

Traffic Analysis in Original Video Data of Ayalon Road

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2019



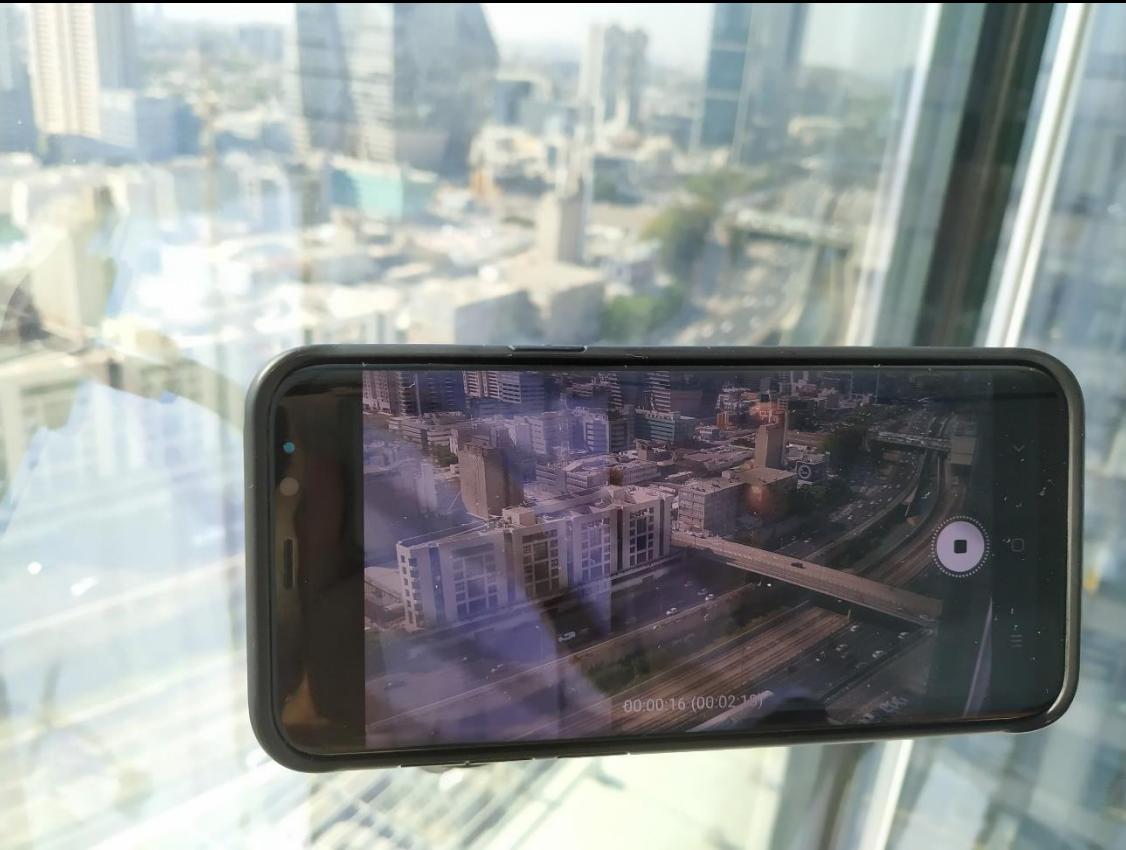
Background



Looking down: data are everywhere

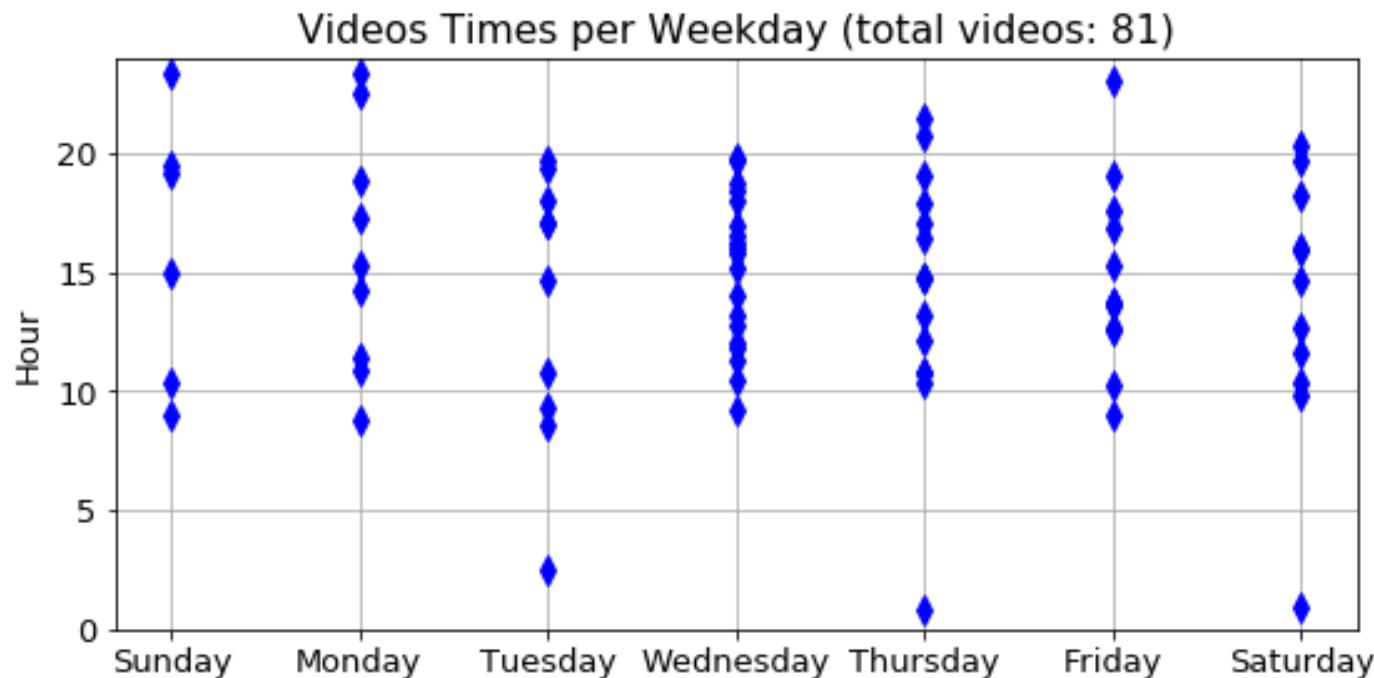
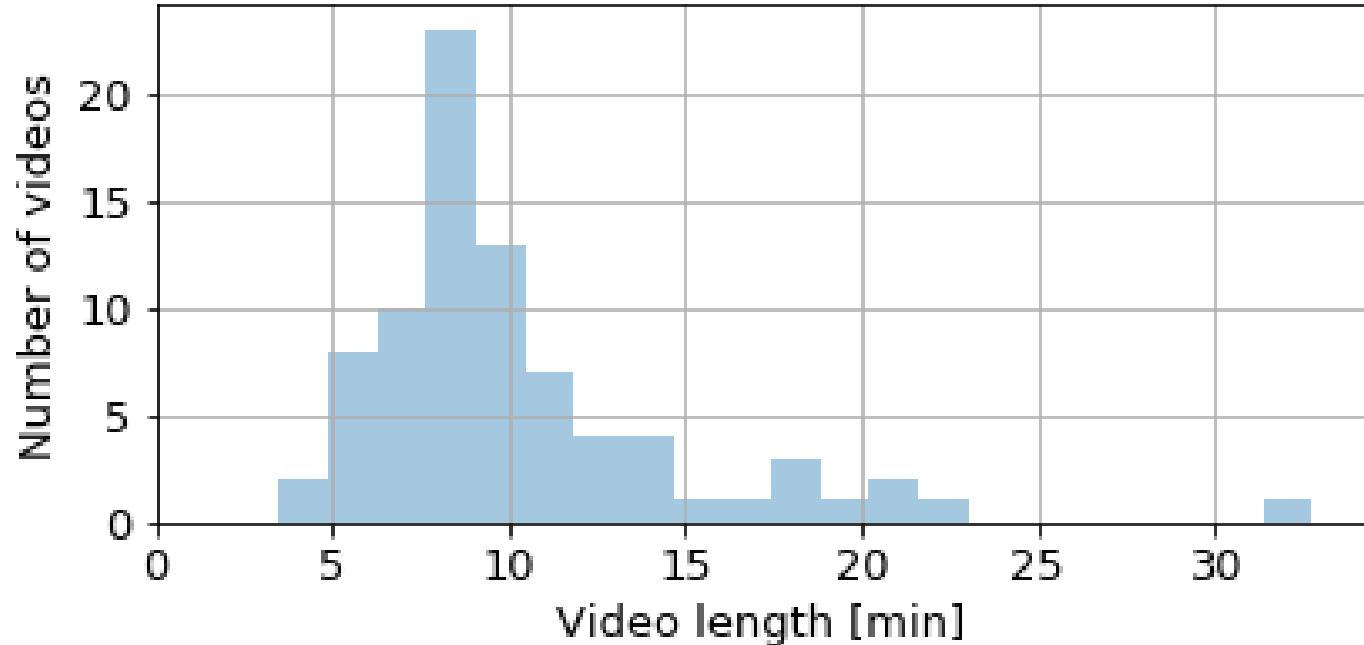


- Hyperlapse, x8 speed, Full-HD
- 120MB for 8 minutes



Collected data

- 81 videos X 8 minutes over 2 months



What we need

- **Detection:** find vehicles in a frame
- **Tracking:** connect the same vehicle in different frames
- **Analysis of traffic**



