I-Street: Data Analytics

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Research Supported by FDOT and NSF

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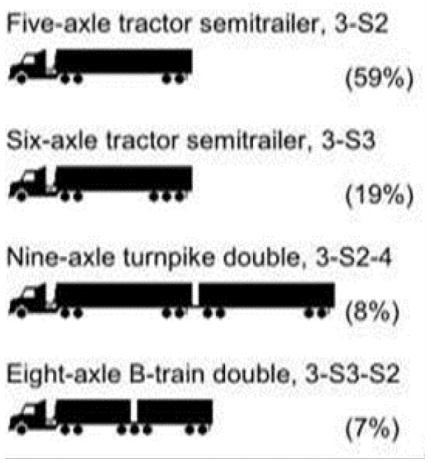
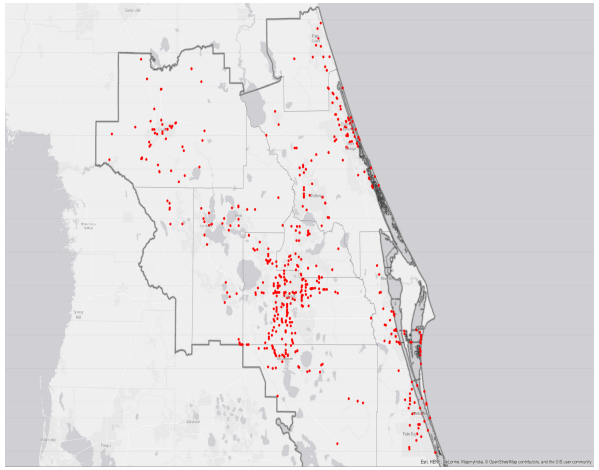
I-Street: UF Smart Campus

Focus on
Communication (DSRC)
Intelligent Data Analytics
Intelligent Signal Control
Security and Privacy
Mixed Mode Traffic

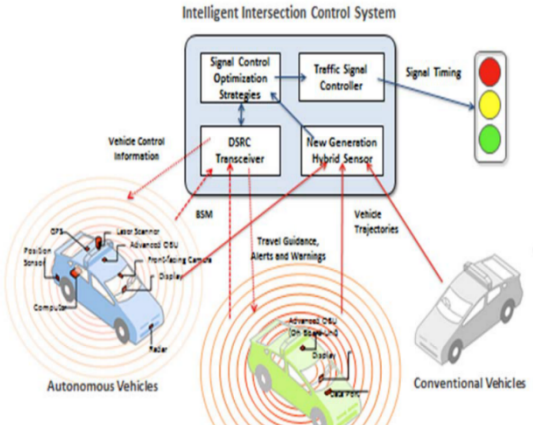
Data Analytics for Transportation Applications



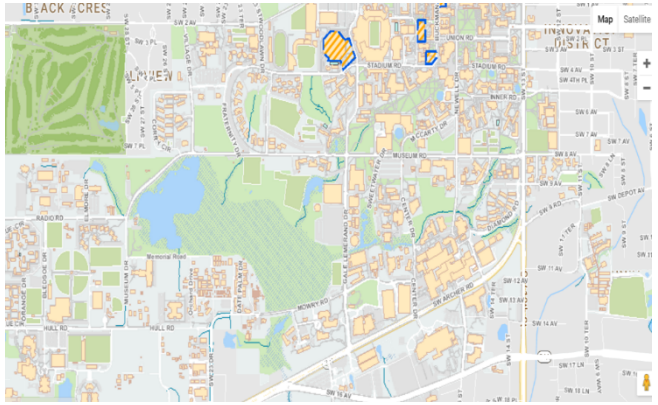
Truck Classification



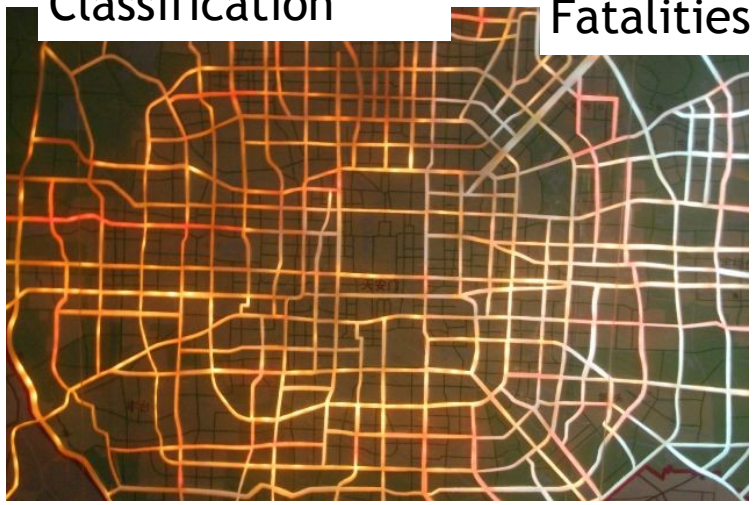
Mining Pedestrian Fatalities



Optimizing for a Single Intersection

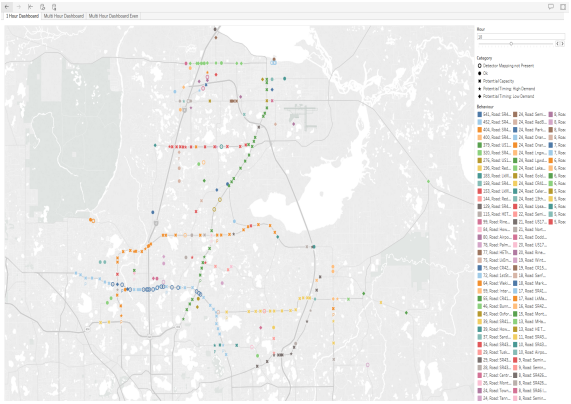


Instrumenting I-Street Testbed



Incident Detection and Optimizing for a Transportation Grid

Multidisciplinary Collaborations between Computer Science and Transportation Engineers



Classifying and Clustering Signals

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ATSPM Data

- High resolution (Deci-second) data for 329 Signalized Intersections from Seminole County, D5, Florida
- 3 key sets of files:
  - Raw Data Files
  - Data Logging Requirements File
  - ATSPM Additional Tables

	A	B	C	D
1	SignalID	Timestamp	EventCode	EventParam
2	1085	2017-01-05 00:00:00	136	0
3	1085	2017-01-05 00:00:00	140	0
4	1085	2017-01-05 00:00:00	142	0
5	1085	2017-01-05 00:00:00	143	0
6	1085	2017-01-05 00:00:00	144	0
7	1085	2017-01-05 00:00:00	145	0

- Raw Data Files
  - 22 comma-separated value files, between 10-17 GB each, contains the data recorded at 10 Hz frequency. Each file contains about a week of raw data.
  - Has 4 columns: SignalID, Time of recording, EventCode: What event at the signal was captured & EventParam: What was the value of the event or attribute at that timestamp

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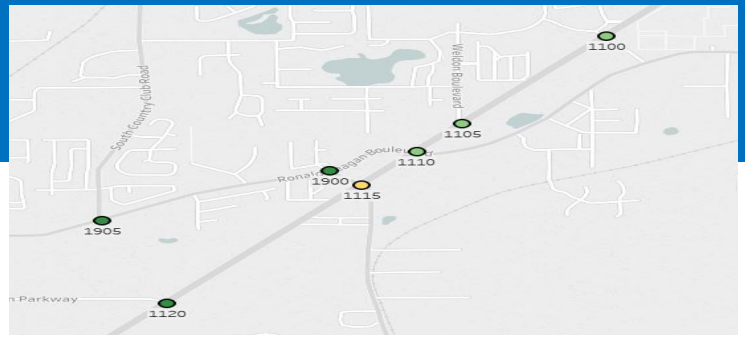
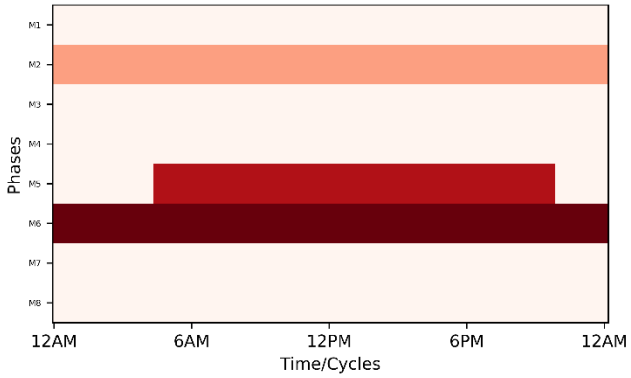
Signal ID 1115
(Potentially Bad Detector, 1/5/16 to 8/5/16)



Sunday



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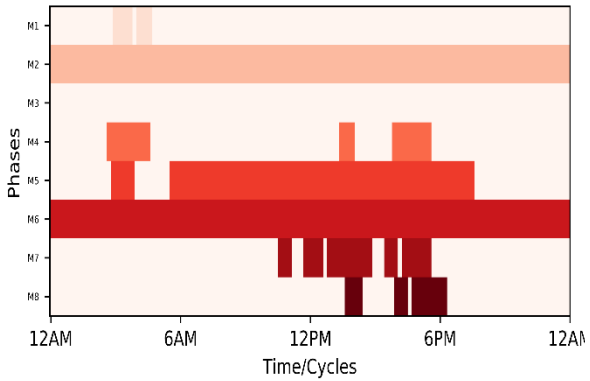
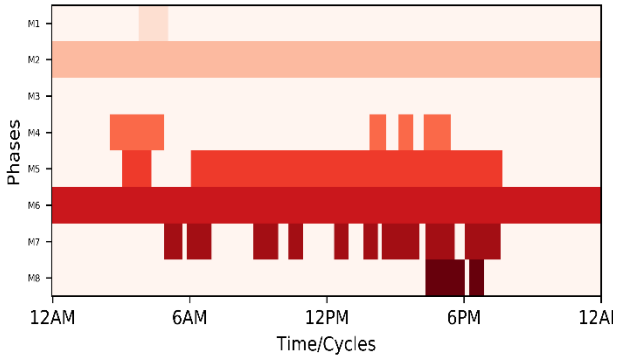


Tuesday



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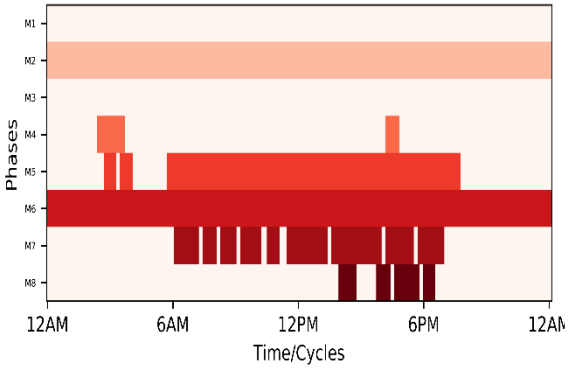

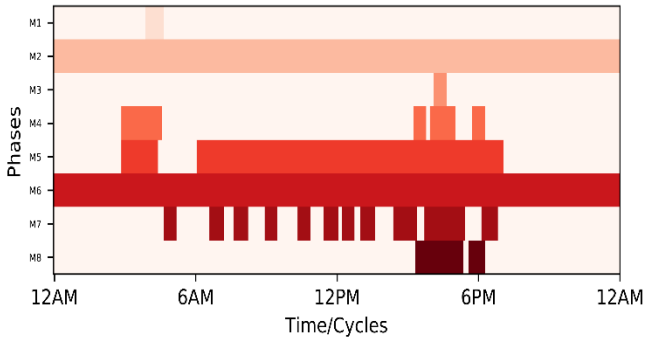

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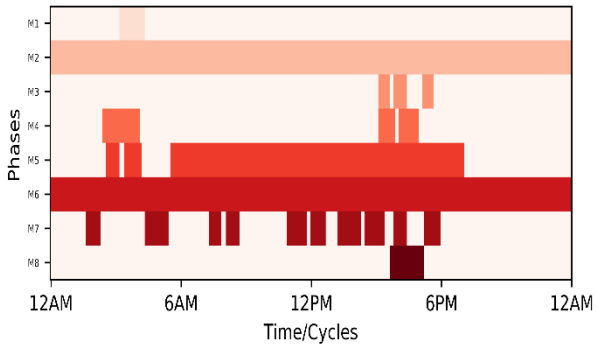

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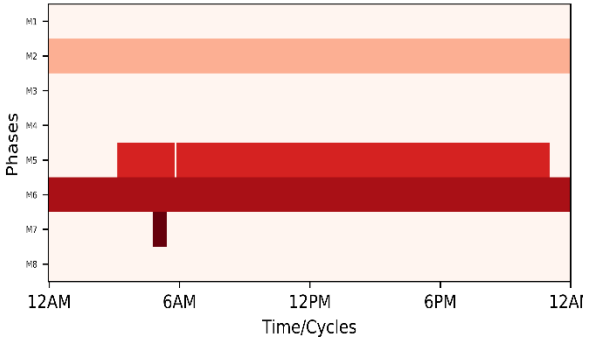

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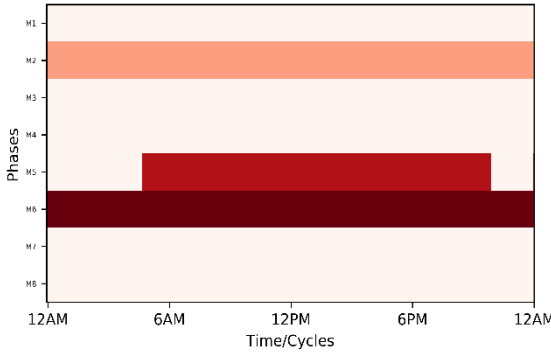

Sunday

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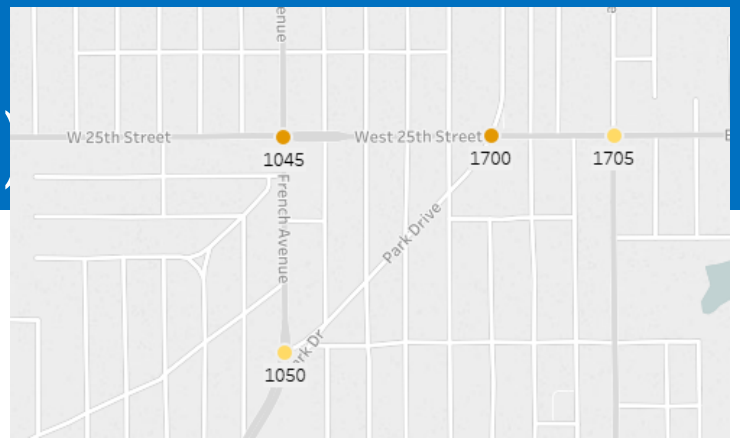
Signal ID 1045
(Potential Overcapacity, 1/5/16 to 8/5/16)



