

# Smart Broward County Transportation: Using Big Data Analytics and Artificial Intelligence



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# Talk Outline

- Smart Societies
- Impact of Technology on Smart Societies
- Broward County Metropolitan Transportation Plan
- Research and Development at University of Florida (with potential applications to Broward County)
  - Analyzing Traffic Signals
  - Video Analysis
  - Incident Detection
  - Smart Intersections
  - Smart Networks
  - Vehicle and Commodity Classification
- Conclusions

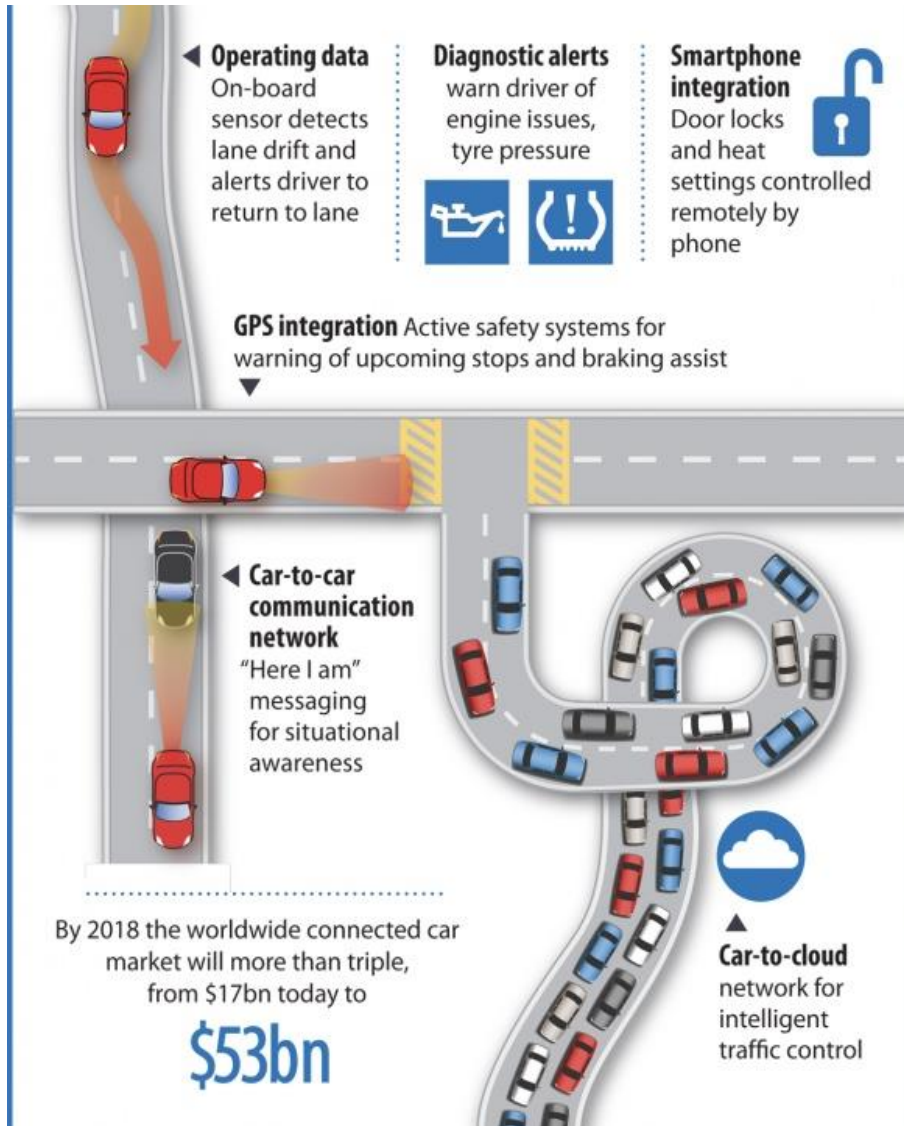
# Smart Broward County Metro Transportation Plan

- Serving the **mobility needs of underserved communities** by providing reliable and affordable transportation alternatives
- Break down digital barriers and **improve transparency** for all residents using innovative technology-based solutions
- Manage **traffic congestion and improve safety** by using big data and related technologies
- Use **data driven approaches** for decision making, planning, evaluation and measurement
- Support efficient movement of goods, services and people by using practices that are **environmentally sustainable**
- Stimulate economic prosperity by **improving access to jobs** using expanded mobility access to major job centers
- Enhance **tourist and visitor experience** by providing easy to access information about mobility alternatives



**Source: 2045 Métropolitan Transportation Plan (MTP)**

# Connected & autonomous vehicles are becoming prevalent



Convergence  
Expected in  
2025

## Autonomous Vehicles

Source: Peter Runcie, CSIRO peter.runcie@data61.csiro.au

Connected Vehicles

Source: <http://gelookahead.economist.com/infograph/car-os/>

# Communication is going through a revolution



Source: USDOT

# Technology convergence will revolutionize transportation, dramatically improving safety and mobility while reducing costs and environmental impacts

Connected Vehicles

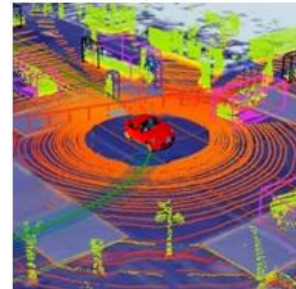
Vehicle Automation

Internet of Things

Machine Learning

Big Data

Mobility on Demand



Connected-Automated Vehicles



## Benefits

- Order of magnitude safety improvements
- Reduced congestion
- Reduced emissions and use of fossil fuels
- Improved access to jobs and services
- Reduced transportation costs for gov't and users
- Improved accessibility and mobility

Source: USDOT Smart City Challenge Presentation

# Impact of tech applications on improving mobility



**City 1**  
 Medium commute times;  
 subway is primary mode;  
 medium congestion; low  
 bus occupancy  
 (eg, New York City)



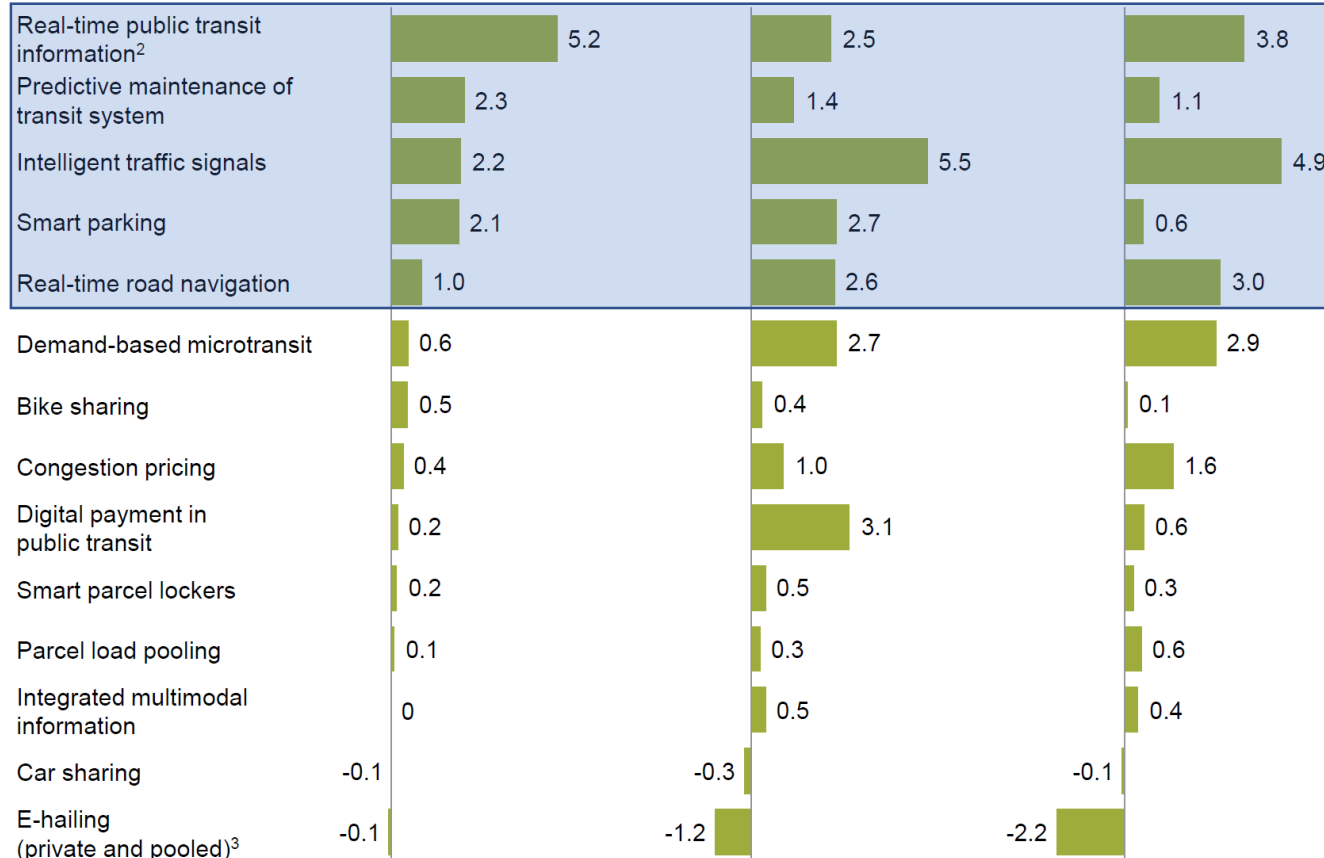
**City 2**  
 Medium commute times;  
 bus is primary mode;  
 medium congestion; high  
 bus occupancy  
 (eg, Rio de Janeiro)



**City 3**  
 Long commute times;  
 bus is primary mode;  
 high congestion; low bus  
 occupancy  
 (eg, Lagos)

## Commuter time

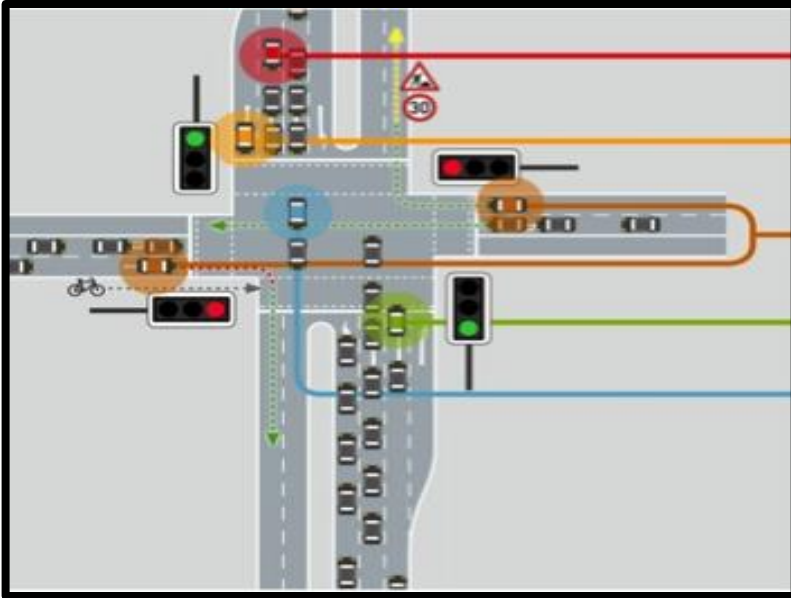
% decrease in average commute time by application<sup>1</sup>



Source: Mckinsey Global Institute, Smart Cities Report

- Real-time public transit information: Real-time information about departure and arrival times.
- Predictive maintenance of transportation infrastructure: Sensor-based monitoring of infrastructure (such as rails, roads, and bridges) so that predictive maintenance can be performed to reduce disruptions.
- Intelligent traffic signals: Improvement of overall traffic flow through dynamic optimization of traffic lights. Give priority to transit and emergency vehicles, public buses, or both.
- Smart parking: Dynamic guidance and variable pricing based on location and availability.
- Real-time road navigation: Real-time navigation tools based on traffic and incidents.

