

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

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1 INTRODUCTION

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

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

18 This report present a novel framework that combines processing of high resolution con-
19 troller log data and machine learning techniques to produce the following outcomes:

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

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

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

1 The rest of the report is organized as follows. We first describe the pre-processing steps that
2 are performed to convert raw controller logs to MOEs. Next, we introduce a Intersection Ranking
3 and Categorization scheme. The third section of the report covers clustering methods to highlight
4 spatio-temporal patterns in the behavior of intersections. In the fourth section, we describe a model
5 to automatically detect significant changes in intersection behavior. The last two sections of the
6 report detail our Visualization framework, and summarize our contributions. We also discuss how
7 our techniques can be used in tandem with existing UDOT ATSPM systems .
8

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

11 RELATED WORK

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

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

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

41 PRE-PROCESSING

42 This section describes the MOEs and corresponding processing requirements.

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

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

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

22 The output of the data aggregation step is a vector with 24×60 entries representing the
 23 behavior of a particular phase over the entire day. Each element in a vector is a binary digit
 24 indicating the reported split failures. We then use a simple sliding window algorithm to deal with
 25 the problem of the outlier events. Our approach takes the vector, v size of the window, w and a
 26 threshold parameter, t as the inputs and produces a smoothing vector, o as output. For example if v
 27 is 11111000010, w is 6 and t is 5, the output that we obtain after smoothing would be 11111000000.
 28 This technique can (optionally) smoothen minor variations in data.

29 RANKING AND CATEGORIZATION

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

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

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

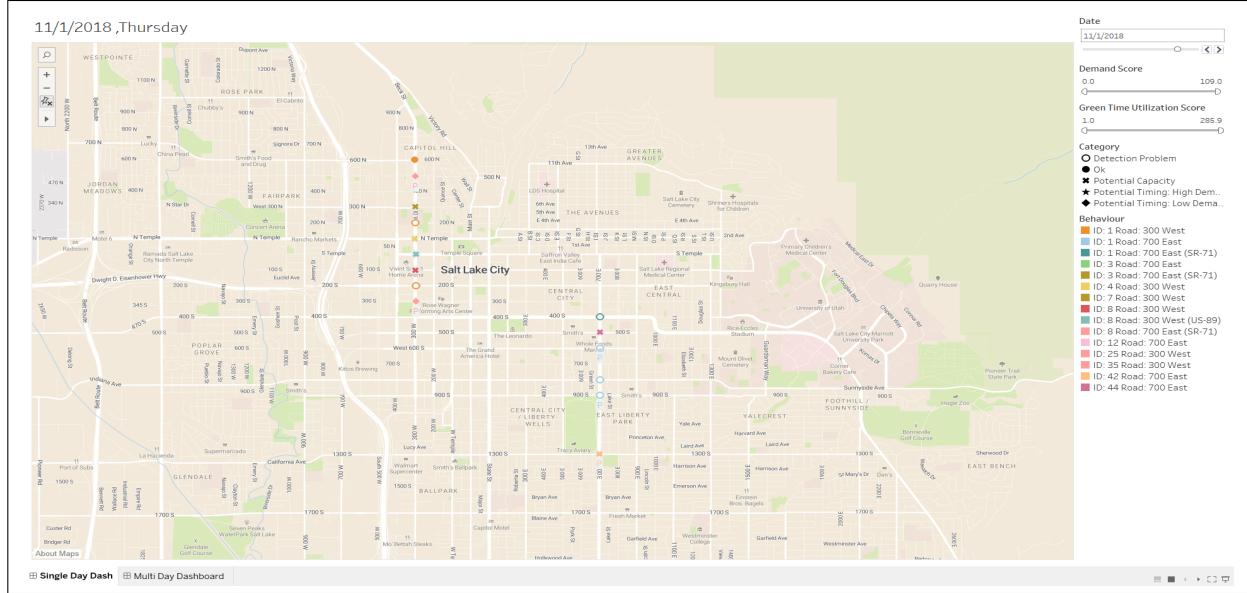


FIGURE 1 Dashboard showing the categorization & ranking results for a single day.

- 1 configure the sliders to categorize the signals based on the two MOEs, we described above.
- 2 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 (Figure4).
- 3 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.