Detection

Out-of-the-box YOLO





Out-of-the-box SSD (better with small, crowded objects)

car: 55.08%

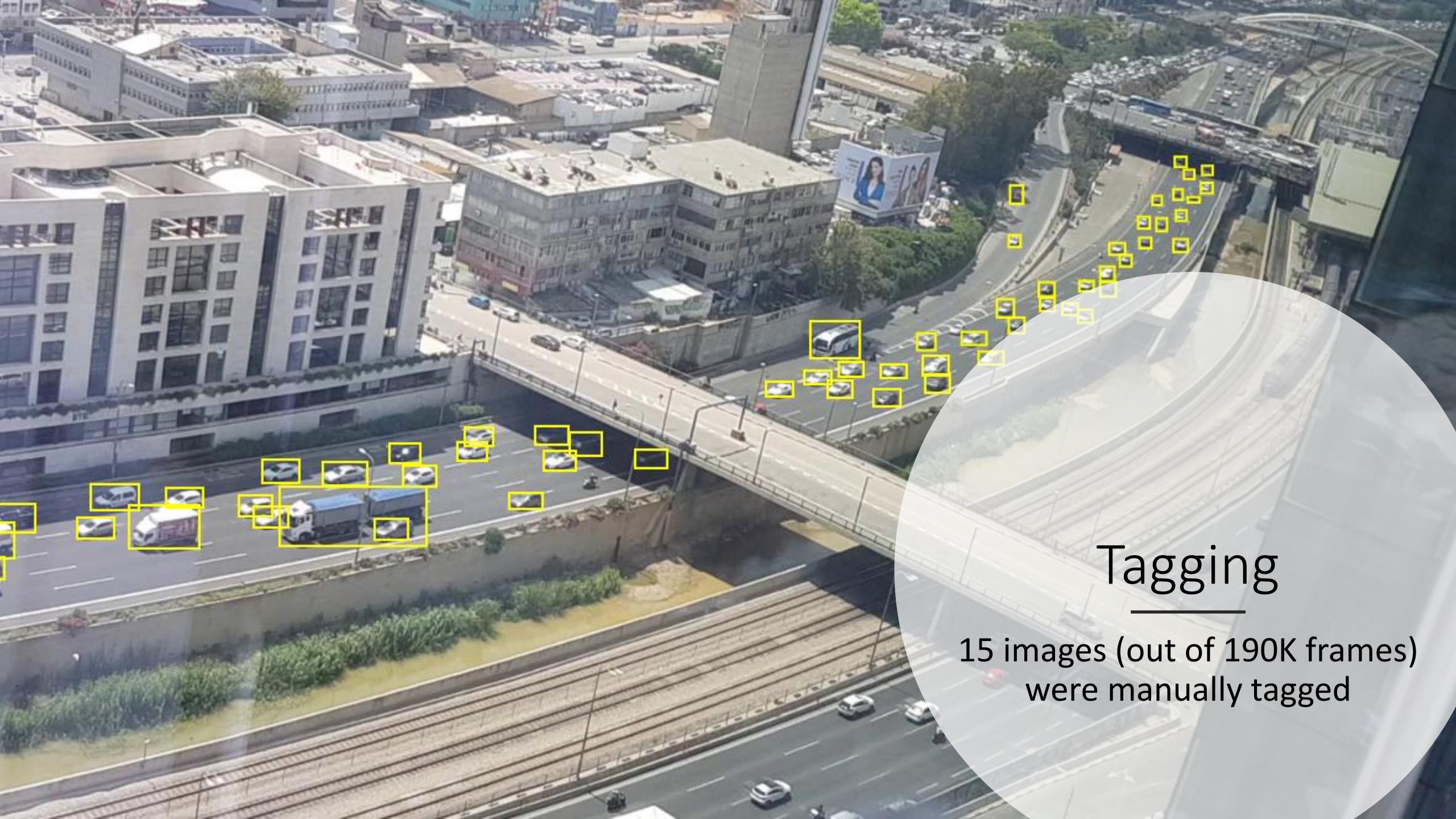
Zoom in?

No one's gonna train for me

- **Train:** tune the detection according to the data
- **Design:** adjust models to fit typical sizes & density
 - Also simplify – no need for multiple object classes



Having to train by myself - illustration

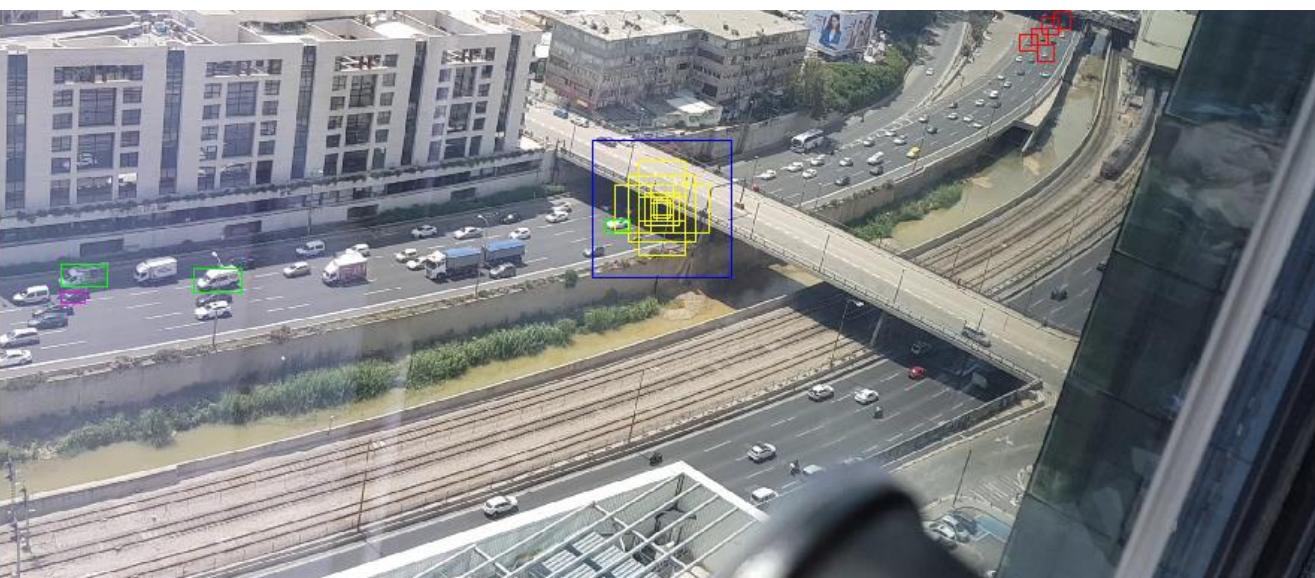


Tagging

15 images (out of 190K frames)
were manually tagged

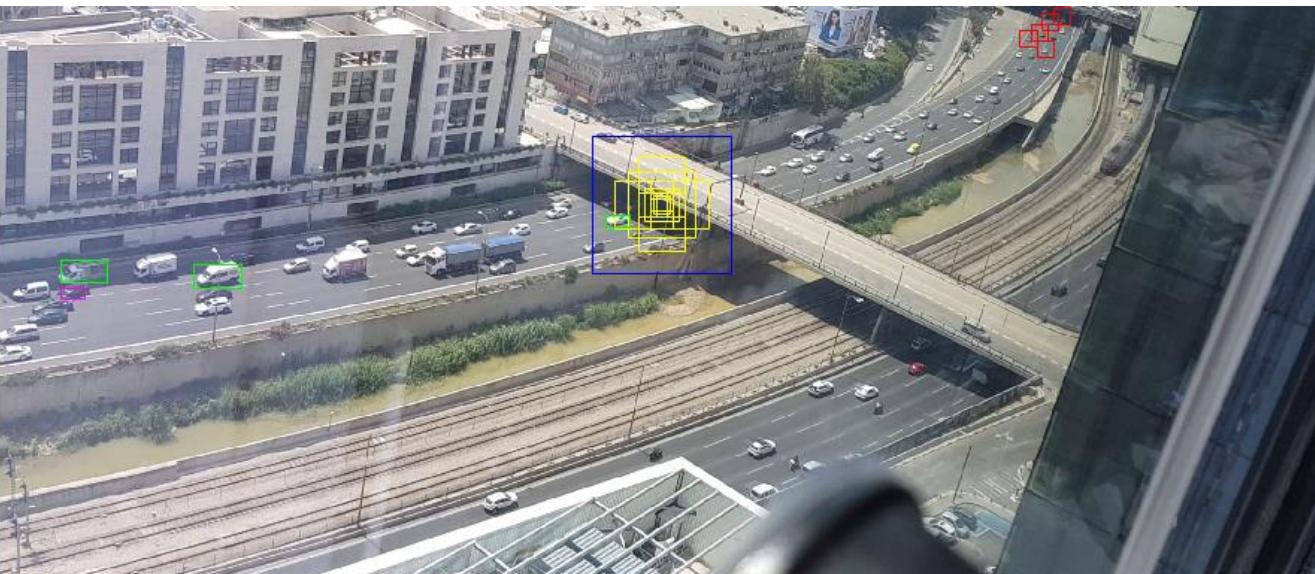
Tagged vehicles → network-compatible output

- Split image to 290K (overlapping) rectangles (***anchor boxes***)
 - 9 boxes per location – various scales & shapes
 - A box receives info from pixels around it (***receptive field***)