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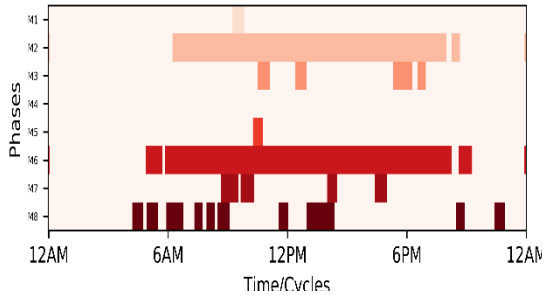

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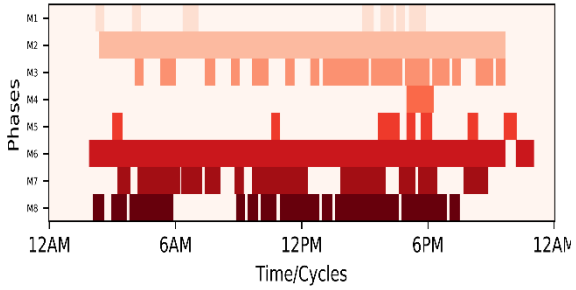

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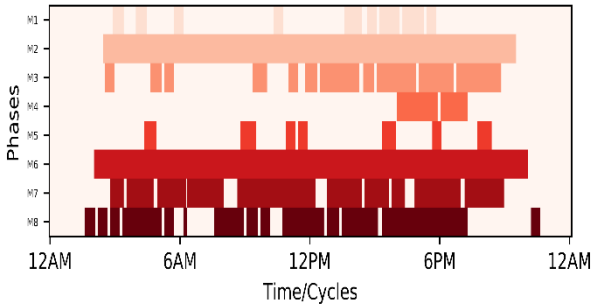

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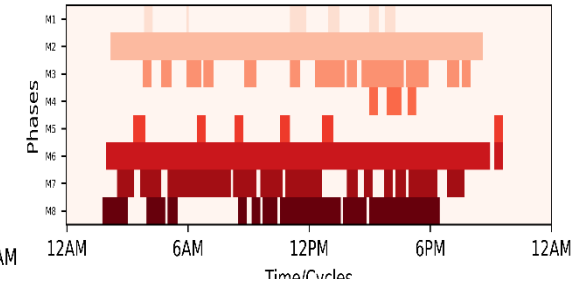

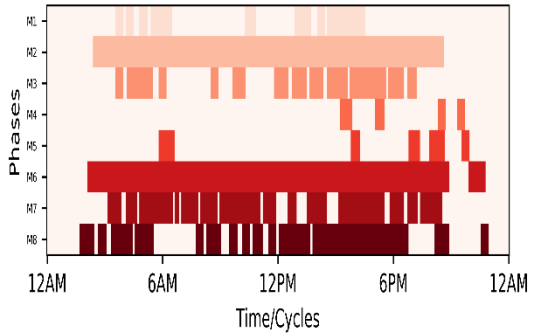

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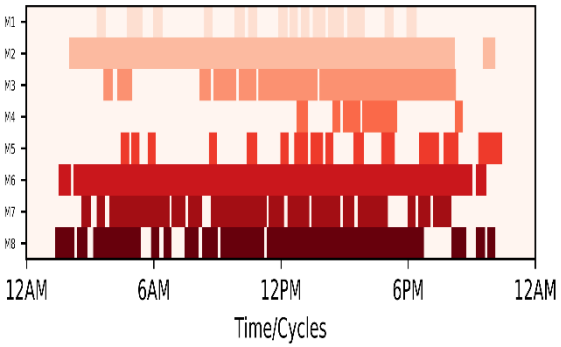

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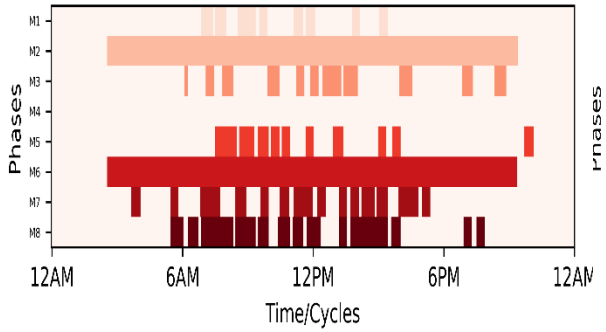

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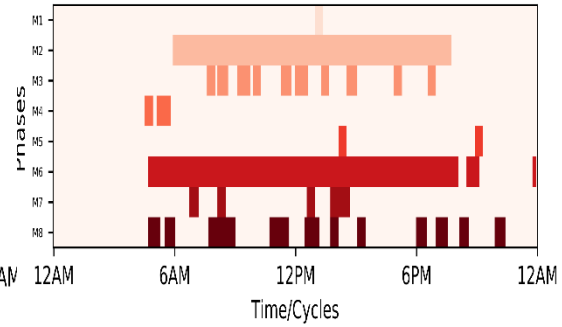

Sunday

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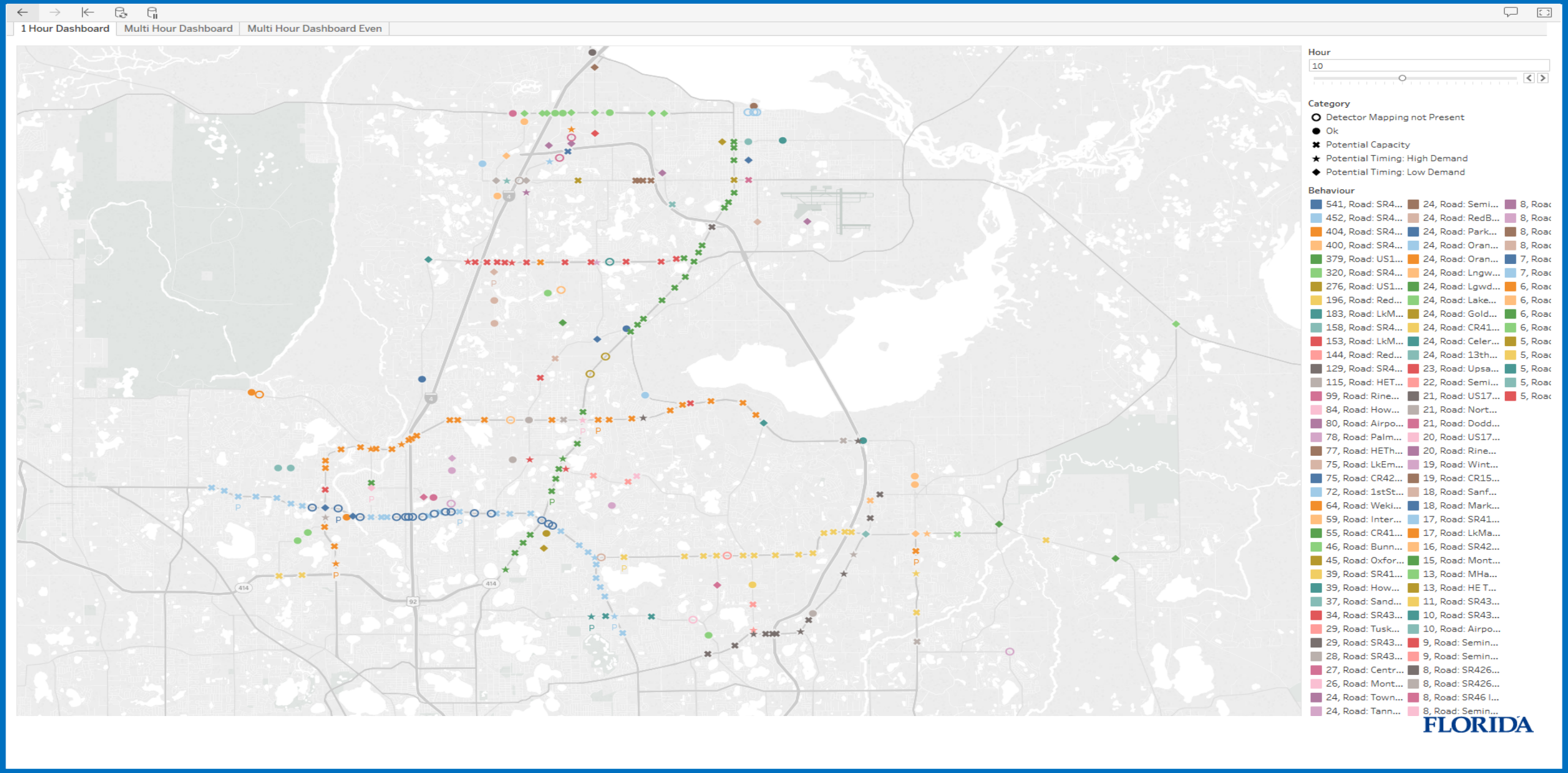
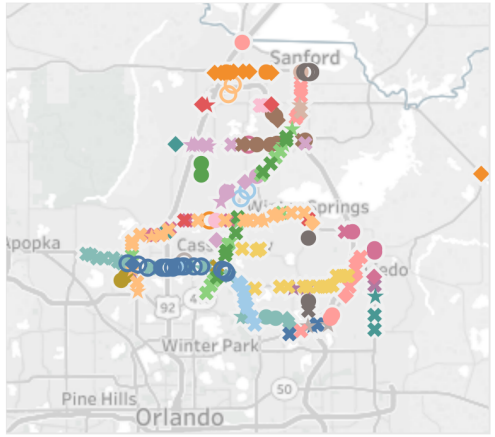
Single Hour Dashboard (Monday - 5/10/16)

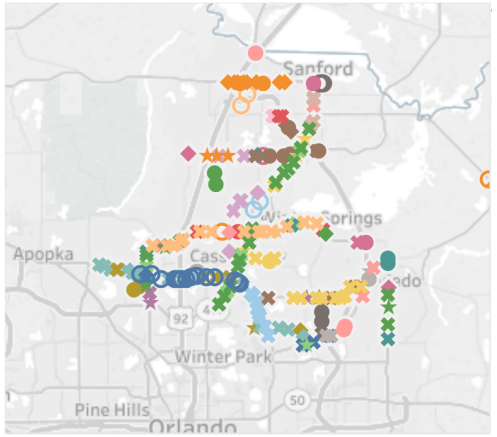


Multi-day Dashboard of Signal Performance

Monday 5/9/16



Tuesday 5/10/16



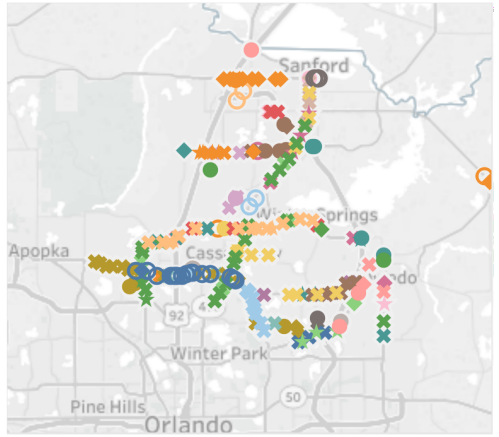
Category

Detector Mappi..
Potential Capac..
Ok
Potential Timin..

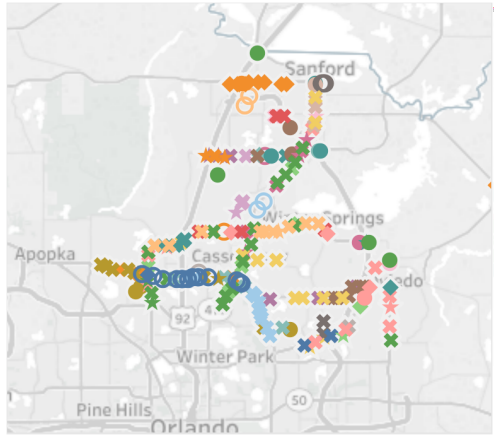
Behaviour

- 136, Road: SR436, Days: MTW, ID: 1_1
- 98, Road: SR436, Days: MTU, ID: 6_2
- 95, Road: SR46, Days: MTW, ID: 1_3
- 71, Road: SR434, Days: MTW, ID: 5_1
- 60, Road: SR434, Days: WFS, ID: 2_1
- 58, Road: US17-92, Days: TWR, ID: 5_0
- 40, Road: US17-92, Days: MFS, ID: 9_0
- 35, Road: US17-92, Days: MSU, ID: 2_0
- 35, Road: SR436, Days: WRF, ID: 9_2
- 35, Road: RedBug, Days: MTW, ID: 5_9
- 34, Road: SR434, Days: WRF, ID: 8_1
- 32, Road: SR434, Days: RFS, ID: 11_1
- 31, Road: SR436, Days: MTR, ID: 5_2
- 28, Road: SR434, Days: MSU, ID: 6_1
- 27, Road: US17-92, Days: WRS, ID: 11..
- 25, Road: SR426, Days: MTR, ID: 12_4
- 24, Road: 1stSt, Days: MTW, ID: 1_27
- 23, Road: SR426, Days: MTS, ID: 8_5
- 23, Road: RedBug, Days: TWR, ID: 9_10
- 21, Road: SR434, Days: MTR, ID: 12_1
- 21, Road: SR434, Days: MRU, ID: 4_1
- 21, Road: RedBug, Days: MFS, ID: 2_17
- 20, Road: SR436, Days: MFS, ID: 2_2
- 20, Road: CR427, Days: MTW, ID: 12_6
- 19, Road: SR436, Days: MSU, ID: 11_2
- 19, Road: LkMaryBlvd, Days: TWF, ID: ..

