A MOBILE VISUAL ANALYTICS APPROACH FOR INSTANT TREND ANALYSIS IN MOBILE CONTEXTS

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ABSTRACT
The awareness of market trends becomes relevant for a broad number of market branches, in particular the more they are challenged by the digitalization. Trend analysis solutions help business executives identifying upcoming trends early. But solid market analysis takes their time and are often not available on consulting or strategy discussions. This circumstance often leads to unproductive debates where no clear strategy, technology etc. could be identified. Therefore, we propose a mobile visual trend analysis approach that enables a quick trend analysis to identify at least the most relevant and irrelevant aspects to focus debates on the relevant options. To enable an analysis like this, the exhausting analysis on powerful workstations with large screens has to adopted to mobile devices within a mobile behavior. Our main contribution is the therefore a new approach of a mobile knowledge cockpit, which provides different analytical visualizations within and intuitive interaction design.

Keywords: Mobile Visual Analytics, Visual Trend Analysis, Decision Support Systems, Business Analytics, Human-Computer Interaction, Information Visualization, Mobile Devices

1. INTRODUCTION

Big data counts as the oil of the 21st century. Massive collection and storage of data does not lead to new insights or knowledge. Hence, appropriate analysis methods and graphical tools are required to be able to extract a meaning from data. In particular, the combination of data mining approaches together with visual analytics leads to real beneficial application to support decision making in business management. However, these big data analyses are predominantly performed with computers which are connected to high-resolution monitors. These high-resolution monitors are essential to show all available dimensions and facets of the data in multi-variate and analytical visualizations – also sometimes named semantics visualizations (Nazemi, Burkhardt, Ginters et al. 2015). Also, combinations of visualization with brushing and linking enables an encompassing view on the data and therewith a solid insight.

Perpendicular to the development of big data analysis, there is also a trend using mobile devices more often in daily business. Smartphones and tablets are more frequently used in mobile environments e.g. on business travels or meetings. Actually, there do only few solutions existing that enable a data analysis in principle on these mobile devices; however, especially for trend analysis, no mobile solutions exist. Due to the fact of small screens, imprecise interactions in visualizations via touch, slow internet connections and missing calculation performance on the devices leads to failure of classic analysis strategies (Booth 2014). So, the pure shift and transformation of appropriate desktop solutions on mobile devices will most probably not lead to a successful solution.

To be precise, there are currently three major challenges that limits practical use of visual trend analysis on mobile devices: (1) limitation of the result visualizations, due to approx. 5-inch displays on smart-phones or approx. 9-inch displays on tablets (Wang 2006), (2) associated with the small screen sizes there is even a much smaller interaction area with imprecise finger touch interaction (Roudaut 2009), and (3) the reduced available performance, in particular due to 2-3 GB memory limitation (Wang 2006). Due to these challenges, most of the transformation of actual desktop solutions to mobile devices had failed (Wang 2006). It is essential to address the challenges and create new approaches that on the one hand takes in to account the limitations and on the other hand makes use of mobile device benefits, such as gesture interactions.

In this paper we present a new approach to handle visual data analytics, in particular mobile trend analysis. To enable a satisfactory user interaction, we aim on reducing visual spaces on the one hand and introducing a Mobile Knowledge Cockpit metaphor on the other hand. The concept of a Mobile Knowledge Cockpit considers the raised issues and tries to find a solution such that the user can comfortably use the visual trend analysis system in mobile environments. The proof the concept, we apply the mobile solution on DBLP data. A followed user evaluation should show the advantage for the concrete mobile usage of our solution.

2. TREND ANALYSIS FOUNDATIONS

Today's markets, in particular in western world, underlay rapid changes, which makes more and more important to be aware of market and business changes. Almost any market branch is going to revolutionized with the ongoing digitalization. This leads to the challenge that business executives and managers needs to be aware of ongoing trends to be able to react on them soon. Otherwise there is the risk that a new trend or market change leads to a business crash. Organizations and businesses can take advantage of such information by identifying new opportunities and ideas for concepts and products and invest in research and development for those ideas (Think Design 2018).

