Research Objective

Problem Statement:

Current traffic management relies on expected recurring congestion.

Rare disruptions (e.g., accidents) are challenging to detect and handle.

Goal of Research:

Develop baseline models for expected traffic conditions.

Identify deviations from baseline (non-recurrent events) using machine learning.

Improve incident detection and traffic management.

Literature Review

Traditional Incident Detection:

Focus on freeways and uninterrupted traffic.

Methods: California algorithm, McMaster algorithm, flow-occupancy diagrams.

Limitations:

Few methods work effectively on arterial roadways.

Existing methods struggle with real-world applications (e.g., holidays, events).

Emerging Approaches:

Machine Learning gaining traction for traffic analysis (e.g., SVM, Neural Networks).

List of Reference

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Research Methodology

Data Collection:

High-resolution data from Automated Traffic Signal Performance Measures (ATSPM).

Data acquisition every 5 minutes.

Model Development:

Focus on location-specific traffic trend models using machine learning.

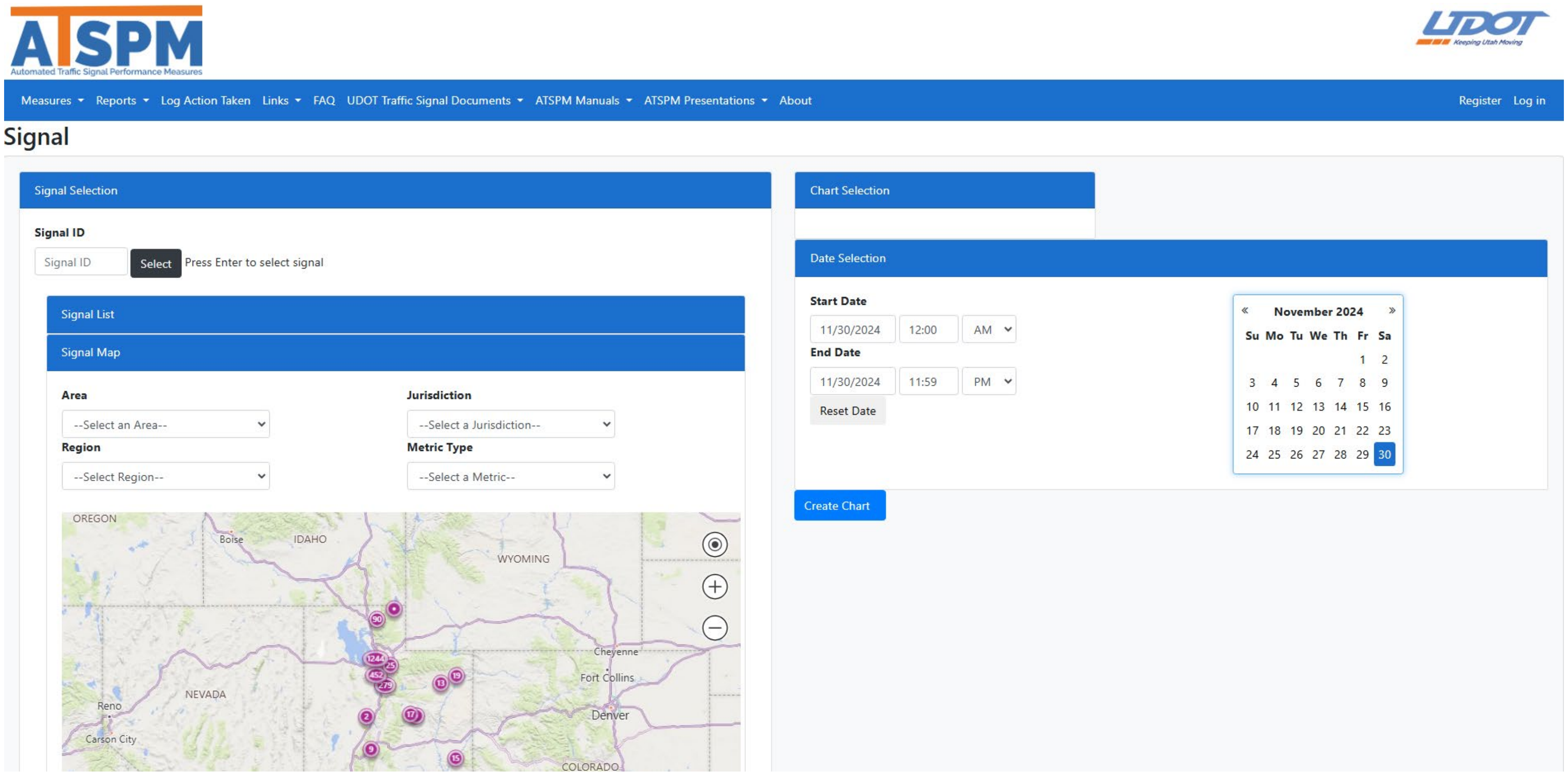
Test and implement algorithms for identifying non-recurrent events (disruptions).

