Visual Analytics in Mobility, Transportation and Logistics

Kawa Nazemi[1(✉)], Dirk Burkhardt[1], Lukas Kaupp[1], Till Dannewald[2], Matthias Kowald[2], and Egils Ginters[3]

[1] Darmstadt University of Applied Sciences, Haardtring 100, 64295 Darmstadt, Germany
{kawa.nazemi,dirk.burkhardt,lukas.kaupp}@h-da.de
[2] Wiesbaden University of Applied Sciences, Kurt-Schumacher-Ring 18, 65197 Wiesbaden, Germany
{till.dannewald,matthias.kowald}@hs-rm.de
[3] Riga Technical University, Kalku Street 1, Riga 1658, Latvia
egils.ginters@rtu.lv

Abstract. Mobility, transportation and logistics are more and more influenced by a variety of indicators such as new technological developments, ecological and economic changes, political decisions and in particular humans' mobility behavior. These indicators will lead to massive changes in our daily live with regards to mobility, transportation and logistics. New technologies will lead to a different mobility behavior with new constraints. These changes in mobility behavior and logistics require analytical systems to forecast the required information and probably appearing changes. These systems have to consider different perspectives and employ multiple indicators. Visual Analytics provides both, the analytical approaches by including machine learning approaches and interactive visualizations to enable such analytical tasks. In this paper the main indicators for Visual Analytics in the domain of mobility transportation and logistics are discussed and followed by exemplary case studies to illustrate the advantages of such systems. The examples are aimed to demonstrate the benefits of Visual Analytics in mobility.

Keywords: Visual Analytics · Mobility behavior · Data analytics

1 Introduction

Mobility, transportation and logistics provide a variety of indicators for analytics systems. These indicators include issues for analyzing the infrastructure, technological development, mobility behavior and many more aspects. Visual Analytics couples machine learning methods to interactive visualizations and thus provides a good way to handle mass and heterogenous data, predict future scenarios or detect patterns. The analytical capabilities of Visual Analytics are due to the mixed usage of machine and human intelligence much greater than exclusive machine learning approaches, but still limited to the correct choice of data and methods.

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In this context, indicators for Visual Analytics are essential. The domain of mobility, logistics and transportation therefore is investigated to set up a first classification of useful and important indicators. These should be seen as a first attempt to identify indicators for Visual Analytics.

First the main idea of Visual Analytics is discussed with the most popular and widely used definitions and also described on the base of most influential model. Thereafter, classification of indicators are introduced and it is justified why these indicators are in particular important for mobility, transportation and logistics. Two different case studies that are using different indicators to illustrate the added value are involved in the paper. The main contribution of the article is the classification and introduction of the relevant indicators with related data examples.

2 Visual Analytics

Visual Analytics applications and approaches are increasingly used to analyze different data in a variety of analytical tasks. Even if the term is often used synonymously to information visualization, Visual Analytics gained clear definitions for a clear differentiation. An early and most influential definition of Visual Analytics was proposed by Thomas and Cook:

> *"Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces"* [1].

Their definition emphasizes the "overwhelming amounts of disparate, conflicting, and dynamic information" [1] in particular for security related analysis tasks. One of the main focuses of Visual Analytics is to "detect the expected and discover the unexpected' [1] from massive and ambiguous data. They outlined that the main areas of the interdisciplinary field of Visual Analytics are:

- Analytical reasoning techniques: for obtaining insights and support analytical tasks such as decision making;
- Visual representations and interaction techniques: for enabling users to explore and understand large amounts of data, and interact with them with their visual perception abilities;
- Data representations and transformations: to convert all types of data, even conflicting and dynamic, to support visualization and analysis;
- Production, presentation and dissemination: to provide a reporting ability for a broader audience and communicate the analysis results [1, 2].

This definition gained a series of revisions to precise the abstract formulation [3–7]. Keim et al. commented that the definition of such an interdisciplinary field is not easy and tried to precise it as follow:

> *"Visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making on the basis of very large and complex datasets"* [7].

