MACHINE LEARNING BASED VISUALIZATION FRAMEWORK FOR RANKING, CLUSTERING AND CHANGE DETECTION USING CONTROLLER (ATSPM) DATA

Dhruv Mahajan,
dhruvmhjn@ufl.edu
Shreya Singh,
shreya.singh@ufl.edu
Tania Banerjee, Ph.D.
tmishra@ufl.edu
Anand Rangarajan, Ph.D.
anand@cise.ufl.edu
Sanjay Ranka, Ph.D.
sranka@ufl.edu
Dept. of Computer and Information Science and Engineering
University of Florida, Gainesville

Word Count: 4047 words + 10 figures× 250 + 1 table× 250 = 6797 words

Submission Date: May 15, 2019

INTRODUCTION

Traffic signals are the universal solution to optimize the flow of traffic at road intersections while ensuring safety. Micro-controller based Traffic signal controllers, that are co-located with the signals are responsible for managing the signal phasing and timing at every intersection. The primary function of the controllers is to ensure safety by eliminating (or reducing) conflicts and optimizing the flow of traffic while adhering to these safety constraints. This is done by displaying right of way information, which is updated based on fixed signal timing plans or based on detector actuated timing plans. Newer signal controllers have the ability to log and report all events (phase changes, vehicle detector actuation etc). at a high resolution.

These controllers have enabled the development of the Utah Department of Transportation (UDOT) Automated Traffic Signal Performance Measures (ATSPM) (*1*) and other related efforts. These tools are being developed and deployed in cities and regions all across the nation and are aimed at enhancing the management of traffic signals by using the high-resolution controller logs (normally, deci-second or 10Hz) to generate operational performance metrics. The newer generation of traffic controllers combined with the ATSPM systems provide vastly improved monitoring capabilities as compared to the older generation systems which were based on coarse-grain data (typically at 15 minute intervals).

This report presents a novel framework that combines processing of high resolution controller log data and machine learning techniques to produce the following outcomes:

1. Ranking and Categorization: Each intersection is ranked based on performance metrics. Several Measures of effectiveness (MOEs) are used in the discipline (*2, 3*). Based on input from traffic engineers, two measures of great interest are: 1) SF - The traffic or demand that the intersections cater to (reported as split failures) and 2) AORG - utilization of allotted green time (AoR/AoG, the ratio of arrivals on red, AoR, to arrivals on green, AoG). Using a combination of these two metrics, we categorize the intersections into several categories.
2. Clustering: Similarly behaving or performing intersections are grouped together using machine learning techniques. This approach is particularly useful when dealing with a large number of intersections and is carried out along both space and time. Using this approach, we discover and highlight spatial and temporal patterns in the data and we are able to find signals on a corridor that tend to behave similarly
3. Change detection: Using a baseline consisting of similar time periods, we develop a change detection algorithm that can detect statistically significant changes at an intersection level. This approach can be used to determine unexpected behavior or change in traffic patterns.

Using the above algorithms, we have developed a decision support system for traffic engineers that allows them to focus on problematic intersections and corridors as well as areas with significant changes in traffic patterns. Hence, this is complementary to the existing ATSPM systems (such as UDOT's) which provide the ability to drill down to specific intersections.

All the steps in the decision support system are automated by a work-flow process that reads raw controller logs, computes key measures, clusters the intersections, detects changes and stores this information in a relational database. The user can interact with this database using a tableau based visualization system that provides configurable filtering thresholds. Although, our work currently uses split failures and AoR/G as key metrics, further enhancements using other metrics of interest can be easily incorporated in the future.

The rest of the report is organized as follows. We first describe the pre-processing steps that are performed to convert raw controller logs to MOEs. Next, we introduce a Intersection Ranking and Categorization scheme. The third section of the report covers clustering methods to highlight spatio-temporal patterns in the behavior of intersections. In the fourth section, we describe a model to automatically detect significant changes in intersection behavior. The last two sections of the report detail our Visualization framework, and summarize our contributions. We also discuss how our techniques can be used in tandem with existing UDOT ATSPM systems .

Keywords: Machine Learning, ATSPM, Clustering, Change Detection, Categorization, Measures of Effectiveness

RELATED WORK

Evaluating the performance of traffic signal systems is important for identifying any problems and addressing them, as well as for assessing and planning enhancements to these systems. Radivojevic *et al.* in (*4*), presents a framework for a comprehensive quantitative evaluation of these signals. Our work in this paper is different because it presents an *automatic* evaluation, analysis and notification system for signal performance using high resolution data from signal controllers and detectors. This will allow traffic engineers to be proactive in addressing issues, instead of addressing them passively as a result of user feedback.

Purdue Coordination Diagrams (PCDs), Arrivals on Green vs Red and other such measures (*2, 3*) give us a precise idea of the arrivals of vehicles and the corresponding signal phase. However a practitioner has to generate and analyze the diagram for each direction of movement at every intersection to analyze signal performance. The method presented in this document would automatically detect the problem areas, which allows the practitioner to review only the diagrams for specific intersections and movements. Li et al. (*5*) present a heuristic based on system wide split failure identification and evaluation. By using this heuristic, they demonstrated performance improvements for specific corridors. This paper builds upon this approach and enhances it by proposing an *automated* way to categorize all intersections in a network based on split failures and hence preemptively identify any corridors that may be under-performing.