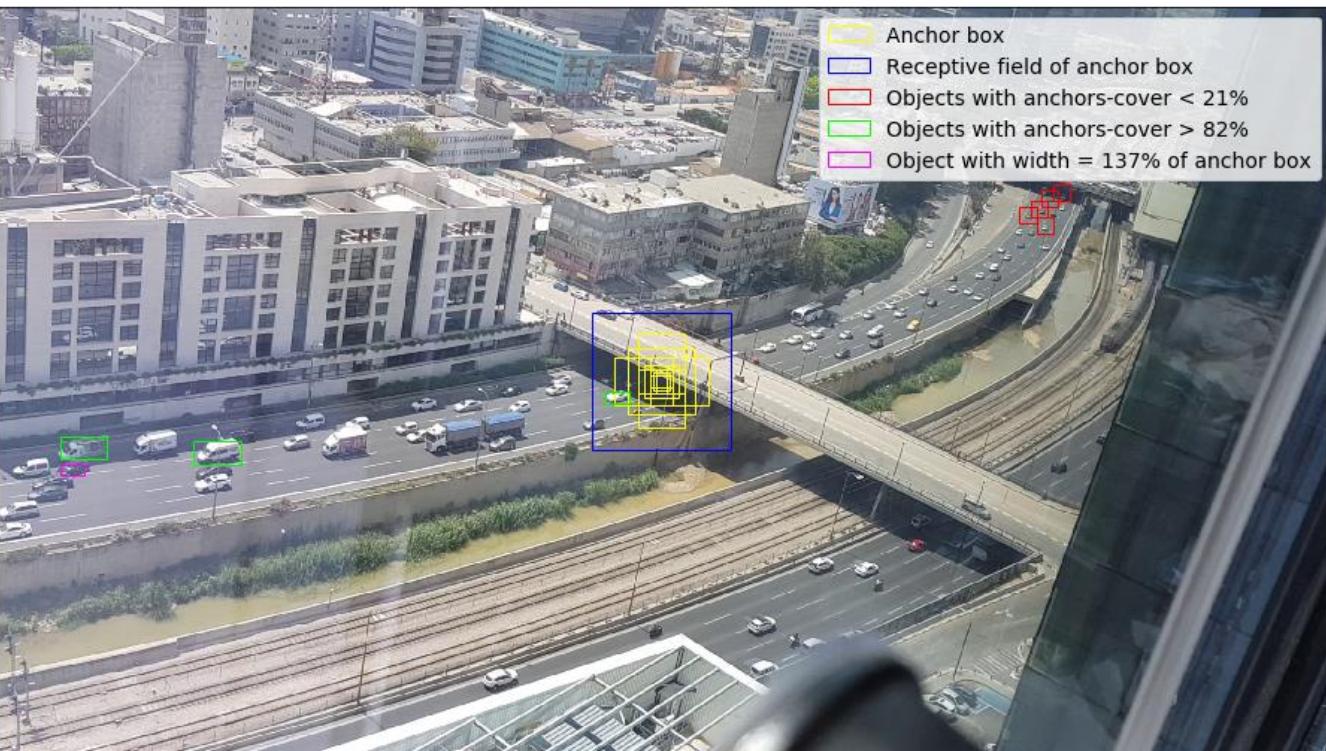


Tagged vehicles → network-compatible output

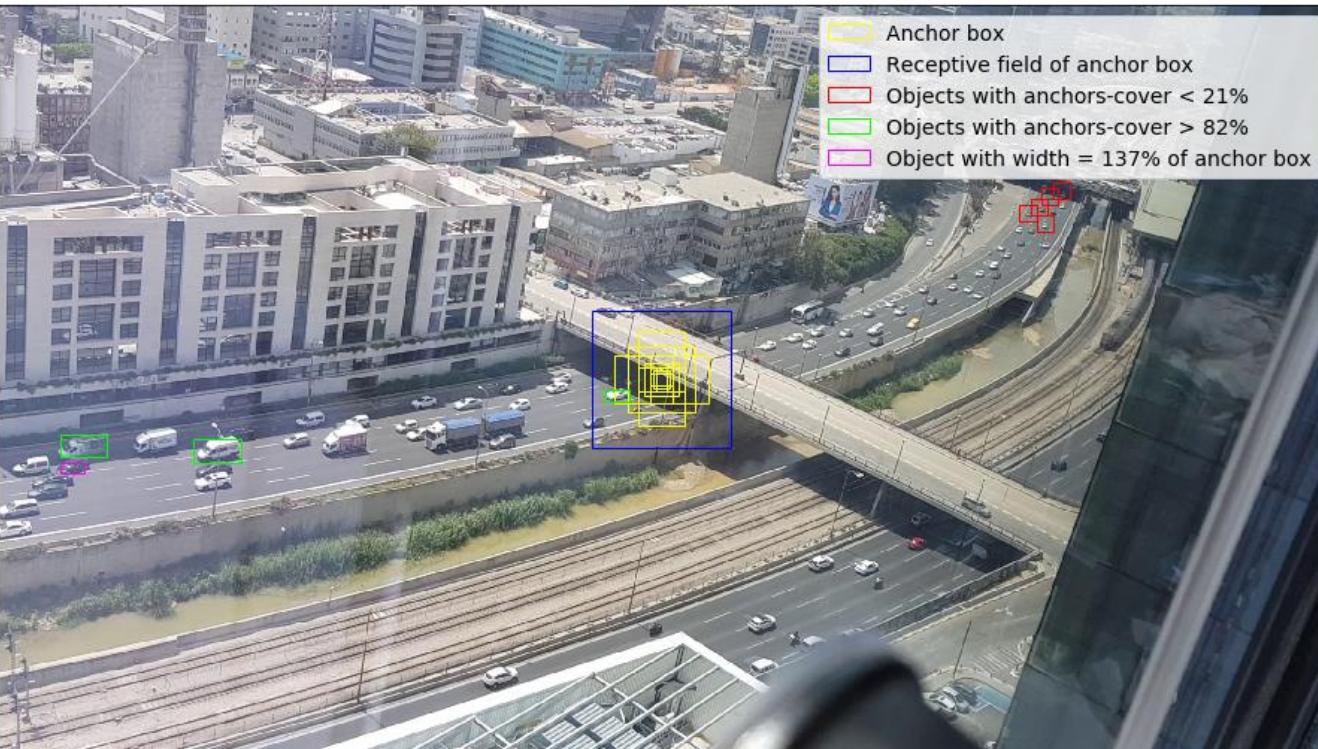
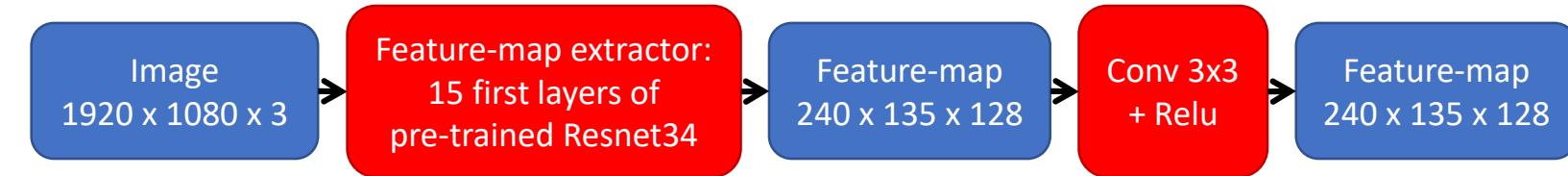
- Split image to 290K (overlapping) rectangles (***anchor boxes***)
 - 9 boxes per location – various scales & shapes
 - A box receives info from pixels around it (***receptive field***)
- Output per box:
 - Highly-overlapping object → (1, object location)
 - Little/no overlap → (0, ...arbitrary...)
 - Somewhere in the middle → drop from training data



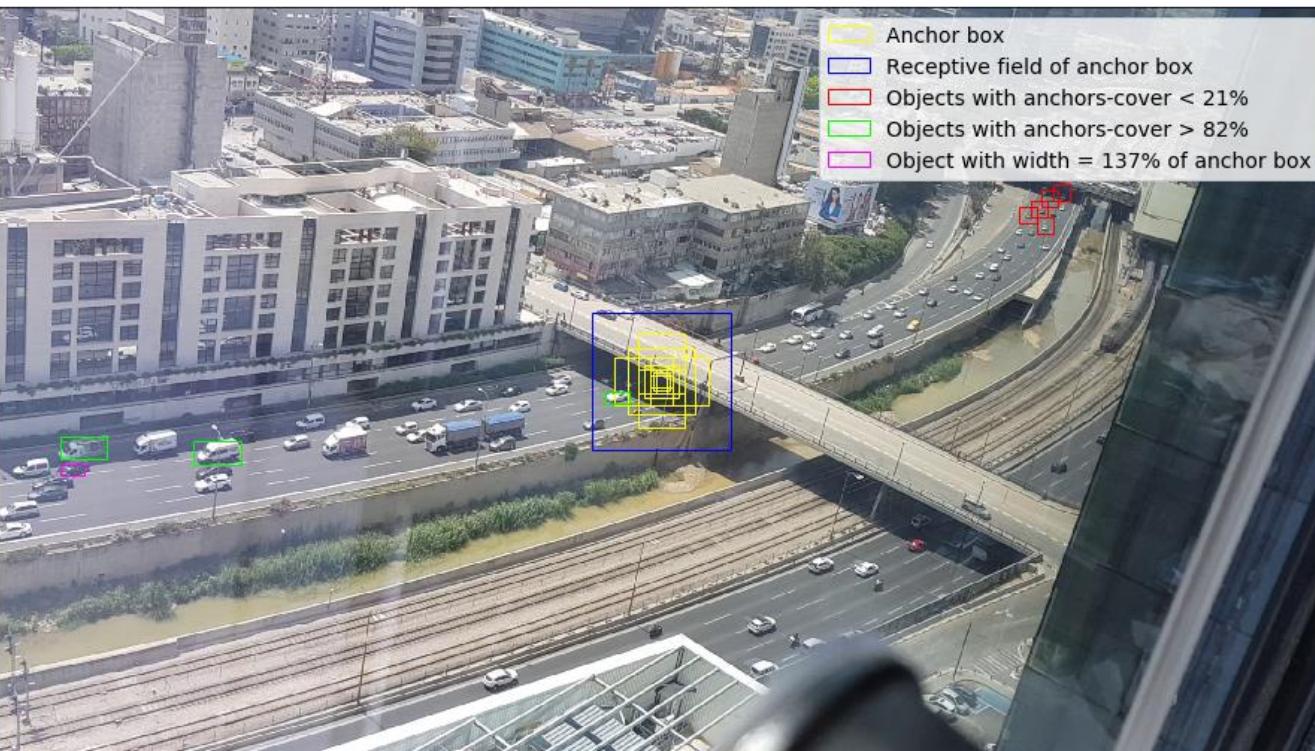
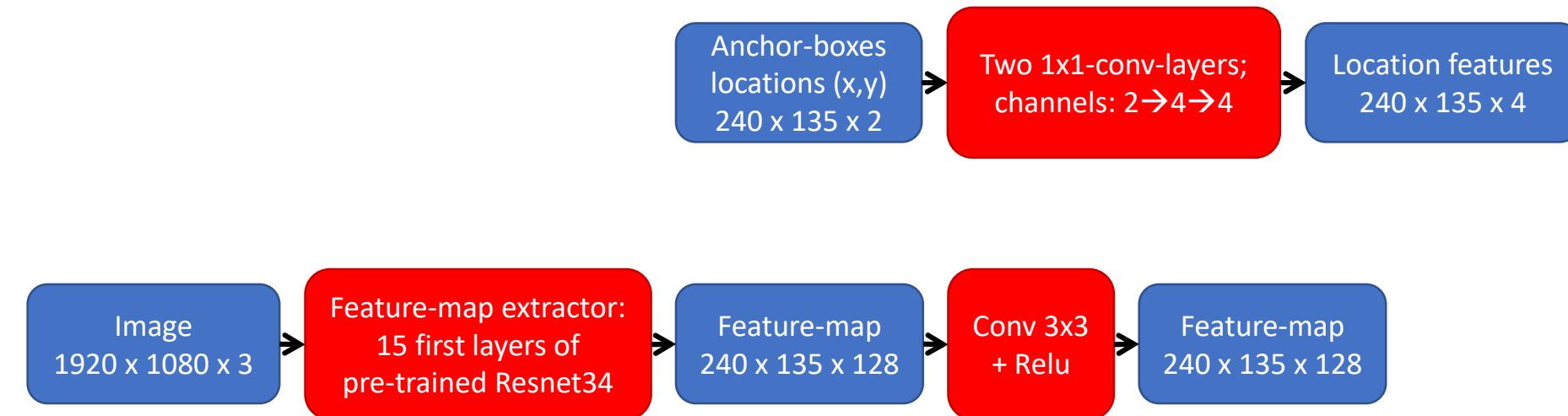
Network architecture



