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FREIGHT MODELING RESEARCH

Need for more freight trucking data in SC

Freight trucking impacts:

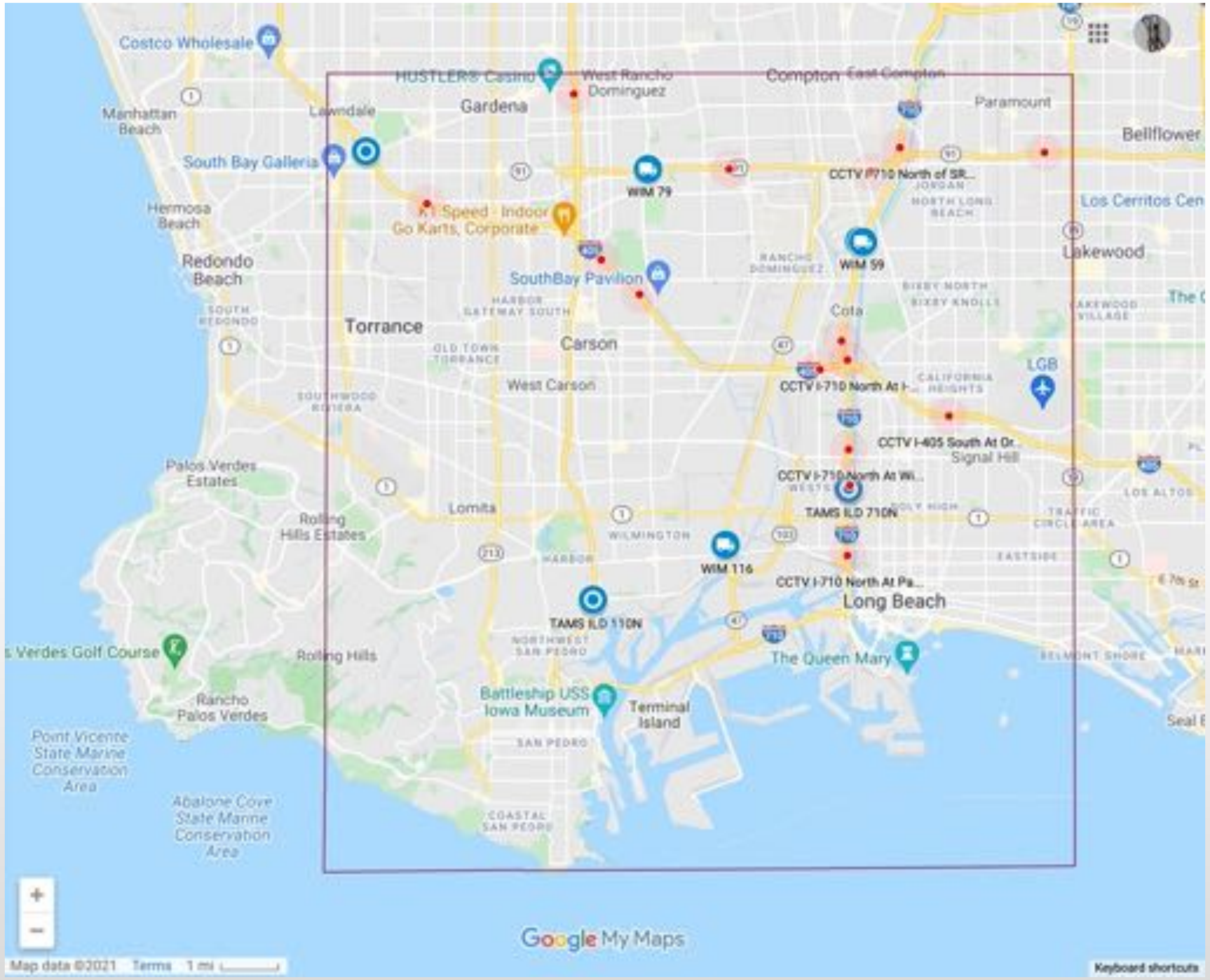
- **Infrastructure:** maintaining roadways, adding charging stations, …
- **Traffic:** planning to limit traffic and accidents that may cause, understand the economic impact, …
- **Health:** understand the health impacts, transition to less polluting technologies, …

Very limited freight data for SC

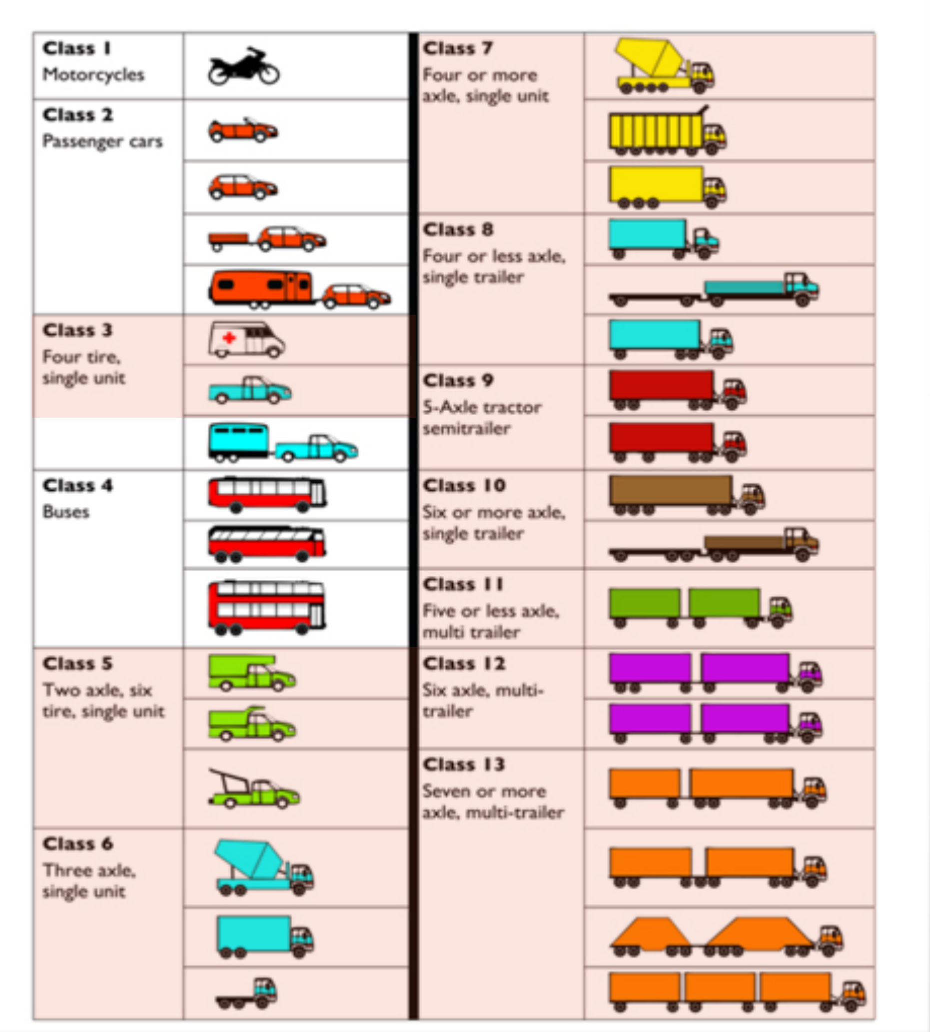
- Little information on trucks **origin** and **destination (OD-matrix)**
- Existing data is indirectly sourced **from surveys** at ports, warehouses, rail stations… leads to **low temporal and spatial resolution** OD-matrix

Current OD-matrix estimates at a time resolution not always compatible with what is needed for urban planning and assessing truck impact on traffic and AQ