As foundation, a *trend* is defined as "a method of identifying and describing specific changes over a long period of time, and the future can thus be predicted using past patterns" (Hwang 2017). And even more, *trend analysis* is defined as "a process of estimating gradual change in future events from past data" (Sharma 2016).

2.1. Goals for Trend Analysis

Trend analysis is a quantitative method that requires precise specification of objectives that will be fulfilled from such investigation of data. Following is a list of goals, presented by Chandler (2011) and Gray (2007), that can be achieved by performing trend analysis:

- To describe the past behavior of a process.
- To try and understand the mechanisms behind observed changes.
- To make assessments of possible future scenarios, by extrapolating past changes into the future.
- To enable analysis of systems where long-term changes serve to obscure the aspects of real interest.
- Detect and estimate the magnitude of a trend.
- Identification of time periods in which there was a substantial trend and times in which there was negligible trend.
- To predict and forecast a trend.

2.2. Trend Detection and Trend Extraction

Trend detection, in principle, can be defined as (Kontostathis 2004): "Knowledge of emerging trends is particularly important to individuals and companies who are charged with monitoring a particular field or business. […] Manual review of all the available data is simply not feasible. Human experts who are tasked with identifying emerging trends need to rely on automated systems as the amount of information available in digital form increases."

Detecting trends are important as well as tricky for an organization to lead a business. Several studies have been conducted in this area. Kontostathis et al. (2004) had evaluated several semi-automatic and fully-automatic systems that detect emerging trends from text data mining. Allan et al. (1998) use single pass clustering algorithm and thresholding model that handles emerging stories in the news stream.

2.3. Trend Analysis in Technology Management

A specific field of trend analysis it the identification of trends for technology management. Especially the computer science domain is driven by rapid changes and there regularly coming new technologies on the market.
To be able to identify a trend, Nazemi et al. (2015, 2019) refers to five important question in that context:

1. *When* have technologies or topics emerged and when established?
2. *Where* are the key-players and key-locations?
3. *Who* are the key-players?
4. *What* are the core-topics?
5. *How* will the technologies or topics evolve?
6. And *which* technologies or topics are relevant for an enterprise?

Even those question refer to technology management, they are also relevant for other trend analysis areas, such as strategy or innovation management as well.

2.4. Trend Analysis on Mobile Devices

Variety of literature exist for trend detection, trend discovery, trend analysis, and trend forecasting techniques in different domains. Kim et al. (2009) created a probabilistic model to discover technological trends from patent text by extracting problem and solution key-phrases comprising a technology and propose a Technological Trend Discovery (TTD) system that automatically captures technological mainstream from several related documents. Lent et al. (1997) address the problem of discovering trends in textual databases by using mining techniques like phrase identification using sequential pattern mining and trend identification and use therefore shape queries and finally visualize the trends over the mined data. Pottenger et al. (2001) used radar system analogy to move out stationary topic areas in a semantic sense with respect to time and user queries the hot topic regions of semantic locality in a set of collections.

Few types of research have also come up with new interesting ideas like ThemeRiver (Havre 2002), which includes a river metaphor along the horizontal axis to depict thematic variations over time from the document collection. Similar to this, yet more detailed, text insight via automated, responsive analysis system TIARA (Liu

2008) performs more complex text analysis and shows detailed thematic contents in keywords.

Trend Analysis has been discussed many times so far, yet the concept for mobile devices has no significant literature and research work. In fact, rare numbers of concepts toward trend analysis concept for smaller devices like mobile phones or tablets do exist. The current work is focused on techniques to derive an efficient solution to achieve trend analysis or visualization for desktop computers.

2.5. Use-Case Scenarios

Trend analysis is commonly a complex task that is made at special equipped high-resolution PCs by experts. However, there are a couple of scenarios where an analysis is required on-demand.

