PerAwareCity'19 - 4th IEEE International Workshop on Pervasive Context-Aware Smart Cities and Intelligent Transport Systems

# A Qualitative and Quantitative Analysis of Real Time Traffic Information Providers

Tim Paul Bauer Chair of Information Systems II University of Mannheim Schloss, 68161 Mannheim, Germany tim.bauer@uni-mannheim.de Janick Edinger

Chair of Information Systems II University of Mannheim Schloss, 68161 Mannheim, Germany janick.edinger@uni-mannheim.de Christian Becker Chair of Information Systems II University of Mannheim Schloss, 68161 Mannheim, Germany christian.becker@uni-mannheim.de

Abstract—Worldwide, traffic congestion is increasingly recognized as a serious public health and environmental concern. Besides, traffic jams cause large economic damages for companies and cities. Many efforts have been made to mitigate these issues. Attempts to reduce the amount of traffic congestion strongly depend on the availability of traffic information in real time. Multiple providers of such data exist. However, there is no generally accepted source that provides accurate and publicly available live traffic information. The goal of this study is to evaluate real time traffic data offered by web map service providers. Therefore, we first identify the most prominent providers and evaluate their range of services. Further, we collect actual data traces and perform a thorough comparison of their scope and granularity. Finally, in a real world case study, we analyze the predicted travel duration for the selected providers. The results indicate not only that the range of services varies widely among traffic information providers but also the travel time predictions diverge.

Index Terms—smart city, traffic control, traffic information systems

# I. INTRODUCTION

Traffic congestions cause increased fuel consumption as well as carbon dioxide emissions, lead to health issues, and result in substantial economic losses. Due to the high density of people and limited infrastructure capabilities, urban spaces are even more vulnerable to these problems than rural areas. In 2017, traffic jams caused a loss of 33.7 billion US dollars only in the city of New York [?inrix2017inrix]. Due to the rapidly growing traffic volumes all over the world, researchers have become increasingly interested in applying accurate traffic information in real time [20]. Traffic operation efficiency can be improved substantially by developing Intelligent Transportation Systems (ITSs). Sophisticated approaches can support road users in making profound travel decisions, in mitigating traffic congestion, and in reducing emissions. However, the output quality of ITS models heavily depends on the availability of accurate traffic information in real time [16].

Due to the pervasiveness of sensors, IoT devices, crowd sourcing, and social media, the availability of traffic information increases steadily. In combination with information obtained from traditional traffic sensors as cameras, radars, and inductive loops, *the era of big data* in transportation research has been entered [16]. Nevertheless, for the most

part, these data sets are not accessible to the general public. In addition, there is no data source that consolidates all the available information and thus can offer researchers data in an aggregated way. Web mapping services such as Google Maps [8] and Here [9] provide *Application Programming Interfaces* (APIs) to make traffic data publicly available. In general, such providers offer services like positioning, routing, and delivering live traffic conditions through websites or mobile applications.

The goal of this paper is to evaluate the comprehensiveness of real time traffic information obtained from web mapping service providers. More specifically, four providers that offer live traffic data via APIs have been analyzed: Bing [18], Google [8], Here [9], and TomTom [24]. The study focuses on the capabilities of the provided APIs and examines the range of services as well as the granularity and scope of the publicly available data sets. Furthermore, strengths and weaknesses of the presented approach are discussed and identified research gaps are outlined.

The remainder of this paper is structured as follows. In Section II, we review state-of-the-art traffic measurement technologies and demonstrates how recent studies have incorporated traffic information in real time, and identify the most popular web mapping providers. Section III performs a qualitative and quantitative analysis of the selected traffic information providers. This includes a real world case study to compare the predicted travel times for the selected providers. We discuss our findings in Section IV and before we conclude the paper and give an outlook on open research questions in Section V.