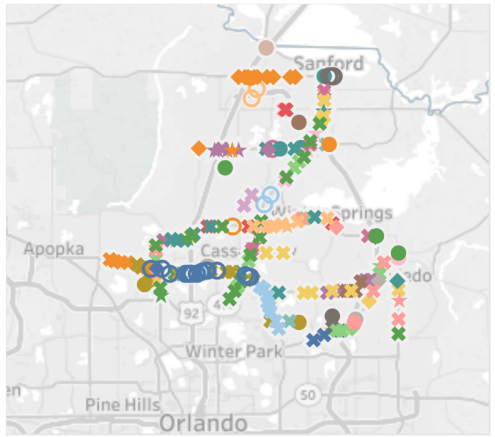
Wednesday 5/11/16



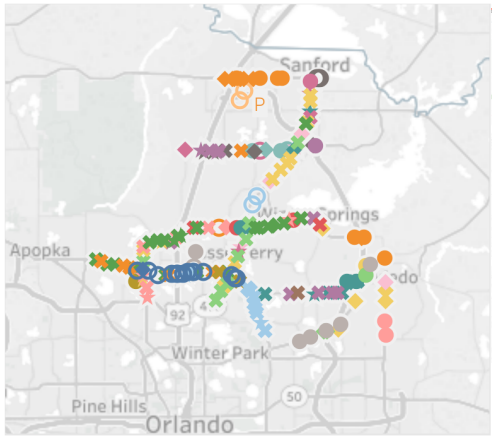
Thursday 5/12/16



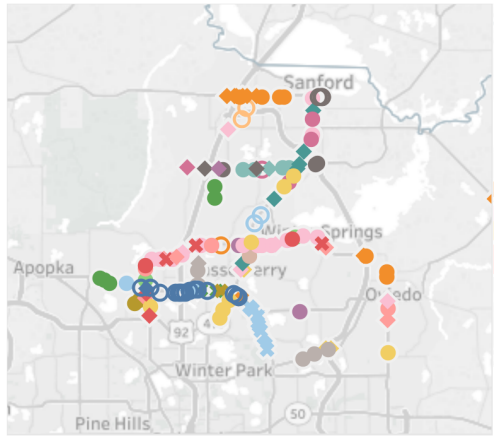
Friday 5/13/16



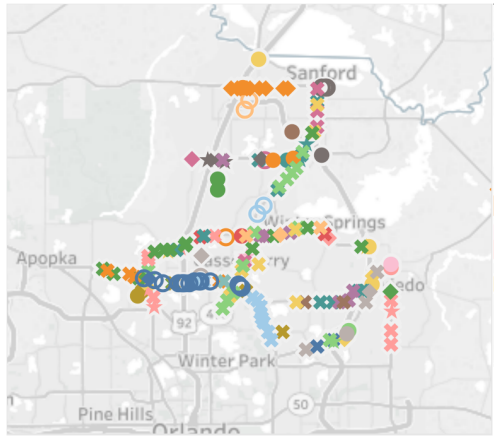
Saturday 5/14/16



Sunday 5/15/16



Monday 5/16/16



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Machine Learning for Detecting Incidents

Machine Learning and Optimization for Signal Control for an entire grid using ATSPM Data, TMC Data, Here.com data

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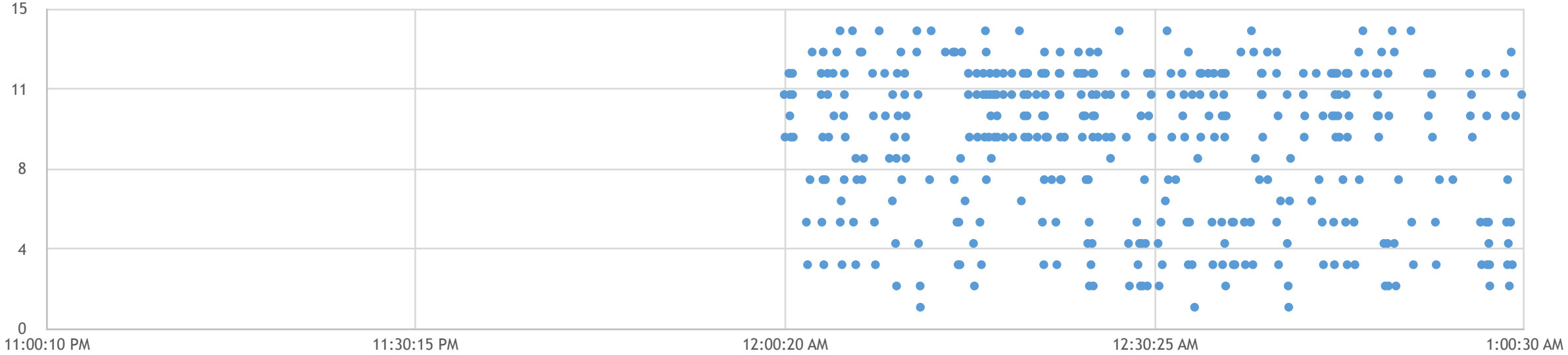
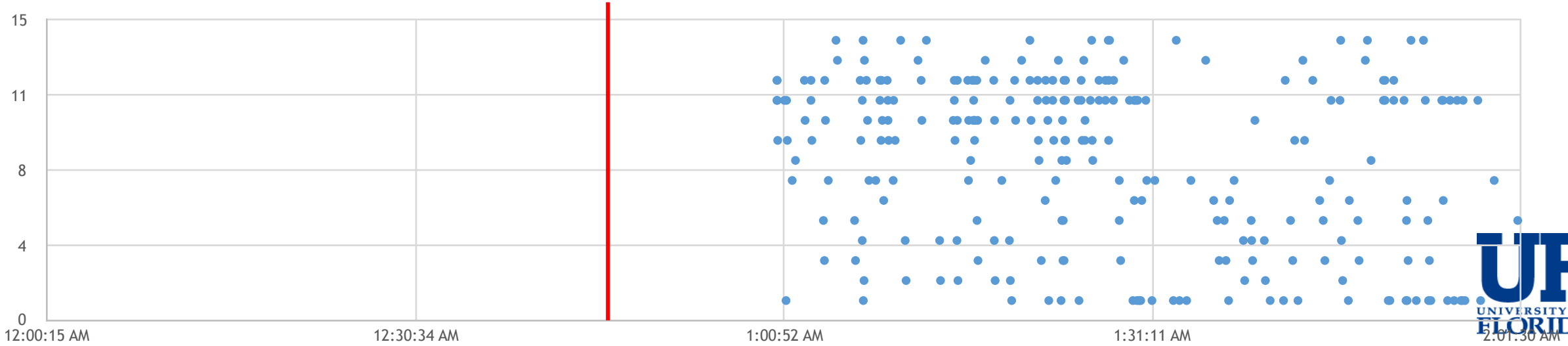
Crash on Seminola Blvd – Signal 1

One Hour Before



Accident at 1:22 AM



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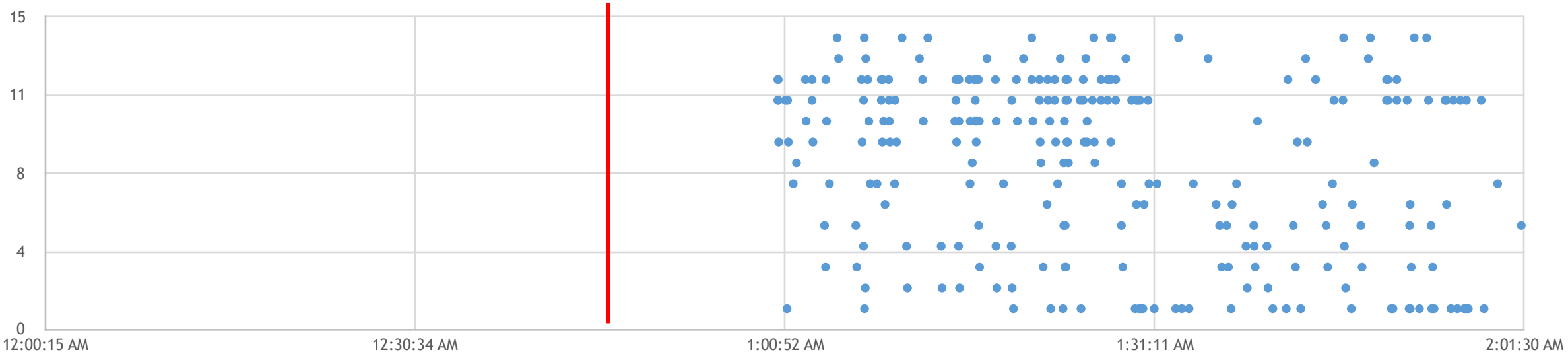
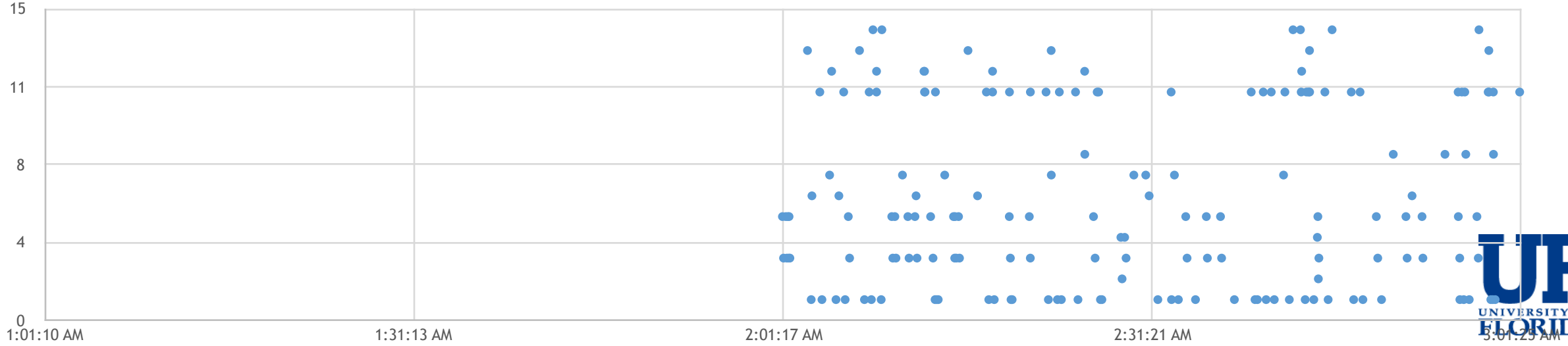
Accident at 1:22 AM



One Hour After



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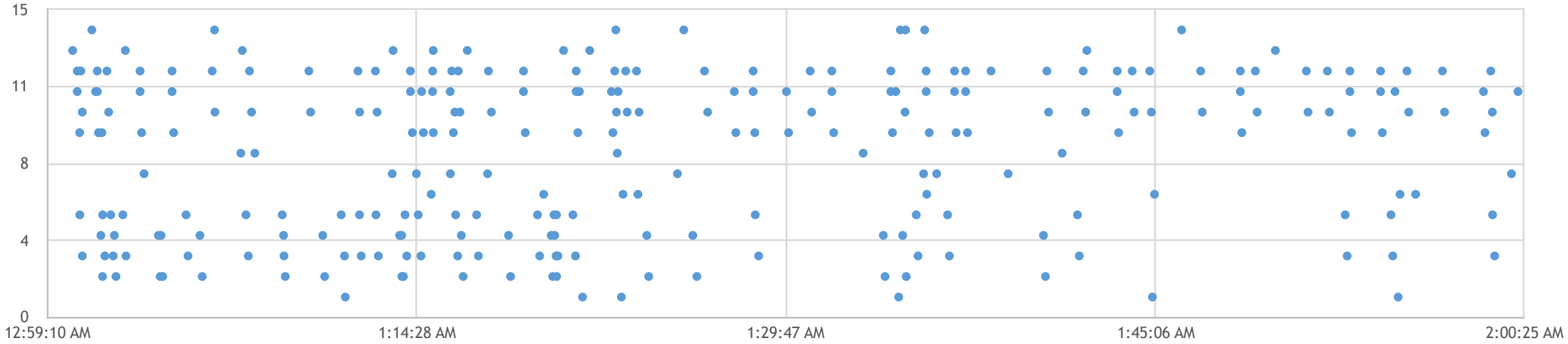
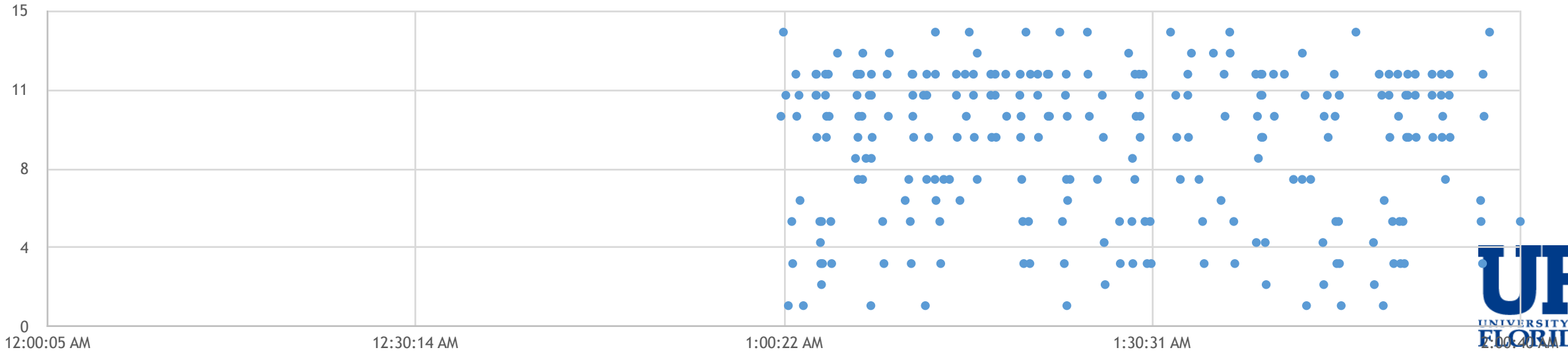
One Day Before



One Day After



Optimizing Traffic for a Grid

Machine Learning and Optimization for Signal Control for an entire grid using ATSPM Data, TMC Data, Here.com data