# Smarter Transportation Research at UFL



Smarter intersections will be equipped with cameras (including infrared) and/or lidar to collect data

1. Better Pedestrian and Bicyclists Safety by examining the conflict points of the vehicle/pedestrian trajectories (near-misses)
2. Better Demand Profiles by understanding real-traffic behavior for more effective signal timing and understanding relationships between existing (loop detector) and new technologies (video).
3. Better SPaT messaging by understanding traffic behavior on the intersections.



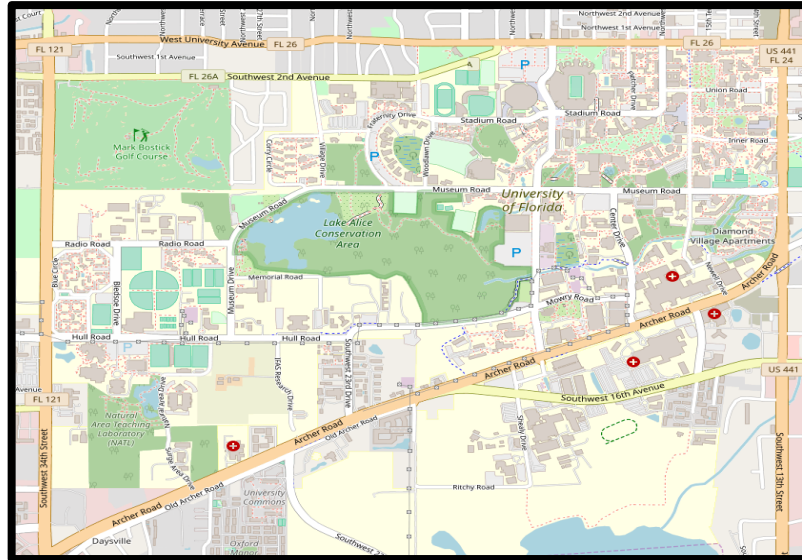
Smarter Streets by use of transit buses with forward facing cameras to continuously collect video data from streets (and intersections).

1. Better Pedestrian Safety by detection of jaywalking/ “mid-block crossing” behaviors that are prevalent in university campuses.
2. Better Resource Management by understanding usage of street parking and signage.
3. Better Lane and Street Sign Design by tracking indicator lights, lane-changing maneuvers undertaken in front of the bus.

Funded by National Science Foundation under their Smart Cities Program and Florida Department of Transportation



# Smarter Transportation Research at UFL



Smarter Network by sensing data from multiple intersections will enable

1. Better Incident Detection for alleviating traffic backups and secondary crashes.
2. Better Signal Retiming for different corridors by time of day and day of the week to reflect the changes in network demand.
3. Better System-wide Network Utilization by utilizing a global view of the entire network and historical traffic patterns based, and potential disruptions.

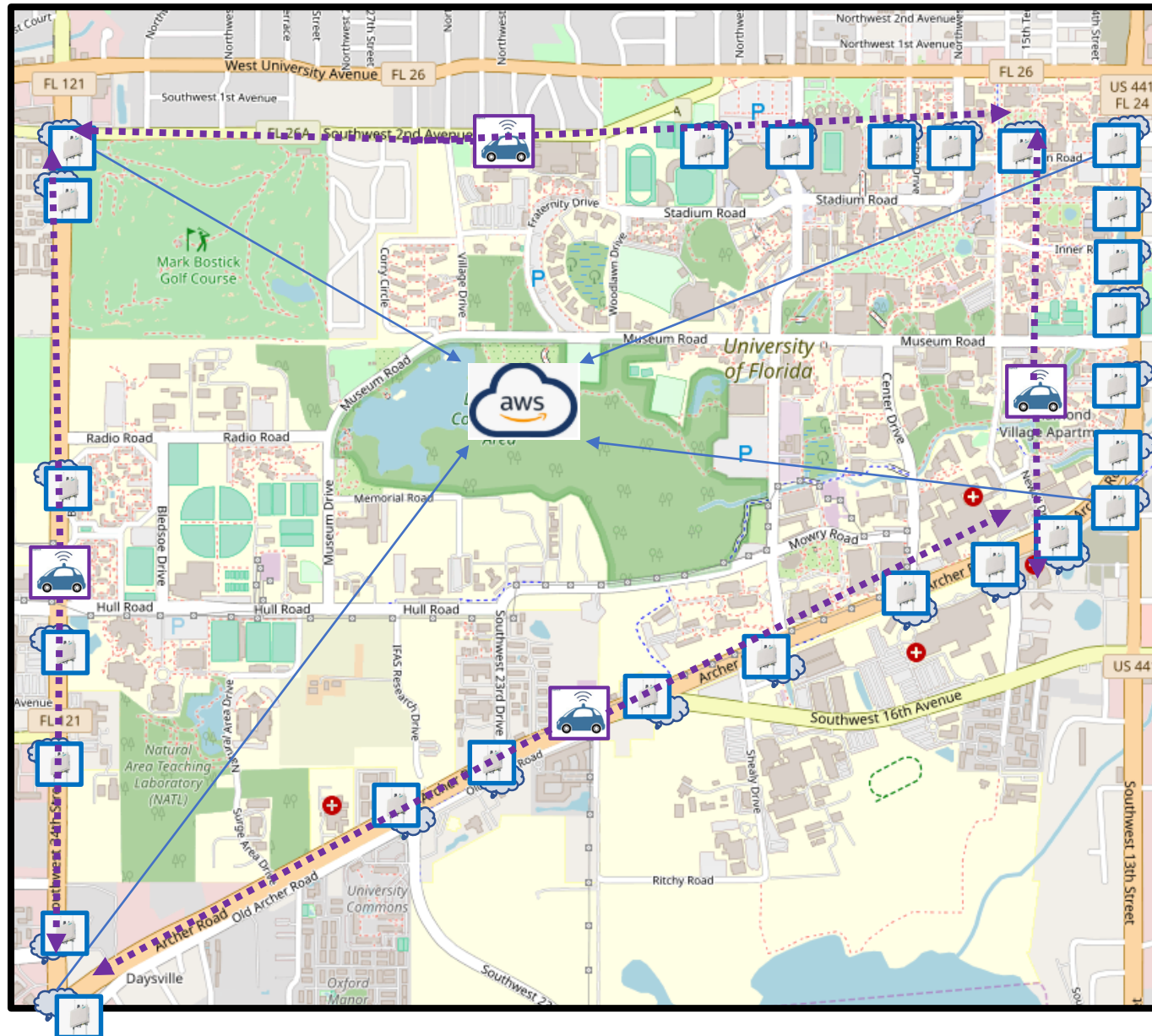


Smarter Interactions with Connected and Autonomous Vehicles by analyzing data collected from CAVs will lead to

1. Improved Safety by effectively managing CAVs.
2. Better Understanding of CAV Behavior and Interaction with Traditional Vehicles.
3. Better Signal Timing and Trajectory Optimization for CAVS.
4. More Accurate Trend Measurements of CAV Penetration.

Funded by National Science Foundation under their Smart Cities Program and Florida Department of Transportation

# Trapezium/I-Street project in Gainesville



## Trapezium after SPaT project

### Data Sharing and ATSPM

Upgraded Linux based 'ATC' Controllers. ATSPM Data sharing to University of Florida and third party (TTS, TrafOps, Live Traffic Data, Connected Signals)

### DSRC Radios

Siemens DSRC Radios with MAP and SPaT Broadcast

### Added value option

Emergency Vehicle Pre-emption and vehicle OBUs

# Trapezium/I-Street project in Gainesville (Additions)



## Trapezium after SPaT project

### Multiple FishEye Cameras

Full intersection view, streaming cameras with full count, presence and queue detectors

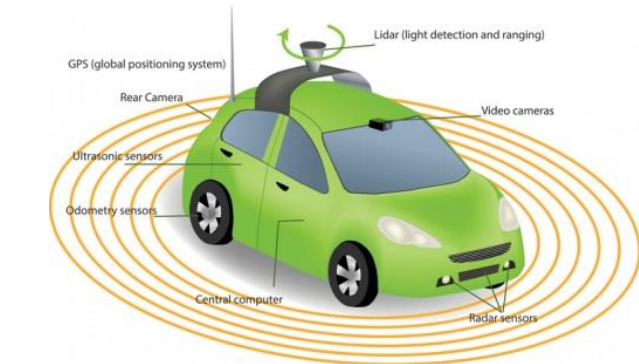
### Multiple Lidars

For ground level ground truth verification and ped and bike application

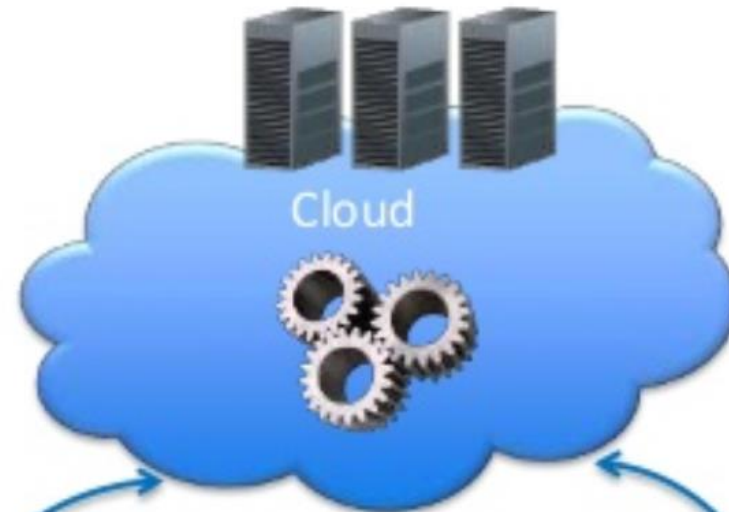
### Several In-bus video

For Dynamic/Vehicle Perspective to supplement Static/Infrastructure.