Region of Study

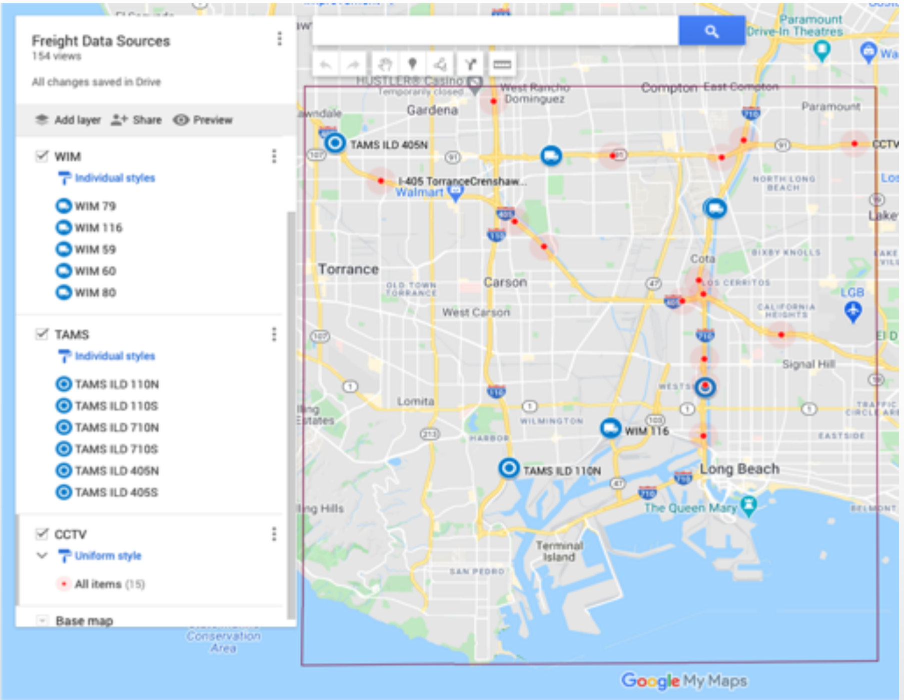


What vehicles to consider



Federal Highway Administration Vehicle Classification

Sources of truck information currently available



Precise but sparse truck sensors:

WIM (5), TAMS (6), RFID,

Caltrans vehicle counting

Sensors used for other applications:

CCTV (15) (monitoring)

ILD (traffic, e.g., ADMS)

Freight Modeling From Sensor Data

Goal: provide high temporal and spatial resolution truck information

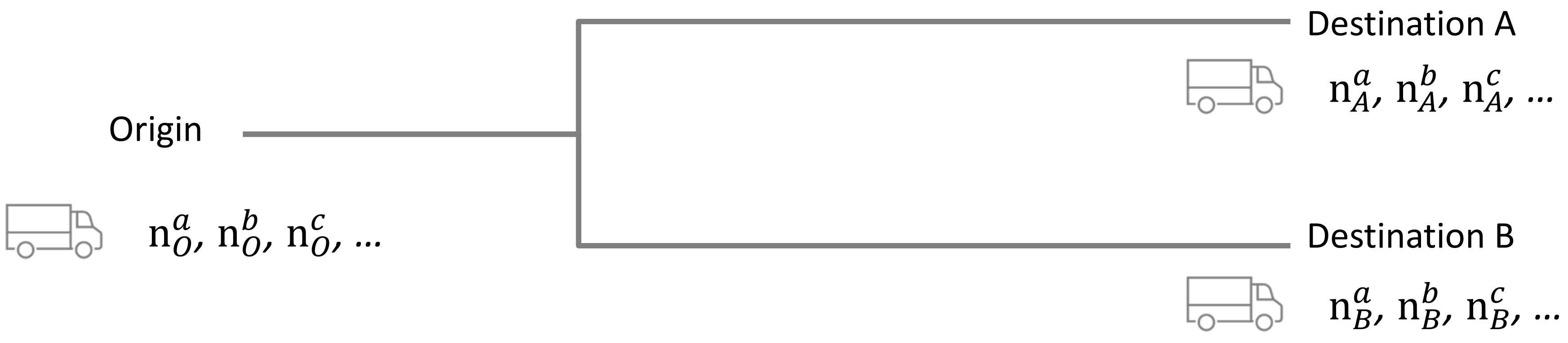
- OD-matrix
- Link-level volume

Approach: integrate truck sensors observations

Some questions we want to answer:

- How to estimate OD-Matrix from sensor observations?
- How accurate can we model flow? For example, how many sensors and what sensor layout is needed to obtain useful estimates?
- Can we use CCTV cameras? For example, can we utilize Caltrans' CCTV monitoring cameras to classify & count trucks?

OD-matrix from surveys



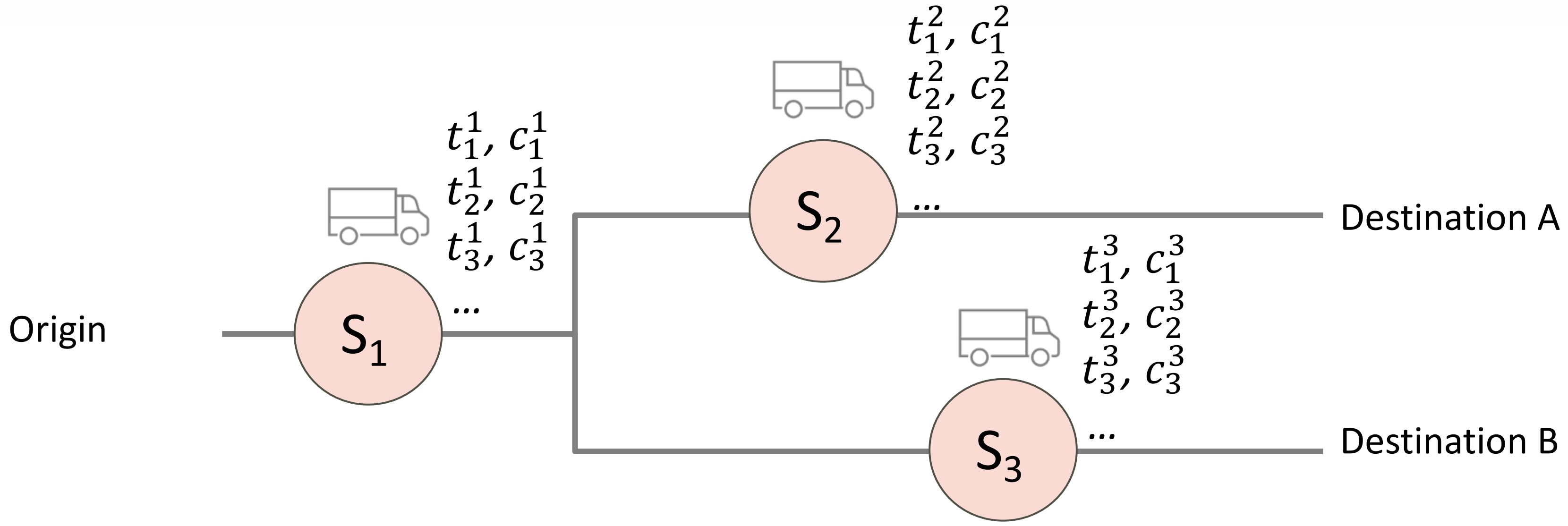
n_i^j: *count of trucks for class* $(a, b, c, \ldots)$ *over a period of time*