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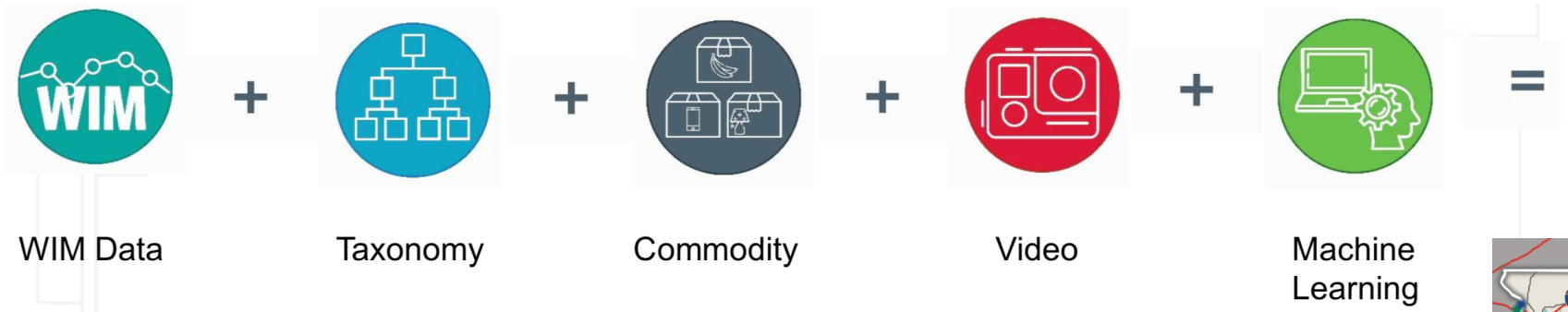
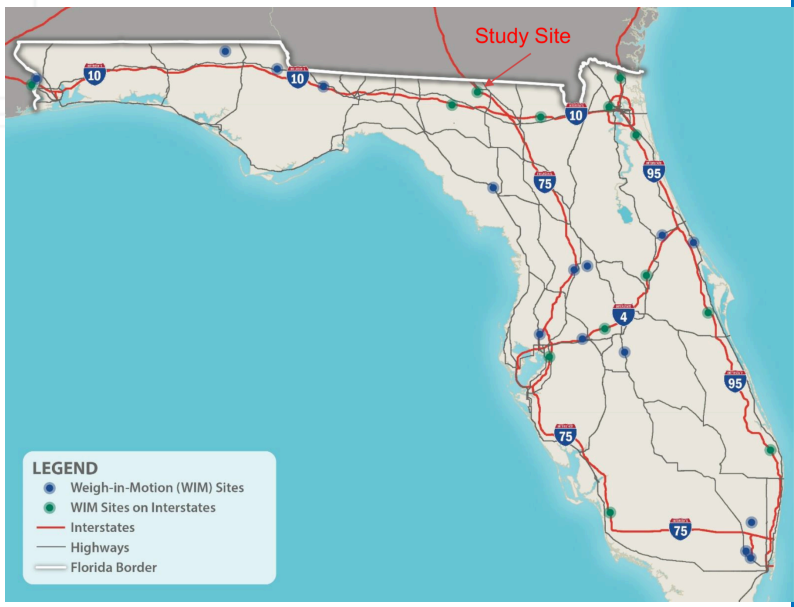
Commodity Movement Using Machine Learning

- Intimate knowledge of WIM data + Roadside cameras
- Advanced knowledge of trucks/trailers + Concept of Truck Taxonomy
- Identify experts of Machine Learning and Application Development



WIM Dataset w/ Truck Attributes & Commodity

project conceptualization, credit to FDOT @ NaTMEC 2018

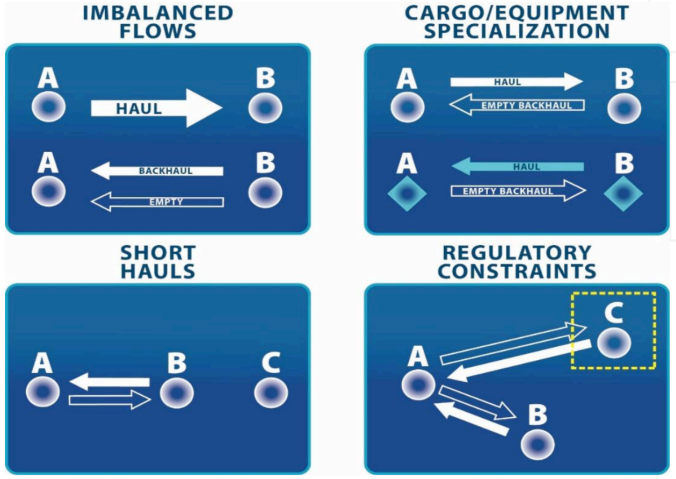


Truck and Commodity Classification Using Machine Learning

Configuration	Body type	Typical commodities	Typical industries
Five-axle tractor semitrailer, 3-S2 (59%)	Vans/reefers (63%)	• Palletized cargo • Refrigerated goods	• Retail • Produce
	Flat decks (16%)	• Equipment • Building supplies	• Construction • Manufacturing
Six-axle tractor semitrailer, 3-S3 (19%)	Hoppers (6%)	• Grain • Granular fertilizer	• Agriculture
Nine-axle turnpike double, 3-S2-4 (8%)	Tankers (4%)	• Petroleum products • Chemicals	• Petroleum • Chemical
	Dumps (6%)	• Aggregate • Grain • Refuse	• Construction • Agriculture
Eight-axle B-train double, 3-S3-S2 (7%)	Containers (2%)	• Palletized cargo • Freight of all kinds	• Retail

Machine Learning on Actuator Sensors and Video Images of Trucks passing on a highway

Text Recognition from Images



VIM sites

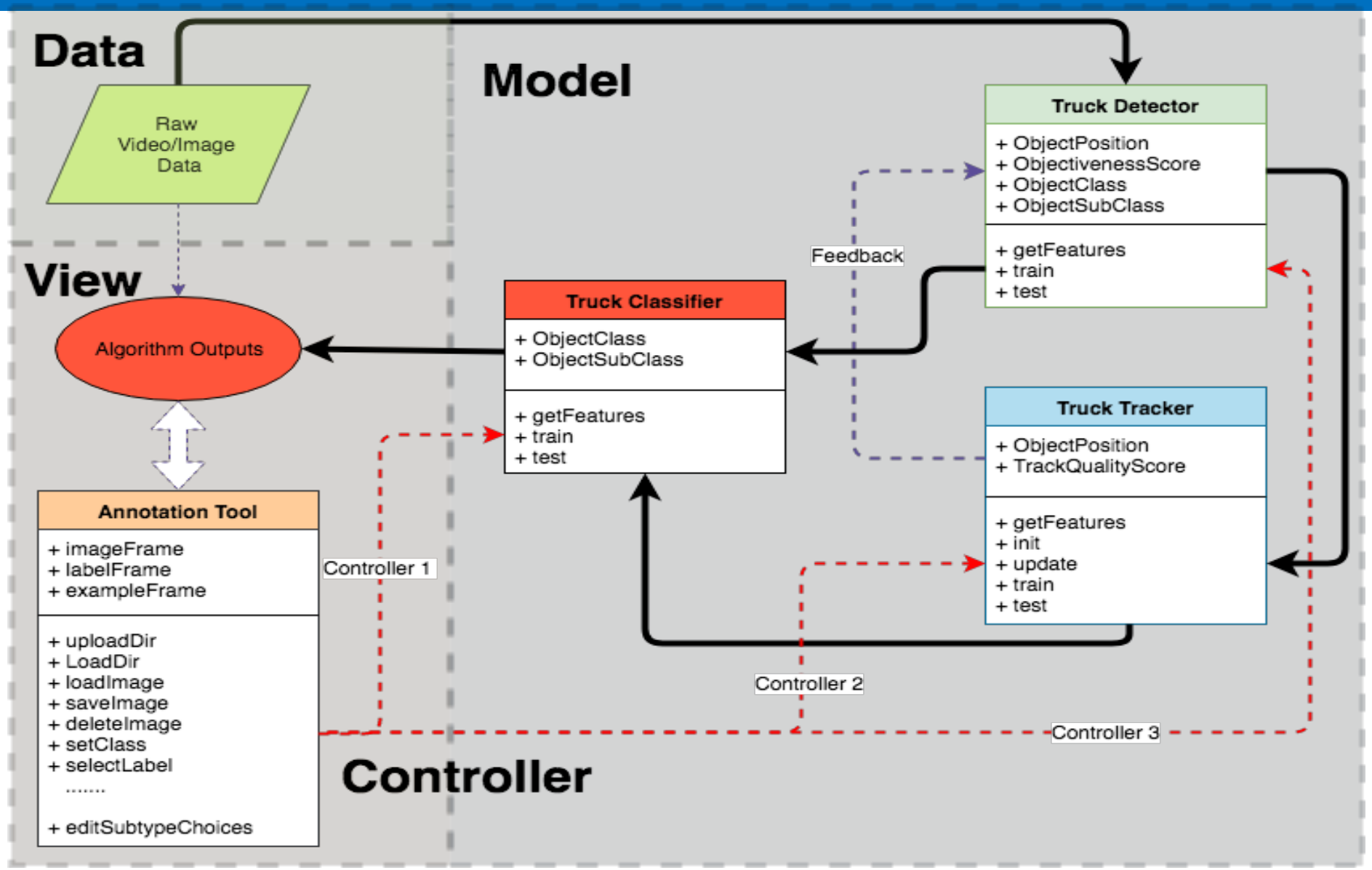
29 Total Statewide

13 on Interstates

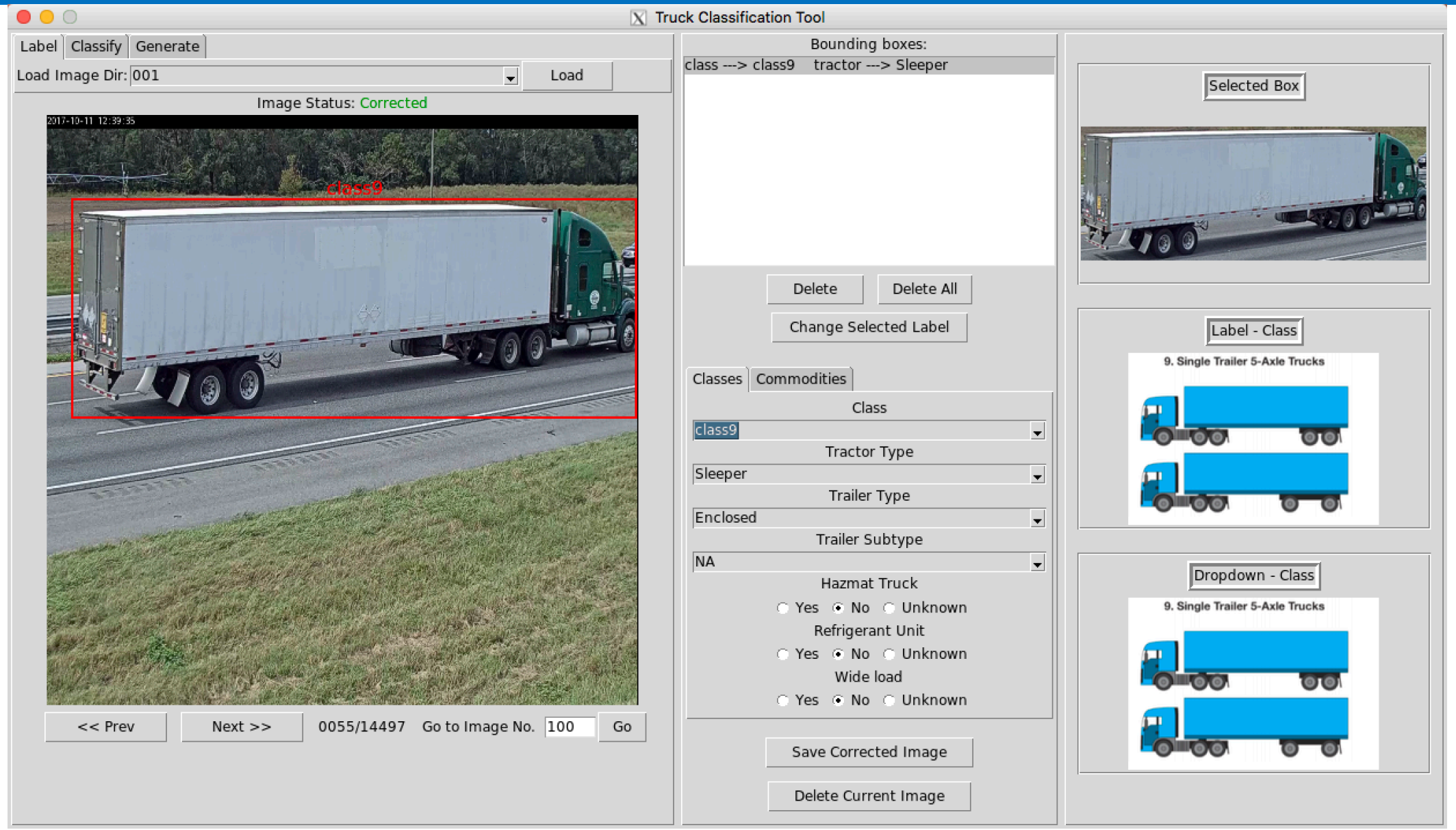
Per Vehicle Records w/ Time Stamp

Study Site – '9956' on I-75 near FL/GA border

Identification using Machine Learning



Annotation Tool



Demo Video

Real-time Multi-Object Tracking and Near Accident Detection for Traffic Video Data

Object Detection

- Leverage deep learning based object detection
- Fine-tune Detection CNNs (YOLO) on Multi-Scale Drone/Satellite Videos/ Images

Object Tracking

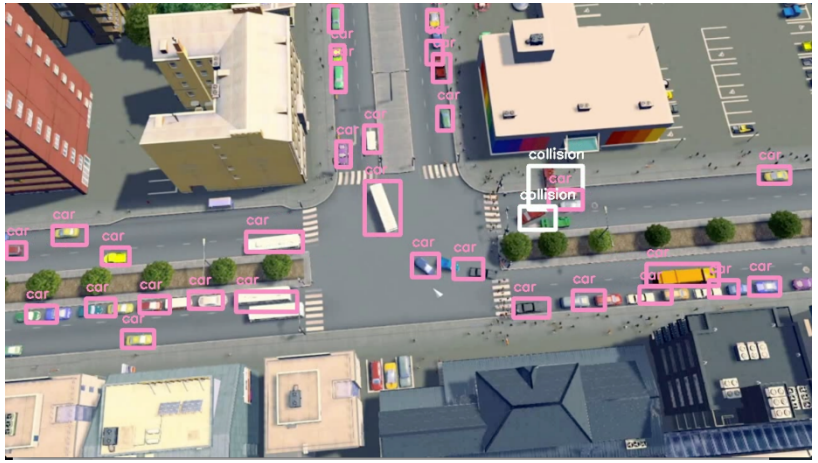
- Implement Real-Time Tracker for road users based on DeepSort (Tracking by Detections with Kalman Filter)

