Visual Analytics Indicators for Mobility and Transportation

Kawa Nazemi
HCI & Visual Analytics
Darmstadt University of Applied Sciences
Darmstadt, Germany
kawa.nazemi@h-da.de

Matthias Kowald
Mobility Management
Wiesbaden University of Applied Sciences
Wiesbaden, Germany
matthias.kowald@hs-rm.de

Till Dannewald
Digital Business Management
Wiesbaden University of Applied Sciences
Wiesbaden, Germany
till.dannewald@hs-rm.de

Dirk Burkhardt
HCI & Visual Analytics
Darmstadt University of Applied Sciences
Darmstadt, Germany
dirk.burkhardt@h-da.de

Egils Ginters
Department of Modelling and Simulation
Riga Technical University
Riga, Latvia
egils.ginters@rtu.lv

***Abstract*—Visual Analytics enables a deep analysis of complex and multivariate data by applying machine learning methods and interactive visualization. These complex analyses lead to gain insights and knowledge for a variety of analytics tasks to enable the decision-making process. The enablement of decision-making processes is essential for managing and planning mobility and transportation. These are influenced by a variety of indicators such as new technological developments, ecological and economic changes, political decisions and in particular humans' mobility behaviour. New technologies will lead to a different mobility behaviour with other constraints. These changes in mobility behaviour require analytical systems to forecast the required information and probably appearing changes. These systems must consider different perspectives and employ multiple indicators. Visual Analytics enable such analytical tasks. We introduce in this paper the main indicators for Visual Analytics for mobility and transportation that are exemplary explained through two case studies.**

Keywords—visual analytics, mobility behaviour, mobility analytics, mobility indicators for visual analytics

I. Introduction

Visual Analytics combines machine learning methods with interactive visualizations to enable analysing complex correlations, predicting future scenarios or detecting 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.

Mobility and transportation are since few years subject of research in a variety of research communities. Heterogenous data and analysis tasks are related to this area and enable through Visual Analytics appropriate analysis capabilities. The related data can be assigned to indicators that are relevant for mobility and mobility research. These indicators include indications for analysing the infrastructure, technological development, mobility behaviour etc. and the related data provide enough information to analyse the entire domain in a systematic and useful way. To enable appropriate analysis and decision-making in the area of mobility and logistics, it is essential to work out and classify the related indicators in an enough was and relate those with data that are not necessarily from the same domain. Such a systemic few on indicators and related data does not exist to our best of knowledge and would fill a massive gap in applying Visual Analytics for mobility and transportation.

We introduce in this paper first the main idea of Visual Analytics with the most influential data classification to illustrate the existing gaps. Bases on works form both areas, Visual Analytics and mobility, we introduce a systematic view and classification of indicators in mobility and transportation and relate them to appropriate data. We conclude this paper with two different application scenarios that are using different indicators to illustrate the added value. Our main contribution is a revised classification of relevant indicators and the relation to data.

II. Visual Analytics

Visual Analytics is widely used for analysing a variety of complex tasks. According to Thomas and Cook *"Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces"* [1]. This definition emphasizes the "overwhelming amounts of disparate, conflicting, and dynamic information" [1] in particular for security related analysis tasks. One of the main aspects of Visual Analytics is to "detect the expected and discover the unexpected" [1] "from massive and ambiguous data" [31]. 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" [1, 2].
- "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" [1, 2].
- "Data representations and transformations: to convert all types of data, even conflicting and dynamic, to support visualization and analysis" [1, 2].
- "Production, presentation and dissemination: to provide a reporting ability for a broader audience and communicate the analysis results" [1, 2].

978-1-7281-9105-8/20/$31.00 ©2020 IEEE

"This definition gained a series of revisions to precise the abstract formulation" [3, 4, 5, 6, 7]. A more precise definition was provided by Keim et al., who defined Visual Analytics as combination of automated analysis techniques with interactive visualizations [7]. Thereby, Visual Analytics leads to a more "*effective understanding, reasoning and decision making"* [7].