## II. REAL TIME TRAFFIC INFORMATION

Nowadays, traffic data is generated by means of various detection techniques. A considerable amount of literature, for example, [1], [6], or [21], has been published that summarizes the temporal development of corresponding sensor technologies. Furthermore, state-of-the-art approaches are presented by studies such as [4] or [12]. G. Leduc [14] provides one of the most cited overviews of traditional and emerging road traffic data collection methods. In addition, in [14], Guillaume Leduc outlines strengths and weaknesses of sensor technologies and

provides a summary of online sources offering real time and historical traffic data in Europe and the US.

In general, traditional technologies collect traffic data by means of sensors located along a specific road segment. Most of the related studies outline that those systems deliver precise information on the current traffic situation but involve high setup costs. Beyond that, the limited geographic coverage is another frequently mentioned drawback of traditional detection techniques [1,6,12].

In the past years, driven by the spread of wireless technologies, data collection methods using *Floating Car Data* (FCD) have emerged [4]. Information is directly received from probe vehicles that are equipped with positioning technologies [2]. Data such as car location, speed, and travel direction is transmitted to a processing center. If the density of probe vehicles is high enough, traffic conditions can be estimated accurately. Methods based on FCD are more cost-efficient and can offer larger coverage capabilities than traditional technologies [12]. However, the main drawback of this approach is the potential limited representativeness of a given group of probe vehicles. Buses, for example, are subject to different speed limits than private vehicles and taxis can use dedicated lanes in specific areas such as airports or train stations [12].

Collecting data in a crowd sourcing manner has resulted in further improvements in the FCD technology [10, 11]. Private vehicle users increasingly report traffic incidents manually and allow mobile devices to send their locations continuously to service providers. In addition, community based mapping services, such as Waze, provide users the opportunity to enrich information about traffic conditions by transmitting predefined alerts [22]. However, the success potential of crowd sourcing approaches relies on the cooperation of a large user group and raises privacy concerns [10].

Using a mobile cellular network overcomes some of the aforementioned obstacles and has been considered in several recent studies as in [5] or [13]. Road traffic information extracted from cellular network data has a high localization accuracy, private information is not forwarded to third parties, and additional investments in infrastructure are negligible [12].

Moreover, Chen *et al.* [28] emphasize the growing importance of real time traffic data that can be obtained from the Internet. In addition to information provided by web mapping services, the authors highlight weather websites, social media, and event data as relevant data sources. Especially extreme weather conditions may deliver useful information regarding the current traffic situation [7, 17]. Since individuals are increasingly posting texts about or images on traffic incidents, social media can serve as a source for real time information as well [23]. Furthermore, public events with a high number of participants constitute a valid indicator for special traffic conditions [28].

The above described variety shows that modern ITSs are confronted with heterogeneous traffic data from a large number of a sources [29]. In this context, a growing body of literature, for example, [3], [16], or [29], has investigated the advantages and corresponding challenges of *Big Data*. Since real world information exhibits incomplete attributes of values, outliers, and inconsistent data formats [30], organizing these massive data sets has become one of the main challenges in transportation research [21]. Likewise, Lopes et al. [15] emphasize the fact that real time traffic information is highly susceptible to noise, redundancy and inconsistent data. These scholars similarly highlight the enormous size of traffic data sets and their origin from multiple sources as explanations for the profound heterogeneity.

For a thorough analysis, however, considering a variety of external data is superior to a single source approach [14]. Therefore, the acquisition and transforming of raw data for further processing have become crucial [16,27,29]. Integrating heterogeneous traffic related information has the potential to provide accurate live data across a wide transportation network [14, 30]. In this regard, Lopes et al. [15] present a suite of methods for data pre-processing and for cleaning of traffic information in real time. Moreover, the authors of [25] define data quality and recommend quality measures with regard to live traffic data.

Many studies, for example, [16], [26], or [28], emphasize the importance of accurate live traffic information for scientific research. However, methods to obtain such data sets in an aggregated way and potential sources are barely discussed. Nowadays, web mapping service providers consolidate many of the aforementioned data sources and, subsequently, offer live traffic information in an aggregated way. However, the origin of the provided data sets is not sufficiently documented in some cases. Furthermore, end users are confronted with heterogeneous information when multiple web mapping service providers are compared.