Keim et al. stated more precisely the interdisciplinary nature of Visual Analytics by introducing and outlining the combined use of automated analysis techniques and interactive information visualizations. In addition, it emphasizes the challenge of data amount, thus this confines Visual Analytics to “very large” data-sets. The main characteristics of solving analytical tasks with interactive information visualizations still remain. Furthermore, they introduced a model that couples the stated techniques in an iterative. Figure 1 illustrates their model that targets on providing a tight coupling of visual and automatic analysis methods through human interaction to enable human to gain insights and knowledge [7].

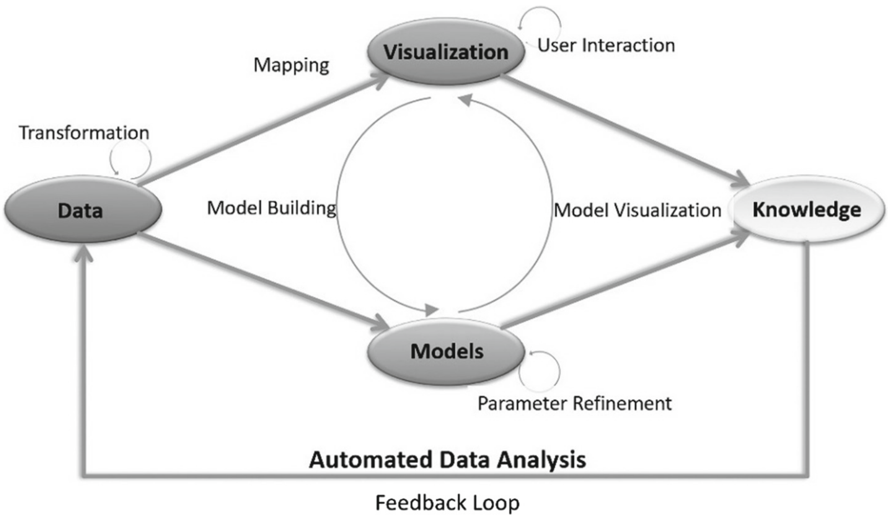

Fig. 1. The Visual Analytics model (adapted from [7]).

The Visual Analytics process models the different stages represented by oval forms and their transitions with arrows. The process starts with the data that may need to be preprocessed and transformed to an adequate way (indicated with the transformation arrow). After the transformation stage, a visual pipeline and model pipeline indicates the different approaches that are combined. The automatic analysis was proposed as techniques for data mining that are applied to generate models from the underlying data. These models can further be evaluated, refined, or specified by interacting with data [7]. Visualizations are used to interact with the models and manipulate and refine the parameters. Further the selection of alternating models can be visualized to evaluate the findings out of the generated model.

Nowadays the “model” is more related to approaches of machine learning and artificial intelligence respectively. Through this enhancement, Visual Analytics combines machine learning methods with interactive visualizations to reveal insights. The role of human and the possibilities to interact in the stages of analytical processing remains as they are proposed in the reference model for visualization [8]. The authors summarize that Visual Analytics is the science of analytical reasoning empowered by interactive visualizations and combines interactive visualizations with models and approaches of machine learning and artificial intelligence. They thus allow to solvi complex analytical tasks by uncovering hidden patterns in data by leveraging human perception of the visual space. The research on Visual Analytics is closely related to the topics of Data Science. Both areas seek to enhance the knowledge discovery process using machine learning, data mining and artificial intelligence methods. Visual Analytics, however, allows commonly a direct manipulation of the underlying models through graphical representations.

