the guidance aspect. It also helps to identify effective tools during certain steps. Since the set of visualization and its features vary significantly, it can be hard to choose the right visualization for a certain task. This includes also personal preferences. We notice especially for the complex analytical visualizations that they are not so often chosen than others. Through assistance model we can consider these task-suitability and preferences in a broader shape. In the future this aspect should be face more dedicate in an additional user model. The advantage would be, that the more a user is using the system, the more it also adapts the interface in relation to personal preferences and needs and individualizes the assistance from general to personal [10][11]. A sperate user model could also enable to consider other aspects, like individual color settings in charts due to color vision deficiencies.

But as already mentioned, even without the additional user model a variety of options can still be considered to adapt. There are also different options to indicate recommended changes. While in guidance we noticed that we

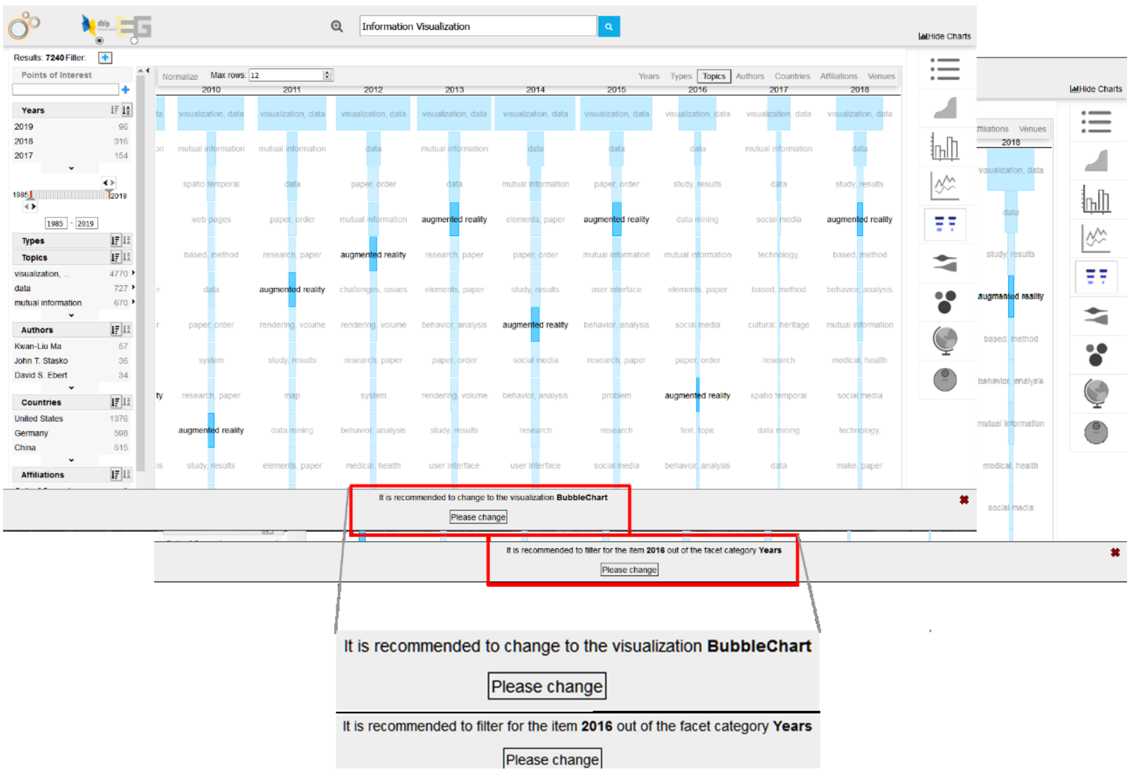

Fig. 5. Example recommendations to assist the user in visual trend analytics, based on previously learned actions by experts.

achieve the best results by requesting the user for changes, e.g. "it is recommended to switch to line chart". In the current prototype two different adaptation capabilities are considered:

- A soft switch or rather a hint.
- A direct adaptation.

The soft switch is used when the planned adaptation seems not to face the user's analysis intention with a high probability. The second method is used, when the system could predict with a close to total probability what the user intents to. This last method is often used only at the beginning of an analysis. However, to guide the view of user also other approaches could be used such as highlighting. So, we currently indicate changes on number (e.g. a change of the number of considered documents in the result set after applying filter changes) by performing an animation that increases the number label and decrease it afterward. Therewith the user gets a direct visible feedback on a performed action to give a him a better causal understanding of the impact of his interaction with the system. Similarly, the order of filter categories or in general recommended filters for current analysis task can be considered. In sum a huge number of visual components of the system can be adapted in respect to the user or task objectives.

C. *Performing the Adaptation.*

In the current prototype we mainly focused on integrating the guidance aspects, since this is the major concern of the trend analytics software. Even further adaptation capabilities are already integrated and can be considered for supporting the user, this feature also would require further investigations how and with which strategy these capabilities can be optimal used.

For that reasons we have integrated recommendations to perform request or direct changes (see Fig. 5), but also the capability to choose a general task and the entire layout will be initialized at the beginning of the analysis. The implementation is being realized in an interactive and dynamic interface. To be able to perform detailed analysis, the interface has an important role, since a solid analysis stays and falls with the analytical possibilities. So, the more interactive and from the analytical perspective dynamical an interface is, the more options it enables to analyze the data and find (unexpected) insights.

IV. CONCLUSIONS

Nowadays, many domains are challenged by the digitization, where upcoming new technologies, business ideas, strategies etc. can revolutionize entire businesses. The industry, especially with Industry 4.0, mobility and logistics are affected by those increasingly [12]. These approaches have to deal with a high variety of changes – to name just a few, there are significant optimizations of the transportation processes, new upcoming logistic ideas such as the delivery via drones or alternative delivery via packaging stations, but also the development of new transportation vehicles that are more sustainable. It is important to use analytical systems to identify such trends, that enable the identification of new trends, next to a rating in perspective of relevance and prediction of the impact on the own business. Even if those tools do exist, they are usually expert tools for professionals and well expertise analysts. These experts are normally rare in SME [13]. Therefore, in this paper a new approach was described to assist and support particularly non-expert users in performing such visual trend analytics through guidance capabilities. As major fundament, process mining is used to generate common analysis processes and additionally extract supporting features that are commonly used by users. On behalf of these processing, a process assistance can be provided that guides and assist especially non-experts through the complex analysis tasks in visual analytics systems.

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