In [14], Guillaume Leduc summarizes online sources that offer real time traffic related information in detail but does not cover rather new sources such as the APIs of web mapping service providers. There are many papers applying live traffic data, but no subsequent survey has been carried out that summarizes and compares sources of live traffic conditions. Moreover, the most recent studies in this field mainly focus on the application of exemplary data. For instance, Wang et al. [26] propose a live traffic monitoring system that is based on FCD limited to Hefei, China. Likewise, Lv et al. [16] and Shi et al. [21] evaluate applications that use real time data restricted to freeway systems in the US. More recently, Chen et al. [28] review different sources of online live traffic data in general. However, the method of requesting APIs is only described theoretically. Furthermore, they restrict their case study on congestion prediction to real time information obtained from a Chinese web mapping service provider without evaluating the data quality or potential alternatives.

Based on the literature review and an online research, we have identified four major web mapping services that provide live traffic data via APIs. These providers are Bing [18], Google [8], Here [9], and TomTom [24]. It should be pointed out that only some web mapping providers offer live traffic data via APIs. Popular providers, such as Waze and OpenStreetMap, do not offer corresponding services.

Provider	<b>Bing</b> [18], [19]		Google [8]	Here [9]		TomTom [24]			
API	Route	Incident	Route	Route	Incident	Flow	Route	Incident	Flow
Access Options	** (50k transactions per day, pricing scheme not published)		** (50k transactions per month, from \$0.01 for any further transaction)	** (250k transactions per month, from \$449 for 1,000k transactions per month)			** (2.5k transactions per day, from \$199 for 50k transactions per month)		
Documentation	**		***	***			***		
Data Origin	not published		** (GPS data from mobile devices using Android and/or Google Maps, journalistic information, road sensors)	** (GPS data from vehicle sensors and mobile devices, journalistic information, road sensors)			** (GPS data from mobile devices, journalistic information, road sensors)		
Geographic Coverage	** (72 countries)		*** (116 countries)	** (63 countries)			* (40 countries)		
Scope of Service	***	**	**	***	**	*	***	*	*
Information Content	***	***	*	*	***	**	**	***	**

TABLE I: Real time traffic information providers categorized by their range of services.

 $*** \equiv$  detailed / high,  $* \equiv$  imprecise / low

# III. EVALUATION

In this section, we perform a qualitative and quantitative analysis of the four selected web mapping service providers. Therefore, we first evaluate their range of services by studying publicly available documentations. Second, we retrieve actual data via the provided APIs and analyze the scope and the granularity of the available information. Finally, in an real world case study, we compare the estimated travel times among the service providers over a six hour period.

# A. Range of Services Analysis

The evaluated web mapping service providers offer a wide range of transportation related APIs to developers. However, when real time traffic information is considered, three basic API types can be distinguished. All of the analyzed providers offer *route* APIs delivering information about traffic incidents along a specified path. The *incident* APIs of Bing, Here, and TomTom provide data on current traffic conditions for a given geographic area. The third type are APIs that deliver information on the *flow* in a road network. Data such as current speeds and corresponding travel times can be requested. Here and TomTom make flow APIs available to developers.

All four providers charge fees for traffic information transactions but offer a free quota for developers per month. The freely available services range from 50k to approximately 600k transactions per month and, except for Bing, all API providers disclose their pricing policies that apply when the free quota is exceeded. The comprehensiveness of the documentations provided forms another key factor of the classification schema. All of the evaluated providers offer extensive online documentations of their APIs. Bing is the only exception since it does not provide any information on the origin of its data and on its pricing model. In general, no provider fully discloses the underlying data sources. Google obtains vehicle locations via GPS from Android and Google Maps users. Here and TomTom receive GPS positions from mobile devices that apply their systems. Beyond that, Here makes use of BMW, Audi, and Mercedes-Benz cars that are, to a certain extent, equipped with vehicle sensors. In addition to GPS data, Google, Here, and TomTom utilize journalistic information that includes incident details and traditional road sensor data. Both types of information are obtained either from public authorities or third party providers. However, details such as the exact number of sources or their geographic distribution are not available to the public. The extent of the providers' geographic coverage is another crucial feature for data acquisition. In this regard, Google covers the maximum of 116 countries and TomTom the minimum of 40 countries.