"Nowadays the "automated analysis" is performed through machine learning and artificial intelligence methods. Through this enhancement, Visual Analytics combines machine learning methods with interactive visualizations to reveal insights" [32]. Thereby, the human plays an essential role, since the entire process of analysing large amount of data through interactive visualizations incorporates human's intelligence and acquiring knowledge. Gathering insights, gaining knowledge and enabling reasoning and analysis are integral part of Visual Analytics [8]. "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 interactive graphical representations of data" [32].

Beside automated analysis methods and human's interaction, data and data characteristics. Andrienko et al. proposed three fundamental types of spatial-temporal data in context of mobility and transportation:

- "Spatial event data." [9, 10].
- "Trajectories of moving objects". [9, 10].
- "Spatial time series" [9, 10].

Spatial event data are related to spatial events emerging on locations on a certain time and exit for a limited time [10]. Examples for this kind of events could be accidents, roadworks or traffic jams. A further classification could be made by planned and unplanned spatial events that was not addressed by Andrienko et al. Roadworks or police inspections could be classified as planned roadwork and accidents or traffic jams are commonly not planned. This issue needs further investigation, since planned spatial events could be managed thoroughly though Visual Analytics. Trajectories of moving data are according to Andrienko et al. "chronologically ordered sequences of records that describe the spatial positions of movement at different times" [10]. Examples for trajectory of moving objects could be the moving path of cars, busses or taxis. These paths could be of great interest for analytics since they provide information about which routes on what times are frequently used.

Various decision could be examined through these data, e.g. traffic light switching to reduce traffic jam. A recent example was provided by Afonso et al. (see Fig.1) with so called rose diagrams [11].

Andrienko et al. define spatial time series data as "*chronologically ordered sequences of values of time-variant thematic attributes associated with fixed spatial locations or stationary spatial objects*" [10, p. 4]. Examples for such objects may be segments of streets or public transportation stops [10]. Thereby, certain values of the spatial time series data change over time. For example, the speed of cars on a certain street segment or the amount of people in transportation stop. According to Andrienko et al. trajectories are the most complex data for analytics [10].

Fig. 1. RoseTrajVis: Trajectory visualization with rose diagrams [11, p. 4].

The data typology provided by Adrienko et al. [9, 10] is a great contribution to the area Visual Analytics. In fact, they have investigated a great number of systems, approaches and existing data to provide such kind of typology.

However, the main question remains:

- For what should these data be analysed?
- What kind of indicators require which kind of data for what kind of task?

There is still a gap that is not really investigated in the literature, namely a concrete definition of indicators for certain analytical tasks that can be solved through Visual Analytics systems. These indicators are strongly related to certain data types. We introduce in the following section these indicators and provide a relation to appropriate data.

III. Indicators for Analytical Tasks in Mobility

"Visual Analytics combines methods of interactive visualization with machine learning to enable complex task solving based on huge amount of data" [27]. "Employing the methods of 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 is possible. We have therefore identified content-based indicators and the related data that lead to solving such tasks in mobility, transportation and logistics" [32]. Aspects of the survey design, such as measurement frequency, sampling issues, and challenges from temporal and spatial correlation, are not discussed in this paper, but can be found in Andrienko et al. [10].

Content-based "indicators that can be extracted from a variety of data should first be identified and categorized for the different analytical tasks in this domain. We identify the following categories of data and can relate four main indicators for the domain of mobility and transportation" [32]. We enhance our first classification [32] to provide a more general and valid classification of indicators in particular for mobility and mobility behaviour.

- *Behavioural Indicators* include data that allow to describe and analyse mobility behaviour. Such indicators often focus on human decisions in terms of transport mode, route and destination choices, as these decisions are essential for building transport demand models. Such models allow computer-based simulations and forecasts of spatial movements of both, people and goods (for information on transport demand models see [12, 13, 14, 15]). Observing human choices is traditional survey work and aims to model these decisions as the foundation of transport models. New and sensor-based information technologies, however, allow to directly observe and analyse peoples´ spatial movements and according mode-, route- and destination choices [16, 17]. Examples for such data are floating phone and floating vehicle information, traffic and passenger counts, and camera-, WIFI- and Bluetooth-based observations (see e.g. [18, 19, 20]). Behavioural indicators enable Visual Analytics systems to investigate the mobility behaviour in a general manner.