Collision Detection

- Two-Stream: Learn collision probability using appearance model and trajectory model
- Identify collision locations and associated objects

Annotation example

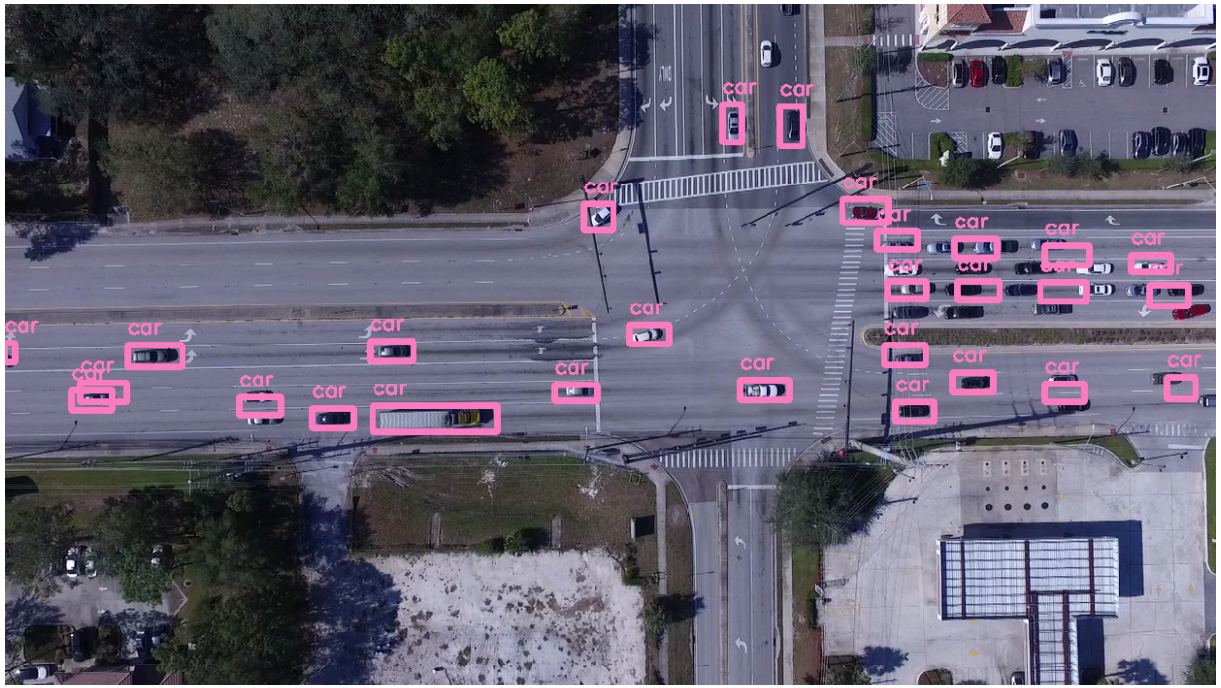
Tracking and trajectory example



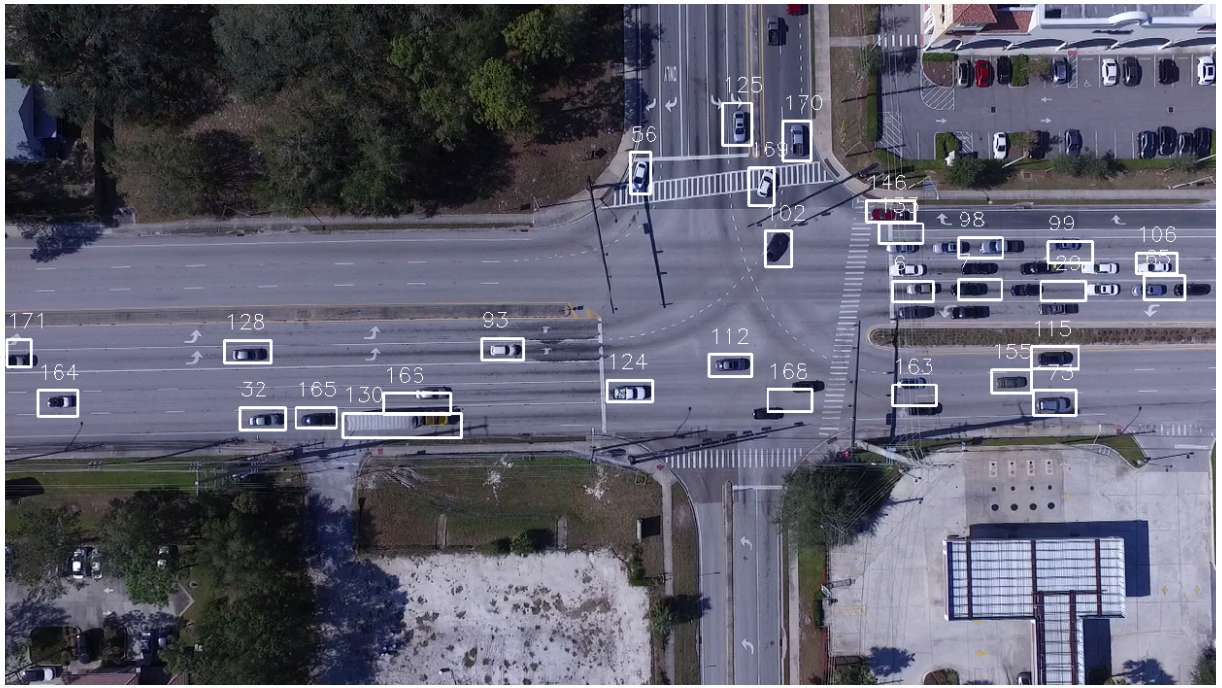
Car Detection and Near Collision Detec

Experimental Results on aerial video

Video 1: ‘400ft.mov’
Duration: 04:45 (24fps)
Resolution: 1280 x 720
Collision Scenario: None



Car Detection Result



Car Tracking Result

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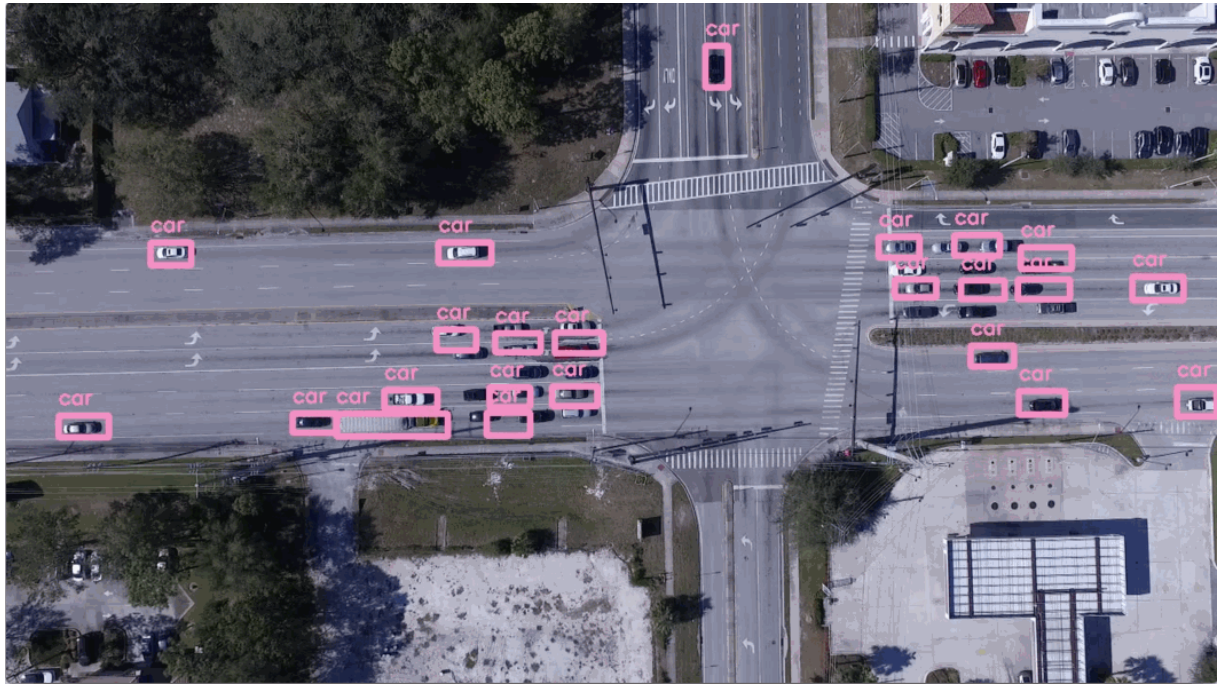
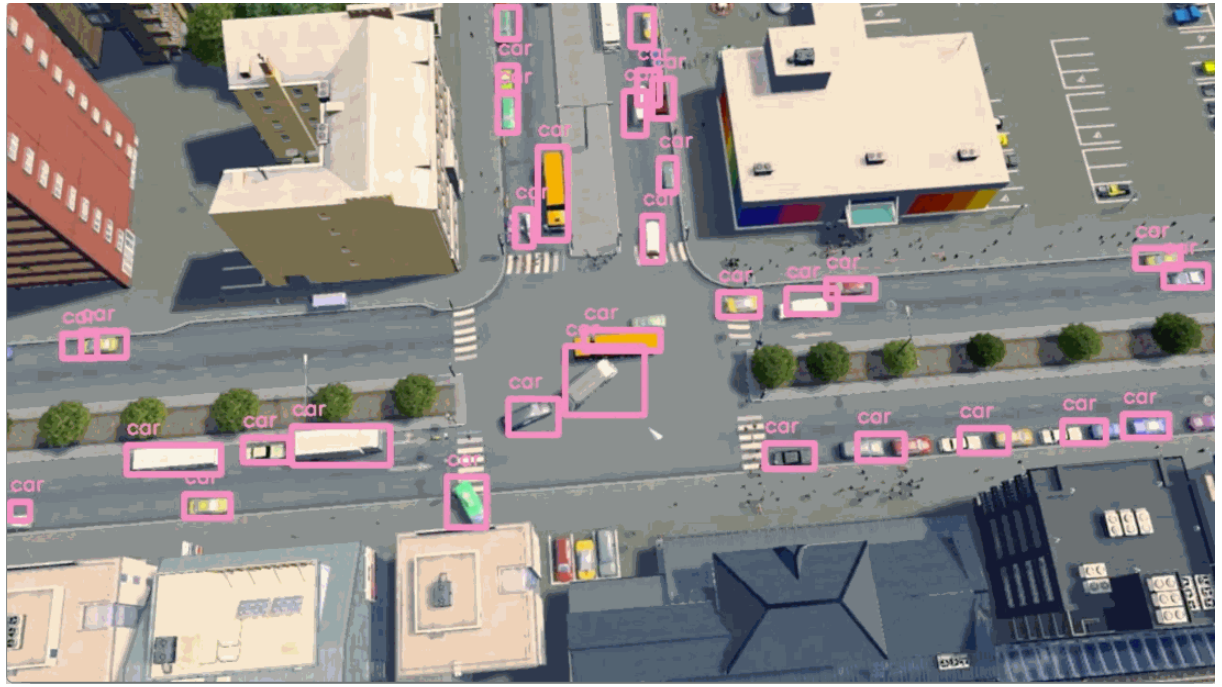
Aerial Video (Real-time)



Result on real video

Video 1: ‘400ft.mov’
Duration: 04:45 (24fps)
Resolution: 1280 x 720
Collision Scenario: None



Result on video created by game simulation

Video 2: ‘Traffic_5.mp4’
Duration: 00:12 (25fps)
Resolution: 1280 x 720
Collision Scenario: ♪ [?]