A further decision criterion is the provided scope of services. It can be specified by defining required and optional parameters in the APIs' HTTP request. For instance, TomTom's route API offers more than 40 optional request parameters, whereas Here's flow API only provides nine additional filters. The specification for optional attributes of the route APIs ranges from the definition of multiple waypoints to avoidance criteria such as tolls, highways, or ferries. Furthermore, Google, Bing, and Here offer different travel modes such as car driver, pedestrian, or cyclist. Bing's and Here's route APIs can be optimized for time or distance and Here and TomTom offer the possibility of specifying vehicle characteristics such as the weight or the engine type. TomTom's incident API only offers format specific attributes. In contrast, Bing and Here provide filters such as the severity and the type of traffic incidents. Both flow APIs have the smallest scope of services. In general, TomTom's flow API provides information about a given road segment closest to the requested point coordinates. Optional attributes can only be used to specify the visualization of traffic flow data on maps. Here's flow API delivers information

Provider	Bing [18], [19]		Google [8]	<b>Here</b> [9]			TomTom [24]		
API	Route	Incident	Route	Route	Incident	Flow	Route	Incident	Flow
Geographic Accuracy	***	***	**	**	***	***	***	***	***
Туре	*** (33)	** (11)	-	-	** (12)	-	* (4)	** (14)	-
Severity	** (4)	** (4)	-	-	** (4)	*** (0.0-10.0)	** (5)	** (5)	-
Travel Duration	***	-	***	***	-	-	***	-	***
Driving Speed	-	-	-	-	-	***	**	-	***
Textual Description	***	***	-	-	***	-	-	**	-

TABLE II: Qualitative analysis of real time traffic information providers.

\*\*\*  $\equiv$  detailed / high, \*  $\equiv$  imprecise / low, -  $\equiv$  not available

regarding the traffic situation for a given area. It offers optional attributes such as the specification of a jam factor and of a variable that defines the to be considered road types. Table I summarizes these findings.

# B. Qualitative Analysis

As described in the previous section, the information content of the obtained live traffic data varies widely over the four APIs. Table II provides an overview of the heterogeneous data sets based on six different attributes.

To establish a connection between the location of a traffic incident and associated observations, detailed geographic information is essential. Each of the analyzed services fulfills this condition by returning the coordinates of the start and end locations of the provided incidents. The only exceptions are Google's and Here's route APIs that do not offer specific incidents at all. Incident types are classified according to different criteria such as road closure, congestion, or construction site. In this context, Bing's route API offers the most detailed level of classification while four of the evaluated APIs do not return this measure at all.

In addition, the incident type is defined by its severity. Attributes such as minor, moderate, or serious are used to make a distinction between four to five levels of criticality. Similarly, Here's flow API assigns a jam factor to the evaluated road segment. It also serves as measure of severity as it indicates the expected quality of travel. Travel speed and duration are further useful attributes that can provide information on live traffic conditions. All analyzed APIs offer data regarding the time required for passing through a specified road segment by returning two values: the free flow travel duration and the required travel time under consideration of the most recent traffic situation. Information on driving speed is only delivered by two APIs, Here and TomTom. Furthermore, there are just two APIs that provide the free flow speed in addition to the current driving speed.

In addition, traffic incidents are specified on the basis of textual descriptions. However, their level of detail differs significantly among the individual APIs. The size of the textual descriptions ranges from empty messages to text blocks that consist of multiple sentences. There is also a high degree of variation if the information contents of textual descriptions of different traffic incidents that are delivered by the same API are compared.