- *Geographical Indicators* describe data that allow to gather information about the geographical infrastructure of mobility, transport and logistics. These indicators are important data inputs for transport demand models as spatial structures have a high impact on the question who or which good travels from which origin to which destination. In terms of peoples´ movements this is influenced by the spatial distribution of e.g. home and work locations, shopping opportunities and places for recreation and leisure activities (see e.g. [12, 14]). In terms of logistics a couple of additional, often cost-based, effects are of importance. Examples are costs for labour, storage, and transportation. Nowadays, such information is often available online and in real time, allowing an inclusion in transport analysis and forecasts as well as approaches of visual analysis. Given transportation incident data for example, visual analytics can be used to derive accident hotpots and help to identify potential causes [21]. "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 analyse specific points-of-interest and enable solving analytical tasks" [32].

- *Environmental Indicators* are based on data that allow us to get insights from the interaction between mobility and our environment: e.g. the built environment in terms of population density or diversity of usage, its accessibility, weather, emissions (e.g. NO2, NOx), pollution (e.g. air, noise), etc.. Including environmental indicators into a certain mobility framework requires nowadays in most cases dealing with (urban) big data. Especially large-scale sensor data on transportation emissions are currently of high interest in many fields of scientific research (see e.g. [20, 21]). For these applications the advantages of visual analytics lie at hand: the vast amount of information and the complexity of surrounding interactions makes it almost infeasible to gather a deeper understanding of the underlying mechanisms without the help of Visual Analytics. Even more environmental indicators enable Visual Analytics systems to investigate the link between mobility and the environment.

- *Technology and Innovation Indicators* allow to gather insights in current and future mobility trends and predict possible future scenarios. Especially social media applications such as Twitter, among others, provide access to large-scale information that could be used to derive new trends (see e.g. [24]). Additionally, other sources like patent data can be also incorporated further enrich the information pool [25]. "Technology and Innovation indicators enable Visual Analytics systems to provide information about early technological signals" [26], "identify emerging trends" [27], 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" [32].

Visual Analytics helps to get an impression on uni-, bi-, and multivariate structures in the data. However, researchers and project managers must judge carefully if the data sources are reliable and valid to face a certain challenge. In terms of sensor based and transportation related data this includes the following questions [18]:

- Which aspect of spatial movements or human decisions are represented?

- Do the data fit the existing paradigm of travel behaviour analysis?

- Do the data complement or substitute traditional survey information?

- How can representativeness be achieved?

- Are the assumptions of data generation understood or is there a black box?

Sensor data are subject of Behavioural Indicators, Geographical Indicators as well as Environmental Indicators and play thereby a crucial role: "They enable Visual Analytics systems, in particular with machine learning approaches, to gather not only information about the manufacturing and predict maintenance but also to collect usage data. A huge number of internal sensors in manufacturing, cars, rails etc. provide enough information for Visual Analytics" [32].

One of many examples are vehicle emergency notification systems. “The European Commission has already published a regulation for so called “eCall Systems” that is mandatory for all cars manufactured later than April 2018” [28]. In nearby future the amount of sensor data reflecting individual mobility behaviour will continue to increase rapidly and thereby the request for Visual Analytic solutions will rise further.

IV. Applications Scenarios of Visual Analytics for Mobility

A. *An Application Scenario on Analyzing Technological Trends in Mobility*

The early identification of emerging technological advancements and trends in mobility enables decision makers from manufacturing (e.g. car manufacturer, car supplier, traffic signal manufacturer), politics (e.g. municipalities) and strategic analysts (e.g. manufacturing analysts) “to detect technological trends and adapt strategic directions” [27]. For this purpose, several data types such as patent data, company data and scientific publications could be appropriate. “These data would allow to identify technologies at an early stage and react to the market developments appropriately” [27].