10 CLUSTERING

11 Clustering or behavioral grouping is the next step in the data analysis pipeline. It can be used to 12 compare group of collocated intersections with similar behavior over multiple days. After obtaining 13 the processed vectors of length 1440 as described in the previous section, we aggregate the 14 split failure vectors to an hourly resolution and hence obtain a vector which represents the fraction 15 of minutes in a hour for which the split status was reported (this is represented as F).

16 We concatenate the vectors for phase 2 & 6 and get one vector per intersection. We can 17 then use custom distance measures to quantify the similarity between these vectors. The pairwise 18 similarity between two intersections is computed by the difference between the corresponding 19 vectors. We use 1-norm of the difference vector for distance computations. A vector p-norm is 20 defined as:

$$x_p = \left(\sum_i |x_i|^p \right)^{\frac{1}{p}} \quad (1)$$

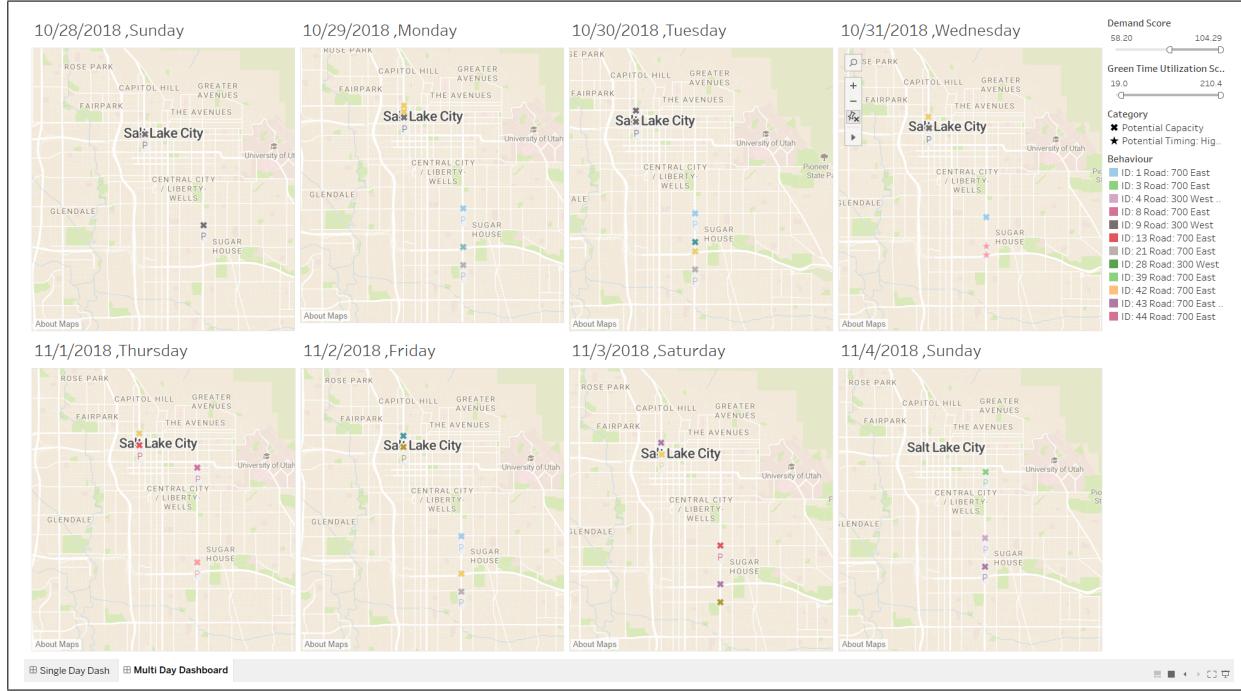


FIGURE 2 Dashboard showing the Ranking results for multiple days. We highlight intersections with demand and high green time utilization (capacity problems). The problems on weekdays are contrasted with those on weekends.