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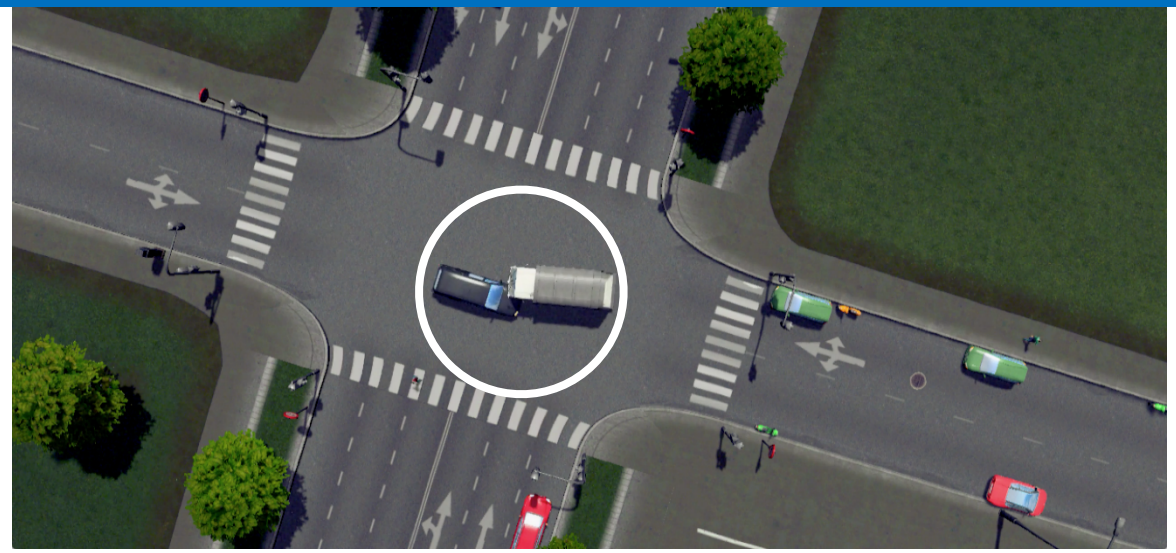
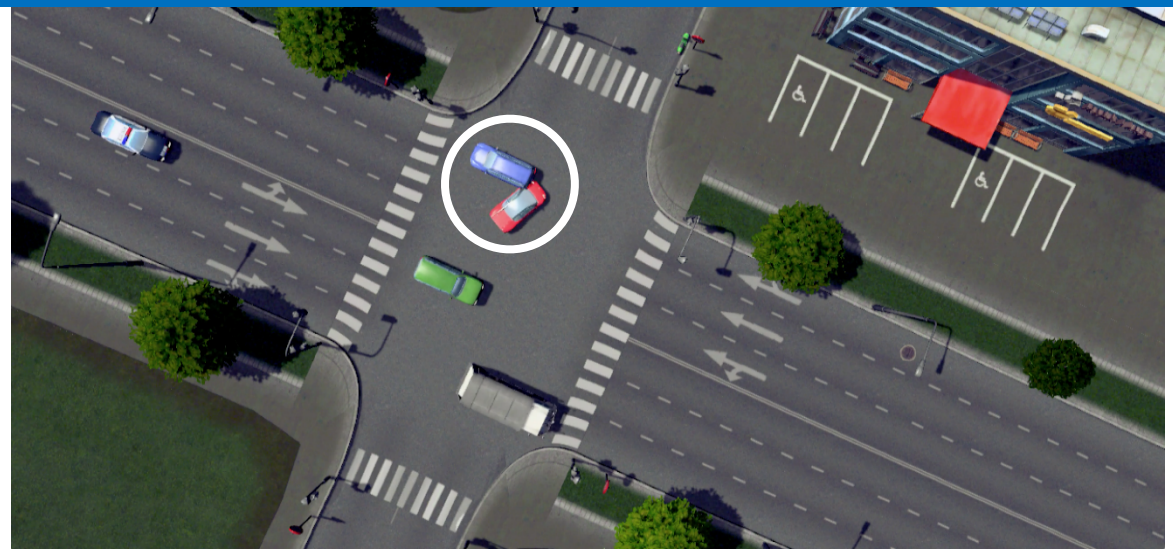
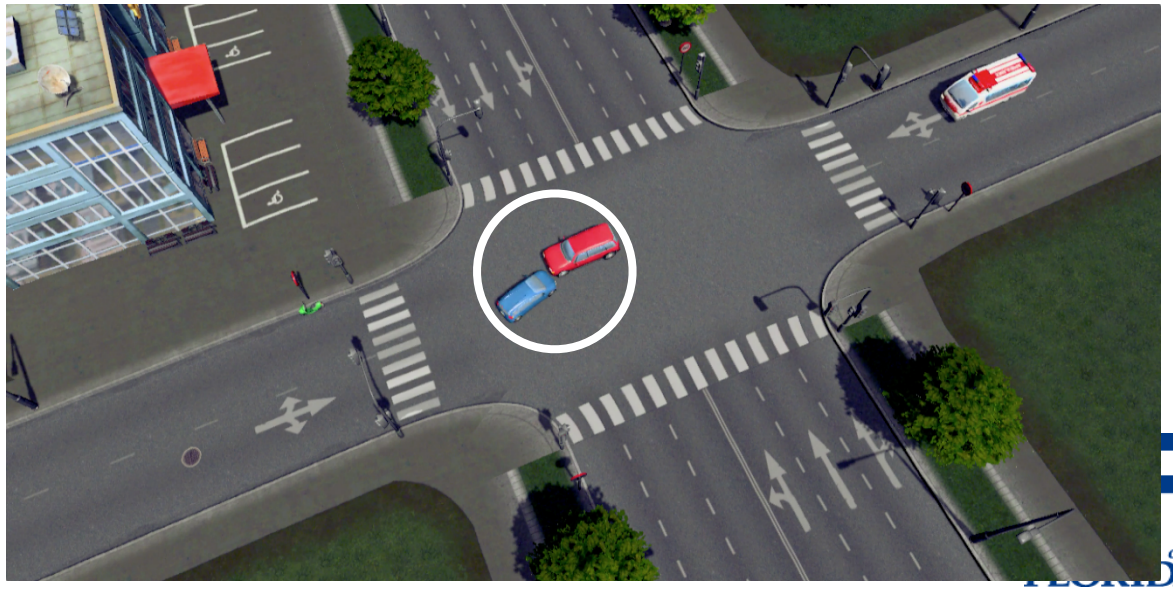
Realistic Simulation: Differential Light Conditions

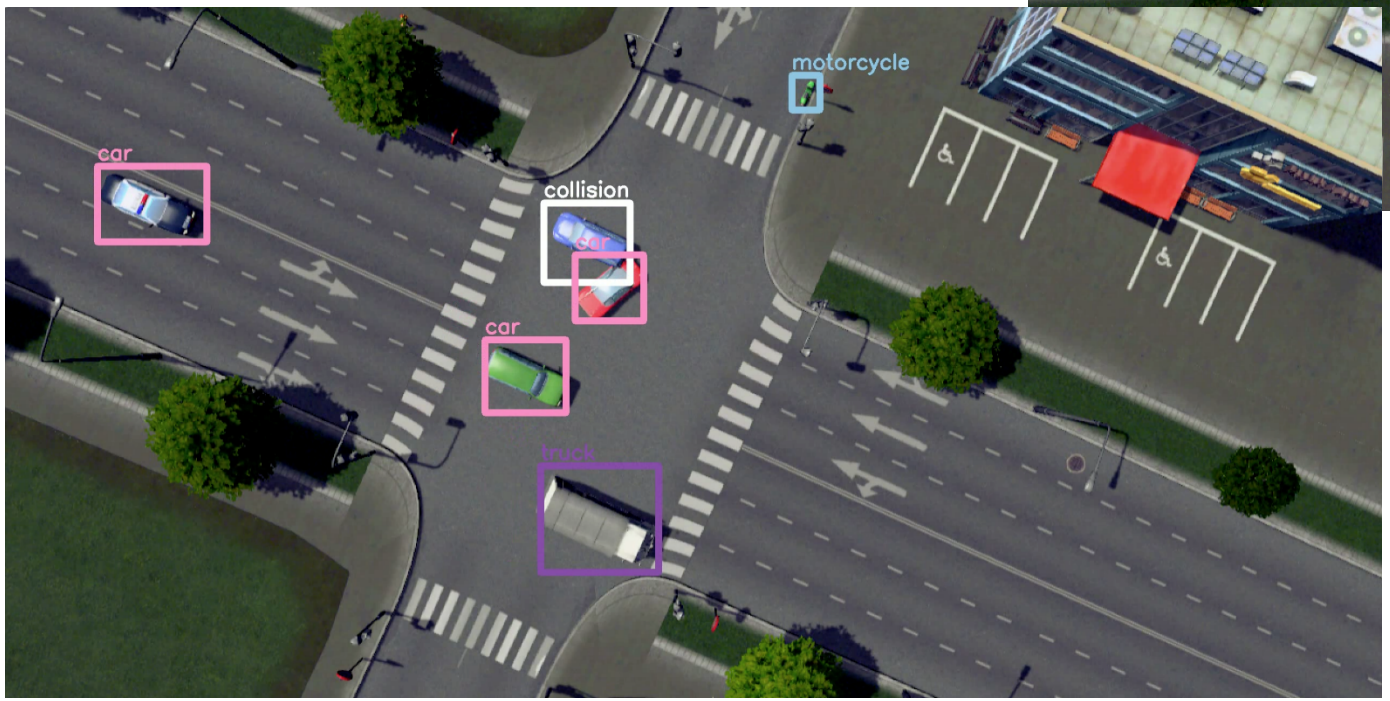






Realistic Simulation: Differential Vehicle Classes

- Motorcycle
- Car
- Truck
- Bus



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Real-Time Demo (Multiple Vehicle Types)

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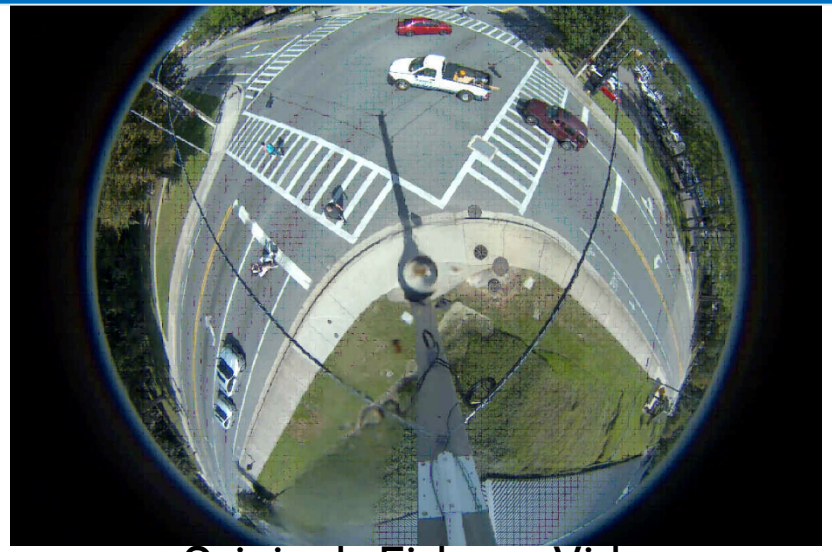
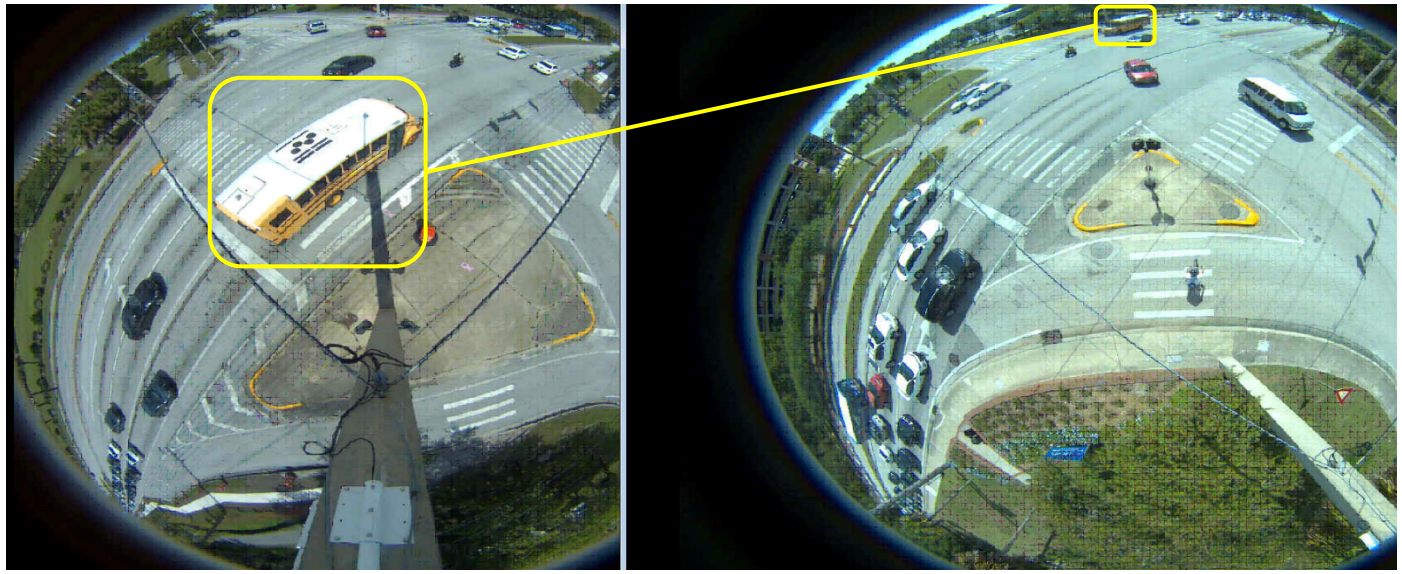
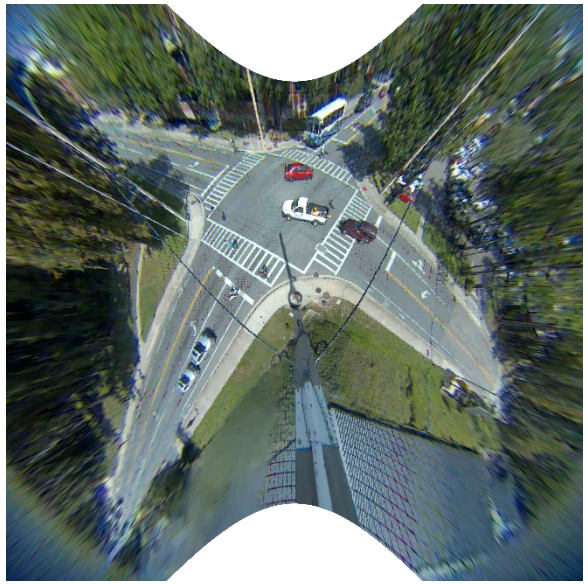
Image Transformation and Stitching