“To illustrate our Visual Analytics system, scientific publications from different sources are used, e.g. Springer, Eurographics, IEEE etc. Thus, the indicators for this case study are” [27] “Technological and Innovation indicators”. In a first step, a common baseline is defined through the identification of appropriate data in certain databases. If these data do not provide any kind of information, data enrichment methods as described in [27, 29] are used to extract though a unique identifier, such as the Document Object identifier (DOI) with further information with web-mining methods [27, 29].

Furthermore, data from other sources are gathered and compared either through the identifier or through the combination of several parameters that lead to a unique identification, e.g. in scientific publications title, year of publication and authors are used for enriching the data base. This method can be applied to eliminate duplicates too [27, 29].

After having an appropriate dataset for technology detection, “topics” are extracted through different methods, e.g. “Latent Dirichlet Allocation” [30] and “LSA” [27]. “With the enriched information a Visual Analytics system can be provided that models the underlying data in different ways and provide different perspectives on the data” [32] as illustrated in Fig. 2 [27]. With this data the emerging technologies are identified [27] and provide on macro- and micro-level analysis capabilities.

Fig. 2 illustrates the technological trends from different perspectives on a micro-level [31]. The micro-level is given after an initial search and focuses on technologies that are directly related to that search-query [31].

In example Fig. 2a provides a temporal spread of all technologies related to the search-term [31]. This kind of visualization enables more the identification of temporal spreads on micro-level.

Fig. 2b illustrates the most relevant sub-technologies that are automatically extracted and illustrates their temporal spread too.

Fig. 2c illustrates the most relevant key-players in a certain domain and their collaborators and provides the temporal spread of the key-player’s works that may indicate, if he or she is still working on this topic.

Fig. 2d illustrates the geographical spread of the technologies by using the saturation to indicate on country-level the amount of works in a certain domain. “Thereby, the exact amount of works and publications can be gathered through a mouseover interaction” [27].

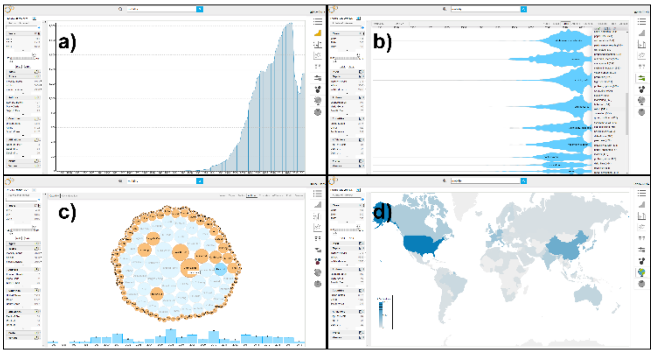

Fig. 2. Our system the uses scientific publication as indicators for “technology and innovation indicators”: a) the temporal spread of a certain technology, b) different sub-technologies and their temporal spread, c) relevant key-players and their collaborators and d) a geographical spread of the technology.

The described case study just introduced a small number of analytical possibilities. A deeper insight can be found in [27, 29, 31].

B. *An Application Scenario for Analyzing the Geographical Spread of Charging Stations*

“Geographical indicators play for a variety of tasks in mobility, transportation and logistics an important role. The main aspect here is to detect geographical paths or points that are relevant to improve aspects of mobility, transportation and logistics. These could be streets, bridges, railway roads and many more. We use in this case study, with the same Visual Analytics System as described above, plug-in-charging-stations worldwide. The goal is to provide a Visual Analytics system for charging station providers but also for political decision makers to analyse not only the charging behaviour but also the needs for further charging stations” [32].

The data used here are from different providers. We tried “to use in particular first-hand data from the charging provider themselves. Redundancies were eliminated by unique identifiers” [32]. We used in this case latitudes and longitudes to identify duplicates in different datasets. “The data were enriched 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” [32]. “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 Frankfurt or Hamburg the coverage is not that good as illustrated" [32] in Fig. 3c.

ecological and economic changes, political decisions and in particular humans' mobility behaviour" [32]. We investigated in this paper "the entire domain of mobility and transportation" to set up a revised classification of useful and important indicators and relate them to appropriate data based on our previos work [32]. We therefore introduced first the Visual Analytics and an influential work on data classification in the domain of mobility and transportation. We could outline that this domain is just investigated through