An example of such a scenario could be a direct client meeting, where certain solutions or ideas will be discussed and the uncertainty is too high to really be able to focus on a selected number of options. Here it can be extremely helpful to be able to eliminate options that are nowadays definitely out of use or relevance. Or imagine the situation you want to gather a certain overview, e.g. about a market, on players or important technologies. An instant analysis could help to gather a rudimentary overview and brings you in the situation to formulate an initial draft of an idea or goal.

Even more, it can help to proof upcoming ideas in meetings toward relevance, current usage etc. This includes also performance of quick evaluations of mentioned market situations by comparing certain topics.

Similar to the use of google for upcoming questions to check the facts, in particular in business and technology management, there are often situation where the uncertainty is high. In contrast to simple fact checks, it is not so easy to say if certain technologies are useful in specific fields. Of course, such a quick trend analysis is never solid, but it can help to make strategy meetings and similar discussions more fruitful since a couple of aspects could be quickly checked and at least help to tight the focus more on real options, that afterwards can be checked in detail.

As principal application scenarios, we defined the following three for the first prototype:

(1) The *general* or *target analysis* should enable to get an overview about a certain field, such as "cloud computing" or "big data analytics". The purpose is to identify most relevant and upcoming topics, but also identifying the most relevant authors or affiliations. However, also the concrete publications can be in scope, to more precisely answer questions about used algorithms etc.

(2) The *author analysis* is a more specialized search toward certain authors. Since authors are sometimes named differently, a disambiguation should help to find all papers from a certain author. The dedicate focus on authors seems at the beginning a little strange, but is to consider that authors of scientific publication are often experts of their domains. So, they are not "only" authors, they are high professionals or experts. From the principal behavior, the analytical capabilities e.g. used visualization are similar to the general/targeted analysis, the major difference is almost the disambiguation feature.

(3) The *comprehensible analysis* is most likely to compare results from two authors, topics etc. On this way competing issues could be analyzed, for instance in perspective of a higher attractiveness or benefits for certain usage scenarios.

3. A VISUAL TREND ANALYTICS APPROACH FOR MOBILE ENVIRONMENTS

In the following sections the concept and design of our new mobile visual analytics approach is described. Since the principal data processing actions are equal to those we already presented (Nazemi, Retz, Burkhardt et al. 2015; Nazemi 2019), we focus strongly on the visual aspects.

3.1. Data Processing and Infrastructure Foundations

Our principal data processing model builds upon on our previous work on visual trend analysis with digital libraries (Nazemi 2015) that uses the reference model of Card et al. (1999) as foundation. According to our previous model, we subdivided the transformation process for visual trend analysis in digital libraries into the steps of (1) Data Enrichment, (2) Data Transformation, (3) Visual Mappings, and (4) Visual Orchestration.

Data Enrichment gathers additional data from external repositories to enhance the quality of data and uses text analysis techniques to extract valuable information from these data. Data Transformation structures the data for a proper visualization. It detects relevance, amount and content of queried data and uses these features to create models revealing certain aspects of the data. Visual Mappings transforms the data models to appropriate visualizations. Visual Orchestration uses textual and visual information gathered in the previous transformation steps to create static and dynamic elements for human interaction.

The existing solutions consists of two major components, the mobile analytics web-service as well as the web-frontend. The mobile analytics web-service provides the main relevant publication data, coming from the already explained digital library web-service, as well as the major pre-processing that are required to show the charts and visualizations on the mobile devices.

3.2. Data Processing Architecture

Since we already have a fully working digital library web-service to process the main publication data for trend analysis, we just added an additional mobile analytics web-service as service between the digital library web-service and the client with the visual frontend (Fig. 1). The additional mobile analytics web-servers has the task to pre-processes the data for the mobile visualization. Herby the calculations focus strongly on the behavior of the mobile devices and the specifically used charts and visualizations, which are limited among other in perspective of performance. Especially the lower memory is a special challenge to enable bigger calculations on a mobile device as it is possible on a desktop PC. Even more the battery consumption is a significant restriction, since a mobile trend analysis would be not user satisfying if it quickly empties the smartphone or tablet battery.