Data analytics techniques have been previously applied to traffic flows and here we present the relevant application areas. Wemegah et al. (*6*) present techniques for management of big data for analyzing traffic volumes and congestion, addressing all the steps in the analytics pipeline namely, data acquisition, data storage, data cleaning, data analysis and visualization. Amini et al. (*7*) describe an architecture for real time traffic control. Machine learning techniques have been applied for predicting traffic flows and thereby traffic congestion. Horvitz et al. (*8*) present a probabilistic traffic forecasting system using a Bayesian structure search. Huang et al.(*9*)propose a set of new, derived MOE's that are designed to measure health, demand and control problems in signalized intersections. The newly proposed MOE's are based on approach volume and platooning data derived from ATSPMs (*1*). Our approach, in sharp contrast, is based on existing MOE's for split status and targets the differences between arrivals on red vs arrivals on green. Our approach *automatically* highlights potential demand and coordination problems in the network.

PRE-PROCESSING

This section describes the MOEs and corresponding processing requirements.

Measures of Effectiveness (MOEs) In order to analyze the performance of intersections, we used a combination of split failures and arrivals on green/red as our primary features. Split failures can be of two types: max-outs and force-offs. In the event when a signal reaches the maximum allocated green time due to high demand, a max-out is said to have occurred. Whereas, Force-offs occur when an intersection reaches the maximum allocated green time without being able to fulfill the demand. High split failures are good indicators of high demand on a particular phase of the intersection.

The arrivals on green and arrivals on red are the number of vehicles arriving at an intersection during a green phase vs a red phase. Higher AoG are a positive indicator for the signal performance. A large number of max-outs or force-offs along with high ratio of vehicles arriving on red as compared to green, are an indication for a high degree of congestion. We also use pedestrian begin-walk events which are useful to explain the reduced intersection throughput. We have calculated the split failures for phases 2,4,6,8 and AOG and AOR for the phases 2 and 6. In the future, we will also develop appropriate metrics for phases 1,3,5,and 7 (e.g. demand based split-failures).

Data Aggregation: This involves transforming the high-resolution data and storing it in one minute bins. We compute the duration of split failure in minutes and store that information in the bins. To ensure that we get useful data in coordinated corridors, we take into account the detector-on events right before a split failure is reported. This is similar to computing the Red Occupancy Ratio (ROR), a metric used both in the literature and field. Henceforth, the term split failures refers only to these **demand based split-failures**. We also count the pedestrian walk events.

The output of the data aggregation step is a vector with $24x60$ entries representing the behavior of a particular phase over the entire day. Each element in a vector is a binary digit indicating the reported split failures.We then use a simple sliding window algorithm to deal with the problem of the outlier events. Our approach takes the vector, v size of the window, w and a threshold parameter, t as the inputs and produces a smoothing vector, o as output. For example if v is 11111000010, w is 6 and t is 5, the output that we obtain after smoothing would be 11111000000. This technique can (optionally) smoothen minor variations in data.

RANKING AND CATEGORIZATION

We introduce controls to filter and rank intersections based on Demand and Green time utilization. This allows traffic engineers to easily zoom in on the most problematic intersections. This is also helpful in identifying which signals need immediate attention in terms of re-timing. We also create a set of pre-defined categories using a combination of split failures and the ratio of arrivals on red to arrivals on green (AoR/AoG), to categorize the signals into five broad categories.

1. Intersections with detection issues or missing data: No Vehicle detection for an extended period of time.
2. Low split failures, Low AoR/AoG: Well timed and utilized intersection.
3. Low split failures, High AoR/AoG: Low demand but potential for timing improvement.
4. High split failures, Low AoR/AoG: Potential capacity problem.
5. High split failures, High AoR/AoG: High demand and potential for timing optimization.

Findings: Figure 1 is an example of all the intersections for a given day. The shape clearly shows which intersections have detection, potential capacity and potential timing problems. The user