# Edge (Fog) and Cloud Computing



Many Devices



WAN

WAN

LAN  
Occasionally



Many Users

Flexible infrastructure



Adapt to changing requirements



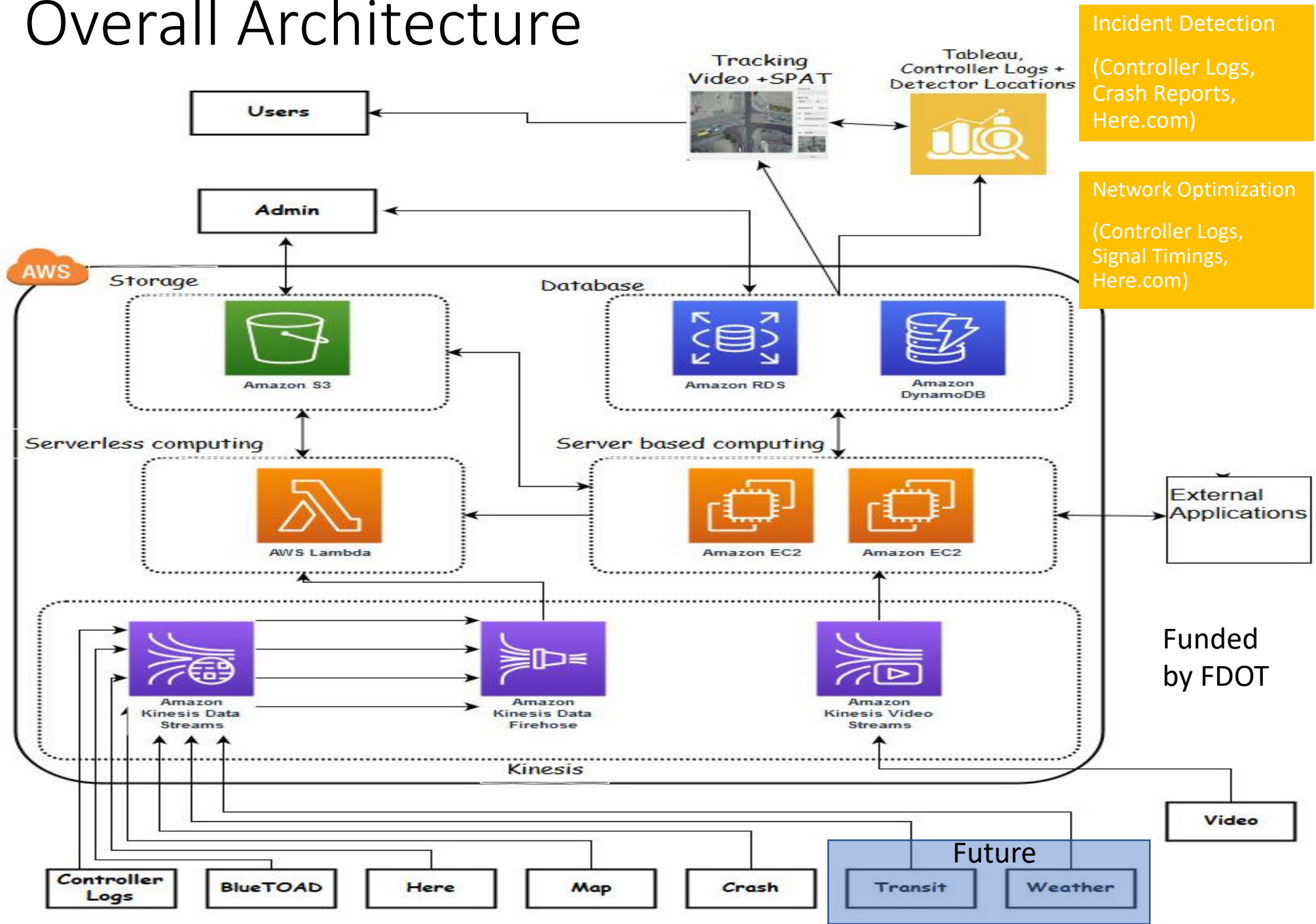
Anywhere, Anytime Availability



Less Hardware, More Storage



# Overall Architecture



**Incident Detection**  
(Controller Logs, Crash Reports, Here.com)

**Network Optimization**  
(Controller Logs, Signal Timings, Here.com)

- Controller logs
  - Gainesville, Jan 2019 Onwards
  - Orlando, Aug 2018 Onwards
- Bluetoad
  - Gainesville, Jan 2019 Onwards
- Crash Data
  - Jan 2018 onwards
- Video Data
  - 2 feeds in Gainesville, Dec 2018 onwards. Option to add more.
- Here.com (Probe car) Data
  - Gainesville, Jan 2019 onwards
- Map, Weather and Transit
- Prototyping stage
- (Option to add Historical records for Here, Bluetoad, and crash data)

Funded by FDOT

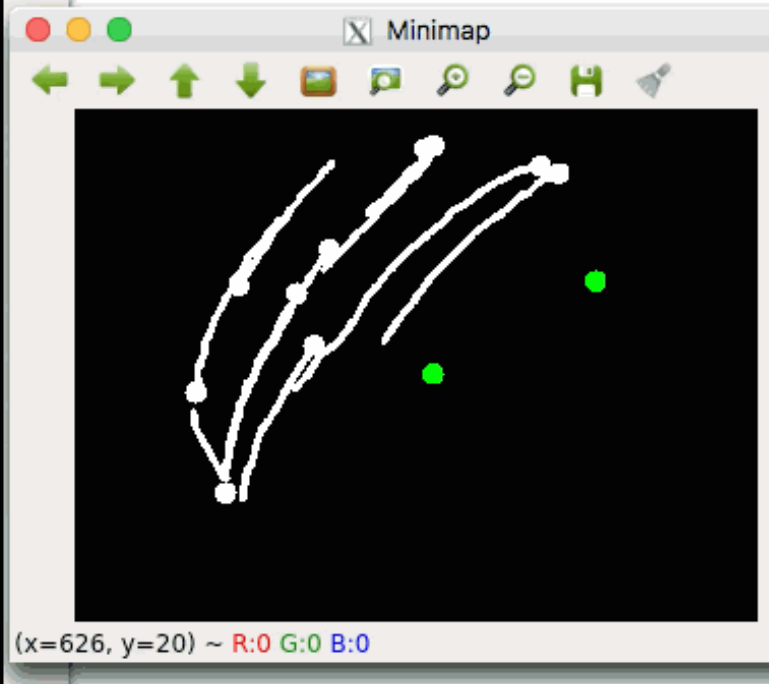
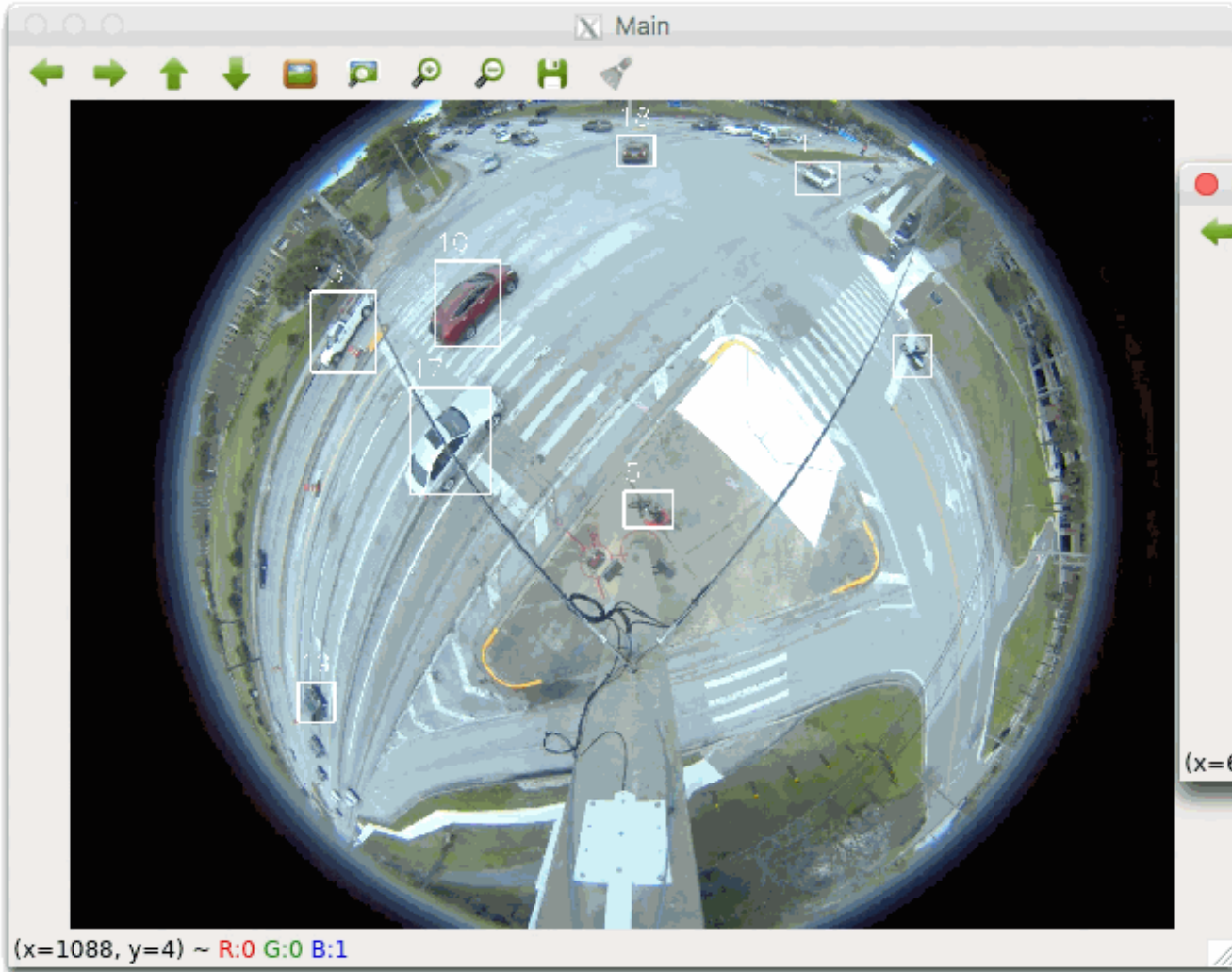
Future  
Transit Weather

# Integrated and Intelligent Data Store

Open data environment containing data from multiple sources

- Monitoring
  - Loop Detectors
  - Video Data
  - PCD data
  - Infrastructure Data
- Evaluation
  - Travel Times
  - Pedestrian Counts
  - Usage of Cross Walks
- Predictive Modeling
  - Incident Detection
  - Response Speed
  - Crash Prediction
- Optimization
  - Signal Optimization
  - Corridor Optimization
  - Network Optimizzation
- Analysis
  - Geographical Analysis
  - Socio Economic Analysis
- Planning and Investments
  - Evaluate ROI
  - Before and After Studies