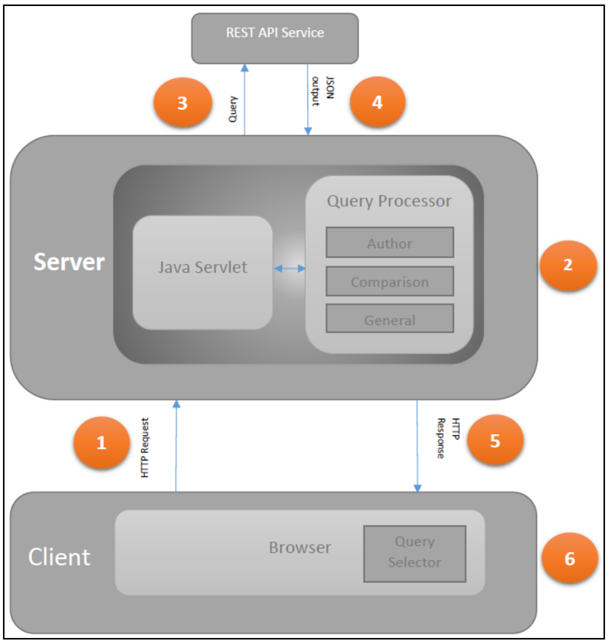

Figure 1: Visual Trend Analysis Architecture

From the data processing side, the user initiates the analysis by performing a request on the client, which sends a query to the query processor on the mobile analytics web-service. Here, the requested data is sliced into further request on the digital library web-service, to get the document-based data. The returning data from the digital library web-service and then further processed on behalf of the required data to generate later on the visualization on the client. The final calculated data is turned back to client, which shows the result on the screen.

3.3. Aspect-oriented Visualizations

For the initial mobile version, we focused on basic visualizations that enable beside trivial trend analysis question also general information gatherings such as most relevant authors or affiliations in a specific field next to the main publications. Since it was not the goal to provide similar encompassing and extensive analytical capabilities as the desktop version does, the focus laid more on easy and intuitive operate-ability that requires from the users only few understandings about visual analytics or trend analytics.

The initial screen (Fig. 2) shows the search field and above the use-case scenario selection. The search enables advanced queries e.g. by concatenating different phrases with "or" and "and". The main visualization that can be further used are the bar charts (Fig. 3). Bar charts are highly intuitive and effective to use visualization types, which are in particular in mobile environments most easy to use and the shown information can be quickly extracted and understood by the user.

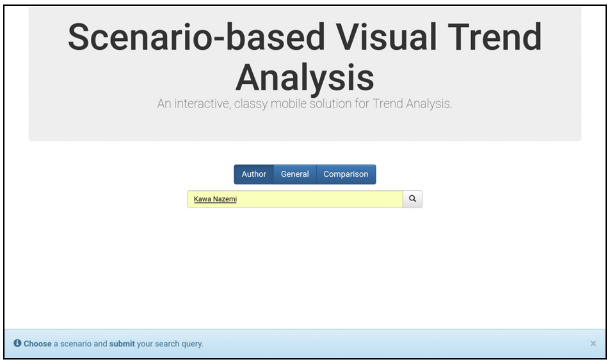

Figure 2: The initial screen where the user performs the search and selects the analysis scenario