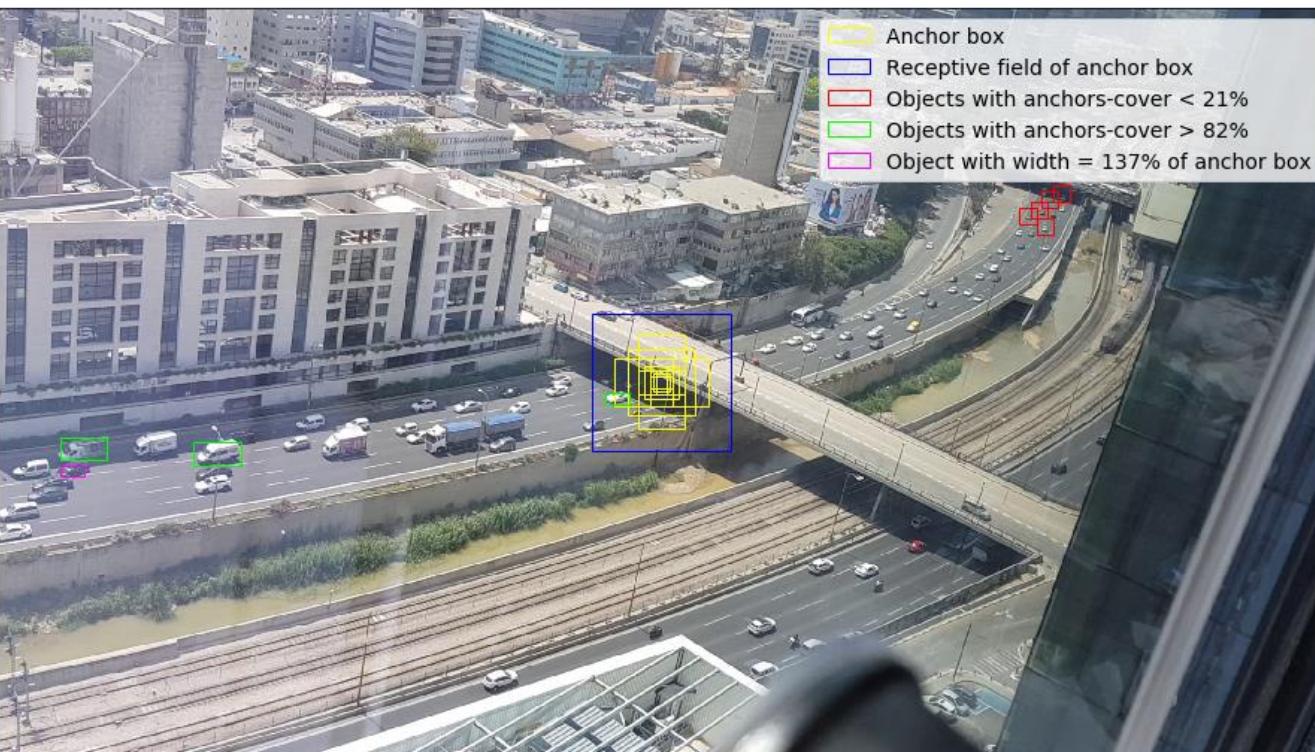
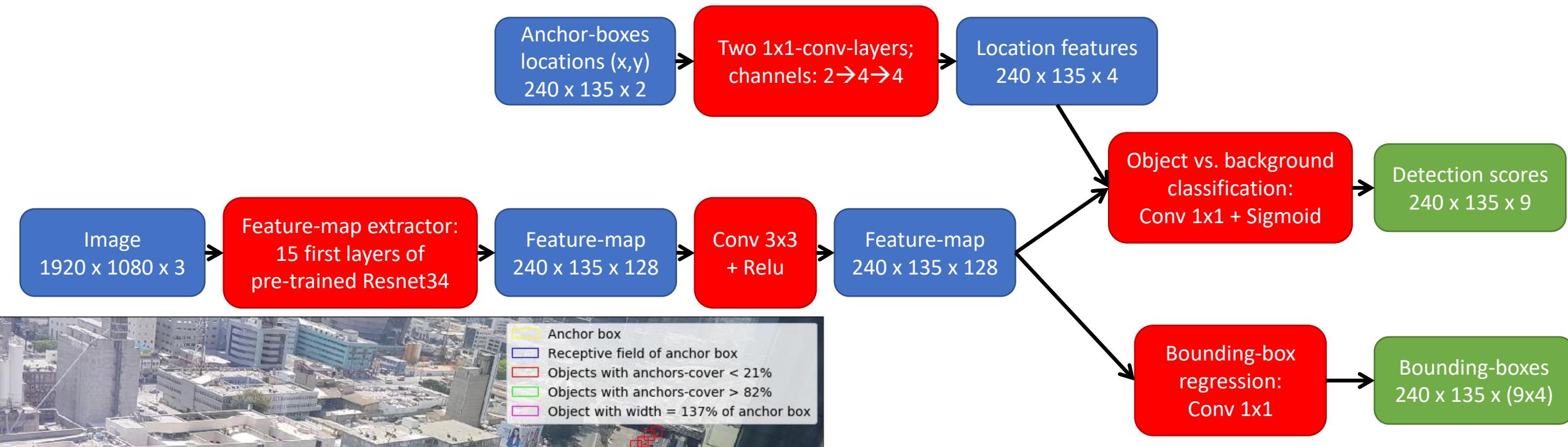
Network architecture



Network architecture

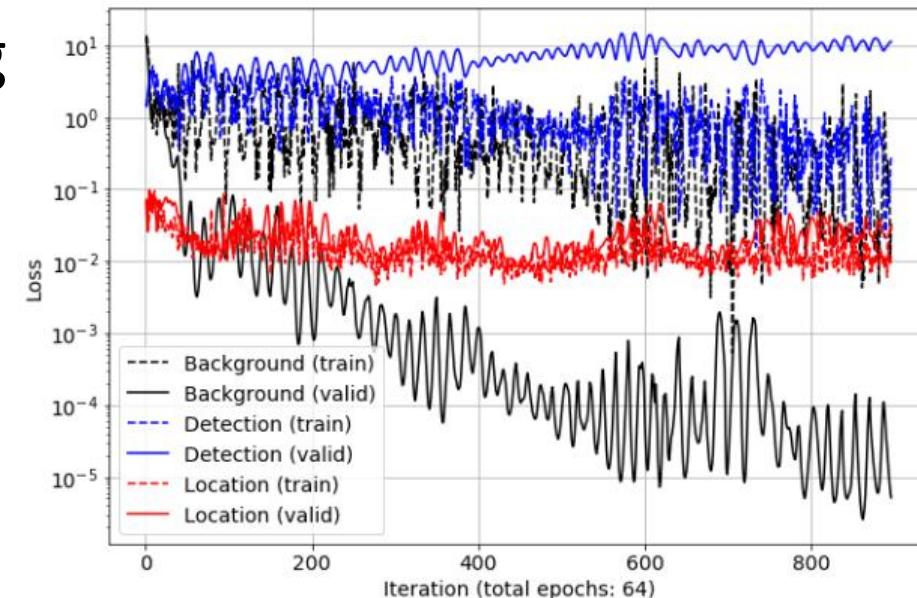


Network architecture



Training

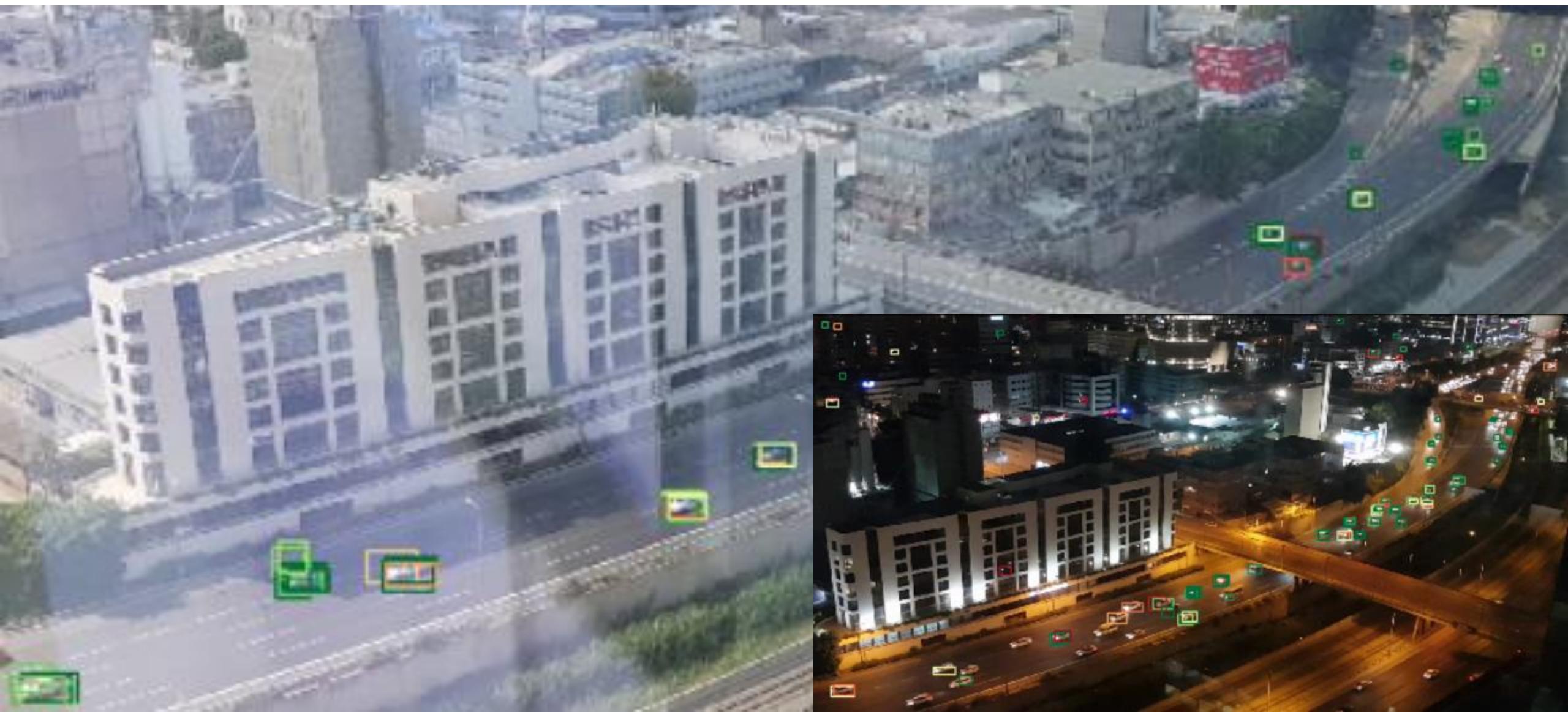
- **Optimizer:** Adam
- **Loss:** Binary cross-entropy (detection) + L1 (location)
 - Manual tuning of the FP/FN tradeoff
- **Transfer learning:** begin with freezed pre-trained Resnet layers
- **Hard negative mining:** up-sample boxes with large loss
- Architecture & hyper-params empirical tuning
- Running time on my laptop:
 - Freezed Resnet-layers: 5 minutes
 - Unfreezed Resnet-layers: +7 minutes