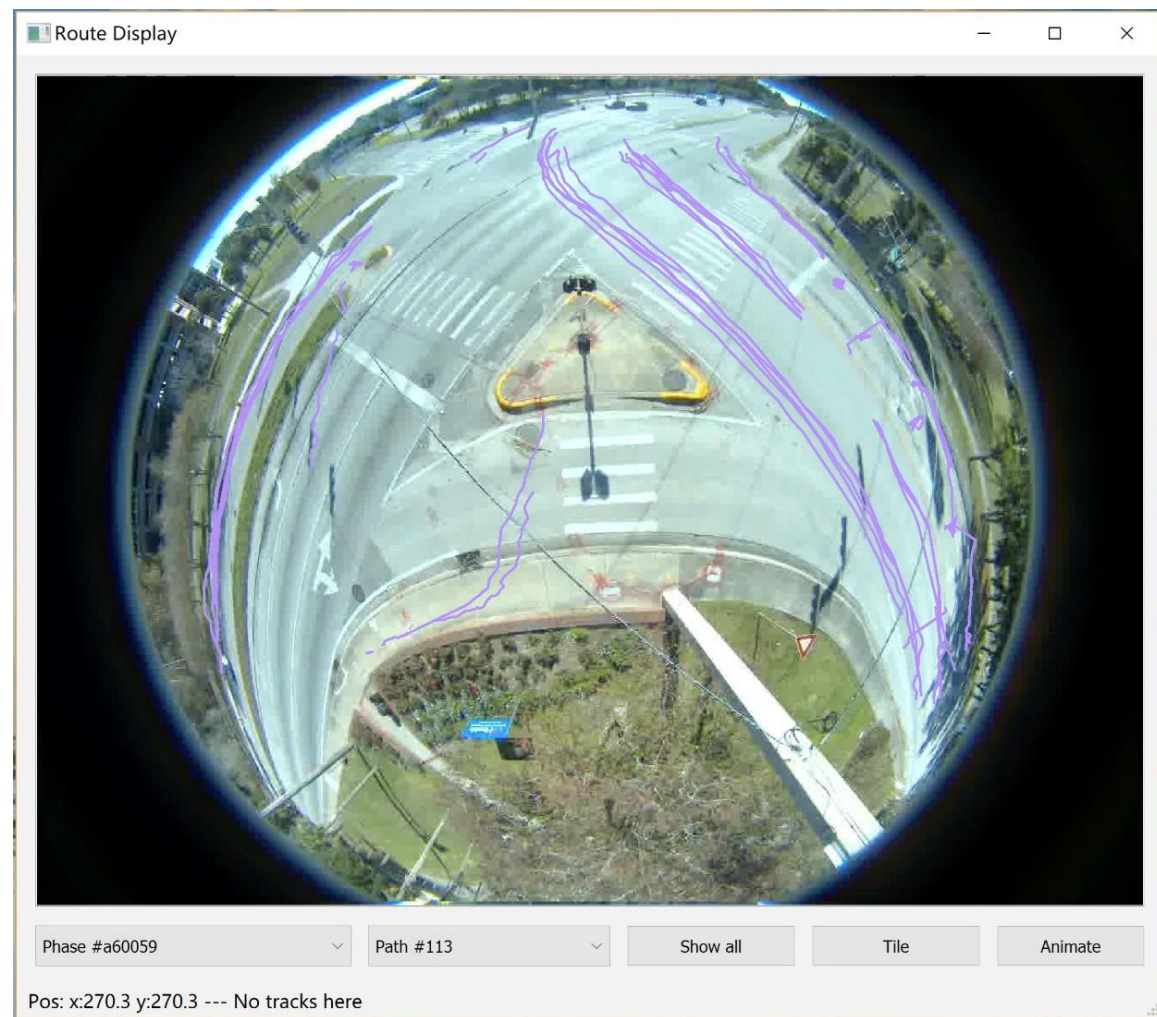
# Real-time Multiple Object Detection



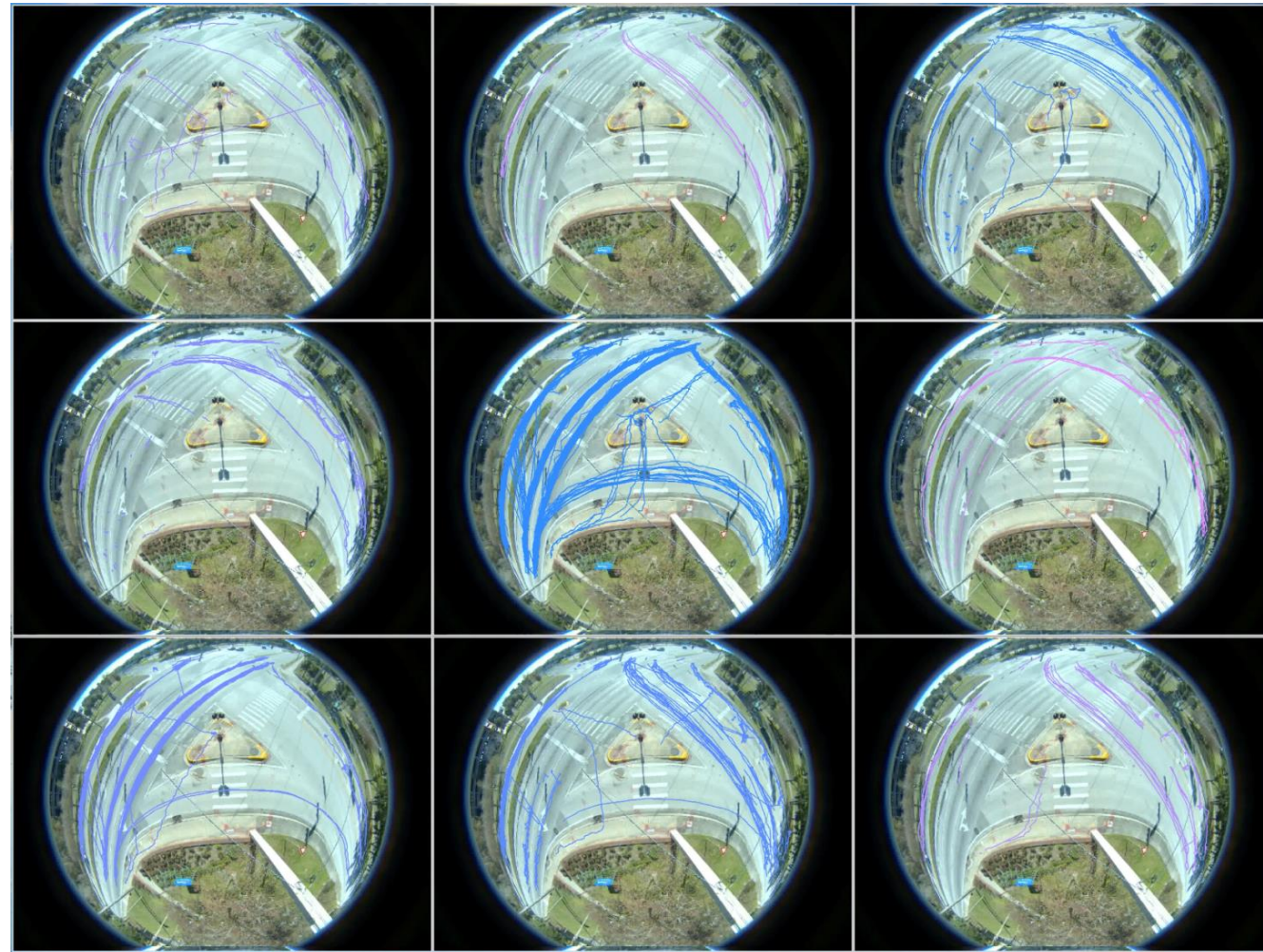
Mini Map Trajectory Demo  
White: car  
Green: bike/motorbike  
Yellow: pedestrian

Funded by Florida Department of Transportation

# Real-time Visualization



Single phase visualization



Multiple phase visualization



# Anomalous Trajectory Detection



Anomalous Track



Video

# Ranking & Classifying Signalized Intersections

- Controller logs from Gainesville:
- Extract-Transform-Load: Downloaded the data, cleaned and reformatted it.
- Identified Relevant MOE, Computed MOE cycle by cycle.
  - Platooning ratio:
    - The ratio of the number of vehicles arriving
    - during the green time/phase to the proportion
    - of the green interval of the total cycle.
  - Arrivals on Green vs Arrivals on Red: Percentage AOG varies from .25 to .45
  - Split Status: Gap out/Max out/Force off
- Rank Signals based on MOE: Best or worse performing intersections.
- Identify Signal behavior based on high resolution plot.
- Automatic Classification of signals based on behavior.

Table 19:1: Relationship between Arrival Type and Platoon Ratio

| Arrival type | Range of platoon ratio( $R_p$ ) | Default value( $R_p$ ) | Progression quality |
|--------------|---------------------------------|------------------------|---------------------|
| 1            | $\leq 0.50$                     | 0.333                  | Very poor           |
| 2            | $> 0.50 - 0.85$                 | 0.667                  | Unfavorable         |
| 3            | $> 0.85 - 1.15$                 | 1.000                  | Random arrivals     |
| 4            | $> 1.15 - 1.50$                 | 1.333                  | Favorable           |
| 5            | $> 1.5 - 2.00$                  | 1.667                  | Highly favorable    |
| 6            | $> 2$                           | 2.000                  | Exceptional         |

Multi-Hour

Select Date:

08/07/2018



Hours (select four):