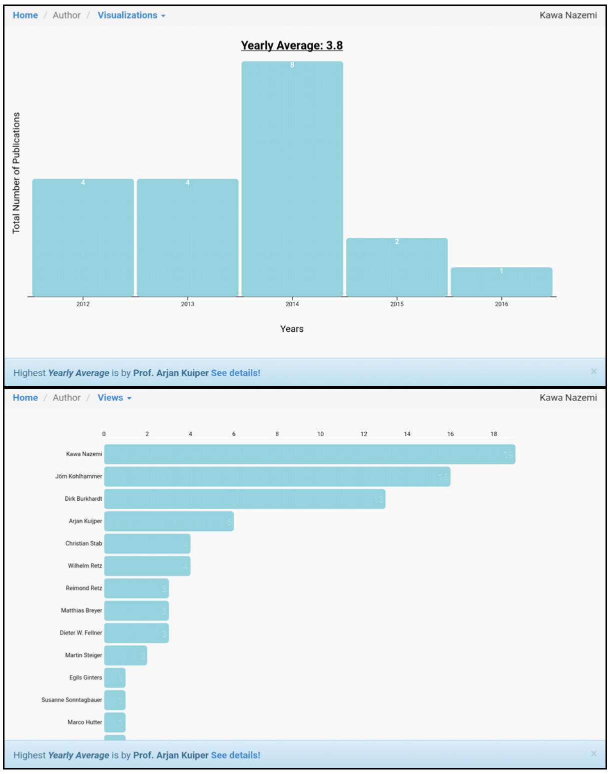

Figure 3: Different forms of the included bar charts, the vertical one (bottom) enables sorting and scrolling

For an advanced view on topics or publications of certain authors per year, the stacked bar-chart is used (Fig. 4). Due to the small amount of space, it is one of the few visualizations that enables still a good readability on small smartphone screens.

The concrete publications will finally be shown in the publication result view (Fig. 5). By clicking on a concrete publication title, further meta-information such as the DOI-link are shown. A click on the URL or DOI-link opens the full paper if the user owns right for it of the corresponding publisher.

The system is designed to allow integration of further visualization layouts. However, the goal of this prototype laid on the general feasibility and the identification of the principal application benefit. And the used visualization set seems to be appropriate to perform an evaluation.

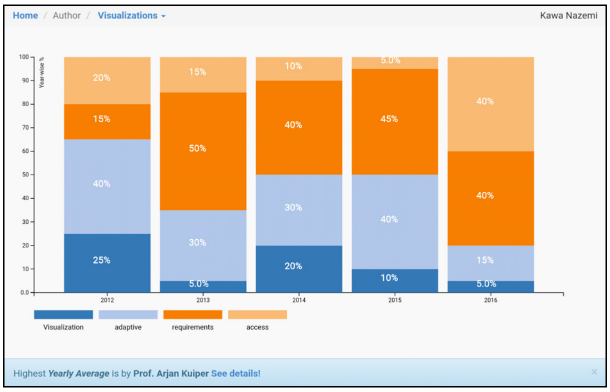

Figure 4: Stacked bar-chart for a comprehensible view on a yearly basis

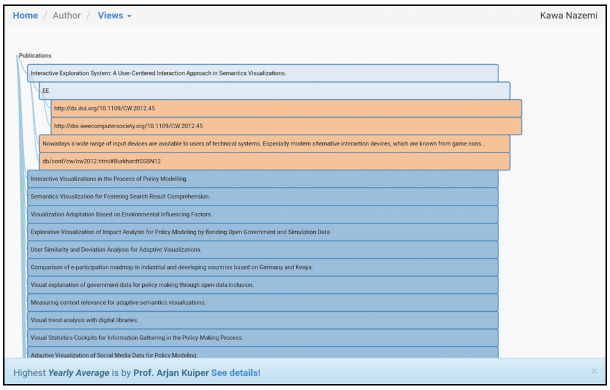

Figure 5: Publication result view as extendable list to show further details on demand

3.4. Mobile Knowledge Cockpit

Especially on small screens, the interaction logic is a very important aspect. Traditional approaches that are well known from (large resolution) displays on workspaces do not work apparently on mobile devices. However, in perspective of intuitiveness we successfully introduced the knowledge cockpit metaphor on stationary computers (Nazemi 2010, Nazemi 2019). The idea we had was to follow this principle idea, but rethink it for the use on mobile devices.

As a result, conceptualized and implemented the idea of a Mobile Knowledge Cockpit that seriously considers the specific limitations but also advantages of nowadays mobile devices. The major difference of the Mobile Knowledge Cockpit is that only a single visualization is shown at a time, but it can be switched between different visualization by the use of moving touch-gestures.