Machine Learning:

Exploration of neural networks, reinforcement learning, and time-series trend models.

ATSPM

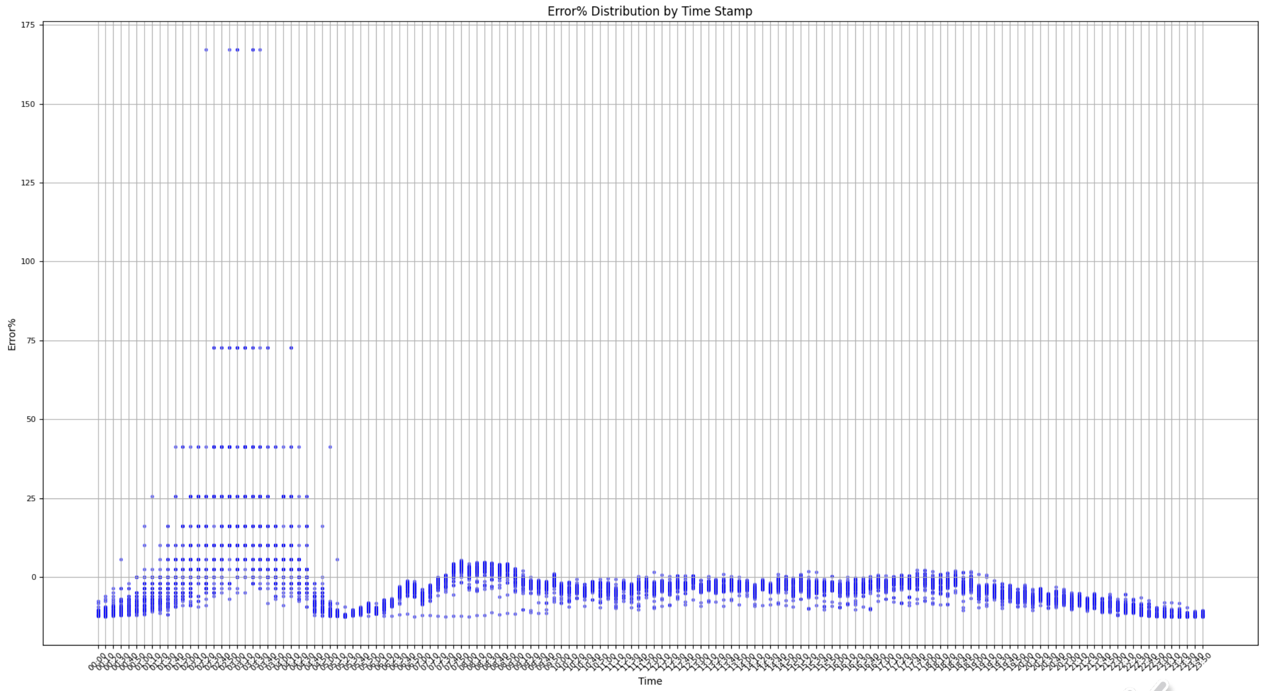
Automated Traffic Signal Performance Measures