# C. Quantitative Evaluation

We ran a case study to compare the estimated travel times between the four providers. Therefore, we periodically requested the travel time for a given section of a German motorway from all four providers over a six hour period. Figure 1 shows the section of the motorway (left) as well as the estimated travel times (right). This analysis gave us valuable insights about the provided data. The results of the case study confirmed the profound heterogeneity of the available data sets. Although only a relatively short motorway section was observed, the estimated travel times differ significantly. A visual analysis of the travel times leads to the following conclusions. First, the TomTom API is least affected by travel incidents and provides estimations with the least variability. It is highly questionable that the travel time remains as constant over time as the TomTom estimations suggest. However, further analysis is required to validate this. Second, even though the absolute values of Bing, Google, and Here differ, similar patterns can be found in all three curves. Third, the flat sections in the curves of Bing, Here, and TomTom indicate that these APIs have an update interval of multiple minutes whereas the Google data is updated in a higher frequency.

We further performed statistical analysis of the case study results which are summarized in Table III. The averages of the absolute differences between the measurement series vary widely. The maximum absolute differences in estimated travel times can be found between TomTom and the other providers. The standard deviation of the differences between the measured values reaches its maximum when the estimated travel times of Google and Bing are compared. The differences between TomTom and Google have the smallest standard deviation.

### PerAwareCity'19 - 4th IEEE International Workshop on Pervasive Context-Aware Smart Cities and Intelligent Transport Systems

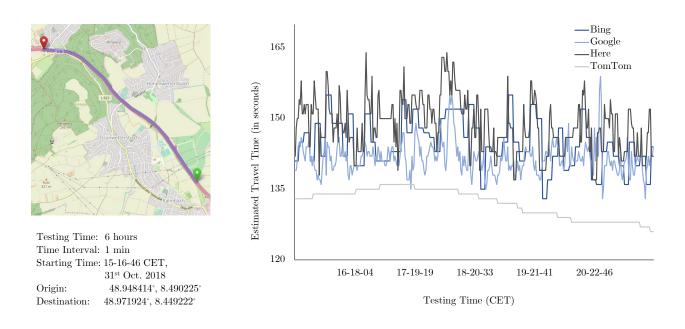


Fig. 1: Required travel time for a motorway section, provided by the route APIs of Bing, Google, Here and TomTom.

TABLE III: Statistical Results of an Exemplary Case Study

	Bing	Google	Here	TomTom					
average of absolute differences									
Bing	-	5.32	5.43	12.75					
Google	6.06	-	7.47	9.55					
Here	5.47	5.61	-	16.48					
TomTom	4.96	4.26	5.23	-					
standard deviation of differences									
				· 1					

#### in seconds

### **IV. DISCUSSION**

Retrieving data of web mapping service providers via APIs constitutes a valid approach to obtain real time traffic information. It includes several essential benefits such as the public availability of cross-continent data. A further advantage is the low manual processing effort that is required to access and to process the obtained information. The provided standard interfaces offer a high level of customization and can be accessed by means of standardized procedures. In addition, web mapping service providers merge various data sources and offer rich consolidated information to end users in an aggregated way.

However, there are also certain drawbacks associated with the use of APIs as a source of traffic information in real time. First, only a limited amount of live data can be retrieved free of charge. The evaluated web mapping service providers charge fees as soon as the number of requests exceeds a certain quota. Developers and researchers with small funding capabilities may be restricted by this limitation. Second, the available live information cannot be compared to real world conditions without further investigations. The lack of empirical results that confirm the accuracy of these data sets constitutes one of the main limitations of this study. Further research is required to analyze to what extent road situation in the real world is reflected by the provided traffic information. Third, the pronounced heterogeneity of the available data constitutes another important challenge for future research. The provided data sets are characterized by a large variety of different attributes. Due to this variability, it is difficult to create a universally applicable ranking for the evaluated APIs. For instance, Google's route API has the largest geographic coverage, but it only returns the travel time under consideration of the current traffic situation. In contrast, services such as Bing's and Here's route APIs offer the most detailed live traffic information. However, their geographic coverage is much smaller than that of Google.

It is most likely that there is no single best API that can deliver the most appropriate real time information for every conceivable situation. Therefore, it is crucial to define the desirable features of data quality for a specific application and then to merge the available data sets accordingly. In this way, a data fusion process could be created that makes use of the prevailing heterogeneity by combining strengths and by eliminating potential weaknesses of the individual APIs.