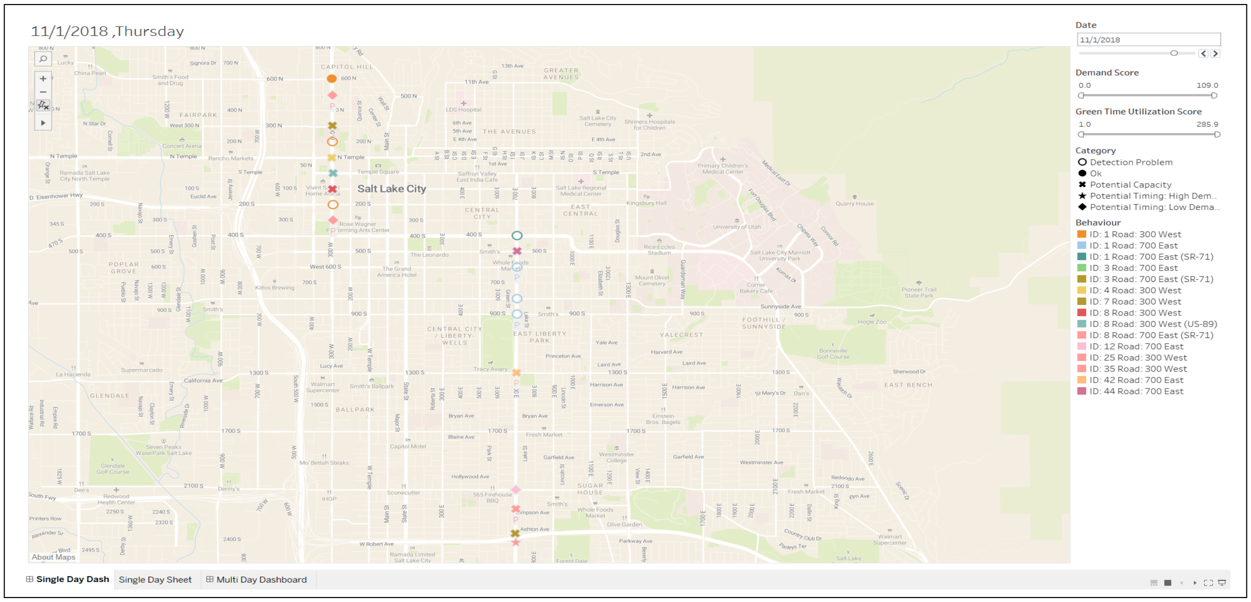

FIGURE 1 Dashboard showing the categorization results for a single day. The screenshot captures the behavior of different intersections on a given day using different symbols. The user can set thresholds for the two MOEs using the two sliders. The demand score and green time utilization score correspond to split failures and AoR/AoG ratio.

can configure the sliders to categorize the signals based on the two MOEs that we have described above. The two sliders, demand score and green time utilization score, correspond to split failures and AoR/AoG ratio.

The user can also investigate the behavior over multiple days and limit the types of intersections of interest. For example in Figure 2, the intersections are filtered based on high demand and highly utilized green times. We can see that the number of such intersections drops over the weekend.

The tool also allows the user to find detailed information on a particular signal by clicking on that intersection. For example in Figure 3, the user highlighted a potential broken (i.e. missing data) signal and can see that no detection is recorded throughout the day. The same detector starts recording on a future date (Figure 4).

CLUSTERING

Clustering or behavioral grouping is the next step in the data analysis pipeline. It can be used to compare groups of co-located intersections with similar behavior over multiple days. After obtaining the processed vectors of length 1440 as described in the previous section, we aggregate the split failure vectors to an hourly resolution and hence obtain a vector which represents the fraction of minutes in a hour for which the split status was reported (this is represented as F).

We concatenate the vectors for phase 2 & 6 and get one vector per intersection. We can then use custom distance measures to quantify the similarity between these vectors. The pairwise similarity between two intersections is computed by the difference between the corresponding vectors. We use 1-norm of the difference vector for distance computations. A vector p-norm is