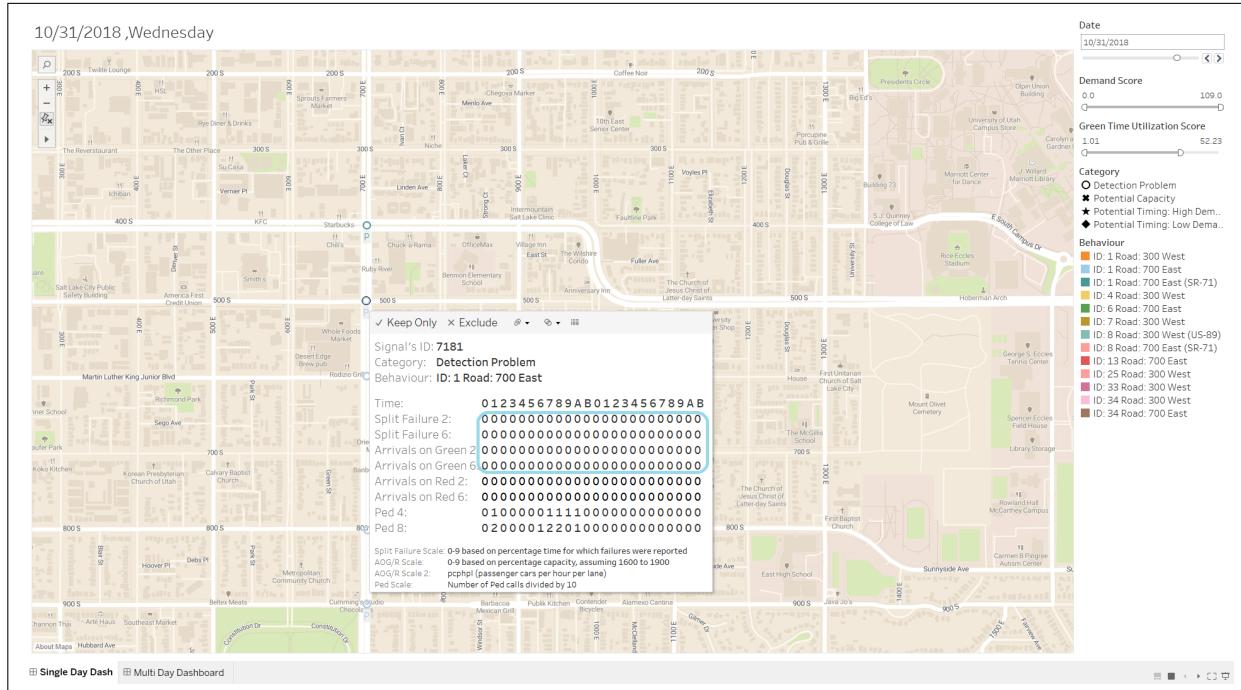


FIGURE 3 We explore the behavior of Intersection ID 7181, which has missing data or a detection problem from January to October 2018. Note that all intersections with missing data or detection problems are assigned to the same cluster or behavioral group.