A further possibility to analyze the practical suitability of web mapping service providers is to evaluate metrics as distribution and popularity. Considering the frequency of use within a certain area delivers valuable insights into the behavior of daily users and other developers. In this way, the selection process could benefit from experiences of a broad range of people who are also interested in obtaining accurate traffic information in real time. To compare the popularity of different APIs, their frequency of occurrence on developer webpages such as ProgrammableWeb or search engine usage based, for example, on Google Trends can be taken into account.

More detailed case studies will help to compare the quality and comprehensiveness of the available traffic information. Another important step is to evaluate to what extent the real world road environment is reflected. Empirical studies need to be conducted to analyze the quality of the obtained data sets regarding application specific characteristics such as the considered geographic area, varying road types, and different times of day.

# V. CONCLUSION AND OUTLOOK

The application of live traffic information plays a significant role in transportation research. Issues as congestion, traffic accidents, and exhaust emissions can be mitigated by developing ITS models that use real time traffic data. In this study, we have discussed APIs of web mapping service providers as sources of traffic information in real time. The capabilities of the individual APIs have been presented and the heterogeneity of the available data sets has been highlighted. In addition, strengths and weaknesses of the discussed approach have been outlined. Future research needs to prove the suitability of APIs of web mapping service providers as sources of accurate traffic information in real time. Empirical studies have to be performed to compare the different APIs in detail and to analyze to what extent the real world road environment is reflected. The definition of application specific use cases and desirable features will help to identify the most appropriate solution. However, it will require considerable effort to compare the performance of APIs of web mapping service providers to other sources of live traffic data.

### REFERENCES

- [1] E. Bouillet, B. Chen, C. Cooper, D. Dahlem, and O. Verscheure, *Fusing Traffic Sensor Data for Real-time Road Conditions*, Proceedings of First International Workshop on Sensing and Big Data Mining (2013), 1–6.
- [2] N. Caceres, L. M. Romero, F. G. Benitez, and J. M. Del Castillo, *Traffic flow estimation models using cellular phone data*, IEEE Transactions on Intelligent Transportation Systems, vol. 13, no. 3 (2012), 1430–1441.
- [3] Y. Chen, L. Shu, and L. Wang, Poster abstract: Traffic flow prediction with big data: A deep learning based time series model, 2017 IEEE Conference on Computer Communications Workshops, INFOCOM WK-SHPS 2017 (2017), 1010–1011.
- [4] C. Costa, G. Chatzimilioudis, D. Zeinalipour-Yazti, and M. F. Mokbel, *Towards Real-Time Road Traffic Analytics using Telco Big Data*, Proceedings of the International Workshop on Real-Time Business Intelligence and Analytics - BIRTE '17 (2017), 1–5.
- [5] C. De Fabritiis, R. Ragona, and G. Valenti, *Traffic estimation and prediction based on real time floating car data*, IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC (2008), 197–203.
- [6] J. F. Ehmke, S. Meisel, and D. C. Mattfeld, *Floating car based travel times for city logistics*, Transportation Research Part C: Emerging Technologies, vol. 21, no. 1 (2012), 338–352.
- [7] T. F. Golob and W. W. Recker, *Relationships Among Urban Freeway Accidents, Traffic Flow, Weather, and Lighting Conditions*, Journal of Transportation Engineering, vol. 129, no. 4 (2003), 342–353.

