Big Data application in congestion detection and classification using Apache spark

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January 19, 2021

Abstract

With the era of big data, an explosive amount of information is now available. This enormous increase of Big Data in both academia and industry requires large-scale data processing systems. A large body of research is behind optimizing Spark’s performance to make it state of the art, a fast and general data processing system. Many science and engineering fields have advanced with Big Data analytics, such as Biology, finance, and transportation. Intelligent transportation systems (ITS) gain popularity and direct benefit from the richness of information. The objective is to improve the safety and management of transportation networks by reducing congestion and incidents. The first step toward the goal is better understanding, modeling, and detecting congestion across a network efficiently and effectively. In this study, we introduce an efficient congestion detection model. The underlying network consists of 3017 segments in I-35, I-80, I-29, and I-380 freeways with an overall length of 1570 miles and averaged (0.4-0.6) miles per segment. The result of congestion detection shows the proposed method is 90\% accurate while has reduced computation time by 99.88\%.

Keywords: Big Data, Spark, Congestion, Recurrent congestion

1 INTRODUCTION

Given data production speed and different data structures, efficient large scale data processing to analyze and mine patterns is a must. Thereby a number of large-scale data processing frameworks have been developed, such as MapReduce \cite{8}, Storm \cite{4}, TensorFlow \cite{1}. However, while Spark \cite{19} is a fast and general computing system, all frameworks mentioned above lack generality, as each of them is suitable for certain data computation \cite{17}. Spark benefits from

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in-memory data processing. Moreover, as a general system, it supports batch, interactive, and streaming computations. Despite its popularity, Spark has limitations; for instance, it requires a considerable amount of learning and effort to program under the Resilient Distributed Datasets (RDD) programming model. RDD abstraction model is a collection of data records partitioned among several computers [18]. As compared to MapReduce, Spark is faster, more generic, and flexible. It also supports (standalone or on cluster) computations. However, Spark suffers from poor security, and it has a learning curve. Due to the complexity of the programming model, users must learn and be familiar with APIs before programming their Spark application. Big Data is generally saved and managed in distributed file systems or databases. Hadoop Distributed File System (HDFS) is a highly scalable system that enables running jobs on a cluster. It contains a master node called NameNode and several slaves called DataNodes for storing data. Spark supports HDFS to read/write data from/to HDFS directly. Spark support R and Python as high-level languages with SparkR and PySpark [12]. PySpark is a python API for Spark and supports python's lambda function passed to PySpark. As an efficient data processing system, Spark is used in many application domains such as Genomics, Medicine, Finance [15] and Transportation. For instance, Spark-DNAlining [2] exploits Spark’s performance optimization such as broadcast variable, join, partitioning, and in-memory computations for DNA short reads alignment problem. Among other fields, Transportation also gets a direct benefit from an efficient and scalable data processing system.

Rich in information and enormous in size transportation data could enhance understanding of the transportation network. Moreover, it is an enabler for proactive traffic management systems. Traffic network efficiency and safety are among priorities in traffic management and system performance measurement. As efficiency is evaluated in traffic congestion, extensive work is conducted to identify contributing factors in traffic congestion. This study utilized the Spark ecosystem to develop a scalable algorithm to detect Spatio-temporal congestion and further identify Recurrent congestion. The study location is Iowa’s interstates consisting of I-35, I-80, I-380, and I-29 total of 3017 segments between (0.4-0.6) miles length with a total of 1570 miles length. This sizeable geographical location gives a full view of the network performance, serving as Big Data.

2 Background

Intelligent transportation systems (ITS) produce a large amount of data. This enormous input will have a profound impact on transportation networks and ITS. Big Data brings more profit, safety, and efficiency to ITS by designing, planning, and controlling transportation networks. The purpose of ITS is to provide better service to drivers in transportation systems. ITS incorporates advanced technologies including electronic sensors, data transmissions technologies into transportation network [3]. GPS, sensors, cameras, social media are
diverse sources of Terabytes of data in ITS. Given the size, complexity, and production speed of data, traditional data processing systems and models are inefficient. Big Data analytic provides a new technical method benefiting a broad range of disciplines [13]. It can directly benefit from Big Data analytics by resolving data storage, data analysis, and data management problems. Moreover, Big Data analytics can improve real-time traffic operation decisions such as traffic public transportation routing. Traffic engineering covers a broad range of planning decisions, from strategic decisions such as transportation network design [21, 9] to operational such as traffic congestion monitoring [20]. Big Data can improve safety by analyzing the sensors, predicting incidents, and planning rescue scenarios. Big Data analytics can also improve traffic network efficiency by monitoring real-time traffic congestion and introducing controlling policies. Traffic congestion occurs when the demand for a traffic network exceeds its design capacity. The transportation sector is among the largest carbon-dioxide (CO) emission contributors. Traffic congestion is one of the critical issues that concern the sustainability of traffic networks [14]. It contributes to long commuting time, decreases the quality of life, and increase energy consumption. It produces emission and pollution, which is a significant threat to public health [11]. The Spatio-temporal pattern of congestion represents the first step toward developing effective policies for dealing with this issue. Although, sampling error might result in unreliable modeling when scaled [16]. Research in congestion detection literature is limited either spatially for specific zones [6] or temporally for a short period [22]. Thereby, it lacks the Spatio-temporal comprehensiveness.