$i = O$ *at Origin*

$i = A$ *at Destination A*

$i = B$ *at Destination B*

OD-matrix from sensors observations

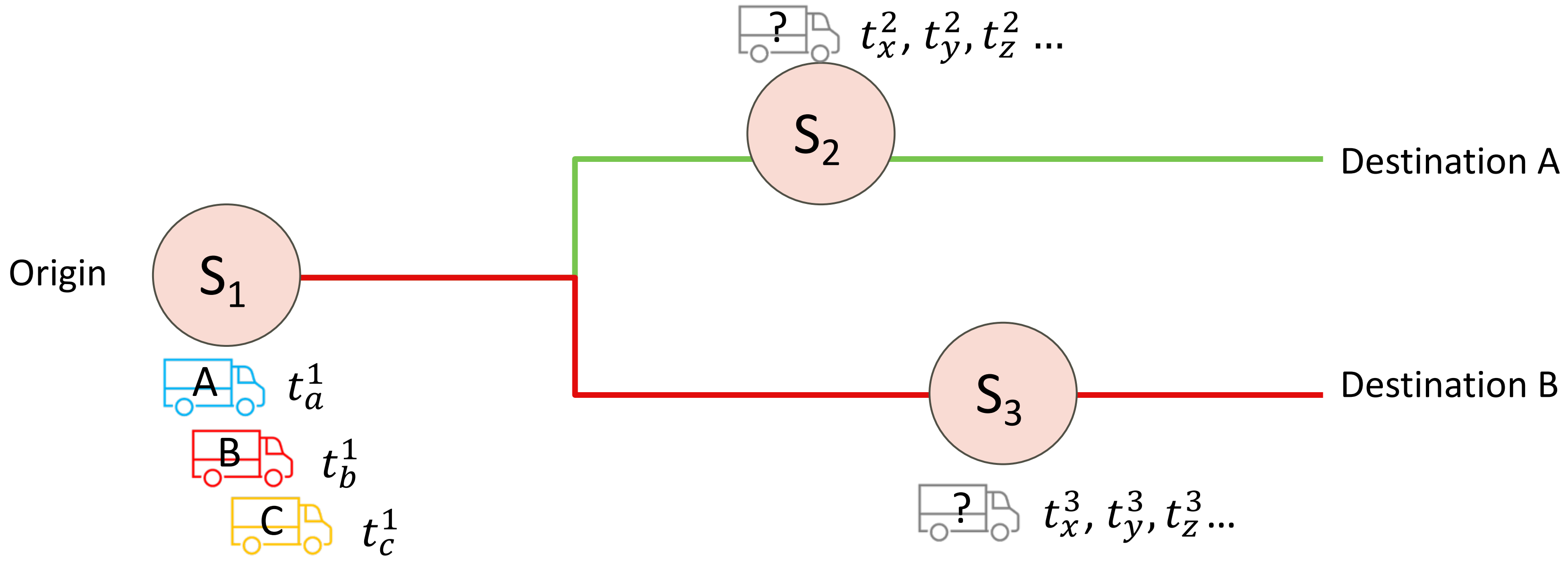


$t_i^j, c_i^j: truck\ observation\ i\ at\ sensor\ j$

$t: time\ of\ observation$

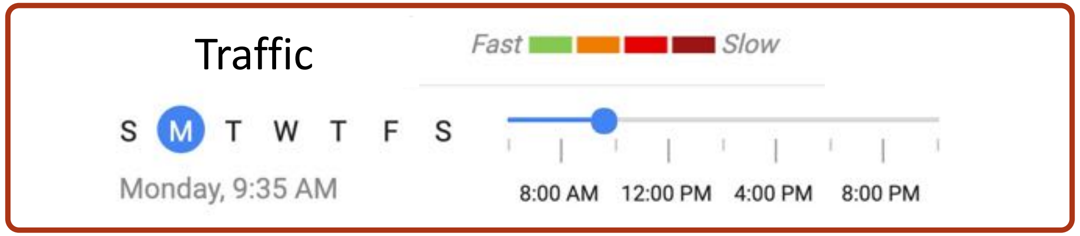
$c: truck\ class\ of\ observation$

Approach: reconcile observations across sensors based on estimated travel times

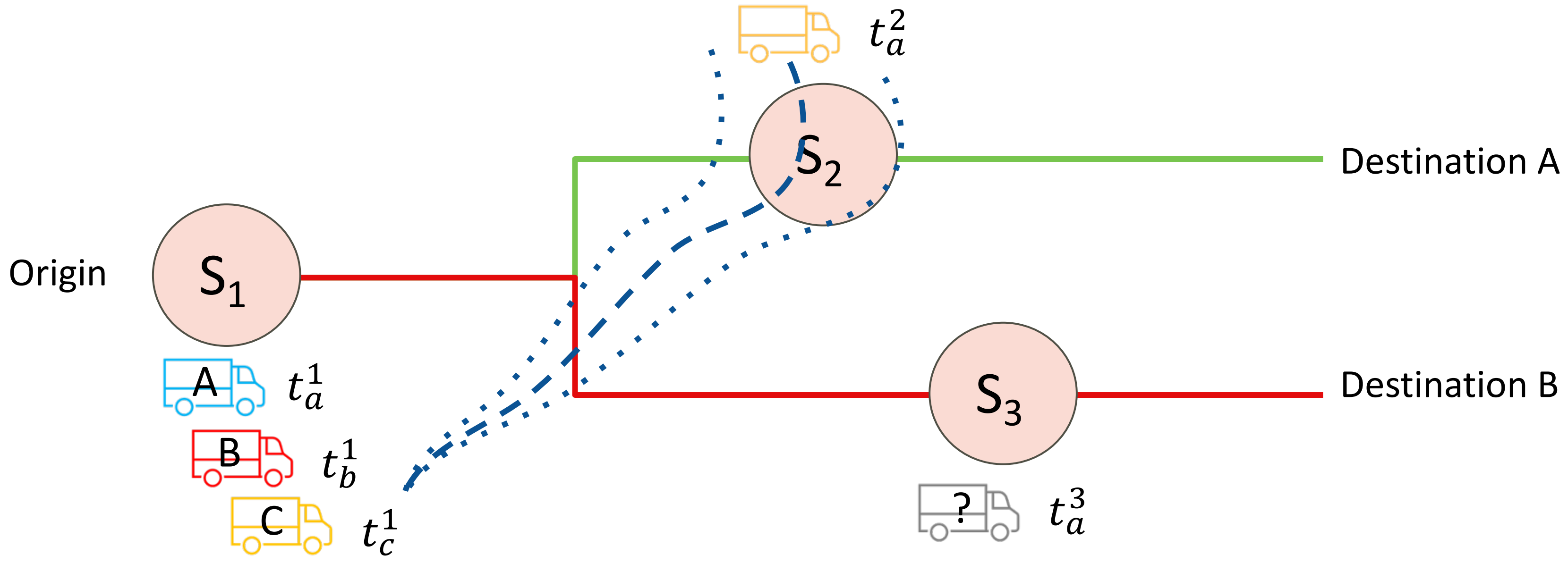


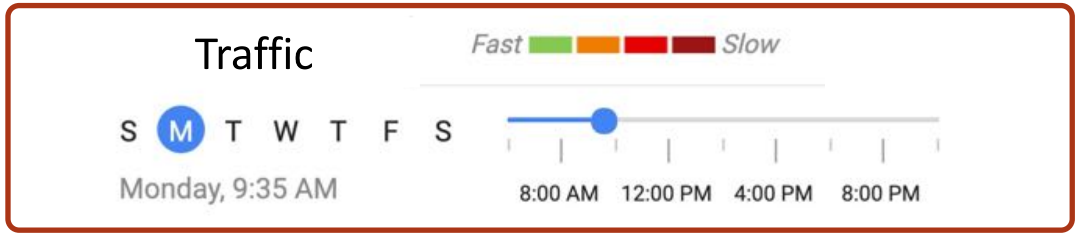
t_i^j : *truck i time at sensor j*

Travel times on links estimated from traffic sensors



Taking into account sensor data uncertainty for truck class, travel time and missing data





Approaches we have developed

Baseline:

- Estimates flow only at road segments where data is sensed

Rule Flow:

- Extends estimation to adjacent edges as long as there is no road fork

Reach Flow:

- Finds compatible observations between sensors and imputes the flow on the edges of the shortest path between the sensors.
- *Observations are compatible if <u>travel time</u> is [approximately] equal to their timestamp difference and detected truck type is the same*