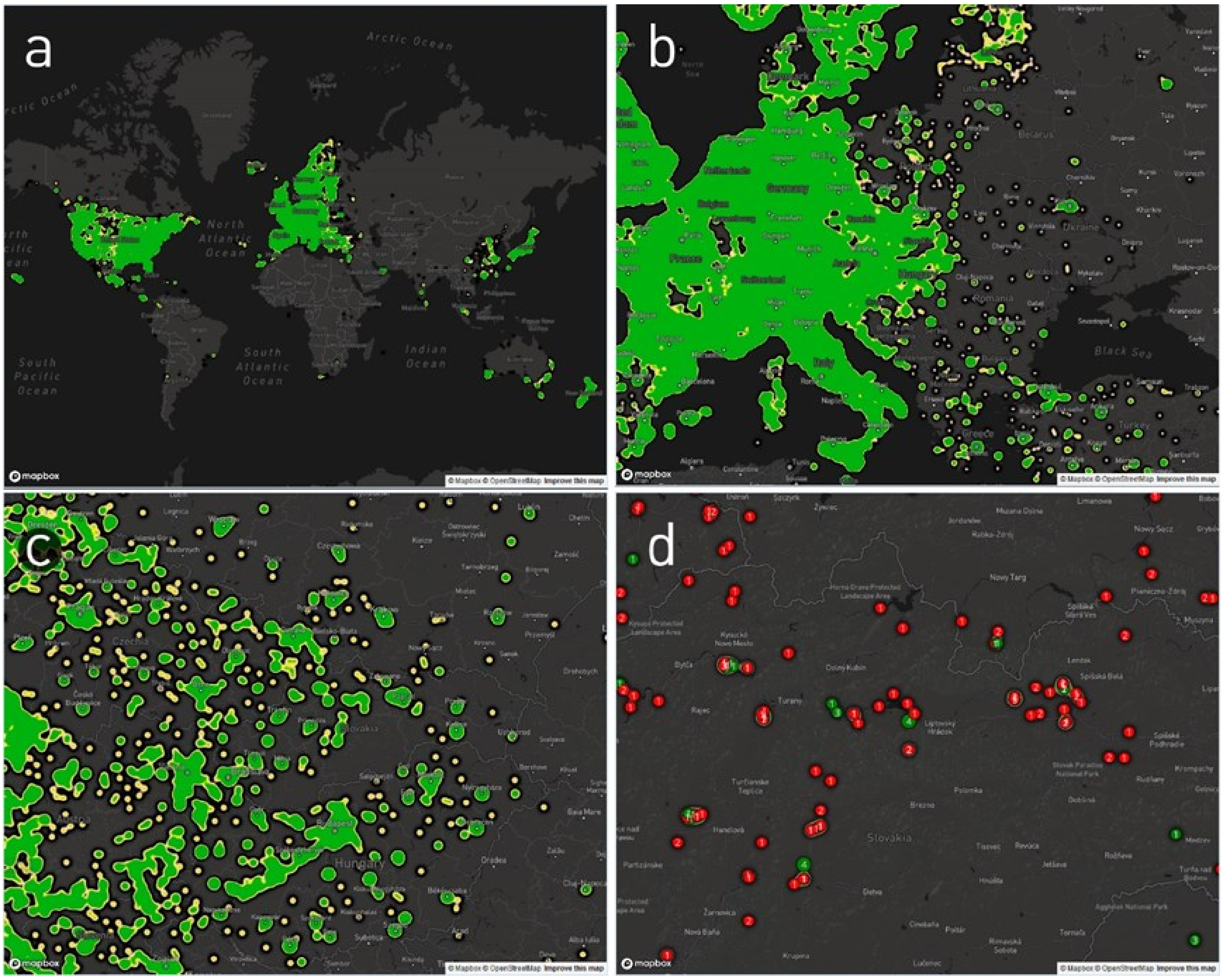

Fig. 3. Our System that make use of "geographical indicators": a) illustrated the spread of the charging station on an overview-level (world), b) illustrates an overview of selected part in Europe, c) illustrates a more detailed view in certain area in Germany and d) illustrates with the semantic zoom, the charging stations. "The geographical spread of charging stations" [32] is visualized with semantic zoom, the more the user zooms into the visualization, the more information are provided.