Through careful application of Big Data analytics, we try to reveal a wealth of hidden traffic data insights. We uncover the Spatio-temporal pattern of congestion for the extensive network under study using a distributed programming model. We introduce a data-driven Spatio-temporal congestion detection framework based on (RRD) programming model. Moreover, travel delay and cost are considered to be a measure of congestion. We report delay and cost associated with detected congestion patterns.

3 Data and methodology

3.1 Study location

Probe vehicle speed data provided by INRIX [10] with a minute-wise reporting frequency for the entire 2018 calendar year were used in this study. INRIX reports average speed data for each segment in one-minute intervals using probe vehicles’ on-board GPS devices. The network of transportation in this study is Iowa’s interstates freeways. As shown in Figure 1 Iowa’s freeways includes (I-35, I-80, I-29, and I-380). This network consists of 3017 segments that partition the network almost equal length (from 0.4 to 0.6 miles).
3.2 Method

The mathematical abstraction of our data corpus is defined here. Consider the weighted graph of the traffic network denoted by $G = (S, E, W)$, where $S$ defines all nodes of the graph, $E$ denotes the edges, and $W$ denotes the weights of the edges. This study node graphs correspond to consecutive road segments that partition the freeway understudy, and average vehicle speeds ($x$) in one-minute intervals are reported for each segment. The nodes corresponding to consecutive segments connect weighted edges along the freeway. Since in our study, freeway segments are approximately equal in length (from 0.4 to 0.6 miles), the weight of the nodes in this study was all counted as equal to 1. The order of road segments describes the connectivity of the graph and the speed values are a (noisy) time-series with the length $N$, for each node $S$ for a given date $v$.

$$X_v^s = \{x_{t_1,v}, x_{t_2,v}, \ldots, x_{t_N,v}\}, \ s \in \{S\}, \ v \in \{D\}$$

Where $t_i$ denotes the $i$th time instant $T = \{t_i \mid i \in N\}$ and $v$ denotes the date.

Overall, we have a third-order tensor $x \in R^+ \times N \times D$ where $D$ defines the total number of days, $n$ defines the total number of nodes (segments), and $N$ defines the length of the time-series for each date. For example, in this study, since average speed values are being reported in one-minute intervals for each segment the length of the time series $N$ is equal to $24 \times 60 = 1440$. Given our tensor, the major challenge that we faced was the scale of the traffic data. After all, there are 54,000 segments in the entire road network of Iowa that produce 4 gigabytes of daily traffic data.

Zarindast et al. (2020) proposed a data-driven definition and machine learning algorithm for congestion and congestion patterns. Their proposed
framework was tested in Des Moines, Iowa; thereby, the proposed regional parameters perfectly match our network. As a result in this work, inspired by [5] and based on [6] important parameters for our algorithm were extracted. These data-driven definitions are the duration of congestion, congestion threshold, and recurrent congestion frequency in the data. We calculated congestion index 2 for congested regime under data-driven method [6]. Figure 2 shows histogram of congestion index for congestion regime with data-driven method [6]. Congestion index (CI) starts from 0.15; in our framework, we consider the congestion threshold equal to 0.15.

\[
CI = \frac{RS - S}{RS + S}
\]  

(2)

\[
Congestion_i = \begin{cases} 
1 & \text{if } CI > 0.15 \text{ for } \{i \mid i \in (1 : 1440) \& \ i - 15 \} \\
0 & \text{otherwise}
\end{cases}
\]  

(3)

\[
Indicator_i = \begin{cases} 
1 & \text{if } \frac{\sum_D Congestion_i}{n} > 3 \text{ for } \{i, D \mid i \in (1 : 1440), D \in (1 : 365)\} \\
0 & \text{otherwise}
\end{cases}
\]  

(4)
4 Computing machine specifications

Big Data is generally saved and managed in distributed file systems or databases. Hadoop Distributed File System (HDFS) is a highly scalable system that enables running jobs on a cluster. Spark support read/write from/on HDFS; hence our data storage structure is HDFS. We used PySpark (spark API) to conduct our experiment with the cluster under (RRD) programming model. The experiments were hosted on-prem Cloudera based high-performance cluster. The cluster was composed of 33 high power machines, including two master nodes and 31 worker nodes.