Validation of Freight Modeling

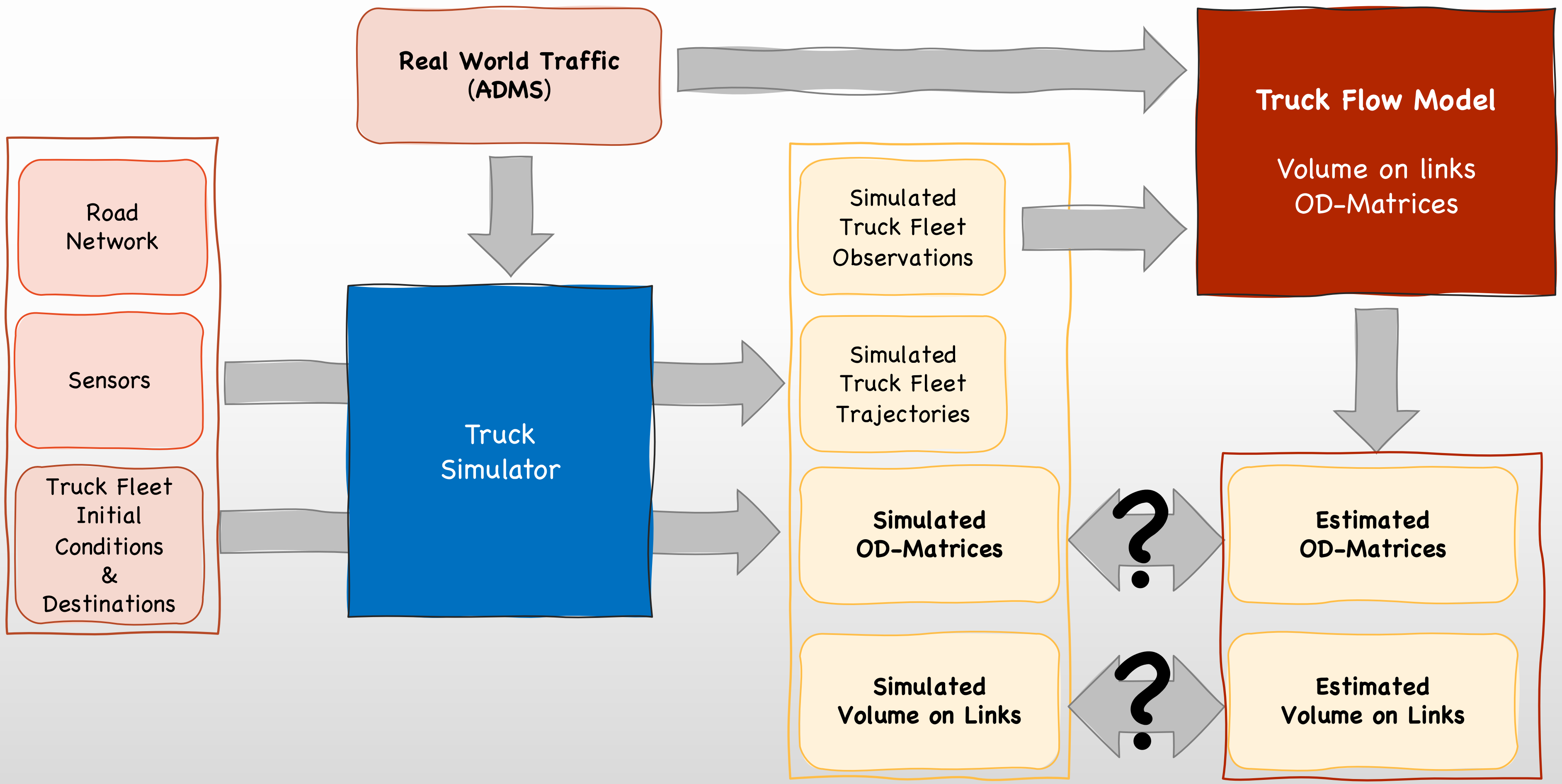
Challenges:

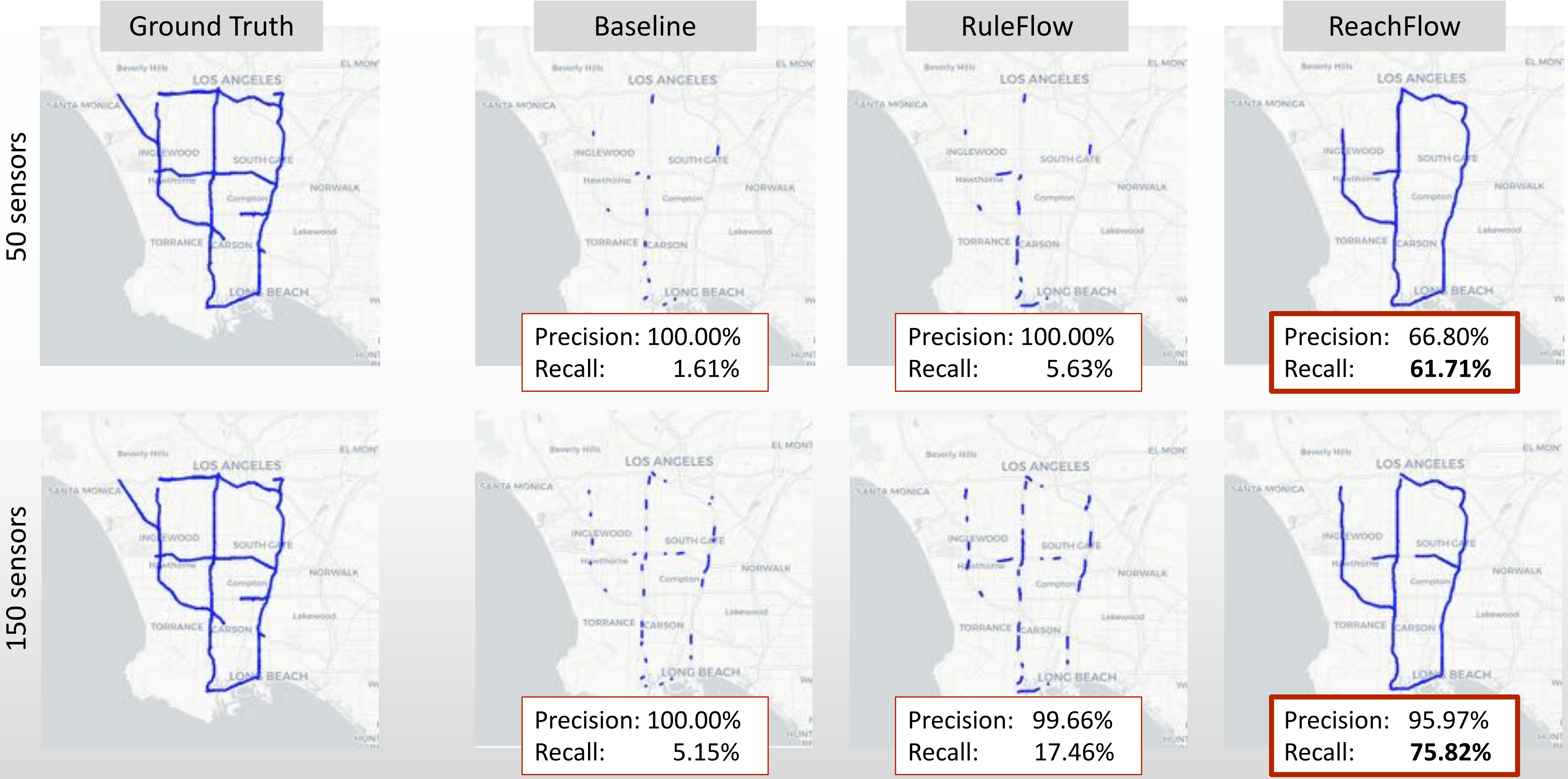
- No data was available last year with COVID-19 pandemic
- Lack of ground truth data (truck counts) for validation

Therefore:

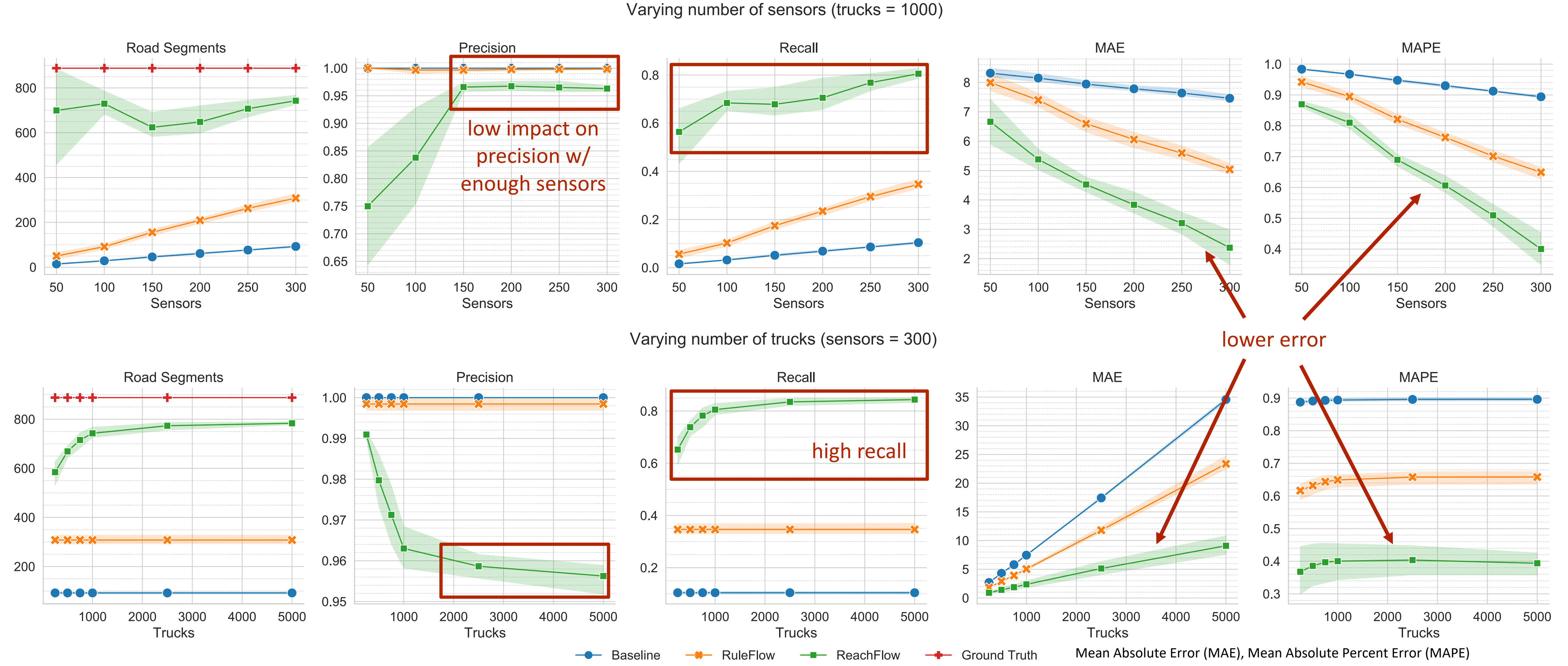
- We built a truck simulator that uses historical traffic to simulate trajectories under different conditions
- Scraped Caltrans CCTV footage from off available webcams