"The system makes use of semantic zoom and visualizes each charging station as a coloured dot as illustrated in Fig. 3d. Green colour dots are used for free charging stations, whereas red dots are used to indicate that these charging stations are fee-based" [32]. Further "visual variables" can be used to provide more information, such as the availability of the stations, the usage-count or number of plugs in each station.

V. Conclusions

Mobility and transportation "are influenced by a variety of indicators such as new technological developments,

a view on data and a systematic view on indicators is not existing. We introduced through a systematic investigation of literature and real-world scenarios a classification of four main indicators: behavioural indicators, geographical indicators, environmental indicators and technology and innovation indicators. Our approach goes beyond the current state of the research, where only spatial-temporal data are considered with a comprehensible classification. We concluded our paper with two different case studies that are using different indicators. The cases studies were introduced to illustrate the added value from different perspectives on mobility.

ACKNOWLEDGMENT

"This work was partially funded by the Hessen State Ministry for Higher Education, Research and the Arts within the program "Forschung für die Praxis" and was conducted within the research group on Human-Computer Interaction and Visual Analytics (https://vis.h-da.de)."

REFERENCES

[1] K. A. Cook and J. J. Thomas, "Illuminating the Path: The Research and Development Agenda for Visual Analytics.", National Visualization and Analytics, 2005.

[2] K. Nazemi, Adaptive Semantics Visualization. Cham: Springer International Publishing, 2016.

[3] D. Keim, G. Andrienko, J. D. Fekete, C. Görg, J. Kohlhammer and G. Melançon, „Visual Analytics: Definition, Process, and Challenges." in *Information visualization*, Berlin, Heidelberg: Springer, pp. 154-175, 2008.

[4] D. A. Keim, F. Mansmann, J. Schneidewind, J. Thomas, and H. Ziegler, „Visual Analytics: Scope and Challenges," in *Visual data mining*, Berlin, Heidelberg: Springer, pp. 76-90, 2008.

[5] J. Thomas, "Visual Analytics: A Grand Challenge in Science: Turning Information Overload into the Opportunity of the Decade", *Journal of Computing Sciences in Colleges*, 23(2), pp. 5-6, 2007.

[6] J. Thomas and J. Kielman, "Challenges for Visual Analytics," *Information Visualization*, 8(4), pp. 309-314, 2009.

[7] D. Keim, J. Kohlhammer, G. Ellis, and F. Mansmann, "Matering the Information Age Solving Problems with Visual Analytics", Goslar: Eurographics Association, 2010.

[8] S. K. Card, J. D. Mackinlay, and B. Shneiderman, "Readings in Information Visualization: Using Vision to Think", Morgan Kaufmann, 1999.

[9] G. Andrienko, N. Andrienko, P. Bak, D. Keim, and S. Wrobel, Visual Analytics of Movement, Springer Science & Business Media, 2013.

[10] G. Andrienko, N. Andrienko, W. Chen, R. Maciejewski, and Y. Zhao, "Visual Analytics of Mobility and Transportation: State of the Art and Further Research Directions," *IEEE Transactions on Intelligent Transportation Systems*, pp. 99, 2017.

[11] A. P. Afonso, A. Ferreira, L. Ferreira, and R. Vaz, "RoseTrajVis: Visual Analytics of Trajectories with Rose Diagrams," in *Proccedings of the 24rd International Conference Information Visualisation*, IEEE Press, 2020.

[12] J. D. Ortuzar and L.G., Willumsen, Modelling Transport, New York: Wiley, 2011.

[13] JASPERS "The Use of Transport Models in Transport Planning and Project Appraisal," JASERS appraisal guidance (transport). Available: www.jaspersnetwork.org. [Accessed: August 13th, 2020].

[14] Department for Transport "Priciples of Modelling and Forecasting, Transport Analysis Guidance (TAG), Unit 1," 2019. Available: https://www.gov.uk/transport-analysis-guidance-webtag. [Accessed: August 13th, 2020].