04:00 AM, 05:00 AM, ▾

03:00 AM

04:00 AM ✓

05:00 AM ✓

06:00 AM

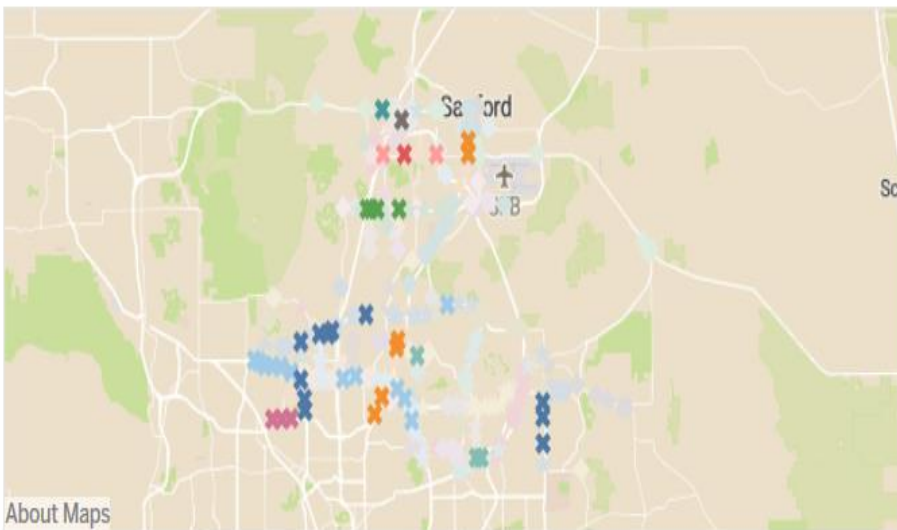
07:00 AM

08:00 AM ✓

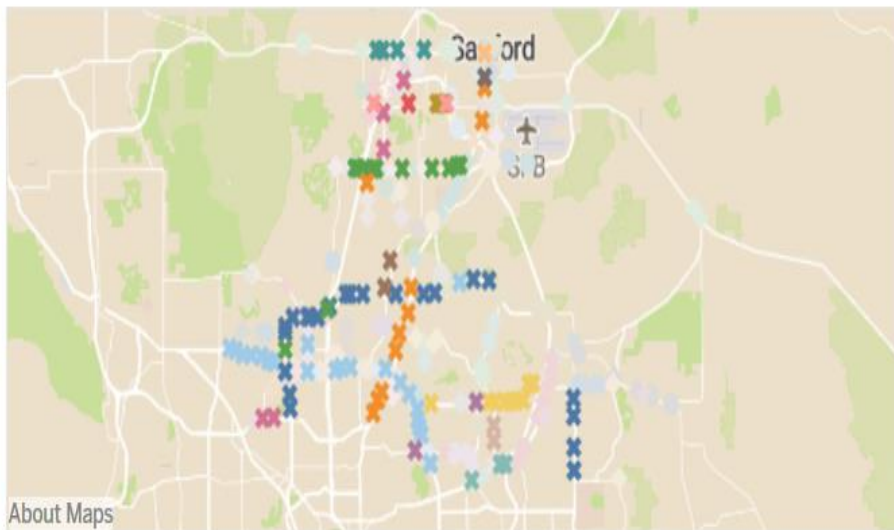
09:00 AM ✓

Submit

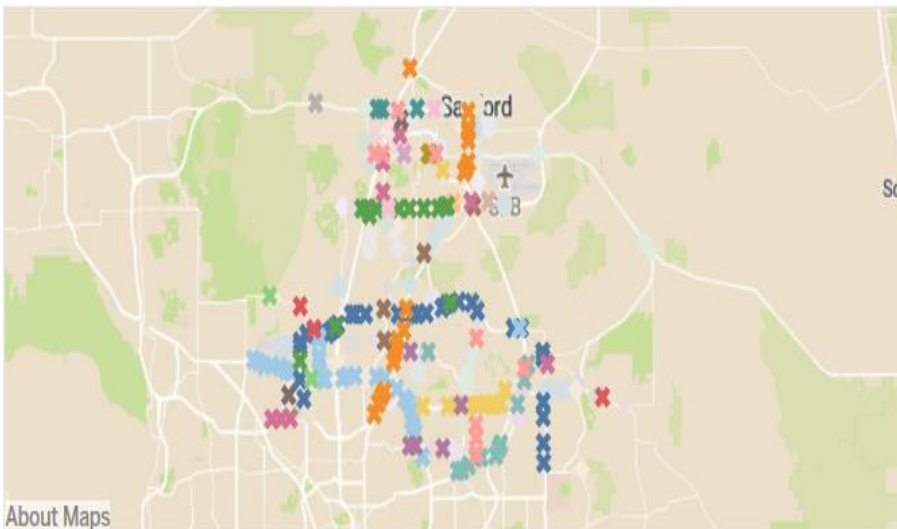
4:00



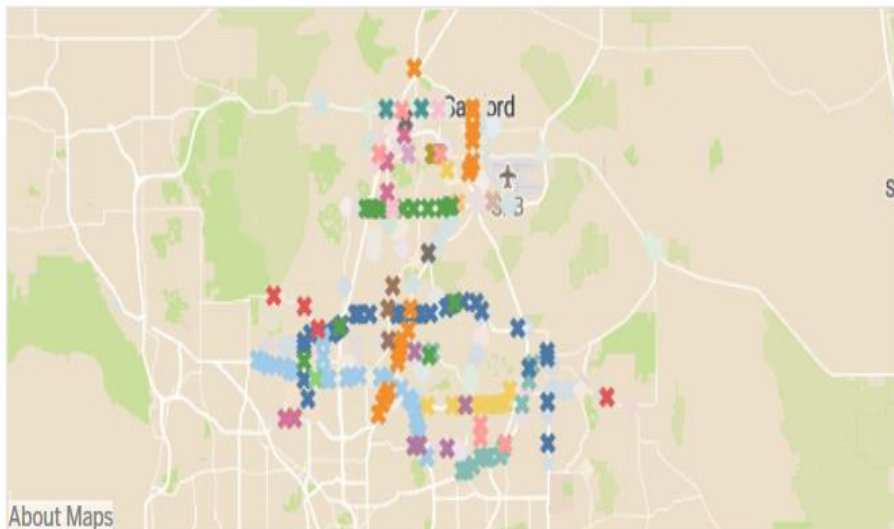
5:00



8:00



9:00



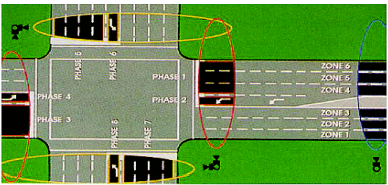
Category

- Ok
- ✖ Potential Capacity
- ★ Potential Timing: High Dema
- ◆ Potential Timing: Low Dema

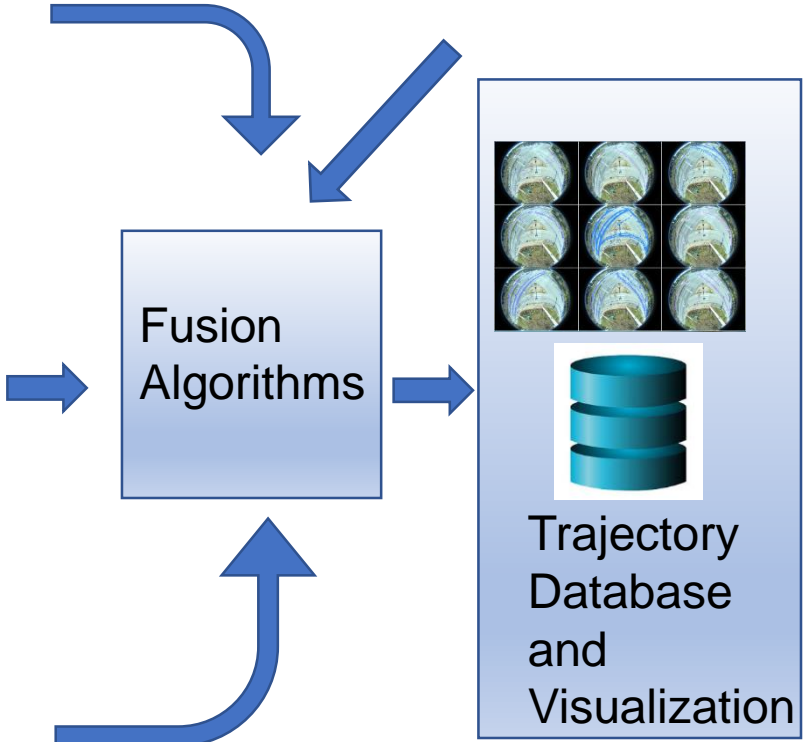
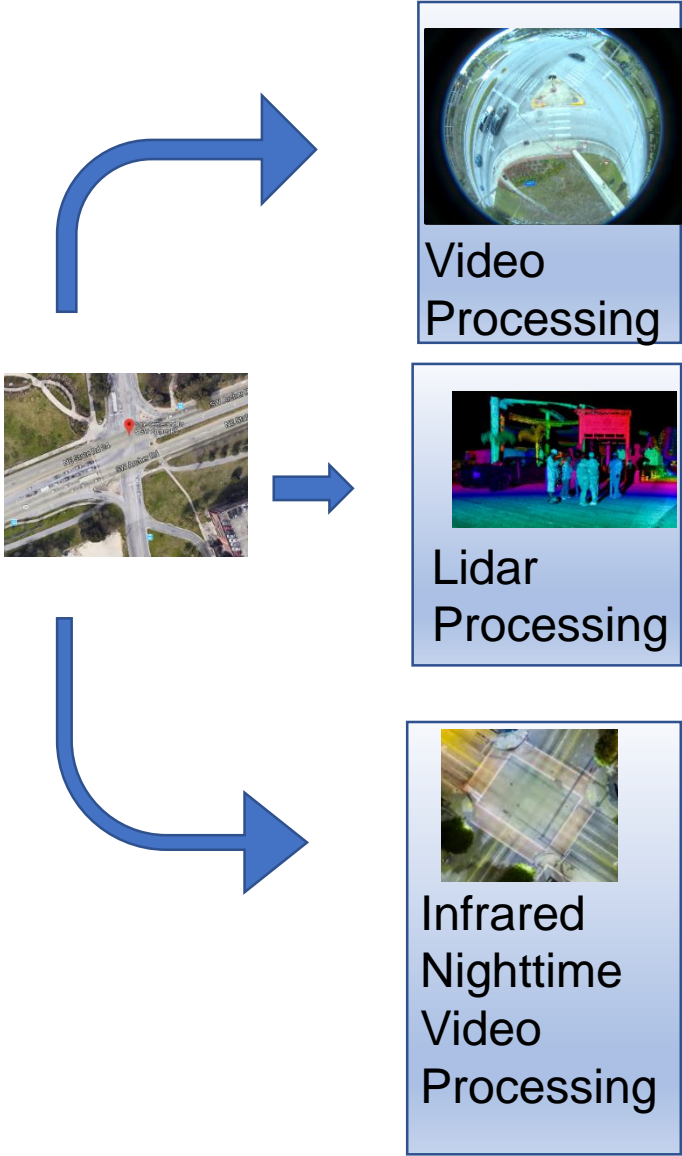
Behaviour

- 912, Road: SR434, ID: 1\_1
- 954, Road: SR436, ID: 1\_2
- 605, Road: US17-92, ID: 1\_0
- 957, Road: SR436, ID: 0\_2
- 326, Road: LakeWay, ID: 1\_1
- 923, Road: SR434, ID: 0\_1
- 313, Road: SandLkRd, ID: 1\_1
- 329, Road: SR46, ID: 0\_3
- 609, Road: US17-92, ID: 0\_0
- 375, Road: CR419, ID: 1\_6
- 84, Road: SR419, ID: 0\_5
- 138, Road: ELkMary, ID: 1\_9
- 385, Road: SR426, ID: 0\_6
- 91, Road: SanfordAve, ID: 0\_1
- 160, Road: RinehartRd, ID: 1\_1
- 70, Road: ELkMary, ID: 0\_11
- 82, Road: HowellBrRd, ID: 0\_1
- 90, Road: PalmSprings, ID: 0\_1
- 93, Road: LkEmma, ID: 0\_18
- 99, Road: InternationalPkw
- 118, Road: MontgomeryRd,