A touch movements form left to right lead to show data visualization from abstract to concrete, in regards of Shneiderman's (1996) visual information seeking mantra. And touch movements upward or downward lead to switches between different aspect-oriented visualizations but of similar data granularity level (see Fig. 6).

The combination of single shown visualization and inclusion specific visualization arrangement in the background that can be controlled via gestures ensures that the user could find and understand a logic.

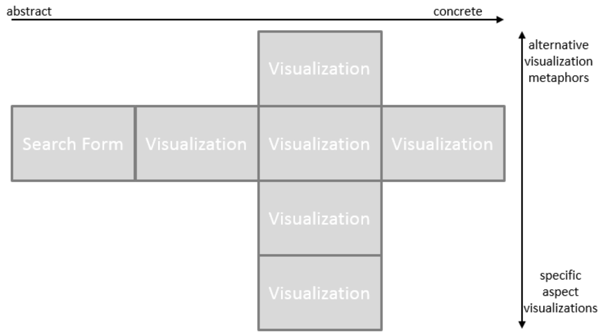

Figure 6: The different axis-meanings of the Mobile Knowledge Cockpit metaphor

From the application look and feel, the user will only see the current selected visualization. The other available visualization layouts are hidden, but can be indicated on the edges (see Fig. 7).

Figure 7: An example mockup of a current active visualizations next to hints of other available visualizations on the screen edges

In the current Mobile Knowledge Cockpit prototype, we considered only a few visualizations and charts, but the system is designed to extend it with further visualizations (Fig. 8).

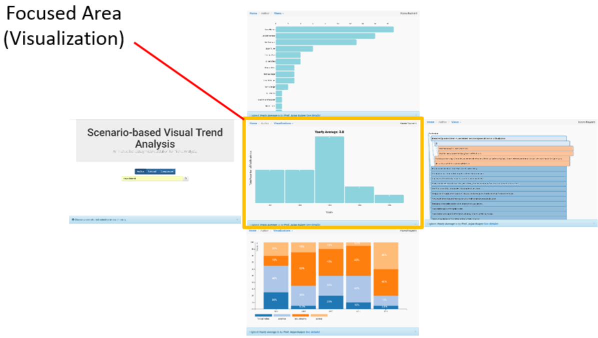

Figure 8: The arrangement of the visualizations in the background between which the user can switch by wiping touch gestures on the screen.

3.5. Use-Case Scenarios Integration

As mentioned before, for the initial proof-of-concept, we focused on three scenarios: (1) general/targeted analysis, (2) author analysis including disambiguation and (3) comprehensible analysis. From the principle look & feel the first two scenarios look identical, because the major difference is handled on the backend in the data. But it has no impact on the frontend visualization (as shown in Fig. 9). As sketched, the visualization aiming just on showing results to a single searched author or topic.