- [8] Google LLC, Directions API, https://developers.google.com /maps/documentation/directions/start, Date Accessed: 2018-09-18, 2018.
- HERE Technologies, Traffic API, https://developer.here.com/restapis/documentation /traffic/topics/introduction.html, Date Accessed: 2018-09-18, 2018.
- [10] S. Hu, L. Su, H. Liu, H. Wang, and T. Abdelzaher, *Poster abstract: SmartRoad*, Proceedings of the 12th International Conference on Information Processing in Sensor Networks IPSN '13 (2013), 331.
- [11] A. Jain, S. Raj, Harshit, R. Misra, and B. M. Baveja, *Road congestion sensing via crowdsourcing and MapReduce*, Proceedings of the 14th International Conference on Information Processing in Sensor Networks IPSN '15 (2015), 356–357.
- [12] A. Janecek, D. Valerio, K. A. Hummel, F. Ricciato, and H. Hlavacs, *The Cellular Network as a Sensor: From Mobile Phone Data to Real-Time Road Traffic Monitoring*, IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 5 (2015), 2551–2572.
- [13] B. S. Kerner, C. Demir, R. G. Herrtwich, S. L. Klenov, H. Rehborn, M. Aleksić, and A. Haug, *Traffic state detection with floating car data in road networks*, IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC (2005), 700–705.
- [14] G. Leduc, Road Traffic Data : Collection Methods and Applications (2008), available at arXiv:1011.1669v3.
- [15] J. Lopes, J. Bento, E. Huang, C. Antoniou, and M. Ben-Akiva, *Traffic and mobility data collection for real-time applications*, IEEE Conference on Intelligent Transportation Systems, Proceedings (2010), 216–223.
- [16] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Wang, *Traffic Flow Prediction With Big Data : A Deep Learning Approach*, IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 2 (2014), 1–9.
- [17] T. H. Maze, M. Agarwai, and G. Burchett, Whether weather matters to traffic demand, traffic safety, and traffic operations and flow, Transportation Research Record: Journal of the Transportation Research Board, vol. 1948, no. 1 (2006), 170–176.
- [18] Microsoft Corpoartion, Microsoft Routes API, https://msdn.microsoft.com/en-us/library/ff701705.aspx, Date Accessed: 2018-09-18, 2018.
- [19] \_\_\_\_\_, Microsoft Traffic API, https://msdn.microsoft.com/enus/library/hh441725.aspx, Date Accessed: 2018-09-18, 2018.
- [20] D. Serrano, T. Baldassarre, and E. Stroulia, *Real-time traffic-based routing, based on open data and open-source software*, 2017, pp. 661–665.
- [21] Q. Shi and M. Abdel-Aty, Big Data applications in real-time traffic operation and safety monitoring and improvement on urban expressways, Transportation Research Part C: Emerging Technologies, vol. 58, Part B (2015), 380–394.
- [22] T. Silva, P. Vaz De Melo, A. Viana, J. Almeida, J. Salles, and A. Loureiro, *Traffic Condition Is More Than Colored Lines on a Map: Characterization of Waze Alerts*, In: Jatowt A. et al. (eds) Social Informatics. SocInfo 2013 (2013).
- [23] P. Tejaswin, R. Kumar, and S. Gupta, Tweeting Traffic: Analyzing Twitter for generating real-time city traffic insights and predictions, Proceedings of the 2nd IKDD Conference on Data Sciences '15 (2015), 1–4.
- [24] TomTom N.V., Online Routing, https://developer.tomtom.com/onlinerouting, Date Accessed: 2018-09-18, 2018.
- [25] S. Turner, Defining and Measuring Traffic Data Quality: White Paper on Recommended Approaches, Transportation Research Record: Journal of the Transportation Research Board, vol. 1870, no. 1 (2004), 62–69.
- [26] T. Wang, T. Fang, J. Han, and J. Wu, *Traffic monitoring using floating car data in Hefei*, Proceedings 2010 International Symposium on Intelligence Information Processing and Trusted Computing, IPTC 2010 (2010), 122–124.
- [27] J. S. Ward and A. Barker, *Undefined By Data: A Survey of Big Data Definitions* (2013), available at arXiv:1309.5821.
- [28] Yuan-yuan Chen, Y. Lv, Z. Li, and F. Wang, Long short-term memory model for traffic congestion prediction with online open data, 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) (2016), 132–137.
- [29] J. Zhang, F. Wang, K. Wang, W. Lin, X. Xu, and C. Chen, *Data-Driven Intelligent Transportation Systems: A Survey*, IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 4 (2011), 1624–1639.
- [30] Q. Zhang, D. Jian, R. Xu, W. Dai, and Y. Liu, *Integrating heterogeneous data sources for traffic flow prediction through extreme learning machine*, Proceedings 2017 IEEE International Conference on Big Data (2018), 4189–4194.