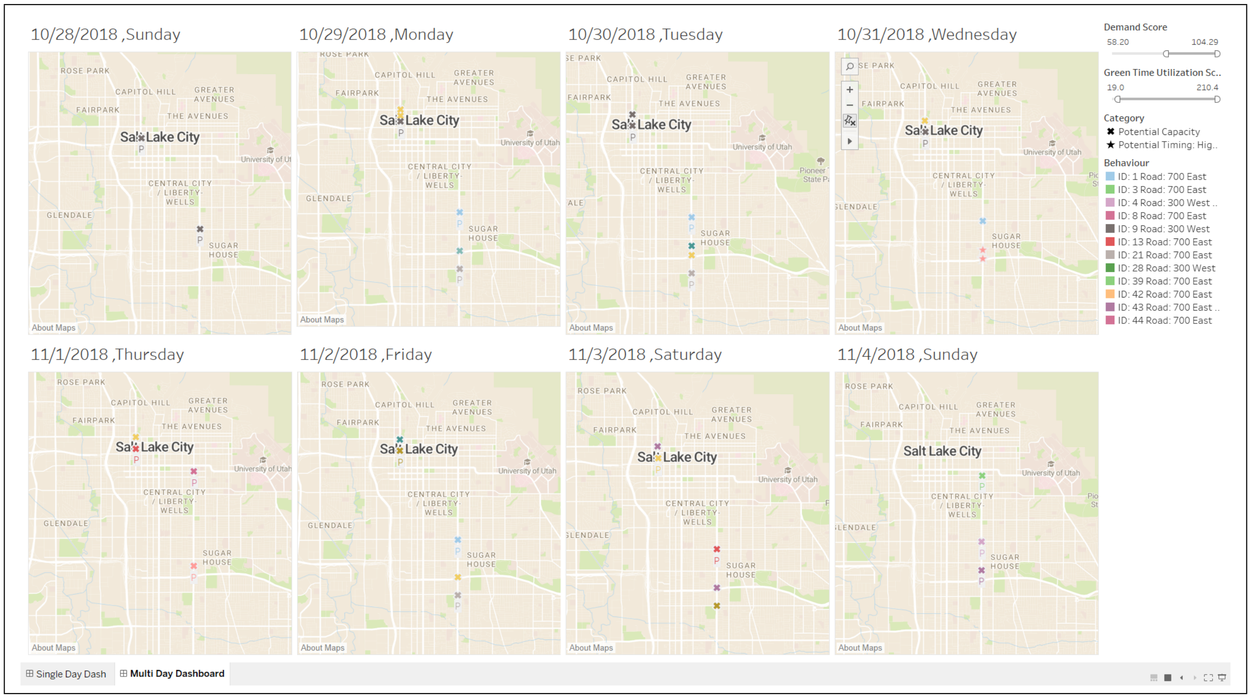

FIGURE 2 Dashboard showing the Ranking results for multiple days. We highlight intersections with high demand and high green time utilization (capacity problems). The problems on weekdays are contrasted with those on weekends.

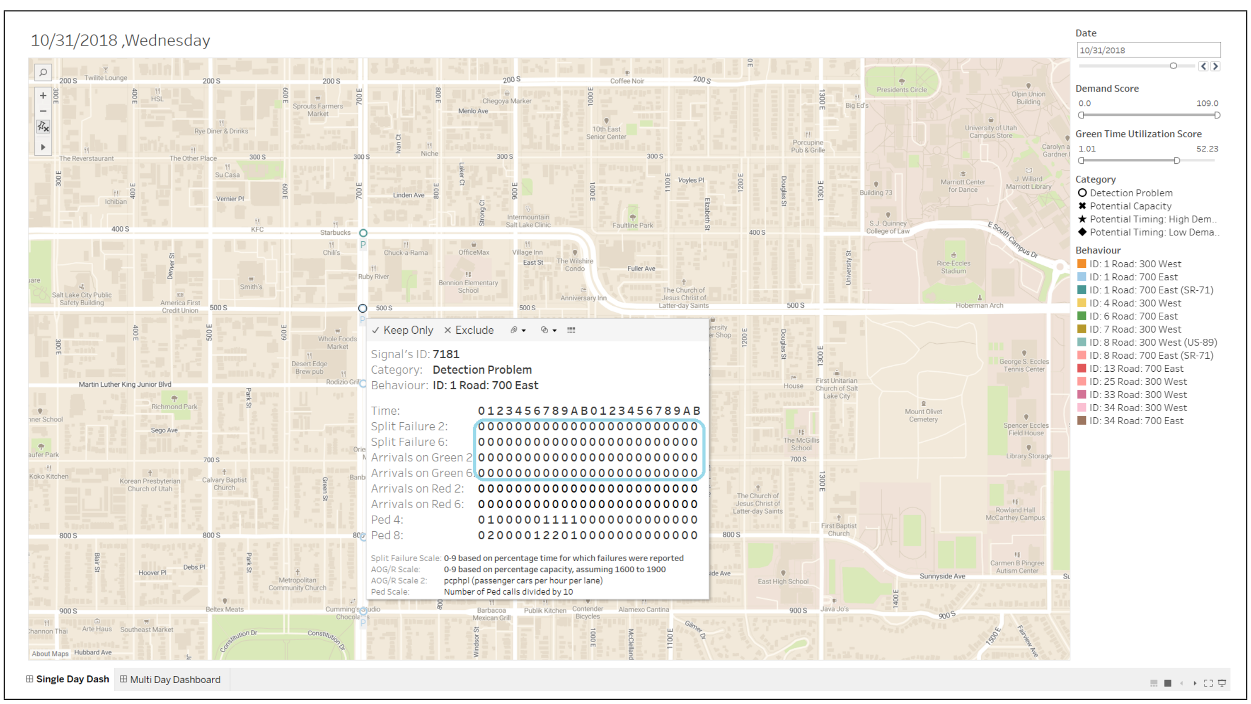

FIGURE 3 We explore the behavior of Intersection ID 7181, which has missing data or a detection problem from January to October 2018. Note that all intersections with missing data or detection problems are assigned to the same cluster or behavioral group.