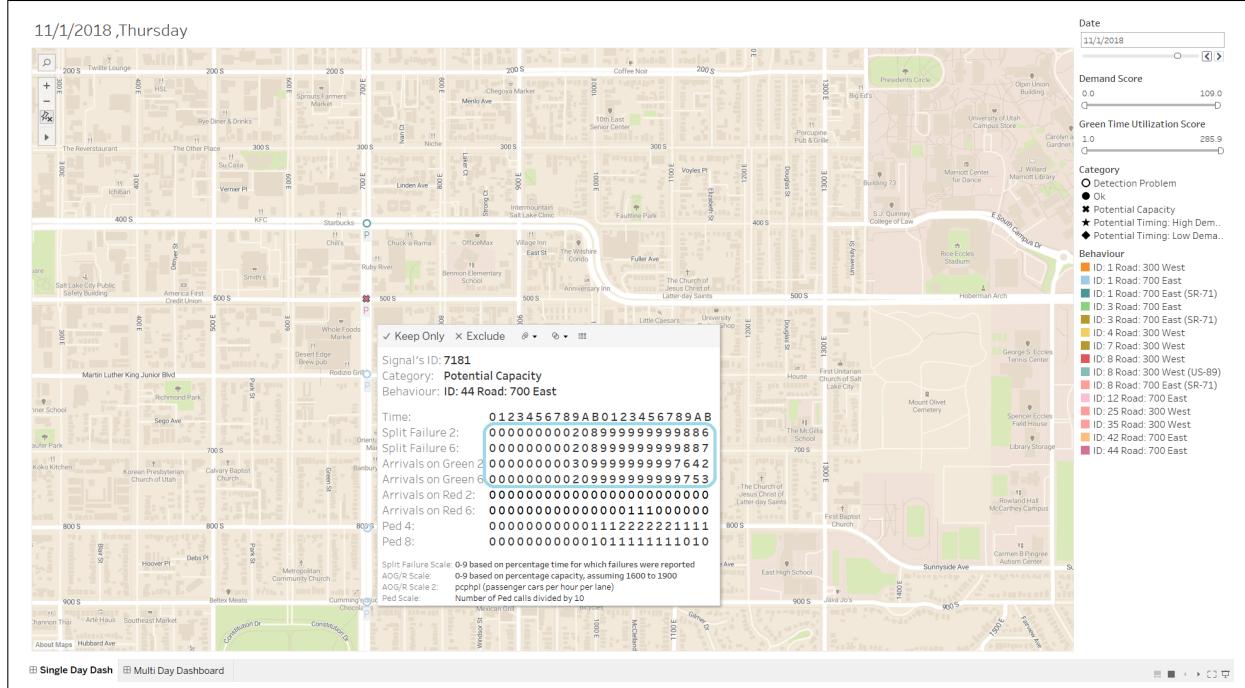


FIGURE 4 Intersection ID 7181, (same as figure 3) with the detection problem fixed on the first day of November. Note both the Cluster ID and the category for the intersection have changed.

and the 1-norm is defined as

$$x_1 = \left(\sum_i |x_i| \right) \quad (2)$$

- 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 technique 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

$$L \equiv D - A \quad (3)$$

- 3 The lowest k eigenvalues of this matrix is used for dimensionality reduction (with k denoting the
4 dimensionality of the nonlinear embedding).

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

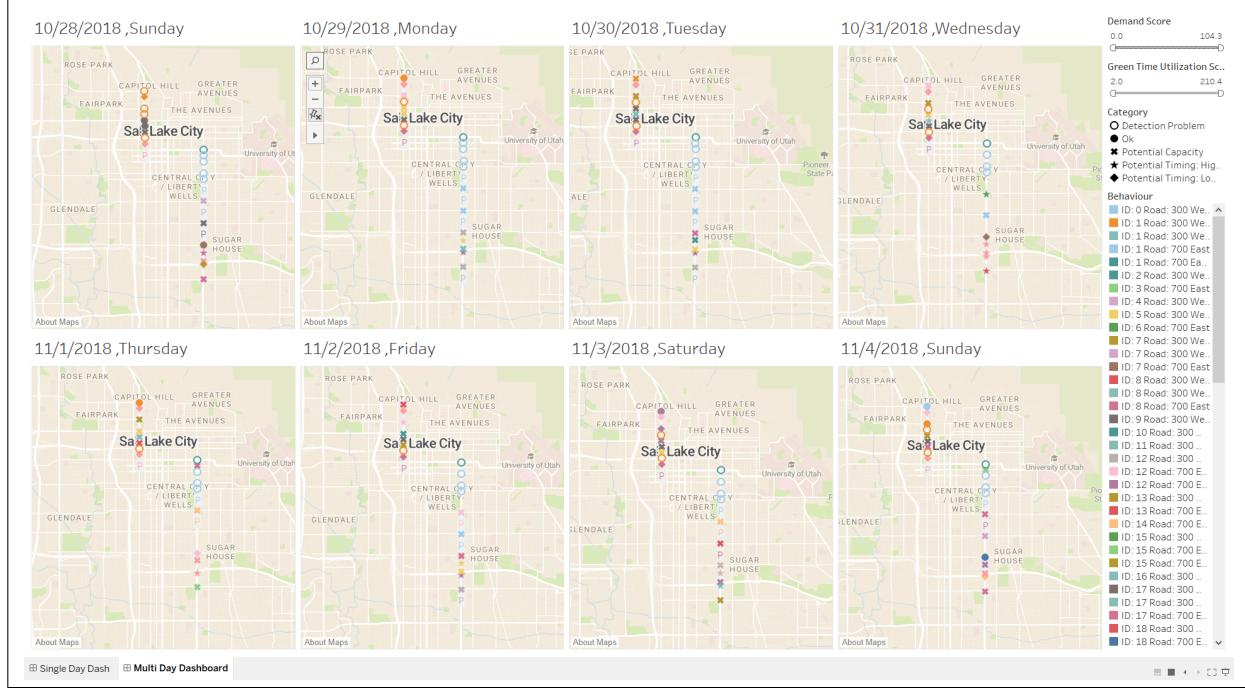


FIGURE 5 Multi-day Tableau dashboard allows for comparison of clustering results across days and highlights temporal patterns in intersection behavior.