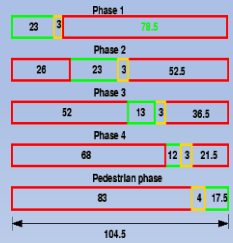
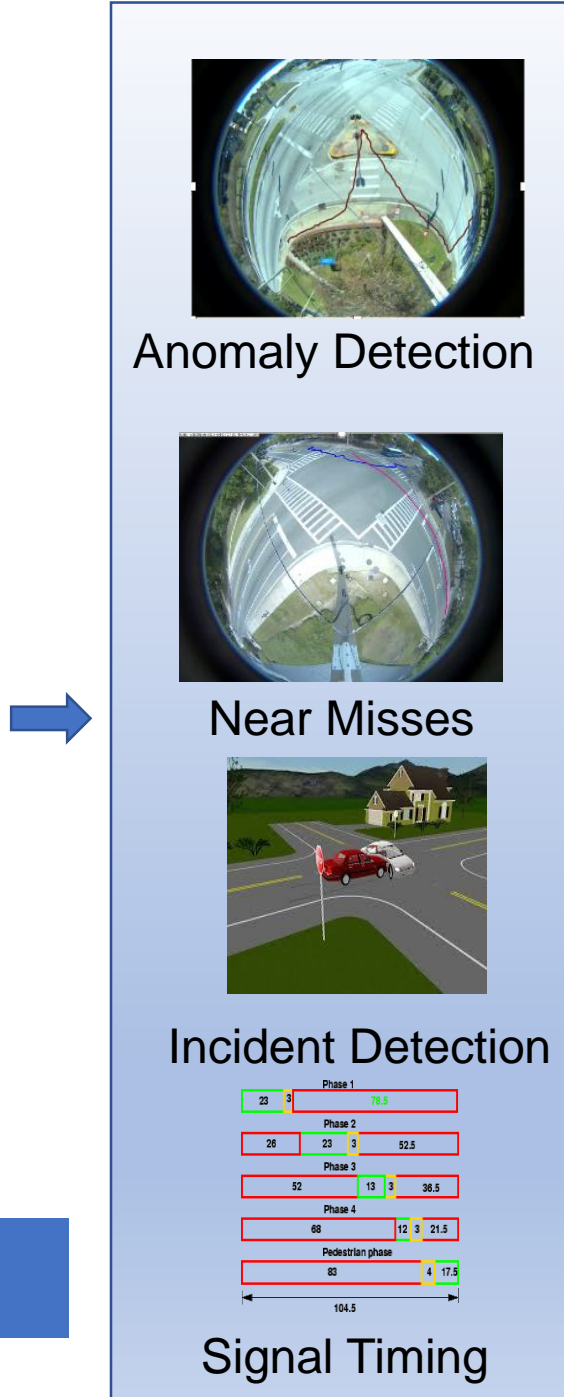
# Smart Intersections



Loop Controller Data



Funded by NSF and FDOT



Signal Timing

# Smart Streets: Artificial Intelligence based Real-time Incident Detection

## Challenge

- Detect Traffic Interruptions ASAP (ideally within 100 seconds)
- Simple Volume Based Approaches (e.g. 80% reduction in volume) create too many false alarms (e.g. 10 false alarms for every correct detection)

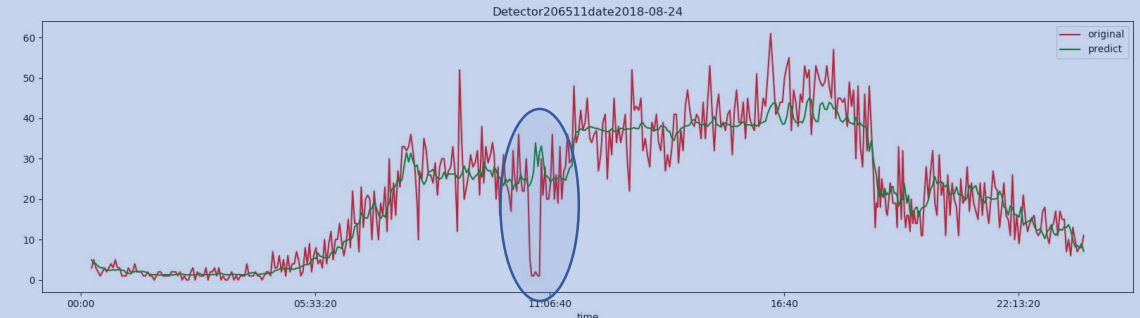
## Opportunity

- Newly installed loop detectors allow for arrivals/departures at a deci-second intervals, but generate 20 GB per day for 1000 signals
- Use Bigdata Artificial Intelligence and Machine Learning for detecting all traffic interruptions (80% reduction for 5+ minutes)

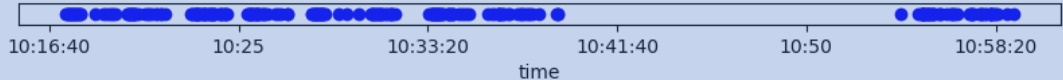
- AI based Solutions (Consensus of three experts)
  - Volume Reduction Expert: Predicts traffic volume using last 10 minutes and previous weeks data for the same time window to detect potential reduction
  - Gap Analysis Expert: Learns gap distribution from current and past history to and determine if current gap is abnormal
  - Platoon Analysis Expert: Learn platoon size distribution from recent history and determine if traffic after a small amount of gap is much smaller
- Tested on 90 day historical data collected from 150 “advance” detectors on 25 intersections
- Close to zero missed traffic interruptions
- Average Wait time 110 secs (2-3 false alarms for every 10 correct detections)

# Smart Streets: Artificial Intelligence based Real-time Incident Detection

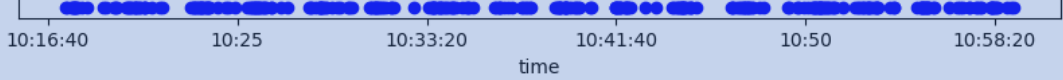
## Incident on Detector ID 206511 at 2018-08-24 10:38:37



2065 phase6 at 2018-08-24 10:38:37  
206511 before = 197 after = 54



206512 before = 146 after = 150

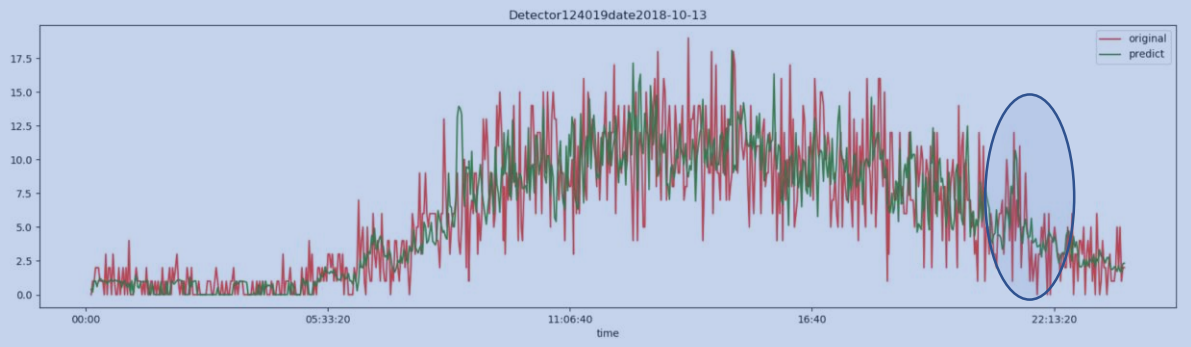


|     |          |              |                |       |            |          |             |          |                     |                    |           |           |   |  |
|-----|----------|--------------|----------------|-------|------------|----------|-------------|----------|---------------------|--------------------|-----------|-----------|---|--|
| 878 | 88613946 | 20182282382  | Casselberry PD | Long  | 08/16/2018 | 4:00 PM  | Casselberry | Seminole | KEWANEE TRL         | TALBOT RD          | 500 East  | Off Road  |   |  |
| 885 | 87707013 | 2018TA011560 | Lake Mary PD   | Long  | 08/28/2018 | 8:20 AM  | Lake Mary   | Seminole | INTERNATIONAL PKWY  | W LAKE MARY BLVD   | 81 North  | Sideswipe |   |  |
| 887 | 87707015 | 2018TA011602 | Lake Mary PD   | Short | 08/28/2018 | 4:10 PM  | Lake Mary   | Seminole | BROADMOOR AVE       | S COUNTRY CLUB RD  | 50 East   | Rear End  | 2 |  |
| 888 | 87707016 | 2018TA011615 | Lake Mary PD   | Short | 08/28/2018 | 5:50 PM  | Lake Mary   | Seminole | LAKE MARY BLVD W    | LONGWOOD LAKE MA   | 600 East  | Rear End  |   |  |
| 889 | 87707012 | 2018TA011521 | Lake Mary PD   | Short | 08/27/2018 | 11:05 AM | Lake Mary   | Seminole | LONGWOOD LAKE MAR W | LAKE MARY BLVD     | 29 South  | Rear End  |   |  |
| 890 | 87508440 | 2018TA011482 | Seminole Co SO | Short | 08/28/2018 | 10:40 AM | Lake Mary   | Seminole | INTERNATIONAL PKWY  |                    |           | Other     | 2 |  |
| 891 | 87707007 | 2018TA011410 | Lake Mary PD   | Long  | 08/24/2018 | 8:58 AM  | Lake Mary   | Seminole | W LAKE MARY BLVD    | N FOREST BLVD      | 501 East  | Left Turn |   |  |
| 892 | 87707007 | 2018TA011410 | Lake Mary PD   | Long  | 08/24/2018 | 10:39 AM | Lake Mary   | Seminole | I-4                 | W LAKE MARY BLVD F | 210 South | Off Road  |   |  |
| 893 | 82232118 | FHPD18OFF085 | FHP            | Short | 08/23/2018 | 5:30 PM  | Lake Mary   | Seminole | INTERSTATE 4 (STATE | FLAKE MARY BOULEVA | 5280 East | Off Road  | 1 |  |
| 894 | 87106401 | FHPD18OFF085 | FHP            | Short | 08/23/2018 | 5:30 PM  | Lake Mary   | Seminole | COUNTY ROAD 46A     | COLONIAL CENTER PI | 200 East  | Rear End  | 2 |  |
| 895 | 87707005 | 2018TA011383 | Lake Mary PD   | Short | 08/23/2018 | 5:12 PM  | Lake Mary   | Seminole | N US HIGHWAY 17/92  | WELDON BLVD        | 521 North | Left Turn | 2 |  |
| 896 | 87707003 | 2018TA011283 | Lake Mary PD   | Short | 08/22/2018 | 8:07 AM  | Lake Mary   | Seminole | LAKE MARY BLVD W    | LAKE EMMA          | 200 West  | Sideswipe | 2 |  |
| 897 | 87707009 | 2018TA011307 | Lake Mary PD   | Short | 08/22/2018 | 2:29 PM  | Lake Mary   | Seminole | W LAKE MARY BLVD    |                    | 0         | Other     | 2 |  |