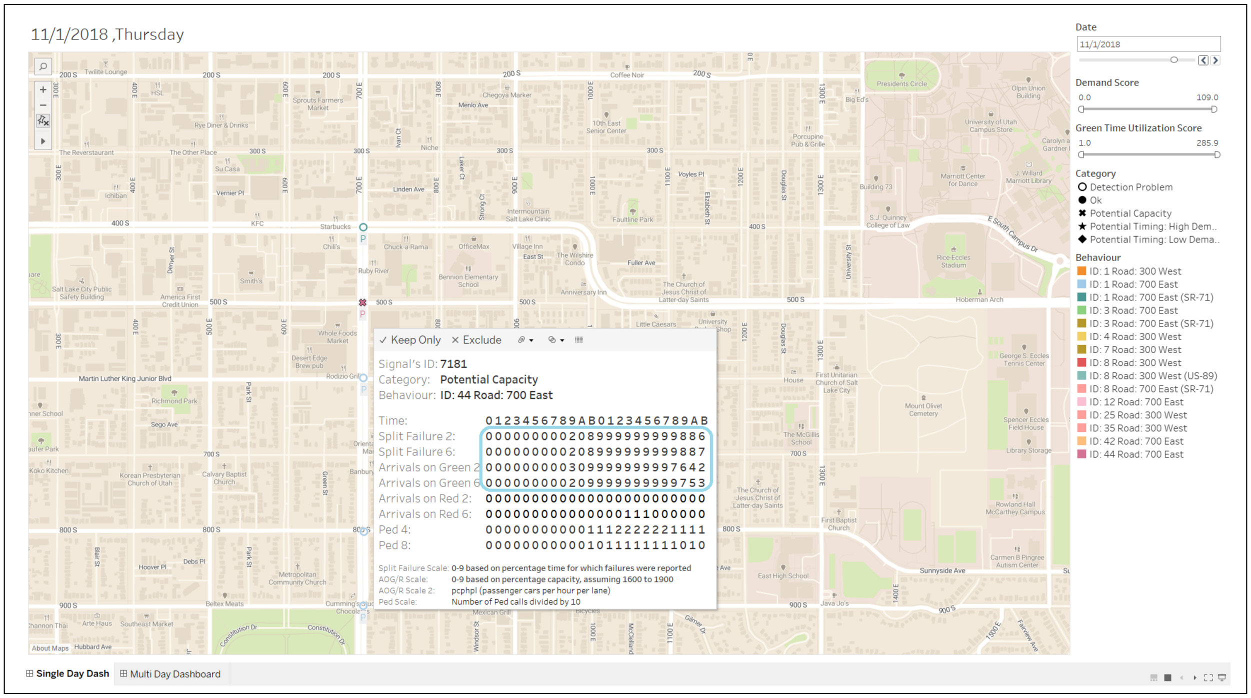

FIGURE 4 Intersection ID 7181, (same as figure 3) now showing that the detection problem fixed on the first day of November. Note both the Cluster ID and the category for the intersection have changed.

defined as:

$$x_p = (\sum_i | x_i |^p)^{\frac{1}{p}} \tag{1}$$

and the 1-norm is defined as

$$x_1 = (\sum_i | x_i |) \tag{2}$$

Given a pairwise distance between the behavior of all intersections, we can use a wide variety of clustering techniques to group similar intersections together.

A popular techniques for doing this is spectral clustering. In the first step, a graph Laplacian is obtained from the distance matrix described in the previous step. A graph Laplacian for a matrix is defined using the parameter D, the degree of the matrix and A, the adjacency matrix. Hence, a Laplacian L, can be defined as

$$L = D - A \tag{3}$$

The lowest k eigenvalues of this matrix are used for dimensionality reduction (with k denoting the dimensionality of the nonlinear embedding).