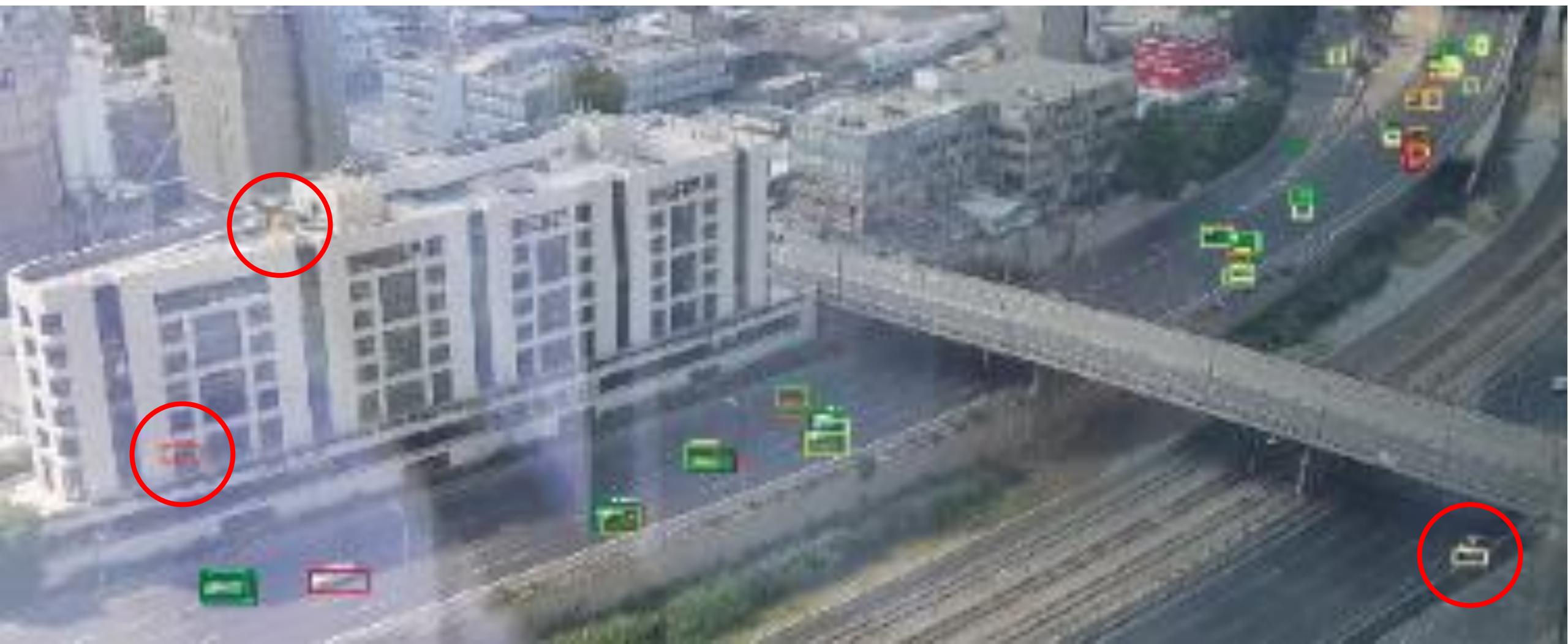
Without Hard Negative Mining



3 training images



Middle of training (15 training images)



Middle of training

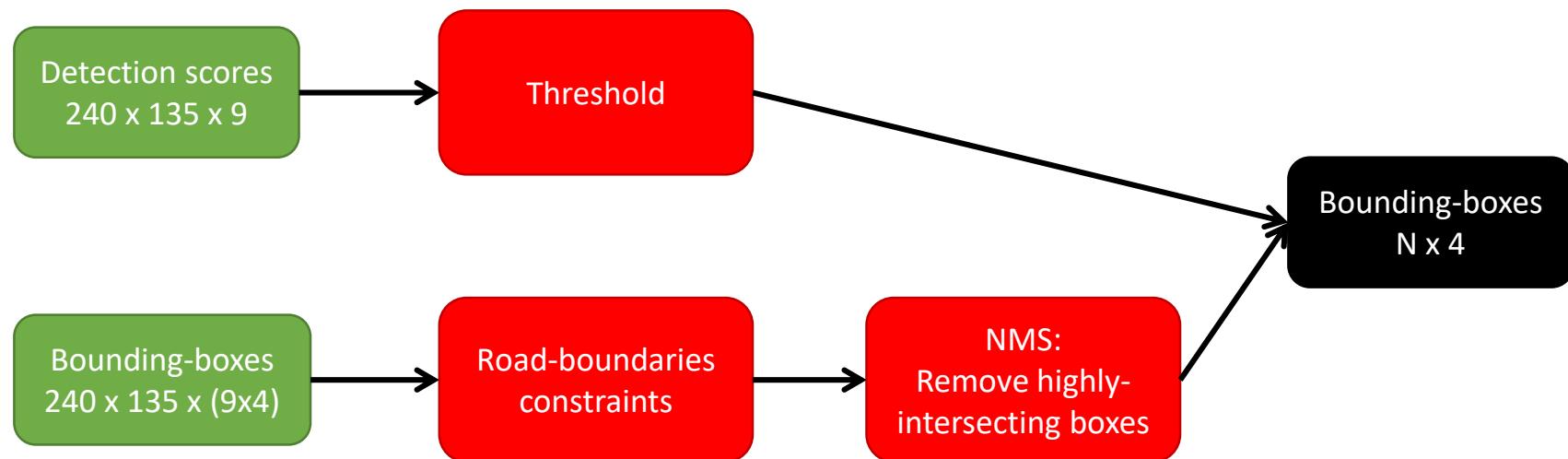


End of training

(15 training images)



Network output → predicted boxes



122 objects (0.315 = red <= certainty <= green)

Road
boundaries

*All results are out-of-sample

42 objects (0.360 = red <= certainty <= green)

Night +
reflections

*All results are out-of-sample



22 objects (0.379 = red <= certainty <= green)

Shavuot

*All results are out-of-sample



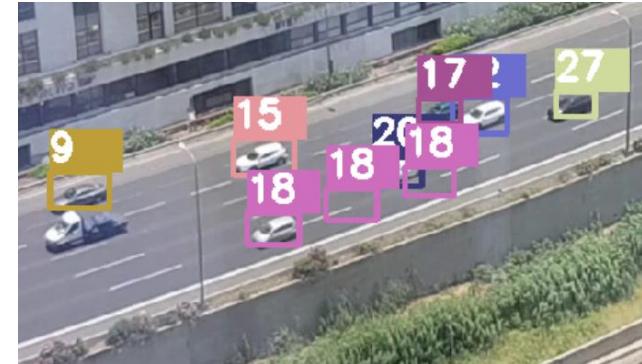
Tracking

SORT: Simple, Online and Realtime Tracking

- New detections \leftrightarrow "active tracks": assigned by intersection (**IOU**)
 - (Hungarian algorithm for linear assignment)



What the engineer had in mind



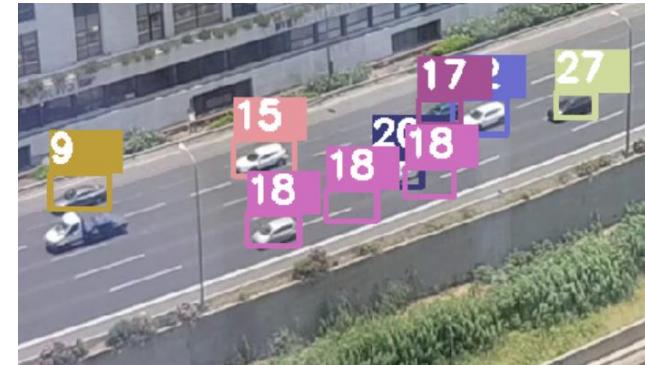
What the customer had in mind

SORT: Simple, Online and Realtime Tracking

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What the engineer had in mind

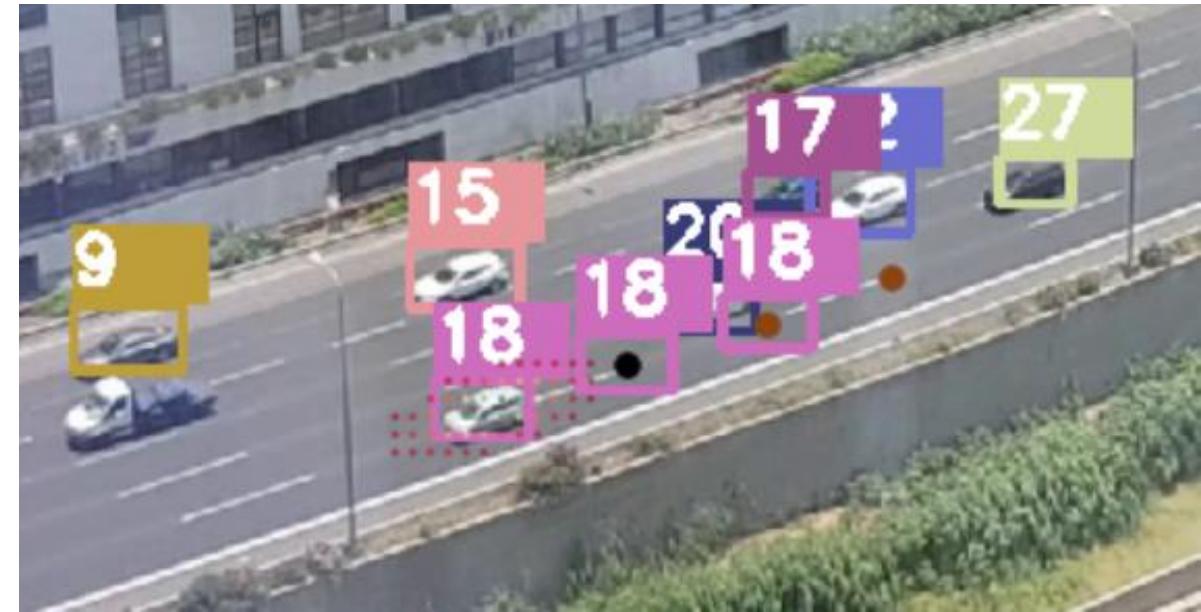


What the customer had in mind

- Active track – represented by ***Kalman Filter***:
 - Iteratively merge info from motion extrapolation & new observations
 - At any time, holds the track location and its uncertainty
- What can we possibly do?

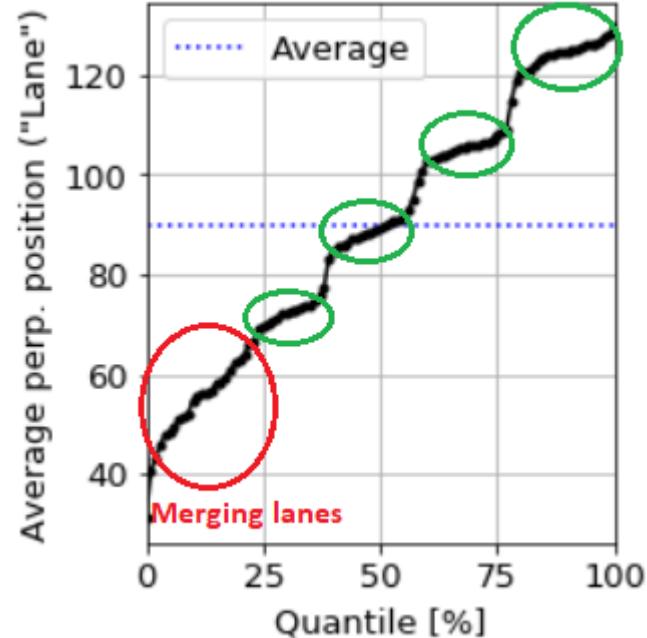
KF-based objects assignment

- Only location-based (no size & shape)
- Predicted-location error: 10 pixels in motion direction (u_1), 2 in perpendicular (u_2)
 - Motion direction: globally-estimated once in a while
 - **Covariance** = $U^T \cdot \begin{pmatrix} 10^2 & 0 \\ 0 & 2^2 \end{pmatrix} \cdot U$ $(U := (u_1, u_2))$
 - \Rightarrow Likelihood (any location | predicted location, covariance)
- [New detections \leftrightarrow tracks] assigned by likelihood