Data Collection and Error Distribution

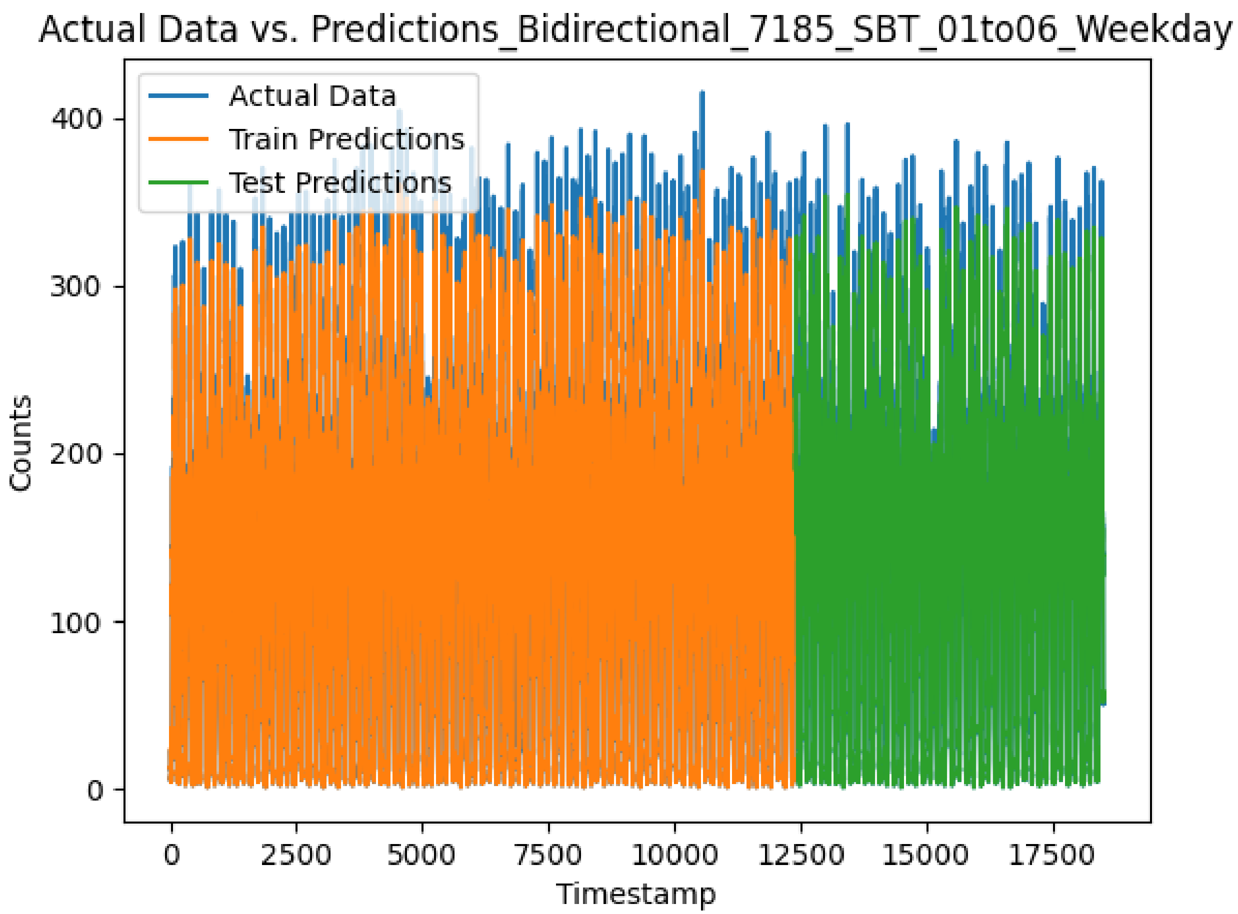
Signal Id	Timestam	Event Cod	Event Parameter
7181	00:00.0	49	3
7181	00:00.0	49	7
7181	00:00.0	316	74
7181	00:00.0	318	28
7181	00:00.0	320	0
7181	00:00.1	82	4
7181	00:00.1	174	0
7181	00:00.3	81	4
7181	00:00.7	82	4
7181	00:00.8	81	4
7181	00:00.9	82	4
7181	00:01.1	81	4
7181	00:01.2	81	3
7181	00:01.2	82	4
7181	00:01.3	44	6
7181	00:01.3	81	4
7181	00:01.3	82	3
7181	00:01.4	43	6
7181	00:02.4	82	33
7181	00:03.5	82	4
7181	00:03.7	81	4
7181	00:03.7	82	37
7181	00:03.7	82	42
7181	00:03.9	81	37
7181	00:03.9	81	42
7181	00:04.2	81	33
7181	00:04.7	82	4
7181	00:04.8	81	4
7181	00:05.5	82	35
7181	00:05.9	81	3
7181	00:06.1	82	4
7181	00:06.1	82	34
7181	00:06.3	81	4
7181	00:06.5	82	47