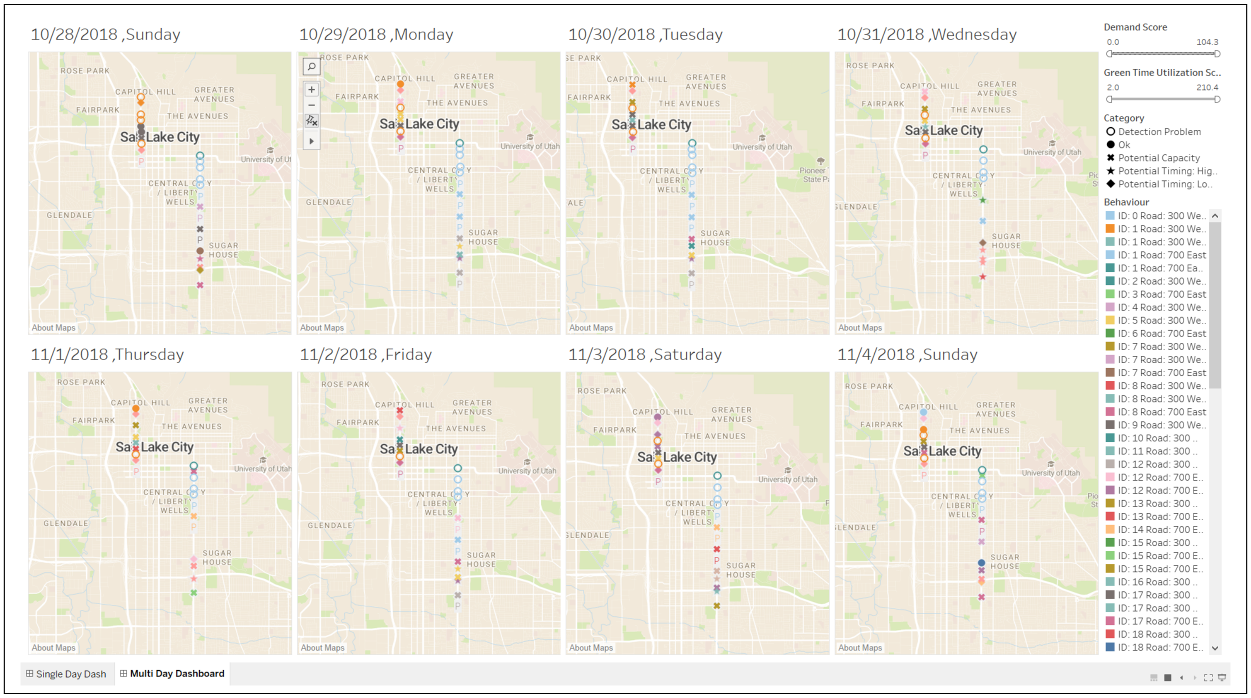

FIGURE 5 Multi-day Tableau dashboard allows for comparison of clustering results across days and highlights temporal patterns in intersection behavior. The color of a signal is based on the spatio-temporal cluster ID & Road Name.

Findings: Figure 5 shows the clustering results based on the data from UDOT. From figures 1 and 5 we can see that intersections with similar behavior (detection/capacity problems) are assigned the same cluster (all similar intersections have the same behavioral ID). It is note-worthy that most of the intersections with similar behavior are on the same corridor. This is in line with expectations. This also allows a traffic engineer to look at intersections which are behaving differently from the others on a corridor.

CHANGE DETECTION

In this section, we present an automated model for detecting significant changes in the intersection behavior. We have developed an algorithm which can be used to identify significant changes in the time-series representation described in the previous section. Using this representation, we detect changes for a given day using a baseline consisting of similar days (example, for a Monday, a baseline consisting of many previous Mondays is used).

The baseline vector is simply the average over all the days in the baseline. Next, we describe how to identify if an incoming vector is different from the baseline. We use the 2-norm of a vector to determine the distance between the baseline and the incoming vector. The norm of the difference between two vectors is obtained and a threshold value identifies whether the change is significant or not. Such intersections/days can then be flagged and our data visualization tool can be used in conjunction with the existing UDOT ATSPM tool to study the problem further.

Findings: Figure 6 shows a comparison of the behavior vectors for intersection 7181 from the month of March and December 2018. Here, Phase 2 and 6 are the split failures for the primary

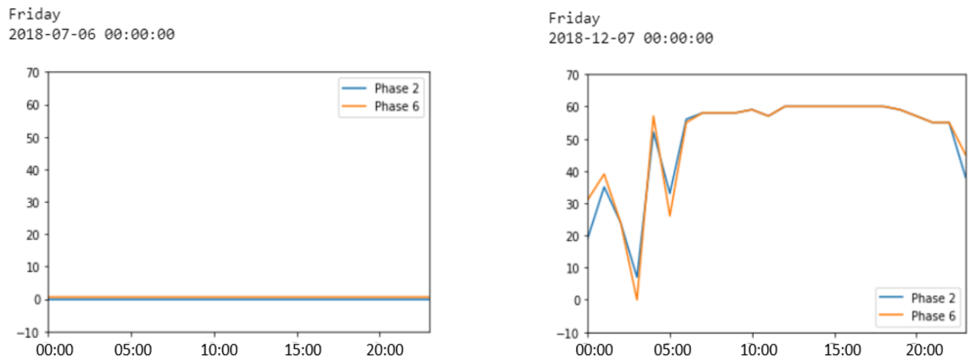

FIGURE 6 A Chart of Split failures for Phase 2 and Phase 6 (intersection ID 7181) showing a significant change between 03/30/2018 and 12/07/2018. This intersection is also highlighted in Figure 3 and Figure 4.

phases. We observe a zero value for P2 and P6 in the month of March and we discovered this was true for the months of January to October. However, we observe a sudden change in the values of P2 and P6 in November and December.

Next, Figure 7 captures the behavior of intersection ID 7124 for three day period from the 2rd of July to the 4th of July. The change for July 4th is automatically detected based on a baseline consisting of a small number of previous days. Of course, for a human this is expected because of it being a national holiday. Our goal is to detect all significant changes, some of which may be easy to anticipate, others not.

Lastly, Figure 8 contains a summary of some of the other changes detected by our algorithm and a discussion about them.

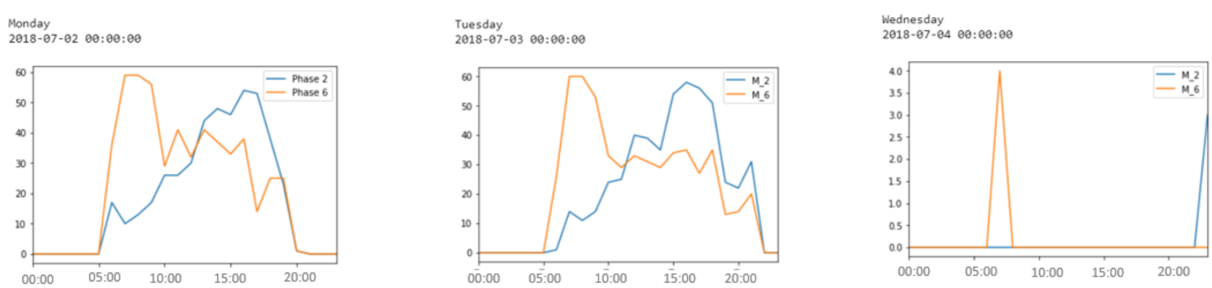

FIGURE 7 Intersection ID 7124 showing an significant deviation from normal behavior on the 4th of July.