Truck Simulator applied to Flow Modeling Validation



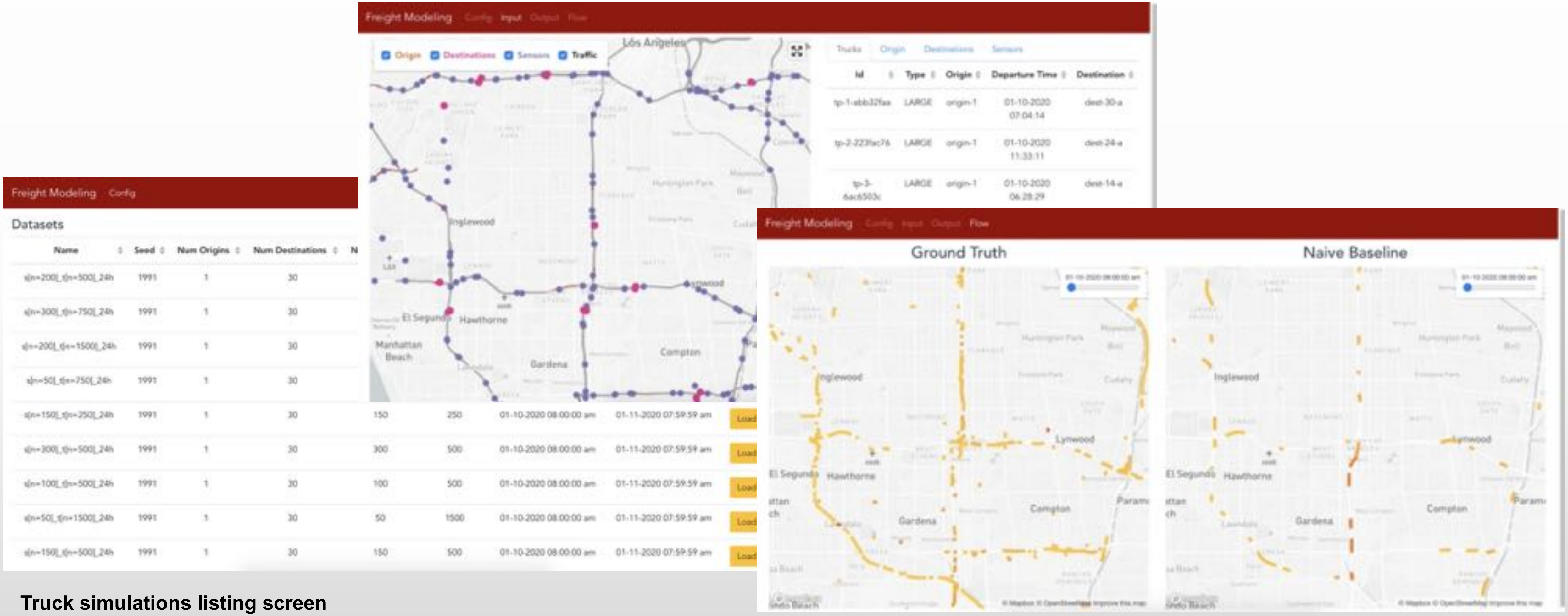

Ground Truth
Baseline
RuleFlow
ReachFlow
50 sensors
Precision: 100.00%
Recall: 1.61%
Precision: 100.00%
Recall: 5.63%
Precision: 66.80%
Recall: **61.71%**
150 sensors
Precision: 100.00%
Recall: 5.15%
Precision: 99.66%
Recall: 17.46%
Precision: 95.97%
Recall: **75.82%**