3 Indicators for Analytical Tasks in Mobility

The authors could outline that Visual Analytics combines methods of interactive visualization with machine learning to enable complex task solving based on huge amount of data. Employing the methods on Visual Analytics in the field of mobility and transport makes it necessary to identify and categorize indicators. These indicators have a strong relationship to data in Visual Analytics. Based on data and task a first classification of such indicators may be possible. The authors therefore identify indicators and the related data that lead to solving such tasks in mobility, transportation and logistics. These indicators that can be gathered from the variety of data should first be identified and categorized for the different analytical tasks in this domain. The authors identify following categories of data and related indicators for the domain of mobility, transportation and logistics:

- *Behavioral Indicators*: uses data that allow to gather mobility behavior;
- *Sensor Indicators*: uses data that allow to gather insights in production, usage and life-cycle in the domain of mobility, logistics and transportation;
- *Environmental Indicators*: uses data that allow to get insights of the impact of mobility to our environment: e.g. the built environment in terms of population density or diversity of usage, and accessibility;
- *Technology and Innovation Indicators*: uses data that allow to gather insights of the current trends in mobility and predict possible future scenarios;
- *Geographical Indicators*: uses data that allow to gather information about the geographical infrastructure of mobility, transportation and logistics.

Behavioral indicators enable Visual Analytics systems to analyze the mobility behavior in a general manner. This kind of data are gathered through mobile devices of drivers, navigation systems, stationary counters on street and a variety of further sources. The European Commission has already published a regulation for so called "eCall"-Systems that is mandatory for all cars manufactured later than April 2018 [9]. Sensor indicators enable Visual Analytics systems, in particular with machine learning approaches, to gather not only information about the manufacturing and predict maintenance but also to gather usage data. A huge number of internal sensors in manufacturing, cars, rails etc. provide sufficient information for Visual Analytics. Furthermore, external devices could be placed to gather these data. Environmental indicators enable Visual Analytics systems to give an insight of the impact of mobility, transportation and logistics to our environment. Therefore, different data gathering stations are available and also cars, trains etc. provide that information. Technology and Innovation indicators enable Visual Analytics systems to provide information about early technological signals [10], identify emerging trends [11], predicting upcoming trends etc. This leads to strategic decision making in industrial manufacturing and investing to more future related concepts and technologies. This area of Corporate Foresight plays more and more an increasing role in mobility, transportation and logistics. Geographical indicators are the most wide-spread data. These commonly occur as longitudes (east-west position) and latitudes (north-south position), and points of interest. These points of interest may be streets to uncover the overall infrastructure or analyze specific points-of-interest and enable solving analytical tasks.

4 Case Studies of Visual Analytics in Mobility

The authors introduce in this section with a Visual Analytics system that makes use of different indicators as described above. The main goal is to provide different examples for Visual Analytics in particular in the domain of mobility.

4.1 A Case Study on Analyzing Technological Trends in Mobility

The identification of technological trends in mobility enables decision makers from manufacturing, politics and strategic analysts to detect emerging technological trends and adapt their strategic directions [11]. For this purpose, patent data and scientific publications are appropriate. These data would allow to identify technologies at an early stage and react to the market developments appropriately. To illustrate the Visual Analytics system, scientific publications from different sources are used, e.g. DBLP, Springer, Eurographics, IEEE etc. Thus, the indicators for this case study are “Technological and Innovation indicators”.

In a first step, the DBLP data are used as baseline. These data do not provide any kind of information beside the authors’ names, titles, years and in most cases a DOI. Using that DOI, the data are enriched through web-mining methods [11, 12]. Further data from other sources are gathered and compared either through the DOI or through the combination of title and authors to eliminate duplicates. Thereafter, topics are generated through different approaches, e.g. LDA [13] and LSA [11]. With the enriched information a Visual Analytics system can be provided that models the underlying data in different ways, e.g. semantics model, geographical model and temporal model [11]. With this data the emerging technologies are identified [11] and provided on macro- and micro-level. On the micro-level an overview about all publications related to mobility are illustrated in Fig. 2a. Further the technological developments in mobility are illustrated in Fig. 2b. With the semantic data model and an appropriate visualization, the most influential author and the co-author relationship can be revealed as illustrated in Fig. 2c. This interactive visual interface further provides the temporal spread of the author’s publications that may indicate, if he or she is still working on this topic. The geographical data model provides information about the amount of publication from each country. Thereby the saturation of the country color is used as indicator, whereas the exact amount of publication can be gathered through a mouseover interaction. Figure 2d illustrates the geographical spread of publications about mobility.