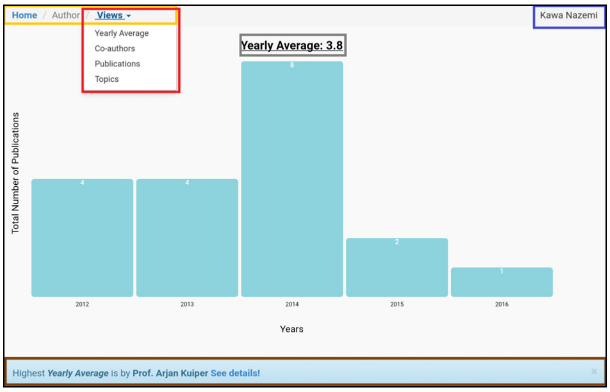

Figure 9: General/targeted and author analysis

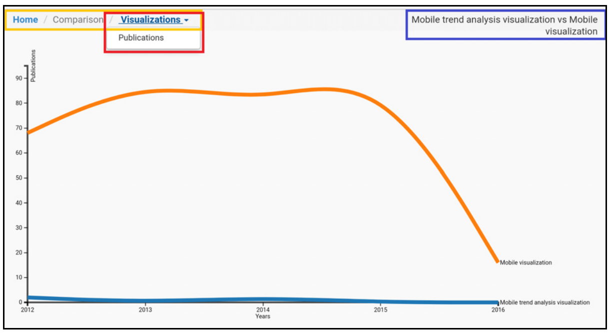

Figure 10: Comprehensible search and analysis

In contrast to the first two scenarios, the comprehensible search is aimed compare two topics. Therefore, some different visualizations are included, that enable to compare the retrieved data visually (Fig. 10). The comprehensible view enables identification of gaps or similarities, which can help to identify the most relevant topic or solution in a certain field.

In the future it is planned to consider our recent introduces search intentions analysis approach (Burkhardt 2016; Burkhardt 2011) to automatically identify the intended search type.

4. EVALUATION

To proof our concept, we performed an evaluation via a web-based evaluation system (Nazemi, Burkhardt, Hoppe et al. 2015). Here, the participants had to perform a couple of tasks online on a mobile device (we recommended a 9-inch tablet). To ensure that the participants really perform the tasks with a mobile device, we checked the send browser agent string for names that match to mobile devices.

On the mobile device the users had to perform a couple of tasks on two different analysis systems. One system was our new developed mobile trend analytics prototype, the other was our desktop-based trend analysis tool (Nazemi, Retz, Burkhardt et al. 2015; Nazemi 2019).

The evaluation was performed with 24 participants consisting of 17 (approx. 71%) males and 7 (approx. 29%) females, all of them have an academic background in computer sciences and declared to own basic understandings in visual analytics. Furthermore, the participants where between 25 and 36 years old, with in mean 28.4 years of age.

4.1. Methodology

As already mentioned, the evaluation was performed via a web-based evaluation system. So, there was no option to introduce the participant face to face or give some hints. However, the evaluation system is designed to guide the participant along the full predefined procedure. At the beginning he will also be introduced to do not guess and to perform the evaluation in a row without brakes, since we measure the time for better quantitative insights.

At the initial screen the user gets introduced about the evaluation itself, the goals, principal procedure and what information will be collected during the evaluation. After the participant clicks okay, the evaluation starts.

The first view is a questionnaire about some principal demographic information, such as age, highest degree etc.

In the next block the participant has to use the new mobile trend analytics system as well as the already existing desktop trend analytics system. It is important to mention that the block selection is randomized, so that one participant starts with the desktop version and another participant will start with the mobile version. The randomization is important to avoid learning effects that gives an advantage to the system that is presented

as second, since some basic metaphors etc. are then still known from the first.
In each of the blocks, the user has to perform three given task (see Tab. 1) which are for each block similar, but not equal. To every block the user could only select one or no answer. In the background the system observes if the answer is correct and how long the user needs to make the choice.
After the practical tasks, the user had to give a feedback based on the INTUI questionnaire, to measure the intuitiveness level.

Table 1: Multiple choice questions, which the user has to answer by using the system practically.

Question	Answer options
How many publications do you find by [author name] for the year [specific year]?	4
With whom does the researcher has most publications?	4
[topic name] is the dominating topic [author name] had worked on. However, he has less publications related to this topic for the past 2 years (2015 and 2016). Do you think this is a diminishing trend for this topic by the researcher?	4

After the participant has performed any task blocks, the evaluation ends.

4.2. Results

The results of the evaluation show that for the given types of the task the mobile trend analytics prototype gains in average and total better results. Except for the first task, the mobile version always achieved a higher task correctness (Fig. 11) and better task completion time (Fig. 12).