X_Values	Probability_Density
-12.4223	0.246833
-12.3743	0.257801
-12.3264	0.26867
-12.2784	0.279386
-12.2305	0.289895
-12.1826	0.300143
-12.1346	0.310076
-12.0867	0.319638
-12.0387	0.328776
-11.9908	0.337437
-11.9429	0.345571
-11.8949	0.353129
-11.847	0.360065
-11.799	0.366335
-11.7511	0.371902
-11.7032	0.376729
-11.6552	0.380786
-11.6073	0.384048
-11.5593	0.386491
-11.5114	0.388102
-11.4635	0.388869
-11.4155	0.388788
-11.3676	0.387858
-11.3196	0.386086
-11.2717	0.383483
-11.2238	0.380067
-11.1758	0.37586
-11.1279	0.370888
-11.0799	0.365183
-11.032	0.358781
-10.9841	0.351723
-10.9361	0.344051
-10.8882	0.335812
-10.8402	0.327055

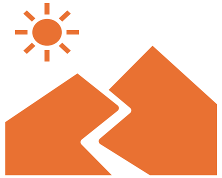


Actual Data vs Predictions

Timestamp	Actual	Train Pred	Test Prediction
1/3/2022 0:00	24		
1/3/2022 0:10	11	26.7034	
1/3/2022 0:20	20	11.39639	
1/3/2022 0:30	12	22.03851	
1/3/2022 0:40	14	12.58897	
1/3/2022 0:50	14	14.96647	
1/3/2022 1:00	13	14.96647	
1/3/2022 1:10	10	13.77899	
1/3/2022 1:20	13	10.20127	
1/3/2022 1:30	18	13.77899	
1/3/2022 1:40	11	19.69119	
1/3/2022 1:50	6	11.39639	
1/3/2022 2:00	5	5.395084	
1/3/2022 2:10	12	4.187083	
1/3/2022 2:20	6	12.58897	
1/3/2022 2:30	9	5.395084	
1/3/2022 2:40	1	9.003585	
1/3/2022 2:50	8	-0.67094	
1/3/2022 3:00	7	7.80333	
1/3/2022 3:10	4	6.6005	
1/3/2022 3:20	5	2.976476	
1/3/2022 3:30	5	4.187083	
1/3/2022 3:40	10	4.187083	
1/3/2022 3:50	6	10.20127	
1/3/2022 4:00	3	5.395084	
1/3/2022 4:10	4	1.763283	
1/3/2022 4:20	4	2.976476	
1/3/2022 4:30	7	2.976476	
1/3/2022 4:40	12	6.6005	
1/3/2022 4:50	19	12.58897	
1/3/2022 5:00	18	20.86609	
1/3/2022 5:10	21	19.69119	
1/3/2022 5:20	26	23.20844	
1/3/2022 5:30	51	29.02112	



Future Research Directions and Variables to Explore



Next Steps in Research:

Adjusting Variables: Modify variables to better capture the influence of accidents on traffic flow, such as:

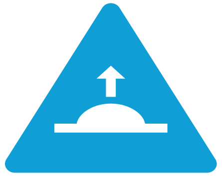
- Road Type (e.g., urban vs freeway): Accidents might affect traffic more significantly on certain types of roads.
- Time of Day: Accidents during peak traffic hours could have a stronger impact on traffic.
- Weather Conditions: Incorporate weather data to understand its role in both accident occurrence and traffic volume changes.

Additional Methods to Explore:

Machine Learning Models: Use more complex models (e.g., Random Forests, XGBoost) to capture non-linear relationships and interactions between multiple variables.

Spatio-Temporal Analysis: Investigate accident impact using spatial and temporal data analysis to see if accidents in specific locations or times create more significant traffic disruptions.

Event-based Clustering: Group accidents and traffic data by types of incidents (e.g., collisions, road closures, weather-related incidents) to understand how different event types affect traffic.



Objective:

To identify clearer patterns and build predictive models that help authorities respond faster to accidents based on anticipated traffic changes.

Thank You

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