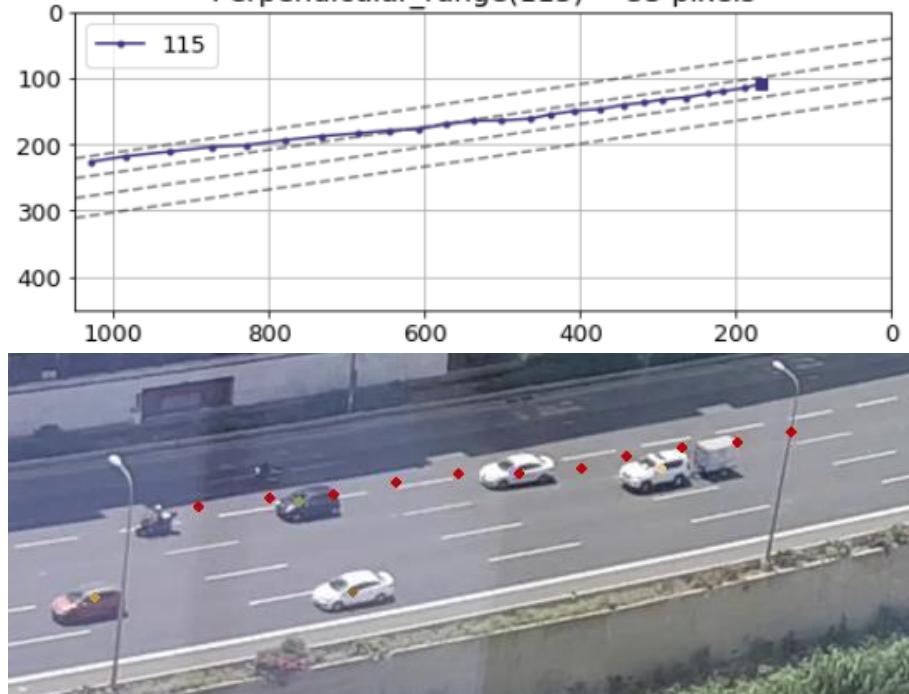
Does it work?

Vehicles distribution among lanes



Detected lane transition

Perpendicular_range(115) = 35 pixels

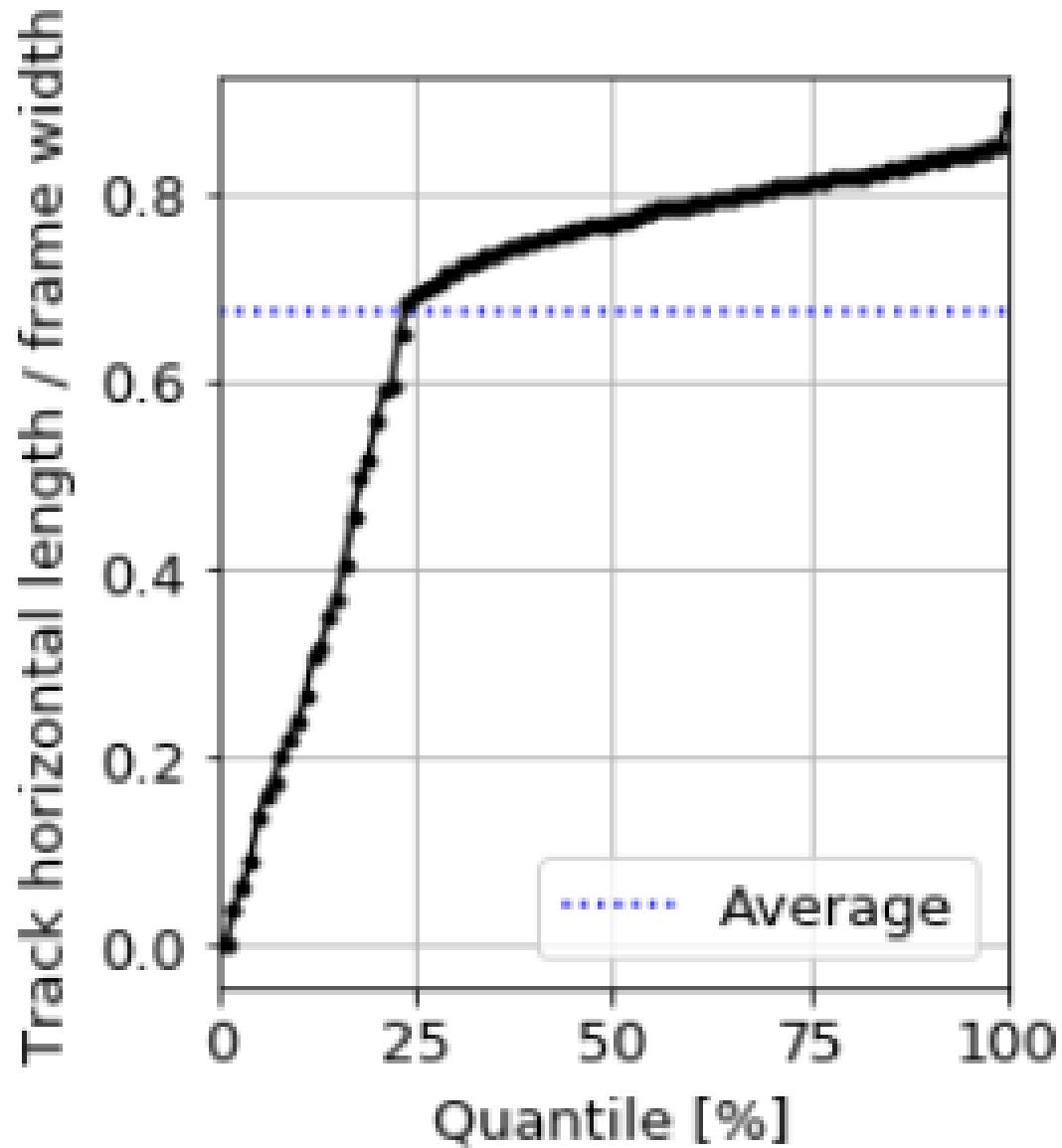


Track over gaps w/o detection



Does it work?

- Do we track the whole path?

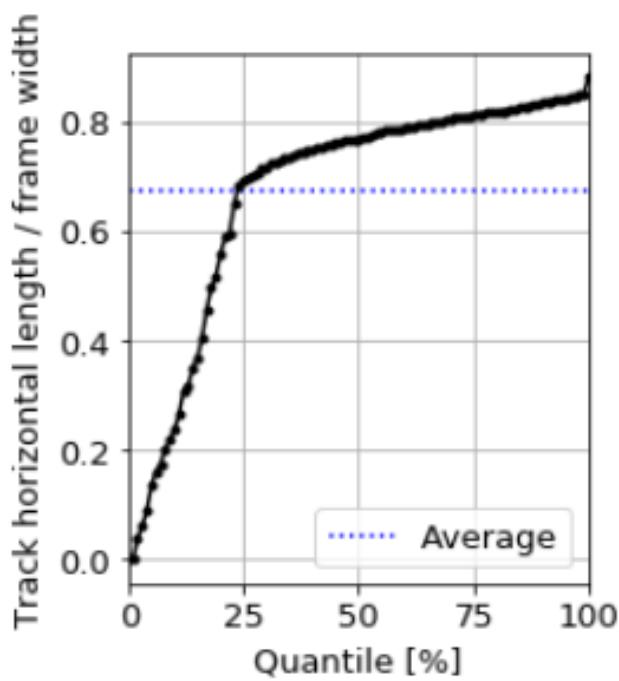


Does it work?

- Do we track the whole path?