Truck Flow Modeling Results



Simulator dashboard

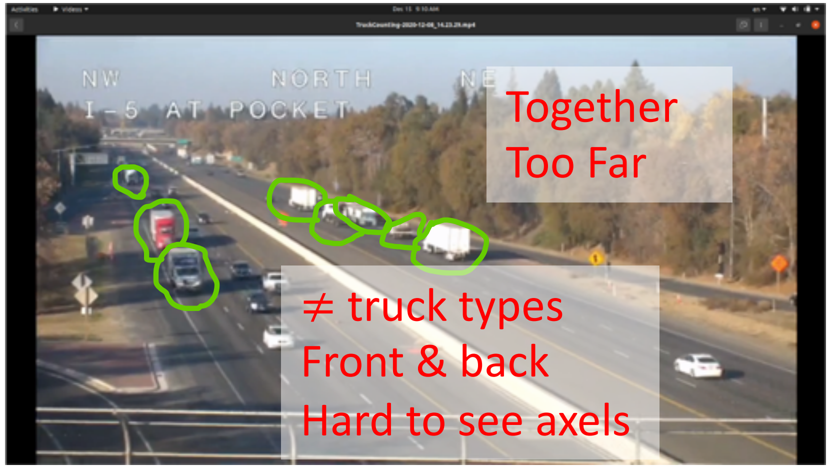
Truck simulation main screen

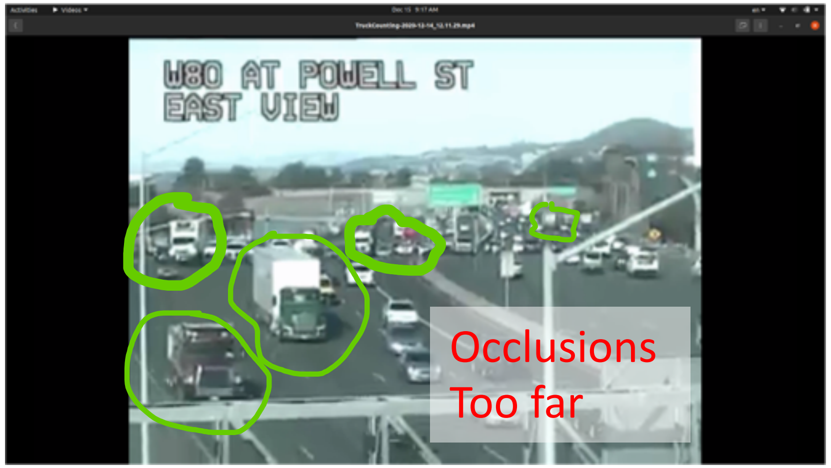


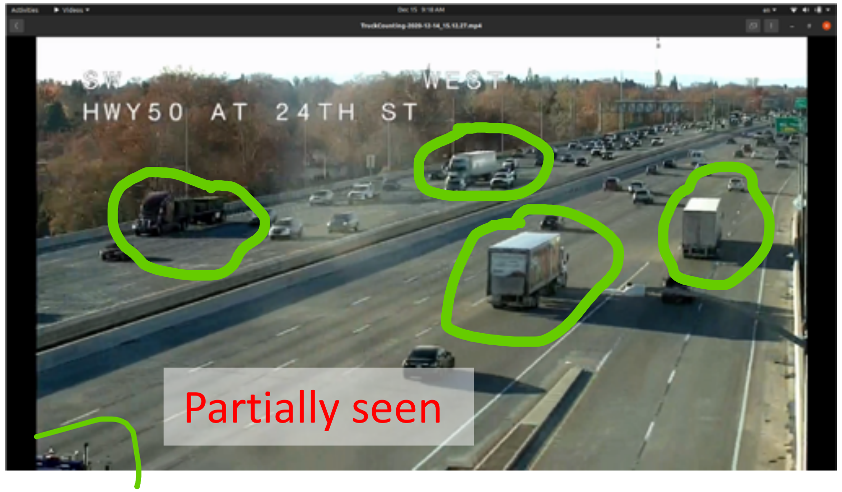
Truck simulations listing screen

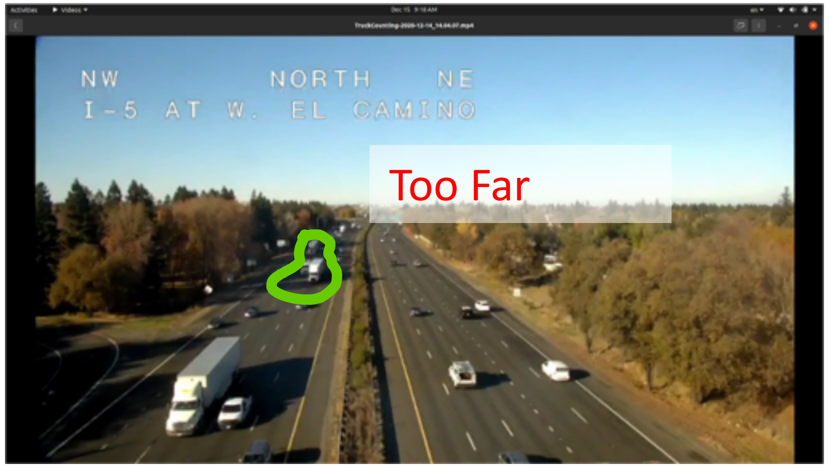
Freight volume results comparison screen

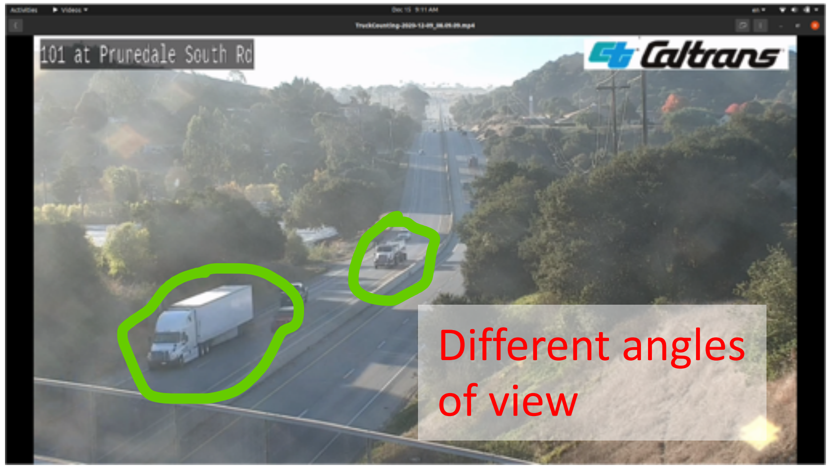
Caltrans Web Cams



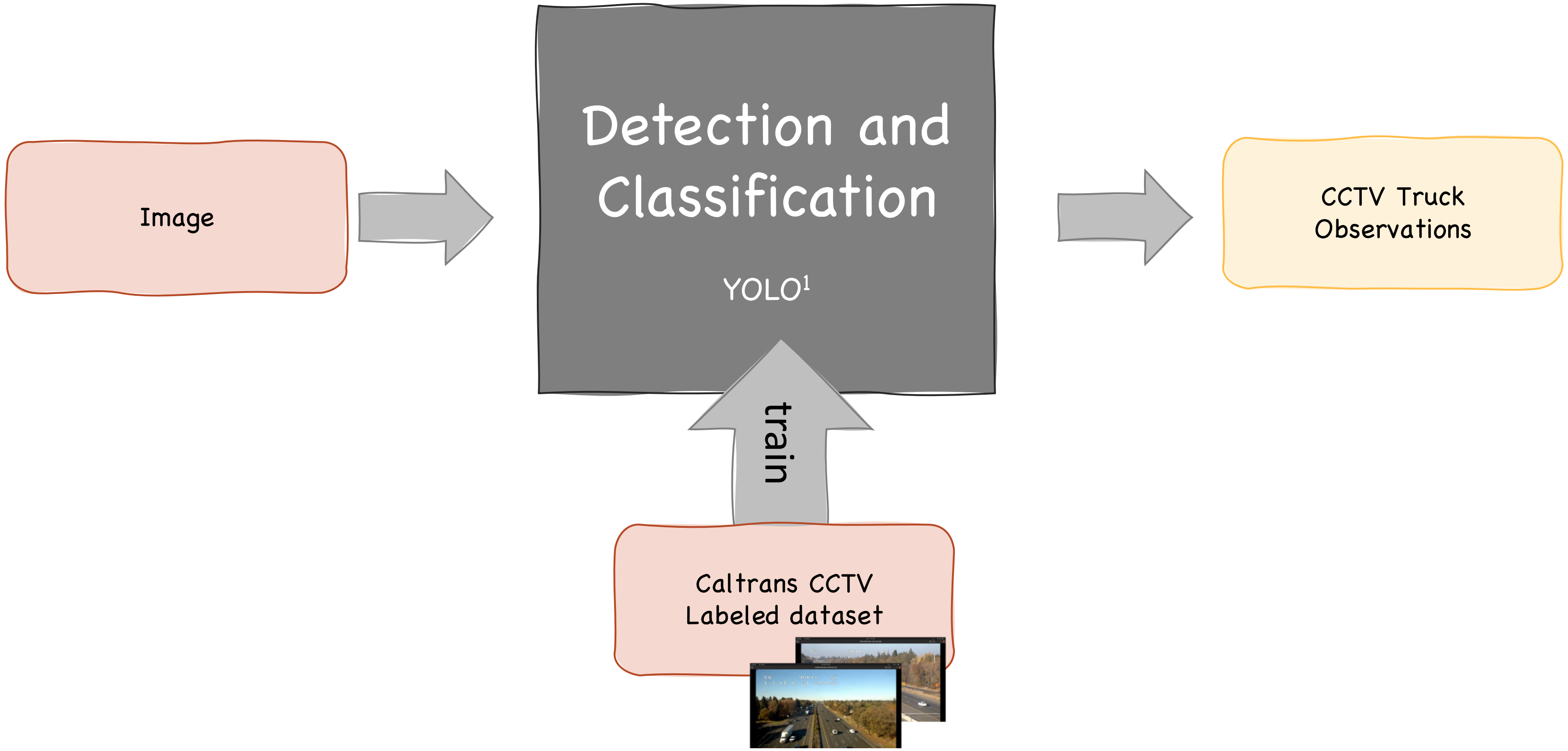








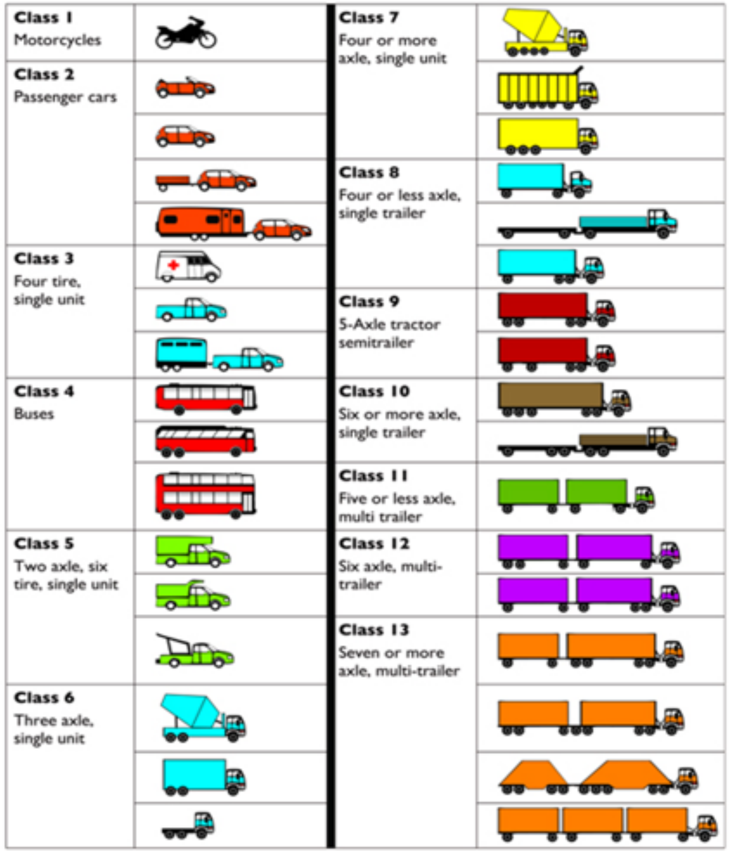
CCTV Detection and Classification on Single Frames



[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” ArXiv150602640 Cs, May 2016, Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1506.02640.