1 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 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. Clearly, this is an obvious change to detect.

Next, Figure 7 captures the behavior of intersection ID 7124 for three day period from the 2nd of July to the 4th of July. This change is easily explained as we observe a sudden dip in demand on the 4th of July. Although, this change is expected, our data-driven algorithm has no way of knowing this. Our goal is to detect all significant changes, some of which may be easy to anticipate, others not.

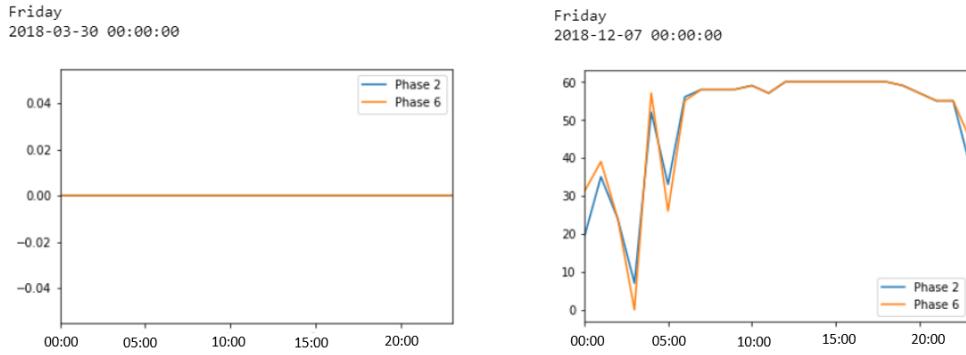


FIGURE 6 A Chart of Split failures for Phase 2 and Phase 6 (intersection ID 7181) showing a significant change between 03/30/2018 and 12/07/2018. This intersection is also highlighted in Figure 3 and Figure 4.

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

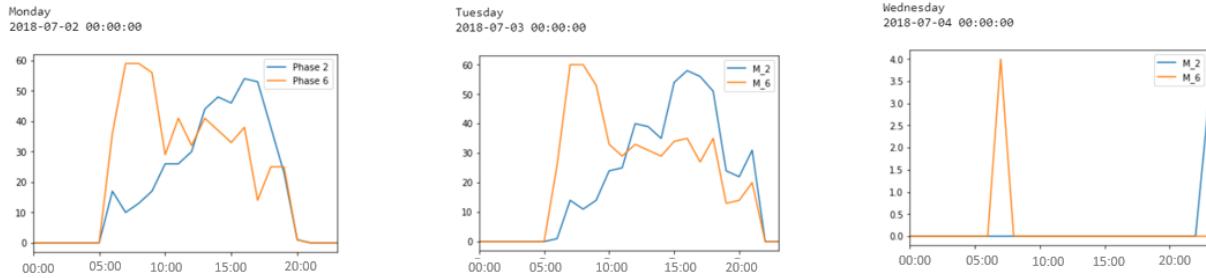


FIGURE 7 Intersection ID 7124 showing an significant deviation from normal behavior on the 4th of July.

3 VISUALIZATION FRAMEWORK

4 Using the techniques described above, we developed a tool leveraging Tableau® to create visu-
5 alizations which can aid traffic engineers. The application makes use of the data visualization
6 capabilities of Tableau and embeds the Tableau Dashboards into a HTML/CSS based web inter-
7 face and a SQL based backed to enable customization of the visuals produced by Tableau. The
8 overall architecture of the application is explained in Figure 9. The application has several screens
9 that cover the description in the previous three sections (e.g. Figures 1 and 5). Table 1 documents
10 the technology stack used for the application.