**Cluster specification:**

- Operating system: Redhat 7.6
- Total RAM: 816 GB
- Total HDFS Storage: 222 TB
- Total number of cores: 156
- Spark Version: 2.3
- Hadoop Version: 2.6.0

The utilized computing power and time for the experiment is described in Table 1.

| Data size (GB) | CPU nodes | Memory (GB) | Computation time (Min) |
|---------------|-----------|-------------|------------------------|
| 76.4 GB       | 64        | 224 GB      | 10 min                 |

5 Result

Figure 3 compares the resource utilization by increasing the input size. This table can give us an example of how input size is effecting computation times.
Consider matrix $[\text{6}]$, in our third-order tensor $x \in \mathbb{R}_+^n \times N \times D$ (Vector $[\text{5}]$). $S$ is constant for each example segment. It should be noted that speed values are presented in Figure 4 only for date and times detected by our algorithm as experiencing an instance of congestion in (b) and RC in (c) for each particular segment.

$$X_s^v = \{x_{t_1}^v, x_{t_2}^v, \ldots, x_{t_N}^v\}, s \in \{S\}, v \in \{D\}$$  \hspace{1cm} (5)

As shown in Figure 4, our proposed framework could detect Spatio-temporal RCs. These congestion hour periods refer to the morning or evening peak traffic hours.
Figure 4: Comparison between (a) actual speed profile, (b) detected congestion, (c) detected RCs for three example segments

Figure 5 shows average congestion hours by segments. As expected des moine loop experiences RC.
Figure 5: Average RC hours by segment for year (2019)-(a) and year (2018)-(b).

Figure 6 shows average congestion hours by segments. As expected, Des Moines loop experiences RC.
We investigated the performance of our proposed method with recently developed data driven method [6] in terms of computation time, computation cost and accuracy. The accuracy of proposed framework has been compared with recently developed data driven method by [6] using INRIX data for calendar year 2016, where study region were Des moine, Iowa, USA. The accuracy has been calculated by comparing the identified congested hours between data driven method proposed by [6] and developed framework in this study. Considering segment $s$ and date $d$ such as $s \in \{S\}, v \in \{D\}$ we have following definitions:

- **True Positive:** Congestion has been correctly identified by proposed method $\forall h, s, d$ (TP)
- **True Negative:** Freeflow has been correctly identified by proposed method $\forall h, s, d$ (TN)
- **False Positive:** Congestion has been identified by proposed method incorrectly $\forall h, s, d$ (FP)
• False Negative: Freeflow has been identified by proposed method incorrectly ∀ h, s, d (FN)

• Accuracy = \frac{TP + TN}{TP + FP + TN + TN}

Based on a given computation power, we compared the estimated cost and processing time between the proposed framework and data-driven framework by [6]. The processing cost estimation has been calculated using amazon web services (AWS) [7] by giving computational power and time. These cost calculation are for processing INRIX 2018 probe data in our study location (see Figure 1) in interstates of Iowa, USA. The data-driven method proposed by zarindast et al. (2020) consists of three phases, namely 1- preprocessing 2-Bayesian change point detection, 3- RC, and NRC identification. Considering computation power given in table 1, the data-driven method took 151 hours of operation, which resulted in a total of 488 $. While proposed framework Considering computation power given in table 1 took 10 minutes, which resulted in 1.34 $. The accuracy of detection is based on detected congested hours for each date and segment between two algorithms. Figure 7 shows the trade-off between computation time and accuracy. By only a 10 percent decrease in detection accuracy, we could decrease the computation time by 99.88 percent. As shown in Figure 7 proposed method was able to detect congestion with 84 percent accuracy as compared to the data-driven method proposed by zarindast et al. in (2020) [6].

Figure 7: Cost, processing time, accuracy trade-off (Zarindast et al. (2020) vs proposed method).