- Fake tracks: false detections

- Failed tracks: missing detections, hidings



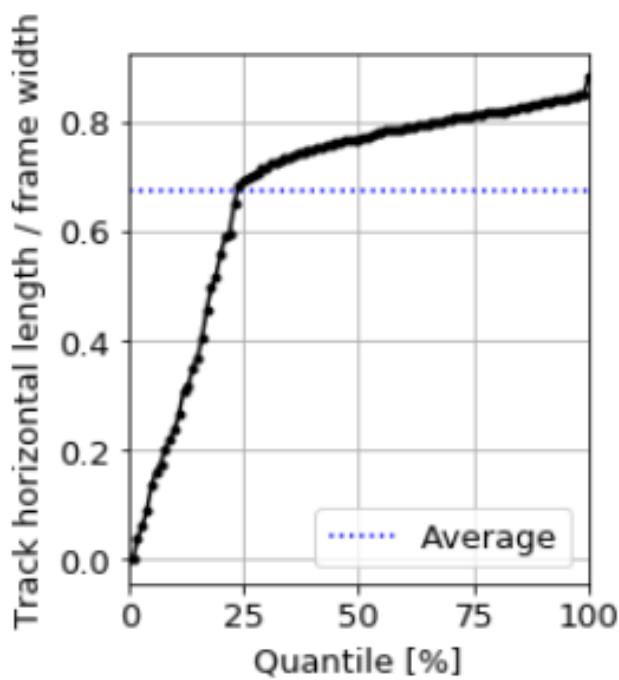
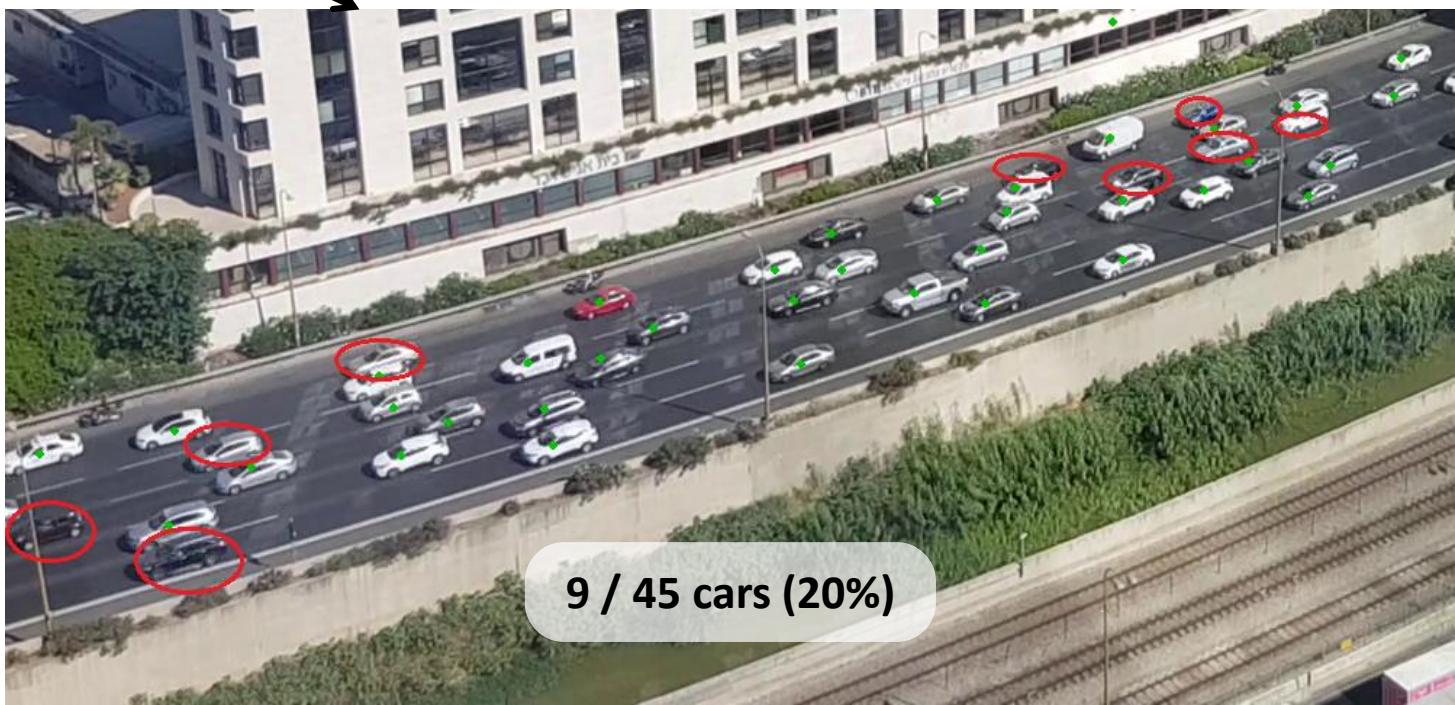
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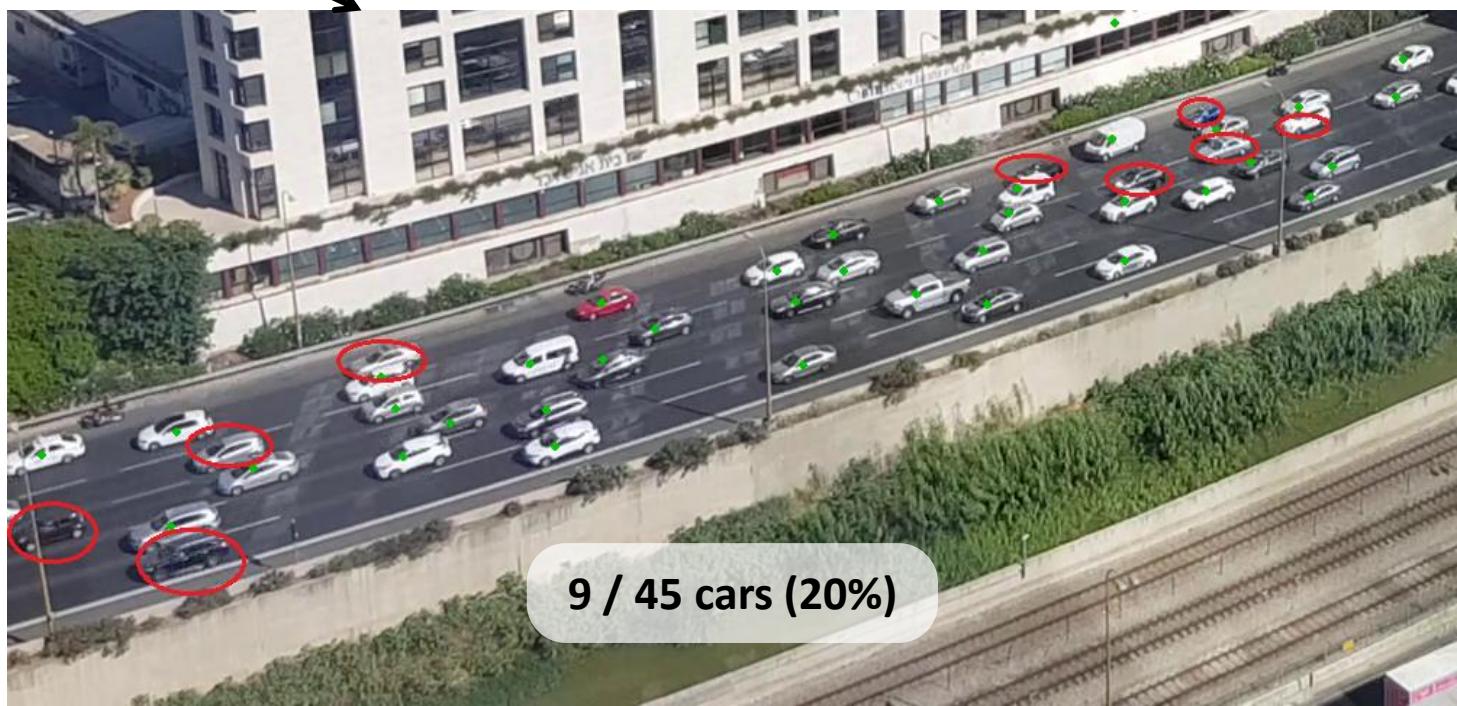
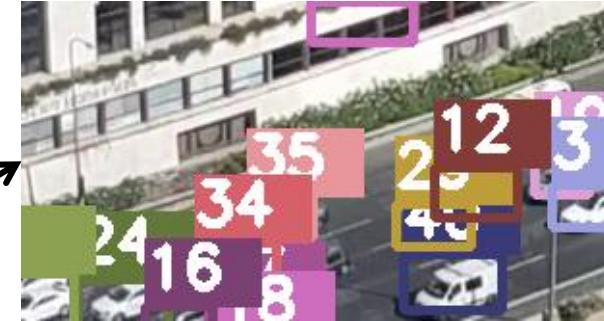
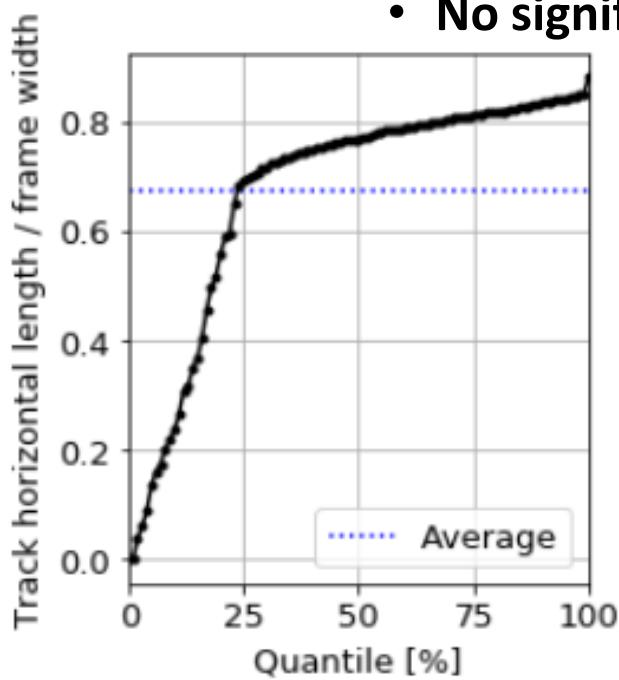
Does it work?

- Do we track the whole path?

- Fake tracks: false detections
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- **Eliminated by removing short tracks**

- **No significant bias expected**



Does it work?

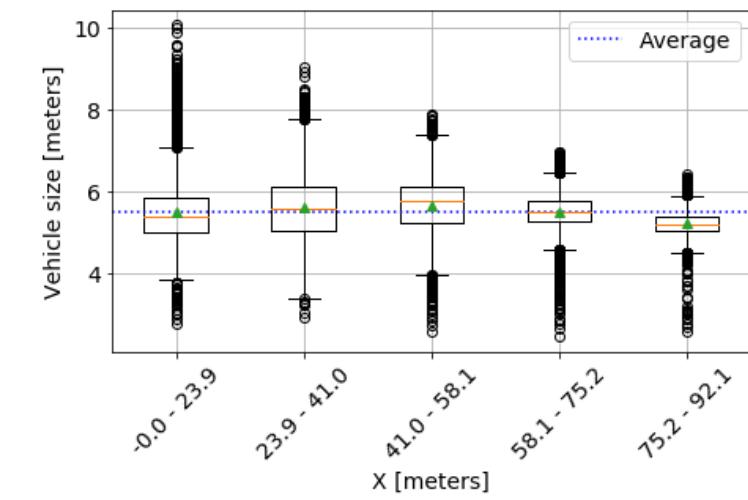
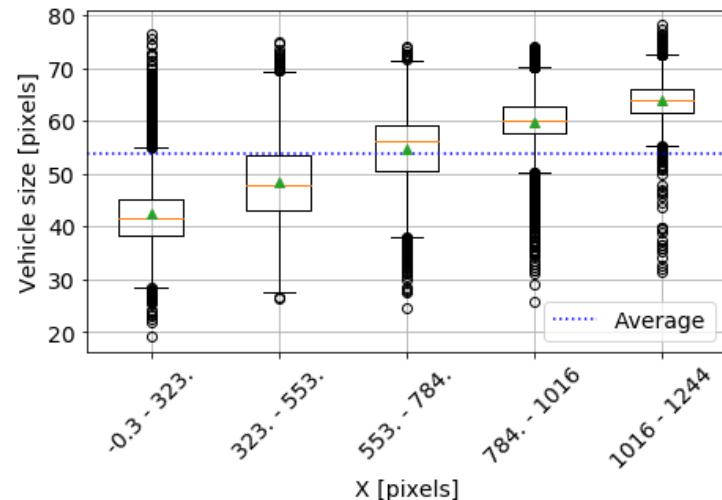
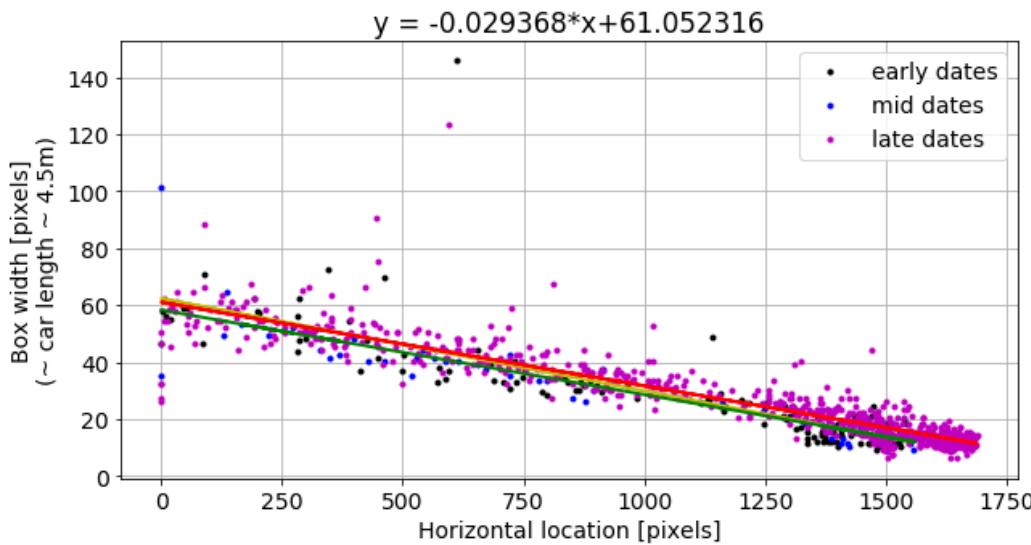
- **Running time** on my laptop:
 - Full frames: 1.2 frame/sec (~25 min/video)
 - **Cropped frames:** 3 frame/sec (~10 min/video)
- **Code profiling:**
 - **Do it** – there're always unexpected pitfalls
 - E.g. data-frames reallocation, GPU memory cleaning
 - **%lprun** in Jupyter Notebook
 - Sync GPU before measuring time