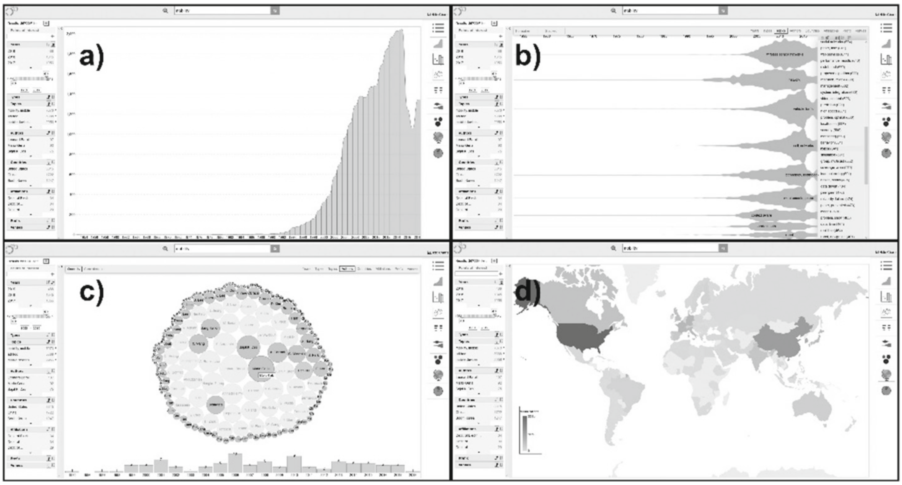

Fig. 2. A Visual Analytics system for trend analysis using technology and innovation indicators.

The above described case study just introduced a small number of analytical possibilities. A deeper insight can be found in [11, 12, 14].

4.2 A Case Study of Visual Analytics for Analyzing the Geographical Spread of Charging Stations for eMobility

Geographical indicators play for a variety of tasks in mobility, transportation and logistics an important role. The major aspect here is to detect paths or points in the infrastructure that are relevant to improve aspects of mobility, transportation and logistics. These could be streets, bridges, railway roads and many more. The authors use in this case study, with the same Visual Analytics System as described above, plug in charging stations worldwide. The goal is to provide an interactive visual system for charging station providers but also for political decision makers to analyze not only the charging behavior but also the needs for further charging stations.

The data used here are from different providers. The authors tried to use in particular first-hand data from the charging provider themselves. Redundancies were eliminated and the data were enriches using data from service providers. As the Visual Analytics system is not a dedicated system just for plug in charging station, the user starts with a search (which is also provided in the overview) for plug charging. Thereafter a world map with a heatmap-visualization is provided to see where the most charging stations are as illustrated in Fig. 3a. Thus, this is a work-in-progress system, the data may have lacks in particular in Asia. The system allows zooming or filtering through the faceted search on the left bar. Zooming into a country shows first the overall coverage, which seems to be pretty good for Germany as illustrated in Fig. 3b.

But it also shows that the north-east part of Germany has a lot of lacks. A further zoom reveals the lacks and illustrates clearly that beside greater cities like Berlin or Dresden the coverage is not that good as illustrated in Fig. 3c. The system makes use of a kind of semantic zoom and visualizes each charging station as a colored dot as illustrated in Fig. 3d. Green color dots are used for free charging stations, whereas red dots are use to indicate that these charging stations are fee-based.

Fig. 3. A Visual Analytics System using geographical indicators.

5 Conclusion

Mobility, transportation and logistics are influenced by a variety of indicators such as new technological developments, ecological and economic changes, political decisions and in particular humans' mobility behavior. The authors therefore investigated the entire domain of mobility, logistics and transportation to set up a first classification of useful and important indicators. First the main idea of Visual Analytics with the most popular and widely used definitions and a model are introduced. Thereafter, the classification of indicators are provided and justified why these indicators are in particular important for mobility, transportation and logistics. The authors added two different case studies that are using different indicators to illustrate the added value.

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