11 CONCLUSION AND DISCUSSION

12 In this work, we propose a fully data driven approach to process high resolution controller logs
13 data and build a decision support system for the traffic engineers. We demonstrated this approach
14 using split failures and AoG/R ratios as MOEs' to rank and categorize intersections according to
15 their performance. This can be used to quickly identify the most problematic intersection in the
16 region. Next, we used clustering techniques to group together signals exhibiting similar behav-

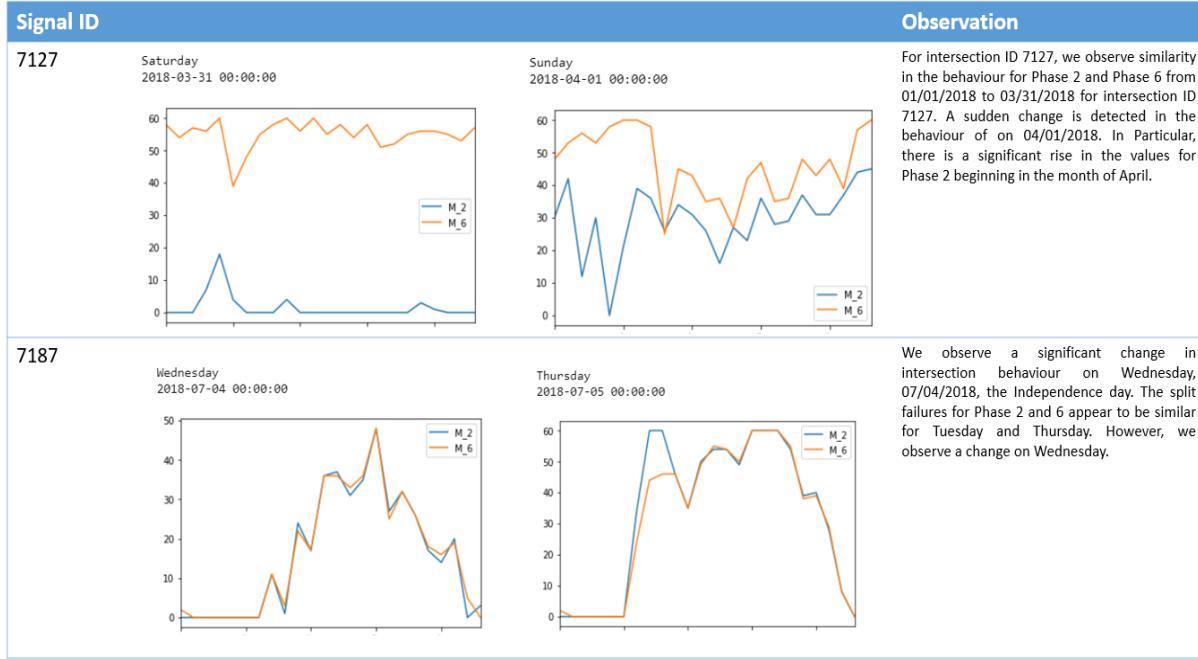


FIGURE 8 Other intersections that were discovered to be showing a significant deviation from their normal behavior.

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

1 ior. Using this approach, we highlight spatial and temporal patterns in intersection behavior and
 2 also detected intersections that may either have broken detectors or missing data. Thus, we au-
 3 tomatically highlight intersections that may need attention in terms re-timing or fixing of broken
 4 detectors. Next, we propose a change detection model to detect statistically signification changes
 5 at each intersection and highlight some of results.

6 We also developed a visualization framework to inform traffic engineers and traffic man-
 7 agers and about the current performance of the signalized intersection in a region. The results can
 8 be used to easily identify problematic signalized intersections in a proactive manner. Once the
 9 problematic intersections are known, the UDOT ATSMP system can be invoked from within our
 10 dashboard (Figure 10) to drill down and analyze the intersections. Hence, our techniques and the
 11 existing ATSPM systems are complementary.