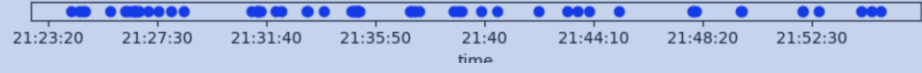
Police  
crash  
report

Note: Not all traffic interruptions are crashes or reported

Example of a case where volume dip happened but the gap/platoon analysis showed that there is no need for an alarm

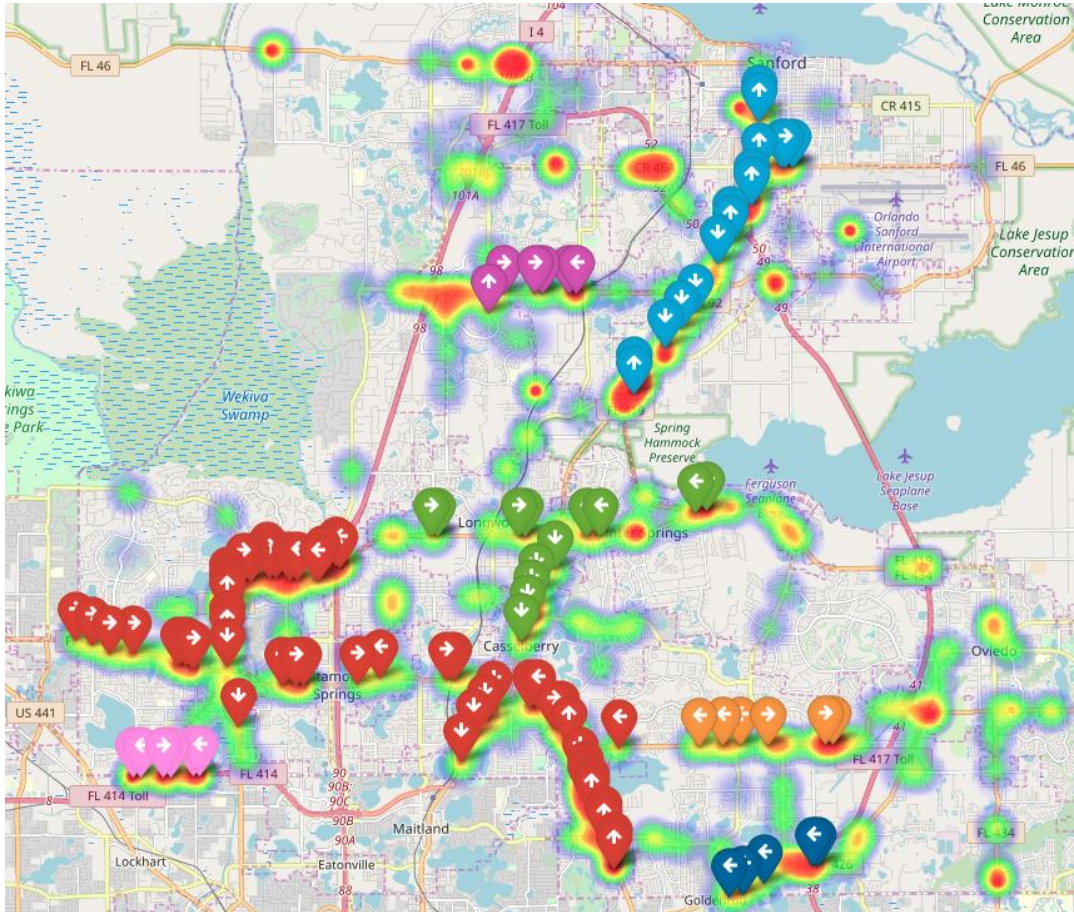


124019 before = 46 after = 17



Funded by FDOT

# Smart Network (of Arterials)



## Historical Analysis

- Day of the week and hour of day patterns of traffic

## Real-time Analysis

- Incidents
- Real-time information

## Machine Learning

- Corridor Optimization
- Network Optimization

Funded by FDOT

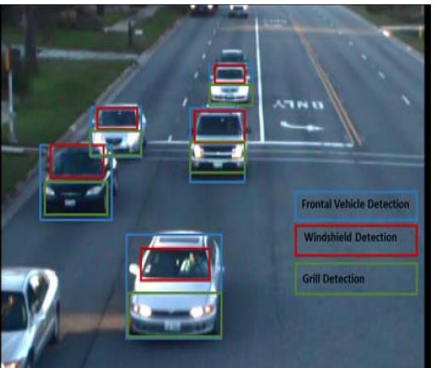
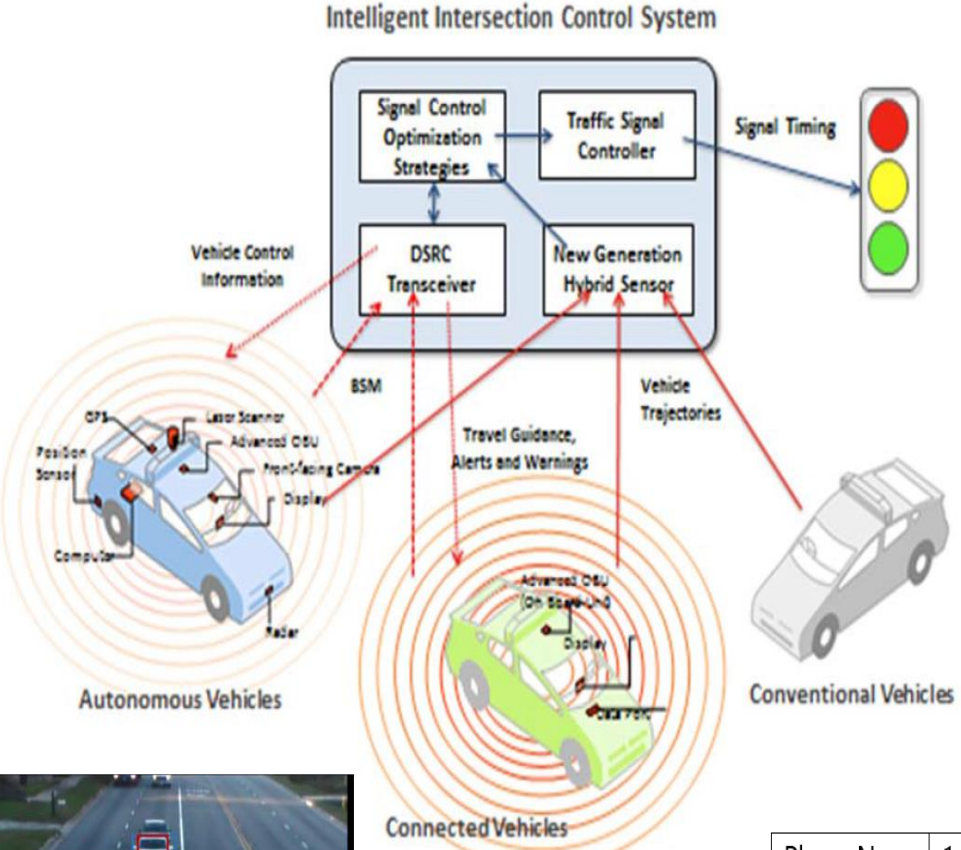
# Highway Vehicle Movement Tracking

- Detecting and tracking highway vehicles
- Vehicle speed computation
- Trajectories – O/D, Exit and Enter Locations