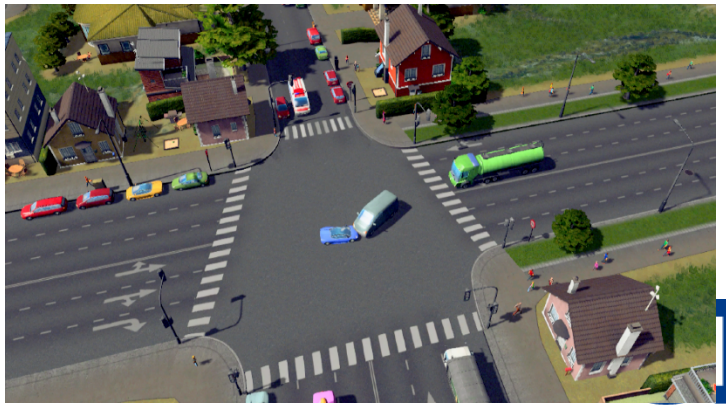
Original Fisheye Video



Multi-camera Video



Lens Correction



Simulated Video

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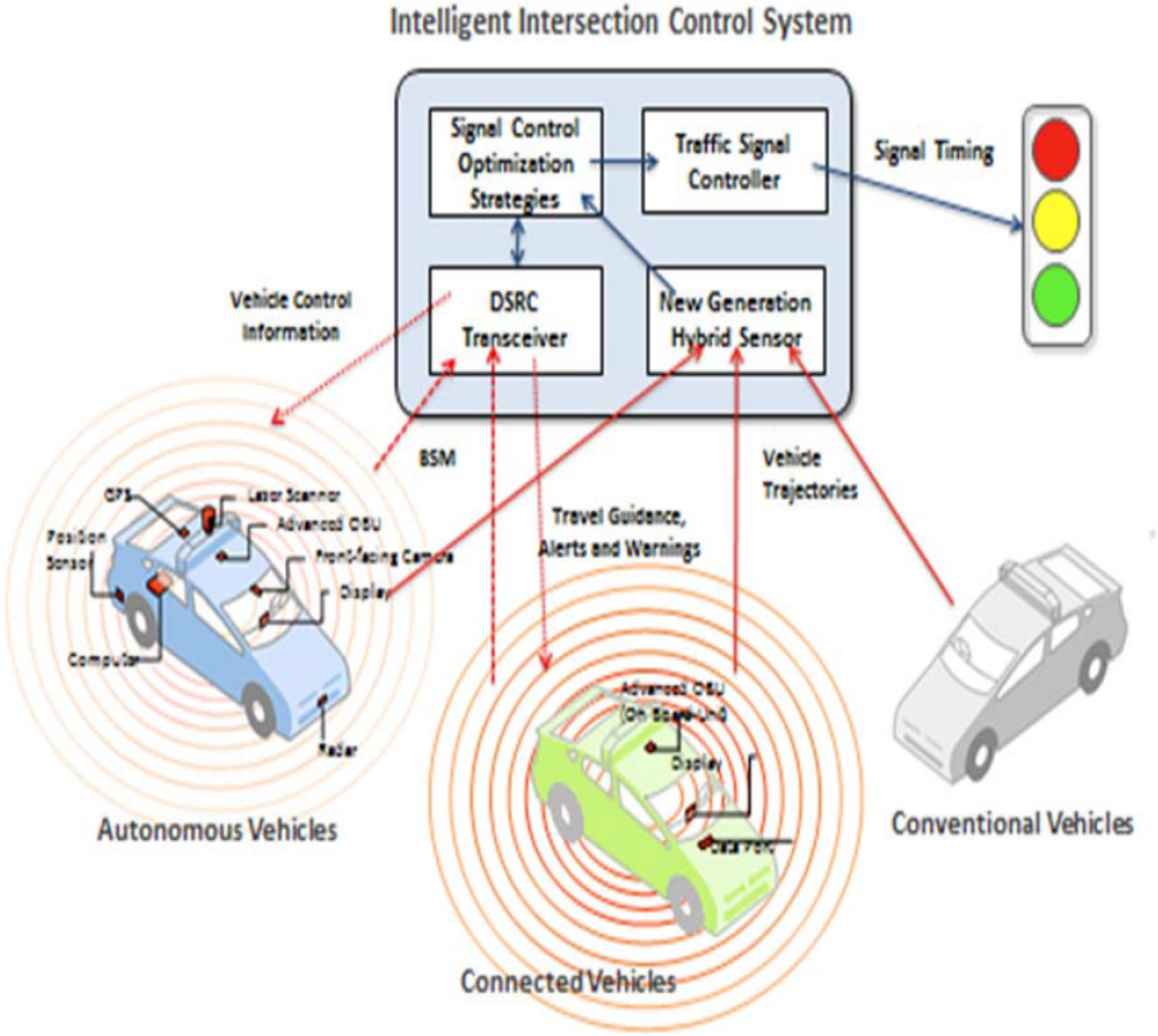
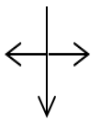
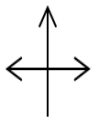
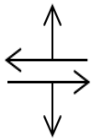
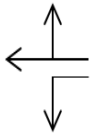
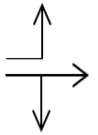
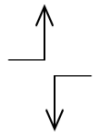
AVIAN: Autonomous and Connected Vehicles Intersection Controller (NSF CPS + FHWA+FDOT)



Phase No.	1	2	3	4	5	6
Lane(s)	1	4	2,5	2,3	5,6	3,6
Movements						

Problem Description

Given: the arrival information of automated vehicles and conventional vehicles

Goal: to optimize the average delay by advising automated vehicles and controlling signal phase and timing

Involves Sensing technologies

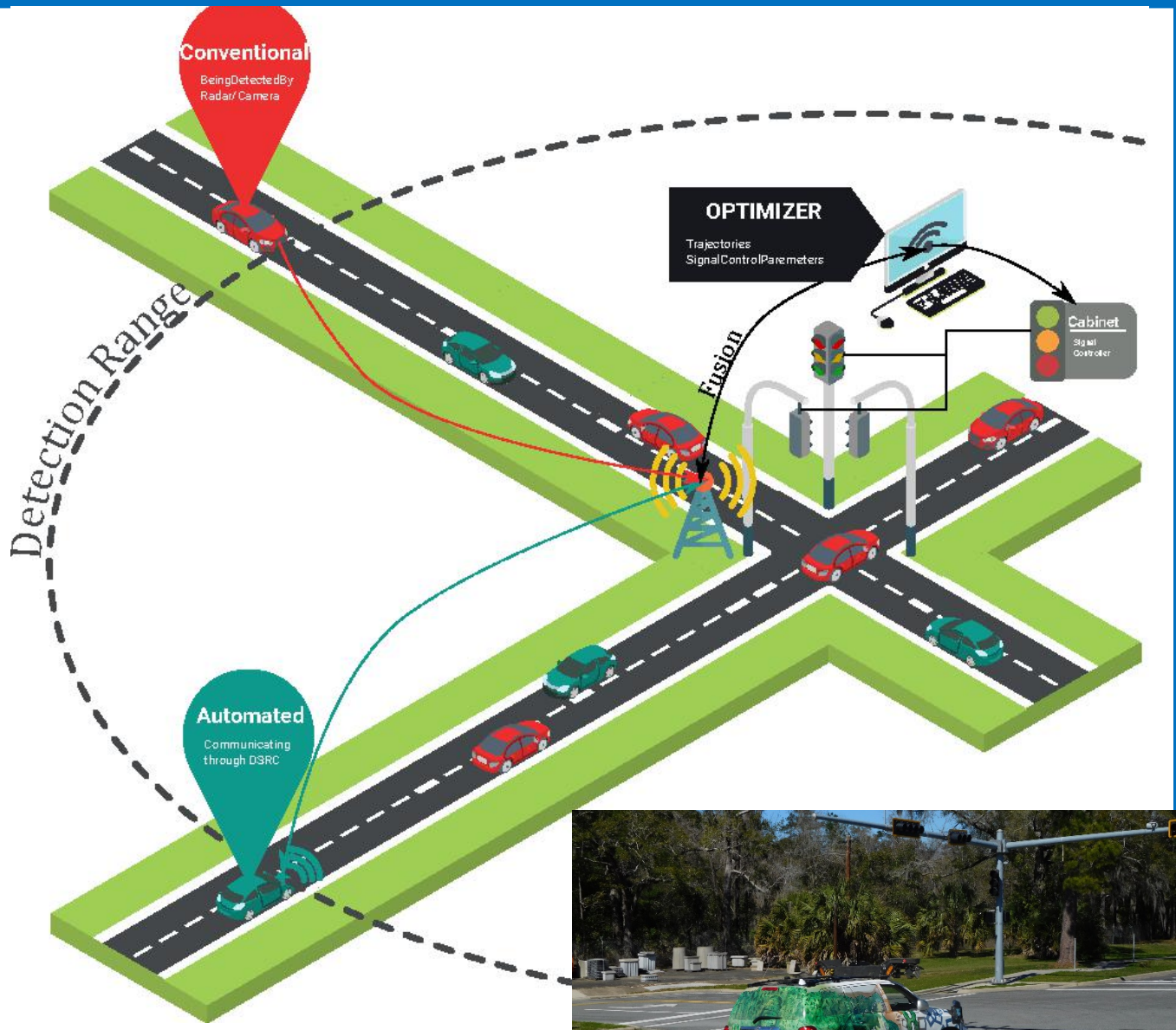
- Dedicated Short Range Communication
- Radar
- (Camera, Lidar)

Autonomous Vehicle Technology

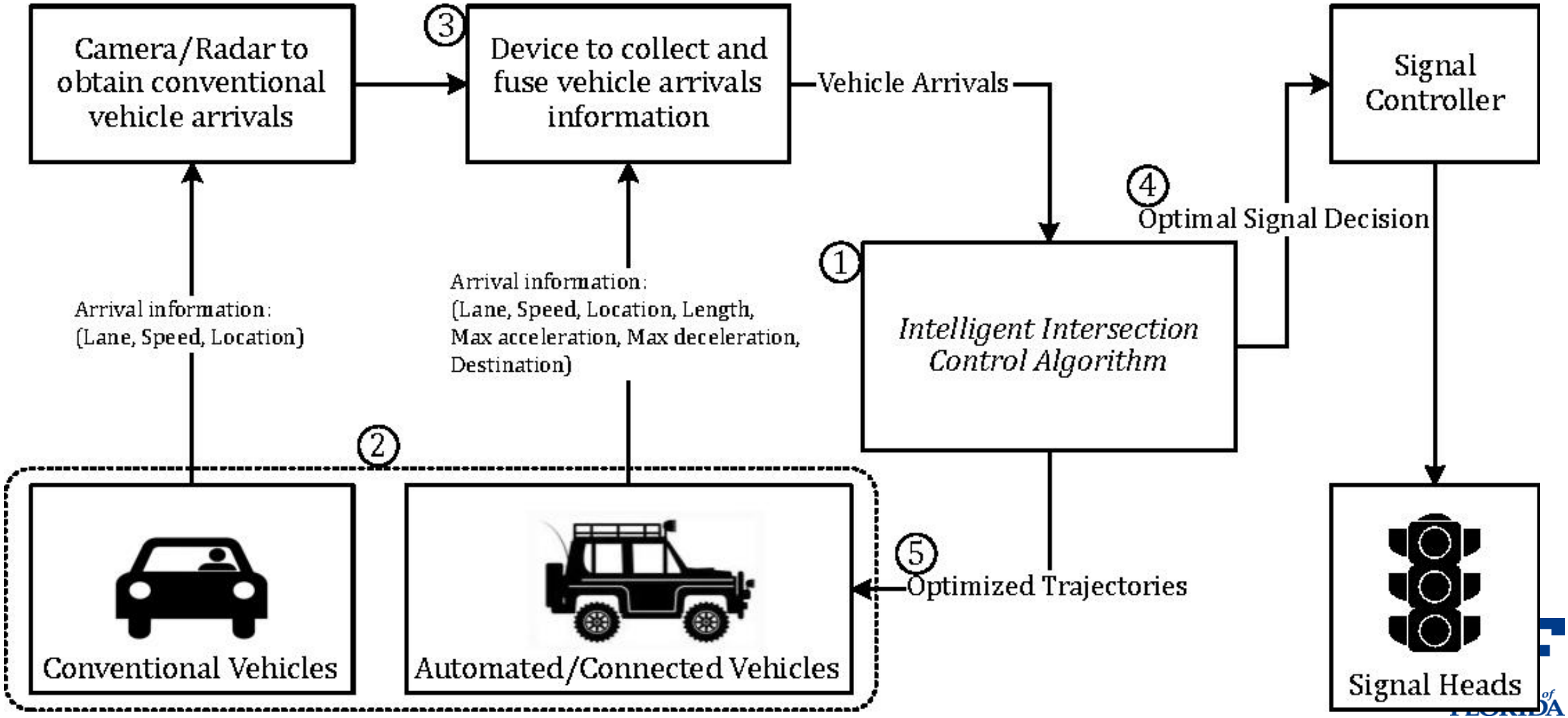
- Navigation and Localization algorithms