6 CONCLUSIONS

In this study, a highly parallelized framework for identifying freeways’ congestion has been presented under RRD modeling. The proposed framework leverages a wealth of data to uncover Spatio-temporal congestion patterns further. We use state-of-the-art Spark as an efficient data processing system and HDFS cluster for computations; thus, the proposed framework is highly scalable and efficient in computation time. Most prior research is bound to a particular location or
specific period. This study is among the first studies that consider a big data framework for identifying congestion and associated patterns to the best of our knowledge. The total input size was 76 GB, and the total computation time was 10 minutes. The proposed big data solution is a path toward real time traffic controlling and management. Comparison between the proposed method and data-driven definition proposed by Zarindast et al. in 2020 showed that the proposed method decreased computation time by 99.88 % while maintained 90 % congestion accuracy. The experiment was conducted on Iowa’s interstates, and the result is presented in terms of RC, delay cost and hours, congestion hours.

References

[1] Martín Abadi et al. “Tensorflow: Large-scale machine learning on heterogeneous distributed systems”. In: arXiv preprint arXiv:1603.04467 (2016).
[2] Maryam AlJame and Imtiaz Ahmad. “DNA short read alignment on apache spark”. In: Applied Computing and Informatics (2019).
[3] Sheng-hai An, Byung-Hyug Lee, and Dong-Ryeol Shin. “A survey of intelligent transportation systems”. In: 2011 Third International Conference on Computational Intelligence, Communication Systems and Networks. IEEE. 2011, pp. 332–337.
[4] Apache storm. 2015. URL: https://storm.apache.org
[5] Zarindast Atousa. A data driven method for congestion mining using big data analytic. https://lib.dr.iastate.edu/creativecomponents/4417 2019.
[6] Zarindast Atousa, Suphadipto Poddar, and Sharma Anuj. “A data-driven method for congestion identification and classification”. In: Expert system with application (submitted).
[7] AWS. 2018. URL: https://calculator.s3.amazonaws.com/index.html?r=fAD&key=files/calc-57352e003337796e7e8ec1a8ce1a5f274428dd7b&v=ver2020031708
[8] Jeffrey Dean and Sanjay Ghemawat. “MapReduce: simplified data processing on large clusters”. In: Communications of the ACM 51.1 (2008), pp. 107–113.
[9] Elif Elçin Günay, Gül E Okudan Kremer, and Atousa Zarindast. “A multi-objective robust possibilistic programming approach to sustainable public transportation network design”. In: Fuzzy Sets and Systems (2020).
[10] INRIX. 2018. URL: http://inrix.com
[11] Jonathan I Levy, Jonathan J Buonocore, and Katherine Von Stackelberg. “Evaluation of the public health impacts of traffic congestion: a health risk assessment”. In: Environmental health 9.1 (2010), p. 65.
[12] pyspark. 2016. URL: http://spark.apache.org/docs/latest/api/python/index.htm

[13] Atefeh Rajabalizadeh et al. “An Exploratory Analysis of Electronic Intensive Care Unit (eICU) Collaborative Research Database”. In: (2020).

[14] Hubert Rehborn, Sergey L Klenov, and Jochen Palmer. “An empirical study of common traffic congestion features based on traffic data measured in the USA, the UK, and Germany”. In: Physica A: Statistical Mechanics and its Applications 390.23-24 (2011), pp. 4466–4485.

[15] Mostafa Mohamed Seif, Essam M Ramzy Hamed, and Abd El Fatah Abdel Ghfar Hegazy. “Stock market real time recommender model using apache spark framework”. In: International Conference on Advanced Machine Learning Technologies and Applications. Springer. 2018, pp. 671–683.

[16] Mohsen Shahhosseini and Guiping Hu. “Improved Weighted Random Forest for Classification Problems”. In: arXiv preprint arXiv:2009.00534 (2020).

[17] Shanjiang Tang et al. “A Survey on Spark Ecosystem: Big Data Processing Infrastructure, Machine Learning, and Applications”. In: IEEE Transactions on Knowledge and Data Engineering (2020).

[18] Matei Zaharia et al. “Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing”. In: Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12). 2012, pp. 15–28.

[19] Matei Zaharia et al. “Spark: Cluster computing with working sets.” In: HotCloud 10.10-10 (2010), p. 95.

[20] Atousa Zarindast. “A data driven method for congestion mining using big data analytic”. In: (2019).

[21] Atousa Zarindast et al. “Determination of Bus Station Locations under Emission and Social Cost Constraints”. In: (2018).

[22] Pengjun Zhao and Haoyu Hu. “Geographical patterns of traffic congestion in growing megacities: Big data analytics from Beijing”. In: Cities 92 (2019), pp. 164–174.