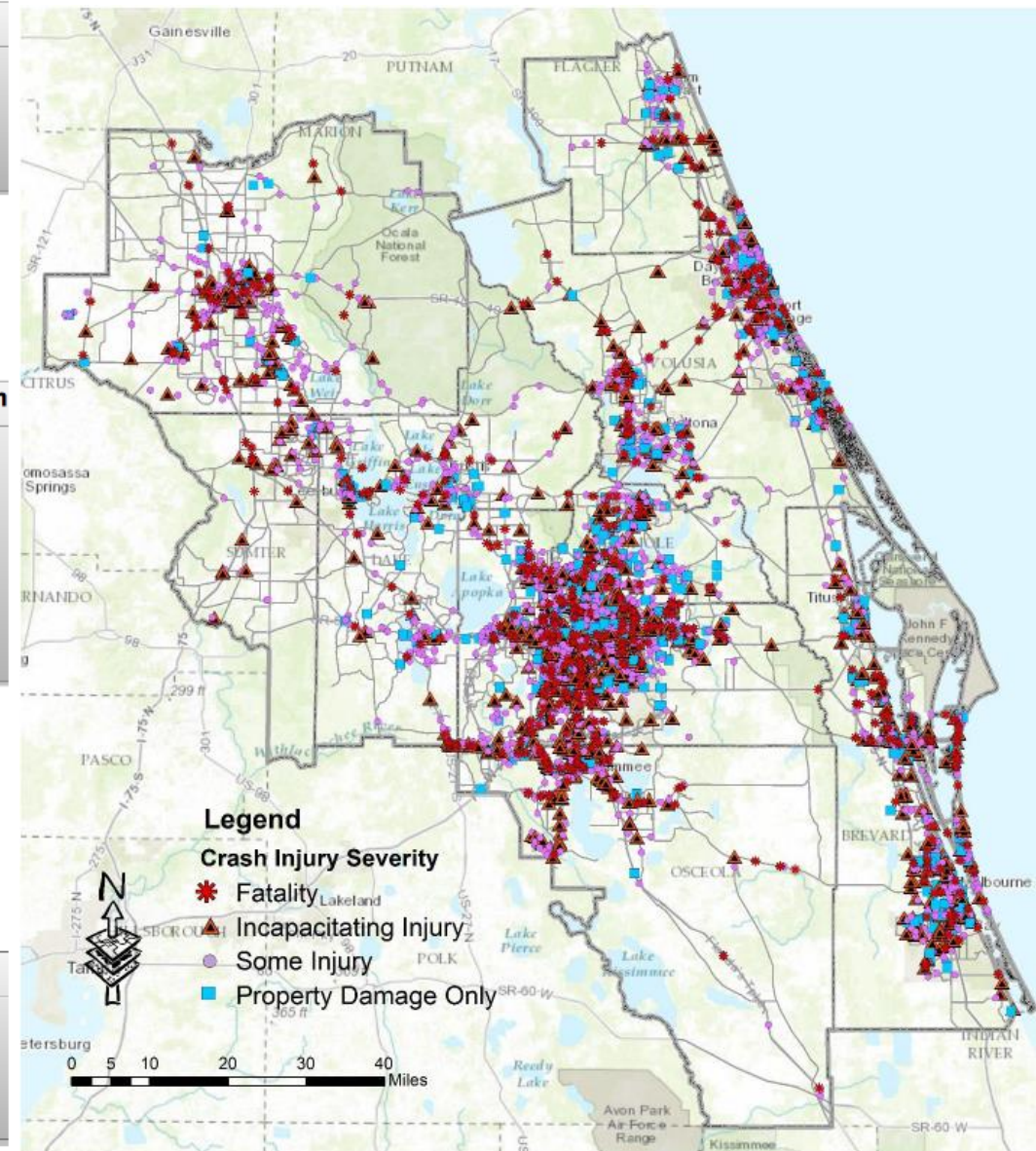
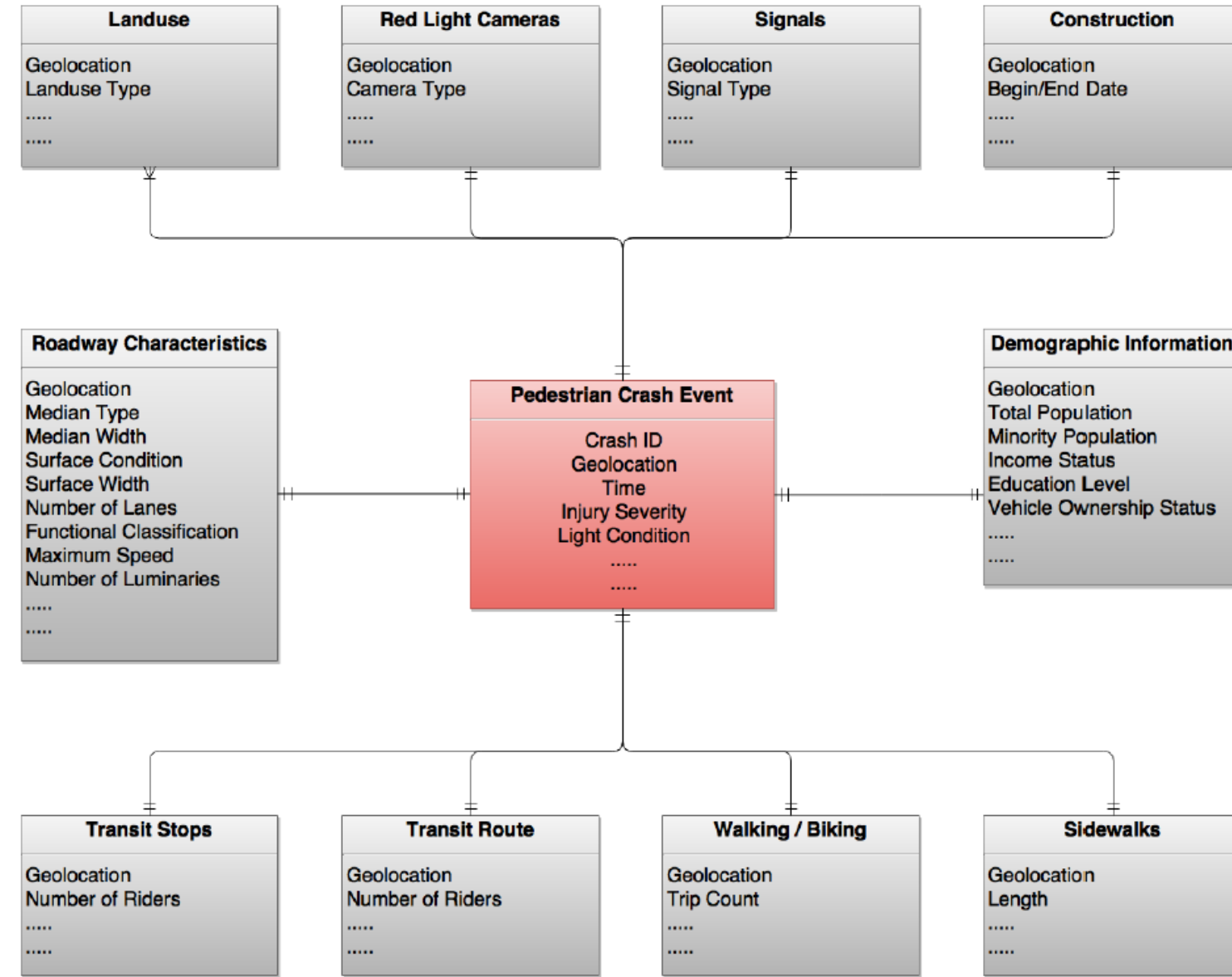
# AVIAN: Autonomous and Connected Vehicles Intersection Controller (NSF CPS + FHWA+FDOT)



Funded by NSF CPS

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

# Predicting and preventing fatal crashes (FDOT D5)



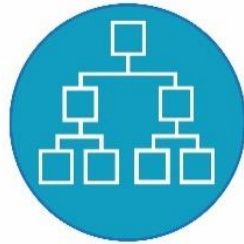
# Truck and Commodity Classification Using Machine Learning

WIM Dataset w/  
Truck Attributes & Commodity



WIM Data

+



Taxonomy

+



Commodity

+



Video





+























Machine Learning

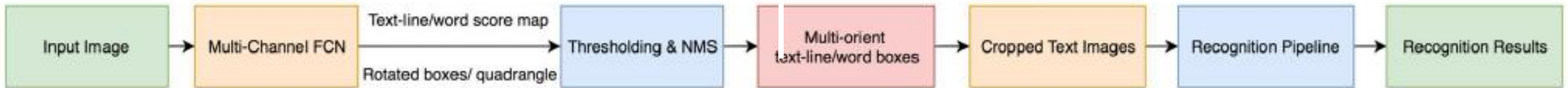
=



| Configuration   | Body type          | Typical commodities  | Typical industries  |
|---|--------------------|--|---|
| Five-axle tractor semitrailer, 3-S2<br> (59%)  | Vans/reefers (63%) | <ul style="list-style-type: none"> <li>Palletized cargo</li> <li>Refrigerated goods</li> </ul>   | <ul style="list-style-type: none"> <li>Retail</li> <li>Produce</li> </ul>             |
| Six-axle tractor semitrailer, 3-S3<br> (19%) | Flat decks (16%)   | <ul style="list-style-type: none"> <li>Equipment</li> <li>Building supplies</li> </ul>           | <ul style="list-style-type: none"> <li>Construction</li> <li>Manufacturing</li> </ul> |
| Nine-axle turnpike double, 3-S2-4<br> (8%)   | Hoppers (6%)       | <ul style="list-style-type: none"> <li>Grain</li> <li>Granular fertilizer</li> </ul>             | <ul style="list-style-type: none"> <li>Agriculture</li> </ul>                         |
| Eight-axle B-train double, 3-S3-S2<br> (7%)  | Tankers (4%)       | <ul style="list-style-type: none"> <li>Petroleum products</li> <li>Chemicals</li> </ul>          | <ul style="list-style-type: none"> <li>Petroleum</li> <li>Chemical</li> </ul>         |
|   | Dumps (6%)         | <ul style="list-style-type: none"> <li>Aggregate</li> <li>Grain</li> <li>Refuse</li> </ul>       | <ul style="list-style-type: none"> <li>Construction</li> <li>Agriculture</li> </ul>   |
|   | Containers (2%)    | <ul style="list-style-type: none"> <li>Palletized cargo</li> <li>Freight of all kinds</li> </ul> | <ul style="list-style-type: none"> <li>Retail</li> </ul>                              |

| FHWA Vehicle Classifications  |   |   |   |
|---|---|---|---|
| <b>1. Motorcycles</b><br>2 axles, 2 or 3 tires<br>   | <b>2. Passenger Cars</b><br>2 axles, can have 1- or 2-axle trailers<br>                  | <b>3. Pickups, Panels, Vans</b><br>2 axles, 4-tire single units<br>Can have 1 or 2 axle trailers<br> | <b>4. Buses</b><br>2 or 3 axles, full length<br>                                 |
| <b>5. Single Unit 2-Axle Trucks</b><br>2 axles, 6 tires (dual rear tires), single-unit<br> | <b>6. Single Unit 3-Axle Trucks</b><br>3 axles, single unit<br>                          | <b>7. Single Unit 4 or More-Axle Trucks</b><br>4 or more axles, single unit<br>                      | <b>8. Single Trailer 3- or 4-Axle Trucks</b><br>3 or 4 axles, single trailer<br> |
| <b>9. Single Trailer 5-Axle Trucks</b><br>5 axles, single trailer<br>                    | <b>10. Single Trailer 6 or More-Axle Trucks</b><br>6 or more axles, single trailer<br> |    |    |
| <b>11. Multi-Trailer 5 or Less-Axle Trucks</b><br>5 or less axles, multiple trailers<br> |    | <b>12. Multi-Trailer 6-Axle Trucks</b><br>6 axles, multiple trailers<br>                           |    |
| <b>13. Multi-Trailer 7 or More-Axle Trucks</b><br>7 or more axles, multiple trailers<br> |    |    |    |

# Logo Recognition – Text Detection



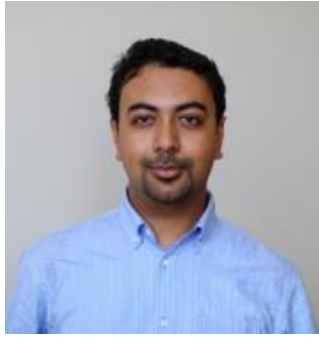
The developed algorithms can achieve a high recall (80+ %) with a competitive recognition accuracy.

Funded by FDOT

# Conclusions

- Our current transportation related projects are leveraging novel physical and cyber infrastructure
  - Autonomous and connected vehicle deployment
  - Advanced sensors and cameras through smart intersection
  - Intelligent data stores, cloud computing and artificial intelligence
- With the following objectives
  - Manage traffic congestion and improve safety by using big data and related technologies
  - Use data driven approaches for decision making, planning, evaluation and measurement
  - Support efficient tracking and movement of goods, services and people
- While Working with a number of key stakeholders from city, county and state

# UFL Team: Artificial Intelligence and Machine Learning for Transportation



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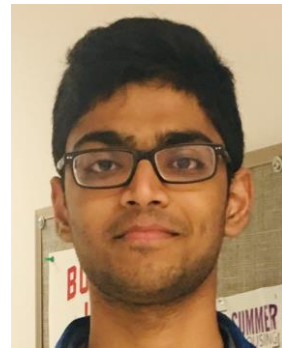
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Cloud Computing

GPU Computing

Computer Vision

Machine Learning

Transportation Applications

Large-Scale Software Development

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