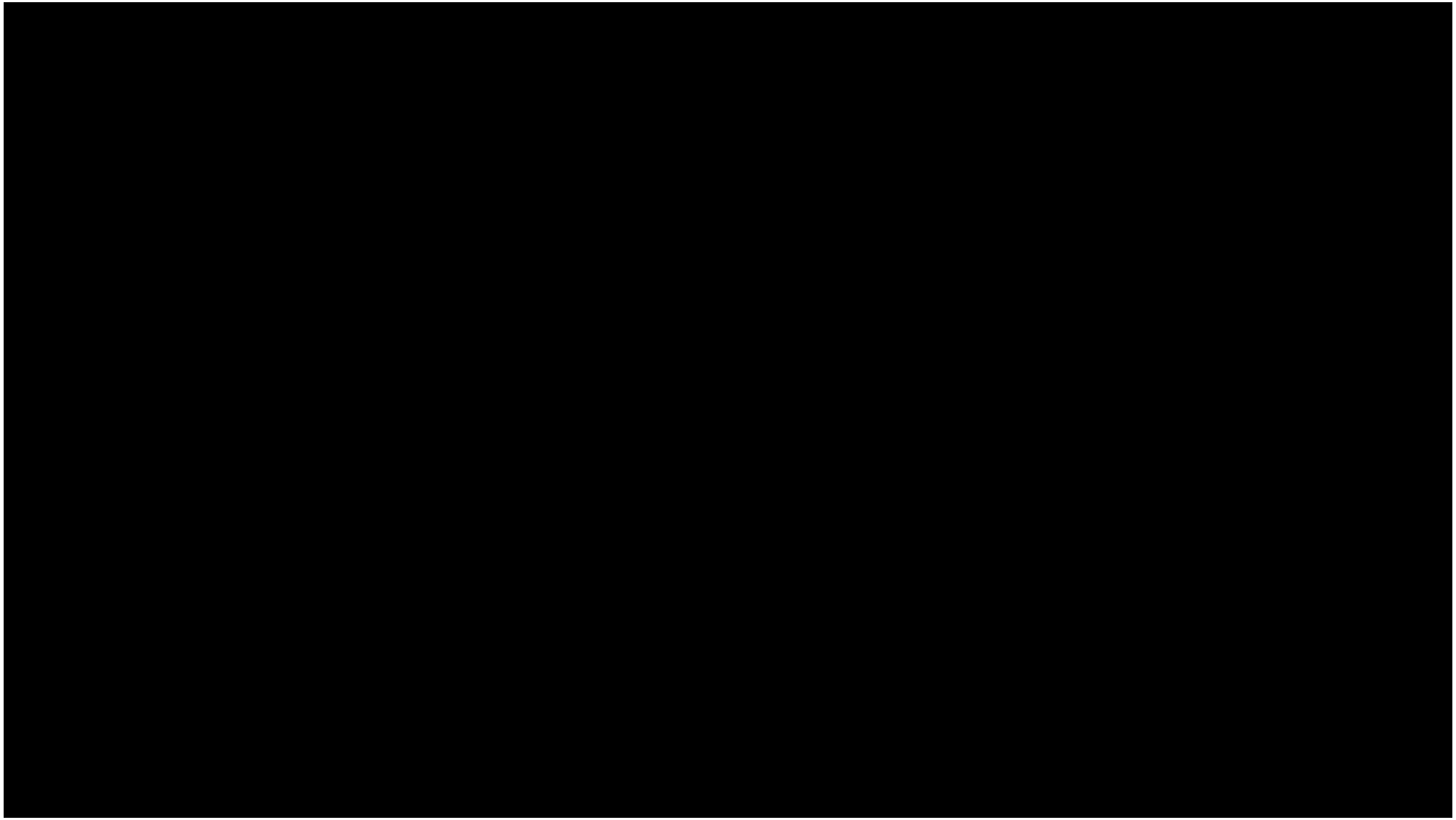
Optimization Algorithm

- Vehicle Path Optimizer
- Signal Status Optimizer

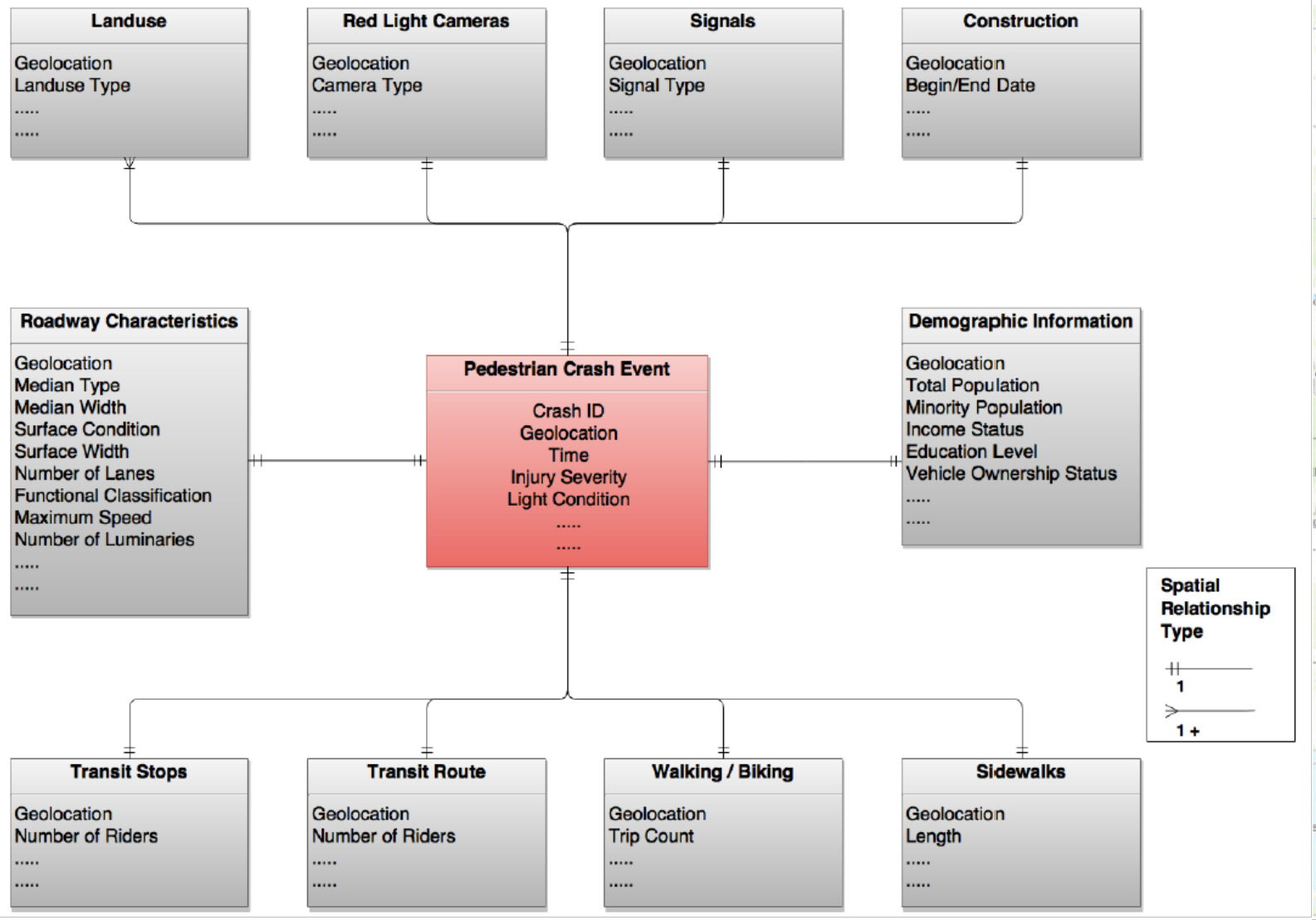


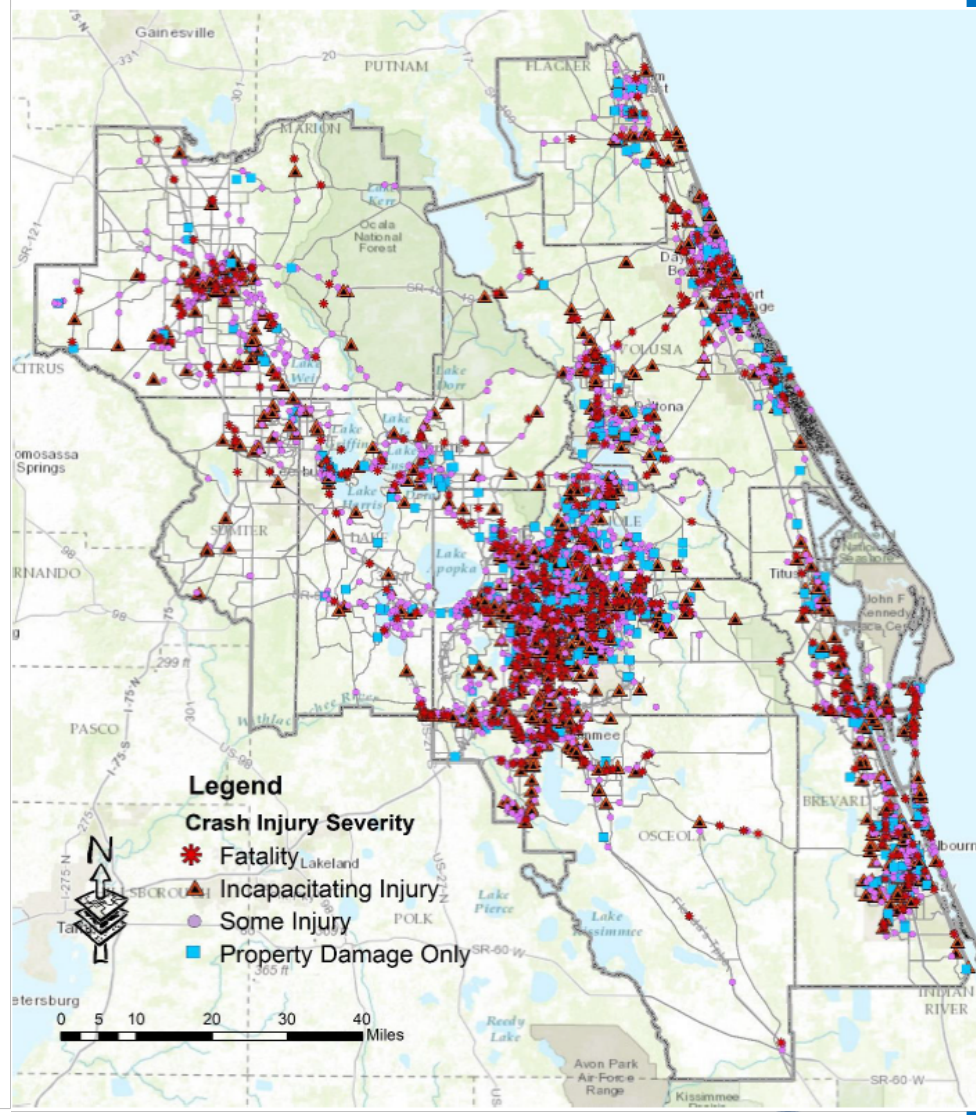
Intelligent Intersection Cyber Physical System





Bigdata: Predicting and preventing fatal crashes (FDOT D5)





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Accuracy of Different Approaches in predicting fatalities

Accuracy Values	Logistic Regression	Decision Tree	DBN	GBM	SVM
Intersection	57%	88%	78%	91%	68%
Roadway segment	60%	77%	68%	86%	63%

Sensitivity Values	Logistic Regression	Decision Tree	DBN	GBM	SVM
Intersection	76%	18%	37%	10%	76%
Roadway	86%	43%	76%	20%	78%

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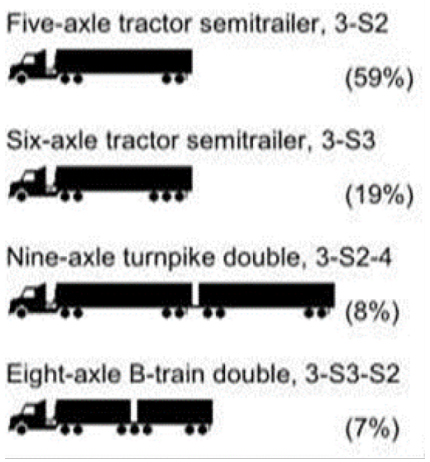
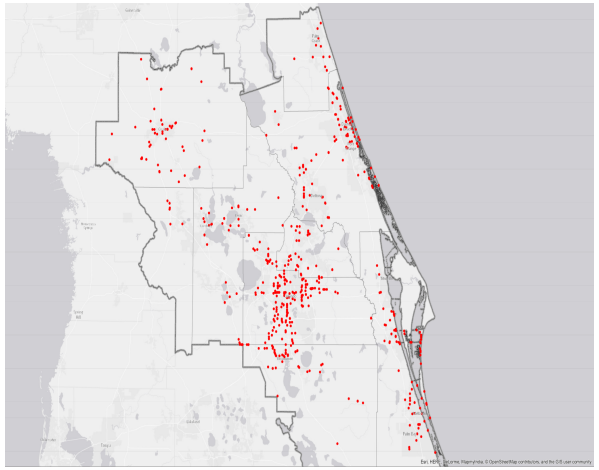
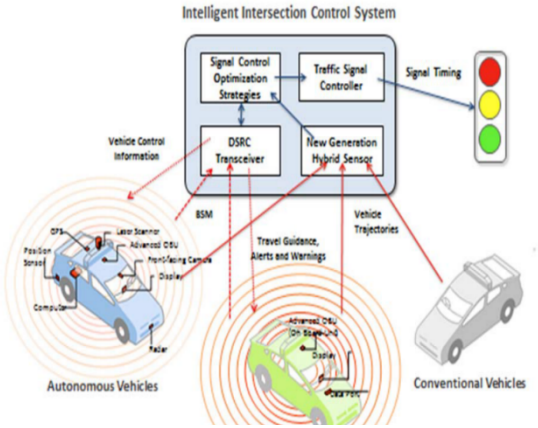
Conclusions



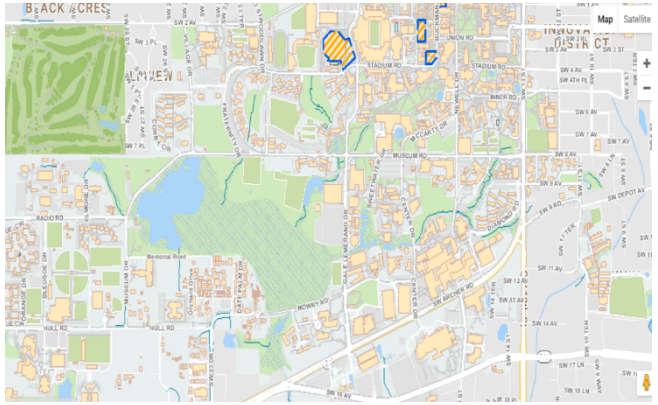
Truck Classification



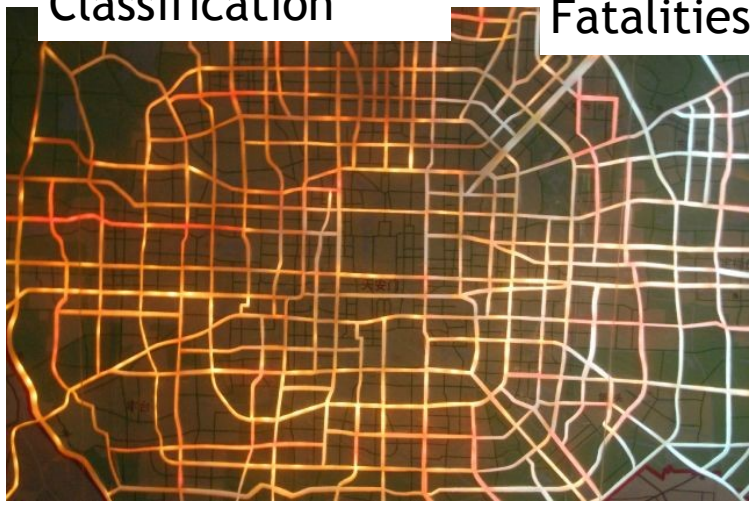
Mining Pedestrian Fatalities



Optimizing for a Single Intersection



I-Street Testbed

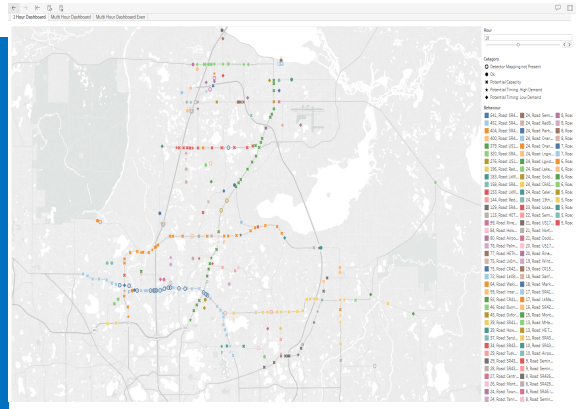


Incident Detection and Optimizing for a Transportation Grid

Significant Progress in Research Development Deployment and Transition to Practice

State-of-the-art Edge and Cloud Computing

Use of Machine Learning, Image Processing and High Performance Computing



Classifying and Clustering Signals

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