VISUALIZATION FRAMEWORK

Using the techniques described above, we developed a tool leveraging Tableau® to create visualizations which can aid traffic engineers. The application makes use of the data visualization capabilities of Tableau and embeds the Tableau Dashboards into a HTML/CSS based web interface and a SQL based back-end to enable customization of the visuals produced by Tableau. The overall architecture of the application is explained in Figure 9. The application has several screens that cover the description in the previous three sections (e.g. Figures 1 and 5). Table 1 documents

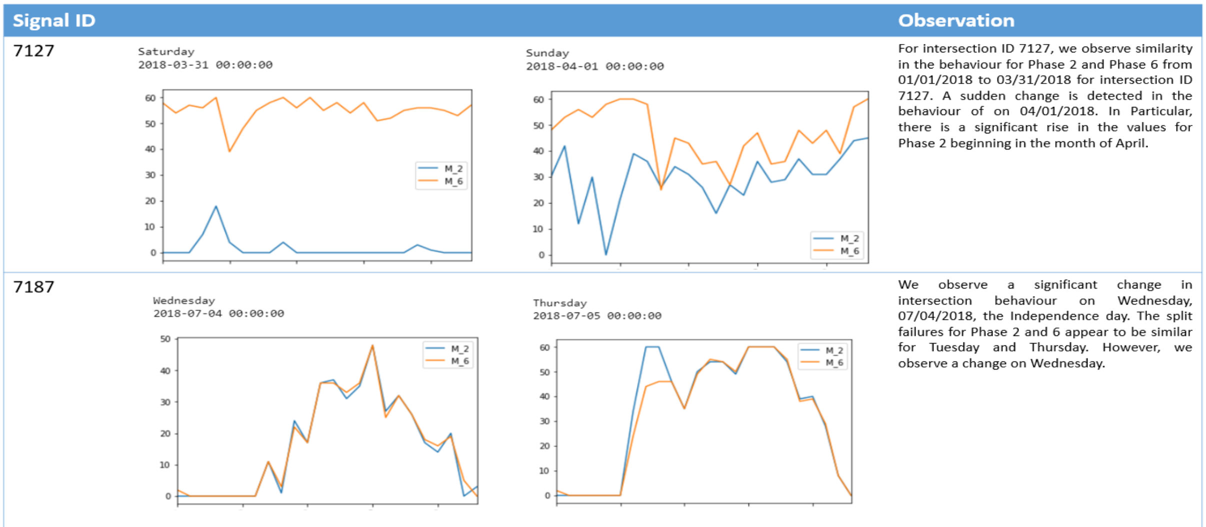

FIGURE 8 Other intersections that were discovered to be showing a significant deviation from their normal behavior.

the technology stack used for the application.

TABLE 1 Technology Stack

Software	Version
Language: JAVA	JAVA 8
Language: JQuery	3.2.1
Framework: Spring Boot	2.0.0
Tableau	2018.1
API: Tableau Javascript	tableau.v8

CONCLUSION AND DISCUSSION

In this work, we propose a data driven approach to process high resolution controller log data and build a decision support system. We demonstrated this approach using split failures and AoG/R ratios as MOEs to rank and categorize intersections according to their performance. This can be used to quickly identify the most problematic intersection in the region. Next, we used clustering techniques to group together signals exhibiting similar behavior. Using this approach, we highlight spatial and temporal patterns in intersection behavior and also detected intersections that may either have broken detectors or missing data. Thus, we automatically highlight intersections that may need attention in terms of re-timing or fixing of broken detectors. Next, we propose a change detection model to detect statistically signification changes at each intersection and highlight some results.

We also developed a visualization framework to inform traffic engineers and traffic managers about the current performance of the signalized intersection in a region. The results can be used to easily identify problematic signalized intersections in a proactive manner. Once the problematic intersections are known, the UDOT ATSMP system can be invoked from within our

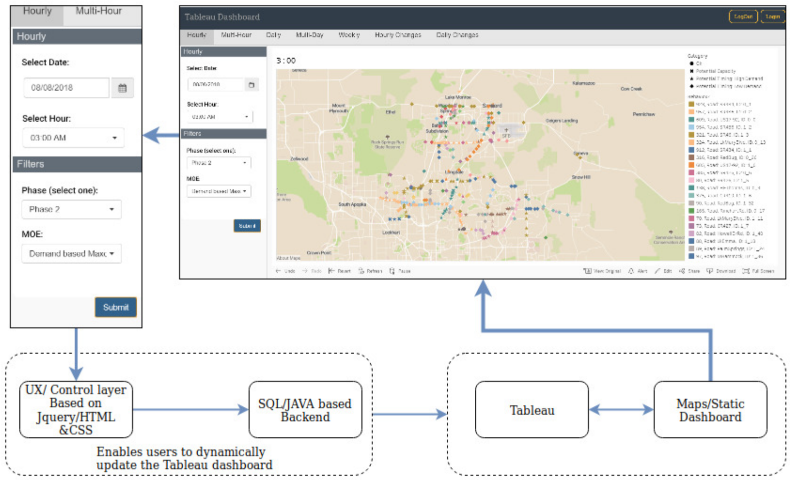

FIGURE 9 The overall framework for visualizations. This architecture enables us to leverage Tableau to build dashboards which can be updated via user queries.