[15] Department for Transport, "Variable Demand Modelling, Transport Analysis Guidance (TAG), Unit 2," 2019. Available: https://www.gov.uk/transport-analysis-guidance-webtag. [Accessed: August 13th, 2020].

[16] L. G. Willumsen, Better Traffic and Revenue Forecasting, London: Maida Vale Press, 2014.

[17] R. Krueger, Q. Han, N. Ivanov, S. Mahtal, D. Thom, H. Pfister, and T. Ertl, "Bird's-Eye-Large-Scale Visual Analytics of City Dynamics using Social Location Data," *Computer Graphics Forum*, 38(3), pp. 595-607, 2019.

[18] National Academies of Sciences, Engineering, and Medicine, Cell Phone Location Data for Travel Behavior Analysis. Washington, DC: The National Academies Press, 2018.

[19] A. Danalet, L. Tinguely, M. de Lapparent, and M. Bierlaire, "Location Choice with Longitudinal WiFi Data", *Journal of choice modelling*, 18, pp. 1-17, 2016.

[20] L. G. Willumsen, "Transport Demand Model Estimation from Traffic Counts", *Transportation*, 16, pp. 3-26, 1989.

[21] K. Wongsuphasawat, M. L. Pack, D. Filippova, M. VanDaniker, and A. Olea, "Visual Analytics for Transportation Incident Datasets", *Transportation research record*, 2138(1), pp. 135-145, 2009.

[22] X. Lu, K. Ota, M.. Dong, C. Yu, and H. Jin, "Predicting Transportation Carbon Emission with Urban Big Data", *IEEE Transactions on Sustainable Computing*, 2(4), pp. 333-344, 2017.

[23] K. Q. Bui and L. P. Perera, "The Compliance Challenges in Emissions Control Regulations to Reduce Air Pollution from Shipping", in *OCEANS 2019-Marseille*, IEEE, pp. 1-8., 2019.

[24] Q. Dang, F. Gao, and Y. Zhou, "Early Detection Method for Emerging Topics Based on Dynamic Bayesian Networks in Micro-blogging Networks", *Expert Systems with Applications*, 57, pp. 285-295, 2016.

[25] X. Li, Q. Xie, J. Jiang, Y. Zhou, and L. Huang, "Identifying and Monitoring the Development Trends of Emerging Technologies Using Patent Analysis and Twitter Data Mining: The Case of Perovskite Solar Cell Technology", *Technological Forecasting and Social Change*, 146, pp. 687-705, 2019.

[26] H. Ansoffi, "Managing Strategic Surprise by Response to Weak Signals", *California Management Review*, 18(2), pp. 21-33, 1975.

[27] K. Nazemi and D. Burkhardt, "Visual Analytics for Analyzing Technological Trends from Text," in *2019 23rd International Conference Information Visualisation (IV)*, IEEE, pp. 191-200, 2019.

[28] European Union: Regulation 2015/758. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32015R0758. [Accessed: August 13th, 2020].

[29] K. Nazemi, R. Retz, D. Burkhardt, A. Kuijper, J. Kohlhammer, and D. W. Fellner, „Visual Trend Analysis with Digital Libraries", in *Proceedings of the 15th International Conference on Knowledge Technologies and Data-driven Business*, ACM, Graz ,pp. 1-8, 2015.

[30] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet Allocation", *The Journal of Machine Learning Research*, 3, pp. 993-1022, 2003.

[31] K. Nazemi and D. Burkhardt, "A Visual Analytics Approach for Analyzing Technological Trends in Technology and Innovation Management" in *Advances in Visual Computing*, Cham: Springer International Publishing, pp. 283–294, 2019

[32] K. Nazemi, D. Burkhardt, L. Kaupp, T. Dannewald, M. Kowald and E. Ginters, Visual Analytics in Mobility, Transportation and Logistics In Ginters, E.; Ruiz Estrada, M. A. & Piera Eroles, M. A. (Eds.) Visual Analytics in Mobility, Transportation and Logistics *ICTE in Transportation and Logistics 2019, Springer International Publishing,* 2020, 82-89 .