12 This work tries to addresses one of the key challenges of this competition (also faced by
 13 most traffic engineers today). *"To make matters worse, these signals are still predominantly being*

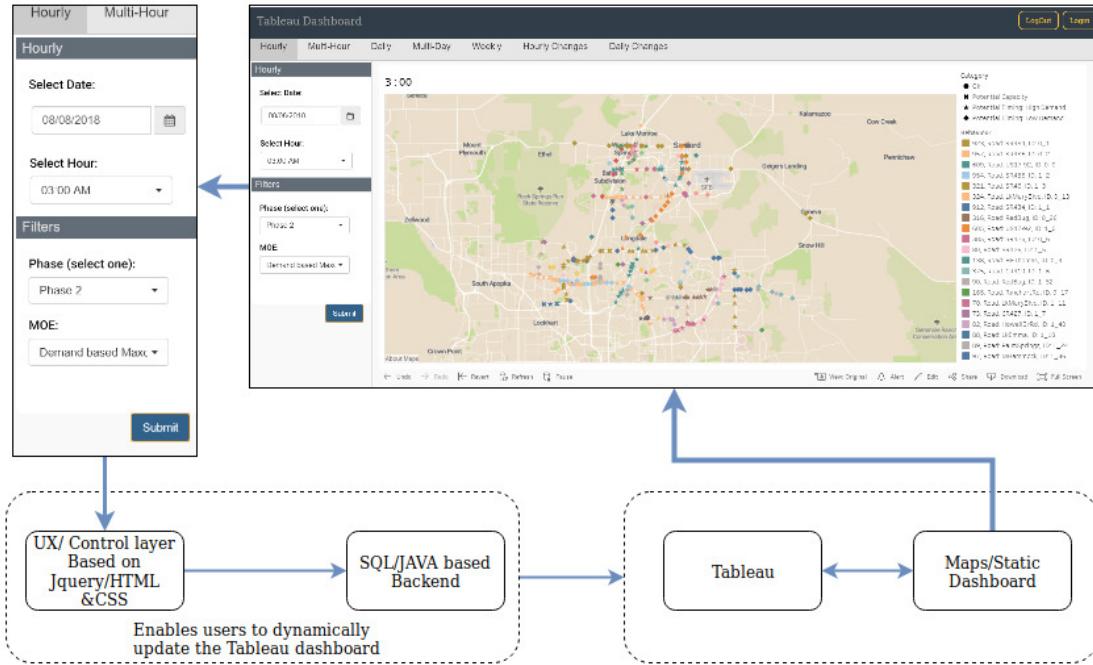


FIGURE 9 The overall framework for visualizations. This architecture enables us to leverage Tableau to build dashboards which can be updated via user queries.

1 managed on basis of citizen complaints".

2 The goal of our solution is to increase the efficiency of traffic engineers by highlighting
3 areas or regions that need their attention and also enable them to be more proactive.

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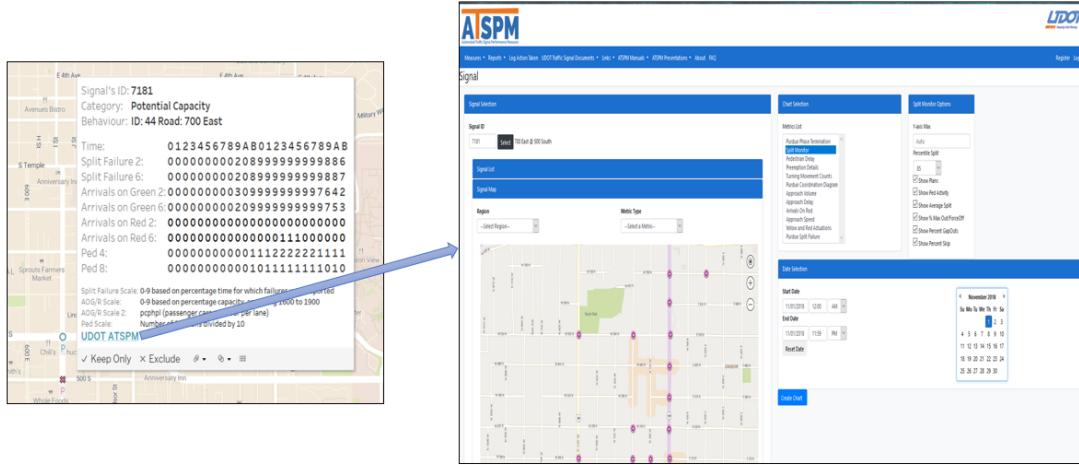


FIGURE 10 An example of possible integration between our systems and the UDOT ATSPM.

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