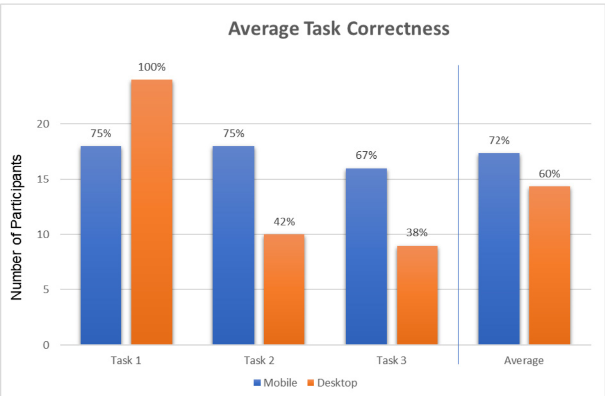

Figure 11: Average task correctness (more is better)

In summary we can say that the mobile trend analysis approach is appropriate for answering immediate upcoming questions in fast and effective manner. However, it is to consider that the results may not be valid and do just provide a quick overview. Also, such kind of mobile analysis solution can not avoid the fundamental analysis regarding solid trends. It is just a small helper that can make consulting, meetings or discussions more fruitful due the opportunity to shrink the agenda and the more relevant aspects.

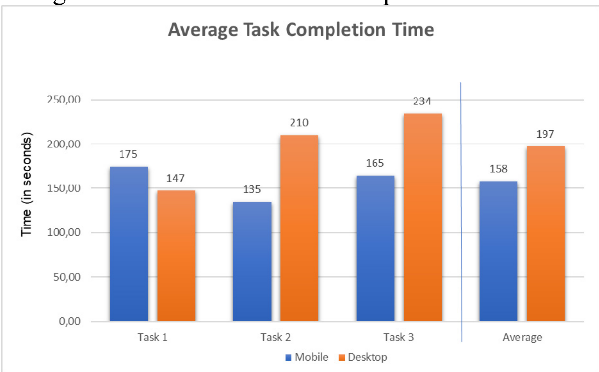

Figure 12: Average task completion time (fewer is better)

5. DISCUSSION

(Visual) Trend Analysis is still a relatively new field with a high relevance for the business domain, but currently there are only a very approaches and systems available that make use of it. To apply this new field into a mobile context at that early stage leads inevitable to the question, if it has a solid fundament and makes sense. Solid trend analysis requires from the analyst large amount of experiences, analytical competences and technologies that analysis the relevant information in a correct manner – and of course needs to be validated by expertise of the analyst. A quick analysis as we intended in this mobile trend analysis is neglecting many of the quality criteria that a good analysis should take care.

Furthermore, it is still open of analysts really see a need for a system like this. The challenge is, that there is indeed a need to quick check certain topics or trends, but it is important that the insights are valid. It can be interesting to check, if it maybe a predefined and analyzed set of topics would be a compromise. However, it is to consider that therewith the validity is given, but upcoming new topics and trends would miss.

Under the framework of FP7 FUPOL project No. 287119 “Future Policy Modeling” was designed Skopje Bicycle Inter-modality Simulator (Ginters 2014) which assisted the municipality and citizens to simulate recommendable bicycle routes in urban area. The aim of the research was finding the appropriate ways to move as much as possible citizens to green transport area. However, it would be reasonable to visualize the trends of citizen habits to assess the sustainability of used approach. There could be applied the findings of current research.

6. CONCLUSION

In this paper we presented a new approach to handle visual trend analytics in a mobile environment. This should help to indicate trends within consulting, meetings or strategy discussion more efficient and fruitful. Therefore, a couple of use-case scenarios where identified, where a mobile trend analysis could make sense. Additionally, a concept and design were made, how the trend analytics could be realized on mobile devices, in regards of the specific limitations of mobile devices, such as small resolution, lower performance and imprecise interaction via touch interaction. One of the major contributions is the new Mobile Knowledge Cockpit metaphor that enables an intuitive interaction through varicose visualizations.

A performed user evaluation could show that the prototype faces the intended goals. However, since the field of mobile trend analysis is a very new one, it is hard to estimate if the idea has higher value for the industry, since flexible use decreases the determined insights in perspective of quality.

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