What Truck classes to consider?

Axle-based US DOT vehicle classes

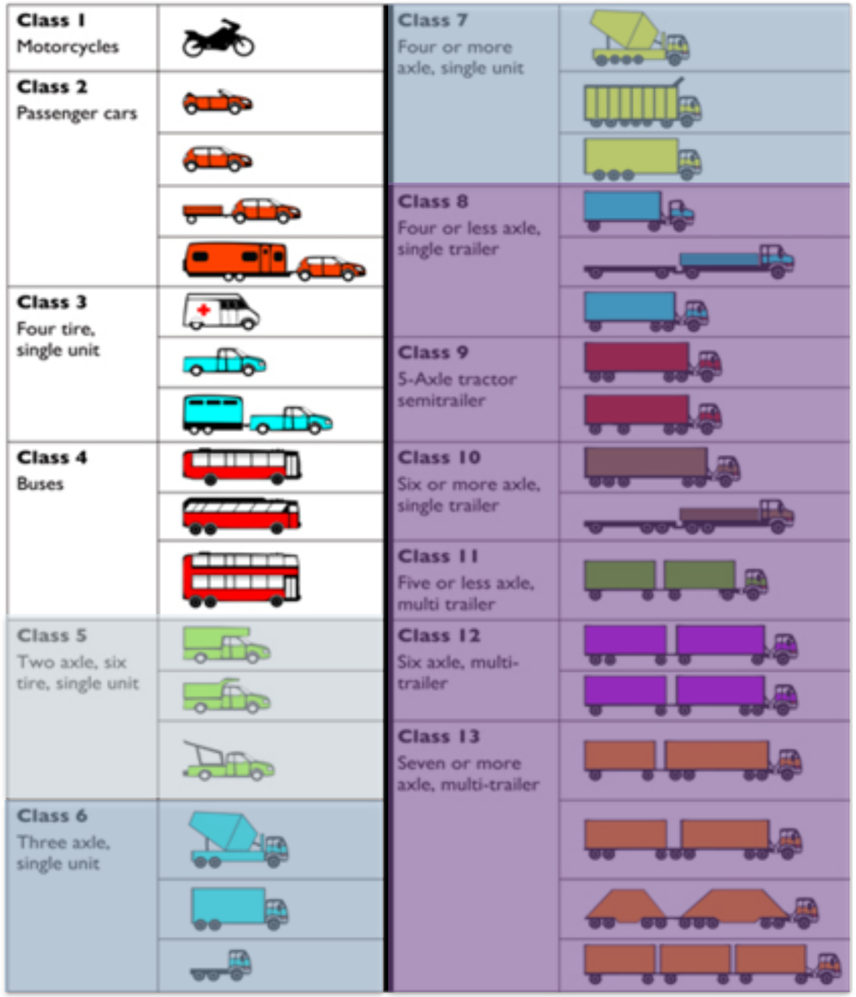


Existing image datasets vehicle classes

MIO-TCD [1]
dataset

1. https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_2013/vehicle-types.cfm
2. Z. Luo *et al.*, "MIO-TCD: A New Benchmark Dataset for Vehicle Classification and Localization," *IEEE Trans. Image Process.*, Oct. 2018.

Three Tiers, Size-based Classes

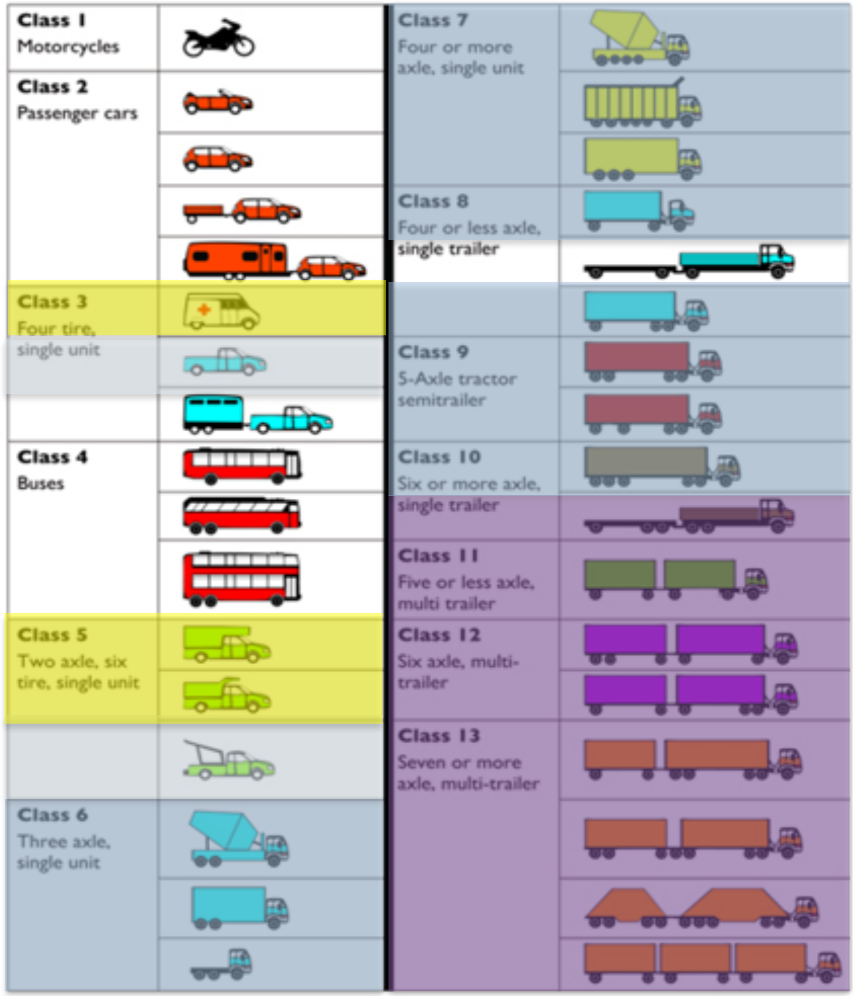


Small (Light-weight)
DoT Class 5

Medium (Heavy-duty non articulated)
DoT Class 6-7

Heavy (Heavy-duty articulated)
DoT Class 8-13

Optimized Classes for Truck Classification



Van
DoT Class 3, 5

Pickup
DoT Class 3, 5

Single Unit
DoT Class 6-10

Heavy-duty Articulated
DoT Class 8-13

Dataset v2

Classes: lightweight single_unit_truck articulated_truck

Dataset v3

Classes : pickup single_unit_truck articulated_truck

Dataset v4

Classes annotations: pickup_rear articulated_truck_front articulated_truck_rear

Figure 2. Dataset v-2 performance results

Classification Results

Dataset v-2 performance results

```
confidence_threshold = 0.25
 - articulated_truck, AP = 86.02%   (TP = 84, FP = 21)
 - single_unit_truck, AP = 84.20%   (TP = 76, FP = 33)
 - lightweight,       AP = 63.00%   (TP = 56, FP = 44)

Precision = 0.69 / Recall = 0.77 / F1-score = 0.73
TP = 216, FP = 98, FN = 65, Average IoU = 55.63 %

confidence_threshold = 0.50
 - articulated_truck, AP = 86.02%   (TP = 75, FP = 11)
 - single_unit_truck, AP = 84.20%   (TP = 74, FP = 18)
 - lightweight,       AP = 63.00%   (TP = 51, FP = 22)

Precision = 0.80 / Recall = 0.71 / F1-score = 0.75
TP = 200, FP = 51, FN = 81, Average IoU = 64.57 %
```

```
mAP@0.50 = 0.777391, or 77.74 %
mAP@0.60 = 0.731565, or 73.16 %
mAP@0.70 = 0.625322, or 62.53 %
mAP@0.80 = 0.357104, or 35.71 %
mAP@0.90 = 0.025788, or  2.58 %
```