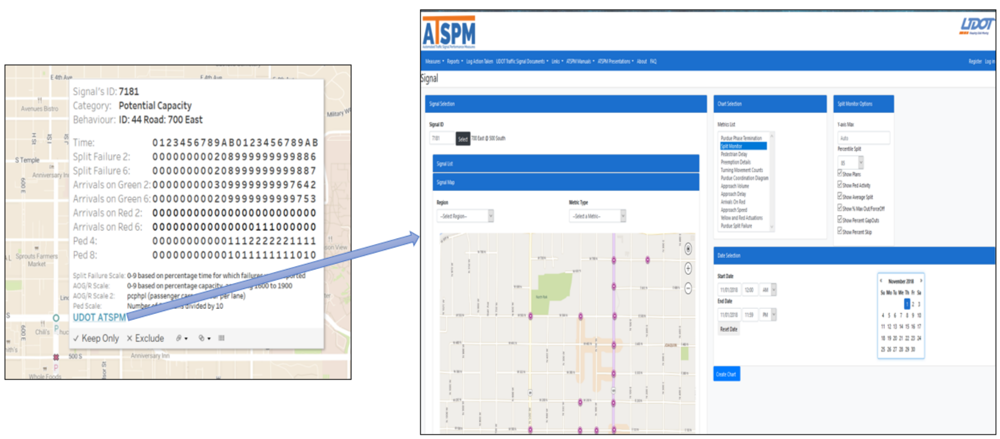

FIGURE 10 An example of possible integration between our systems and the UDOT ATSPM. The user can click and reach the UDOT ATSPM page for same Signal.

dashboard (Figure 10) to drill down and analyze the intersections. Hence, our techniques and the existing ATSPM systems are complementary.

The goal of our solution is to increase the effectiveness of traffic engineers by highlighting intersections and/or corridors that need their attention for operations and planning. Hence, it addresses one of the key concerns highlighted in the competition guidelines ("To make matters worse, these signals are still predominantly being managed on basis of citizen complaints"). In addition, to the dashboard presented in this paper, we are currently developing an email based reporting system that will periodically provide a traffic engineer with a small subset of intersections/corridors that need attention or where traffic has changed significantly as compared to its historical patterns.

We have conducted performance studies (results not presented here) that show that our system can scale to 1000 intersections with a few hours or less of processing every day.

REFERENCES

[1] UDOT, *UDOT Automated Traffic Signal Performance Measures - Automated Traffic Signal Performance Metrics*. https://udottraffic.utah.gov/atspm/, 2017, (Accessed on 12/26/2018).

[2] US Department of Transportation, F. H. A., *Measures of Effectiveness and Validation Guidance for Adaptive Signal Control Technologies*. https://ops.fhwa.dot.gov/publications/fhwahop13031/index.htm#toc, 2013, (Accessed on 12/26/2018).

[3] Day, C., D. Bullock, H. Li, S. Remias, A. Hainen, R. Freije, A. Stevens, J. Sturdevant, and T. Brennan, *Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach*, 2014.

[4] Radivojevic, D. and A. Stevanovic, Framework for Quantitative Annual Evaluation of Traffic Signal Systems. *Traffic Signal Systems: Volume 1*, 2017.

[5] Li, H., L. M. Richardson, C. Day, J. Howard, and D. Bullock, Scalable Dashboard for Identifying Split Failures and Heuristic for Reallocating Split Times. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2620, 2017, pp. 83–95.

[6] Wemegah, T. D. and S. Zhu, Big data challenges in transportation: A case study of traffic volume count from massive Radio Frequency Identification(RFID) data. In *2017 International Conference on the Frontiers and Advances in Data Science (FADS)*, 2017, pp. 58–63.

[7] Amini, S., I. Gerostathopoulos, and C. Prehofer, Big data analytics architecture for real-time traffic control. In *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, 2017, pp. 710–715.

[8] Horvitz, E., J. Apacible, R. Sarin, and L. Liao, Prediction, expectation, and surprise: Methods, designs, and study of a deployed traffic forecasting service. *21st Conference on Uncertainty in Artificial Intelligence*, July, 2005.

[9] Huang, T., S. Poddar, C. Aguilar, A. Sharma, E. Smaglik, S. Kothuri, and P. Koonce, Building Intelligence in Automated Traffic Signal Performance Measures with Advanced Data Analytics. *Transportation Research Record*, Vol. 0, No. 0, 2018, p. 0361198118791380.