Dataset v-3 performance results

```
confidence_threshold = 0.25
 - articulated_truck, AP = 86.13%   (TP = 88, FP = 27)
 - single_unit_truck, AP = 84.87%   (TP = 76, FP = 31)
 - van,               AP = 49.90%   (TP = 13, FP =  8)
 - pickup,            AP = 76.33%   (TP = 46, FP = 30)

Precision = 0.70 / Recall = 0.79 / F1-score = 0.74
TP = 223, FP = 96, FN = 58, average IoU = 56.40 %

confidence_threshold = 0.50
 - articulated_truck, AP = 86.13%   (TP = 83, FP = 18)
 - single_unit_truck, AP = 84.87%   (TP = 72, FP = 22)
 - van,               AP = 49.90%   (TP = 12, FP =  6)
 - pickup,            AP = 76.33%   (TP = 41, FP = 16)

Precision = 0.77 / Recall = 0.74 / F1-score = 0.75
TP = 208, FP = 62, FN = 73, average IoU = 62.45 %
```

```
mAP@0.50 = 0.743076, or 74.31 %
mAP@0.60 = 0.705901, or 70.59 %
mAP@0.70 = 0.614002, or 61.40 %
mAP@0.80 = 0.352933, or 35.29 %
mAP@0.90 = 0.035619, or  3.56 %
```

Figure 2. Dataset v-2 performance results

Classification Results

Dataset v-3 performance results

```
confidence_threshold = 0.25
 - articulated_truck, AP = 86.13%   (TP = 88, FP = 27)
 - single_unit_truck, AP = 84.87%   (TP = 76, FP = 31)
 - van,               AP = 49.90%   (TP = 13, FP =  8)
 - pickup,            AP = 76.33%   (TP = 46, FP = 30)

Precision = 0.70 / Recall = 0.79 / F1-score = 0.74
TP = 223, FP = 96, FN = 58, average IoU = 56.40 %


confidence_threshold = 0.50
 - articulated_truck, AP = 86.13%   (TP = 83, FP = 18)
 - single_unit_truck, AP = 84.87%   (TP = 72, FP = 22)
 - van,               AP = 49.90%   (TP = 12, FP =  6)
 - pickup,            AP = 76.33%   (TP = 41, FP = 16)

Precision = 0.77 / Recall = 0.74 / F1-score = 0.75
TP = 208, FP = 62, FN = 73, average IoU = 62.45 %
```

```
mAP@0.50 = 0.743076, or 74.31 %
mAP@0.60 = 0.705901, or 70.59 %
mAP@0.70 = 0.614002, or 61.40 %
mAP@0.80 = 0.352933, or 35.29 %
mAP@0.90 = 0.035619, or  3.56 %
```

Dataset v-4 performance results

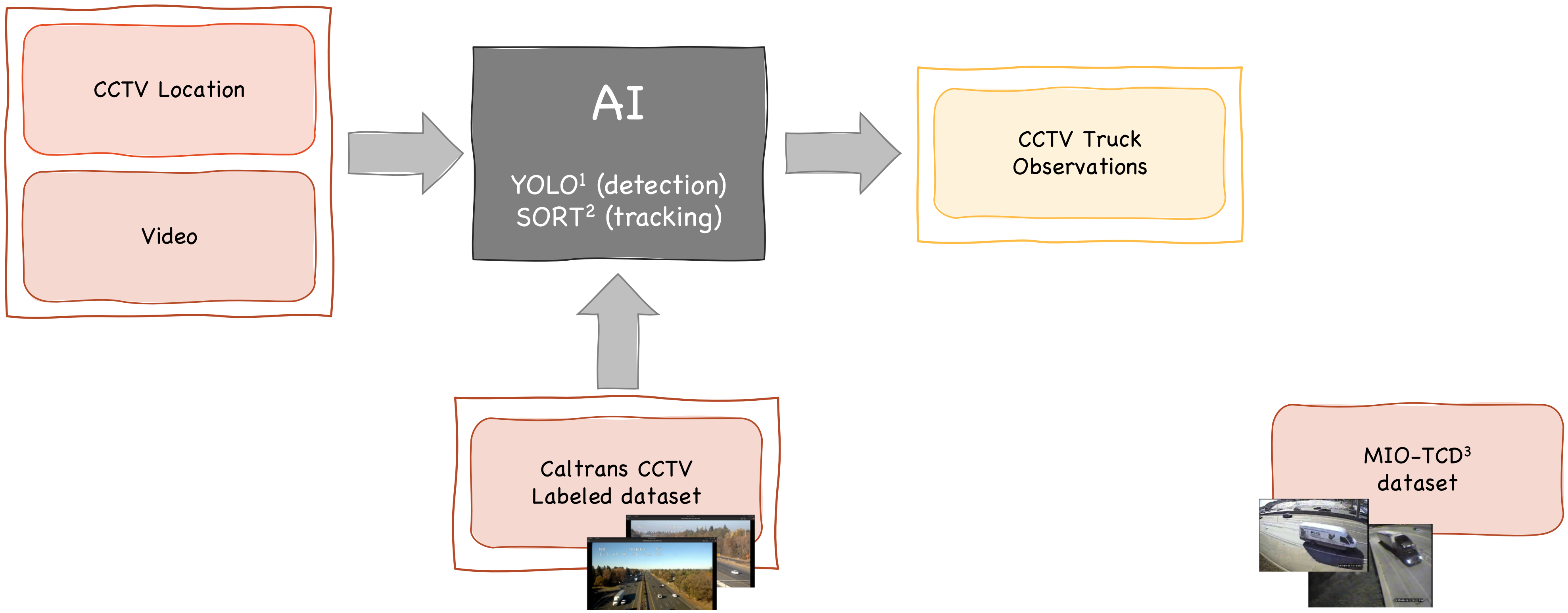
```
confidence_threshold = 0.25
 - articulated_truck_front, AP = 90.93% (TP = 61, FP = 23)
 - articulated_truck_rear,  AP = 84.24% (TP = 29, FP = 12)
 - single_unit_truck_front, AP = 78.12% (TP = 37, FP = 13)
 - single_unit_truck_rear,  AP = 84.53% (TP = 36, FP = 16)
 - van_front,               AP = 30.44% (TP =  7, FP = 10)
 - van_rear,                AP = 59.75% (TP =  3, FP =  4)
 - pickup_front,            AP = 66.82% (TP = 16, FP = 12)
 - pickup_rear,             AP = 69.27% (TP = 25, FP =  7)

Precision = 0.69 / Recall = 0.76 / F1-score = 0.72
TP = 214, FP = 97, FN = 67, average IoU = 56.09 %

confidence_threshold = 0.50
 - articulated_truck_front, AP = 90.93% (TP = 60, FP = 17)
 - articulated_truck_rear,  AP = 84.24% (TP = 26, FP =  5)
 - single_unit_truck_front, AP = 78.12% (TP = 33, FP = 11)
 - single_unit_truck_rear,  AP = 84.53% (TP = 34, FP = 11)
 - van_front,               AP = 30.44% (TP =  6, FP =  6)
 - van_rear,                AP = 59.75% (TP =  3, FP =  4)
 - pickup_front,            AP = 66.82% (TP = 14, FP =  5)
 - pickup_rear,             AP = 69.27% (TP = 23, FP =  6)

Precision = 0.75 / Recall = 0.71 / F1-score = 0.73
TP = 199, FP = 65, FN = 82, average IoU = 61.76 %
```

```
mAP@0.50 = 0.705120, or 70.51 %
mAP@0.60 = 0.675986, or 67.60 %
mAP@0.70 = 0.571626, or 57.16 %
mAP@0.80 = 0.306439, or 30.64 %
mAP@0.90 = 0.032269, or  3.23 %
```

Image datasets

	v2	v3	v4
# of images	1253	1253	1253
# of background images	300	300	300
Total # of images	1553	1553	1553
articulated_truck count	1029	1029	
articulated_truck_front count			634
articulated_truck_rear count			395
single_unit_truck count	922	922	
single_unit_truck_front count			501
single_unit_truck_rear count			421
lightweight count	866		
van count		225	
van_front count			128
van_rear count			97
pickup count		641	
pickup_front count			253
pickup_rear count			388

Future Work: using tracking on videos



[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” ArXiv150602640 Cs, May 2016, Accessed: Oct. 12, 2020. [Online]. Available: http://arxiv.org/abs/1506.02640.

[2] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft, “Simple Online and Realtime Tracking,” 2016 IEEE Int. Conf. Image Process. ICIP, pp. 3464–3468, Sep. 2016, doi: 10.1109/ICIP.2016.7533003.

3. Z. Luo *et al.*, “MIO-TCD: A New Benchmark Dataset for Vehicle Classification and Localization,” *IEEE Trans. Image Process.*, Oct. 2018.