Analysis

Data representation

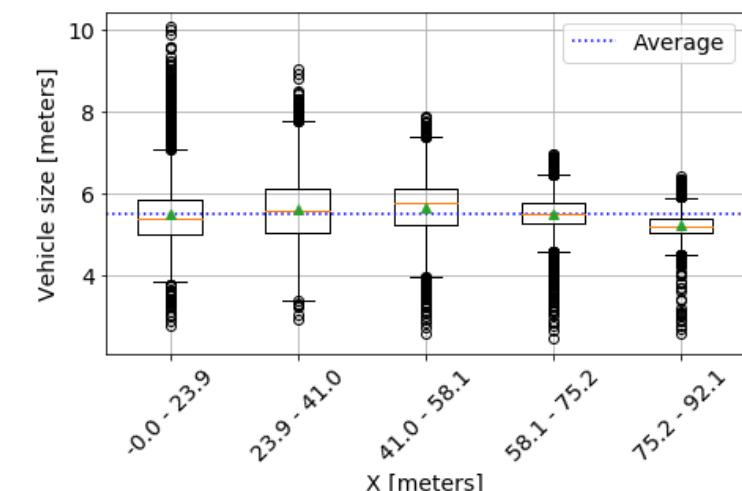
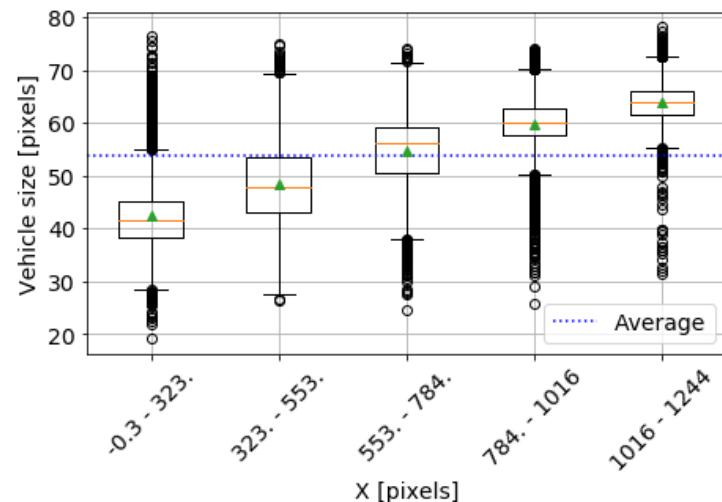
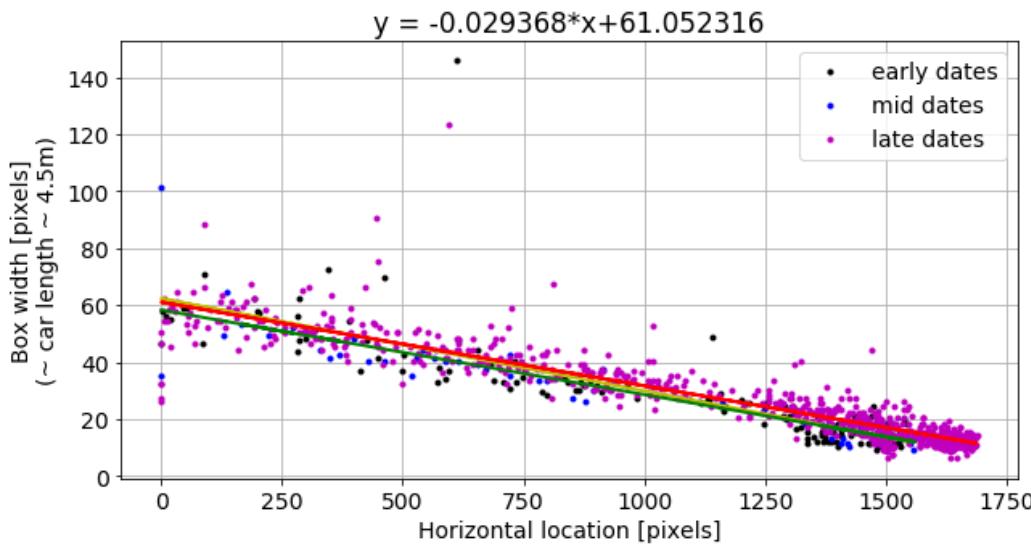
Data structure	Keys	Values	Processing needed
Raw tracking logs	time, vehicle	x, y	Non-linear transformation: pixels → meters



Data representation

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Raw tracking logs	time, vehicle	x, y	Non-linear transformation: pixels → meters
Per-vehicle*	vehicle, x-range	time, y, speed	Interpolation to grid points

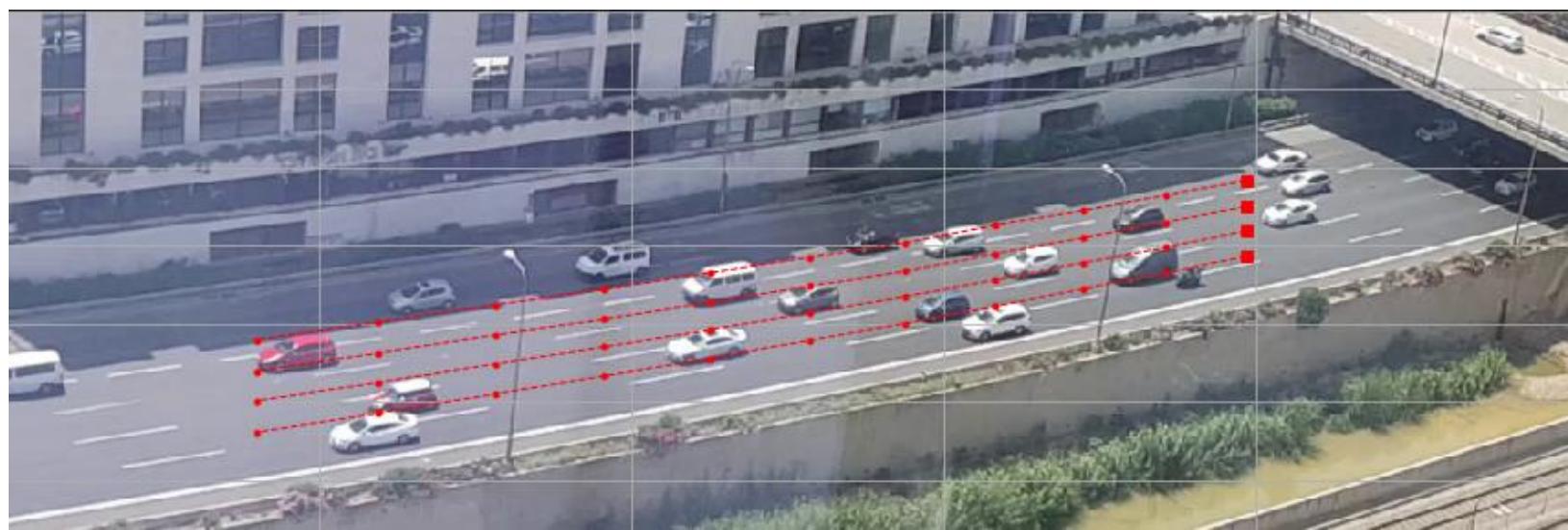
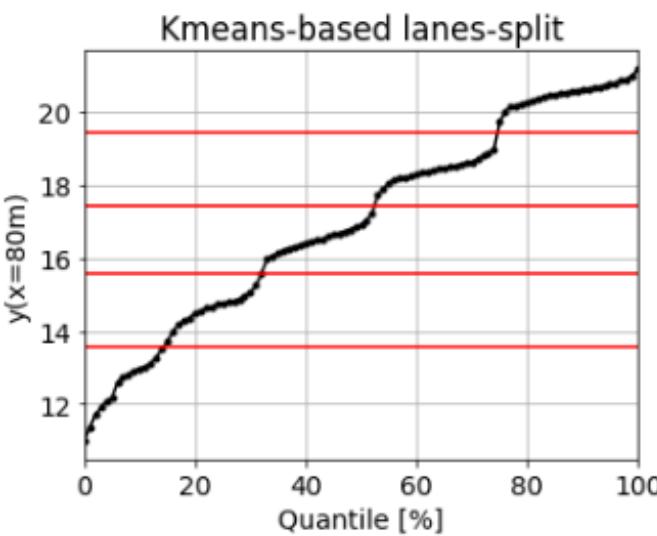
* Can be concatenated over all videos



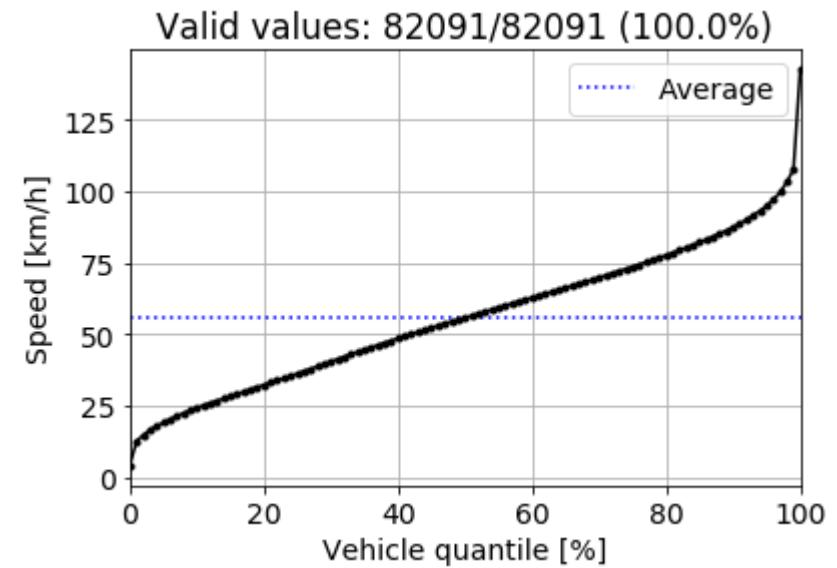
Data representation

Data structure	Keys	Values	Processing needed
Raw tracking logs	time, vehicle	x, y	Non-linear transformation: pixels → meters
Per-vehicle*	vehicle, x-range	time, y, speed	Interpolation to grid points
Spatial*	time, lane, x-range	n_vehicles, speed	Clustering to lanes (K-means with uniform split of the vertical locations range as initial centers)

* Can be concatenated over all videos



Vehicles speed distribution



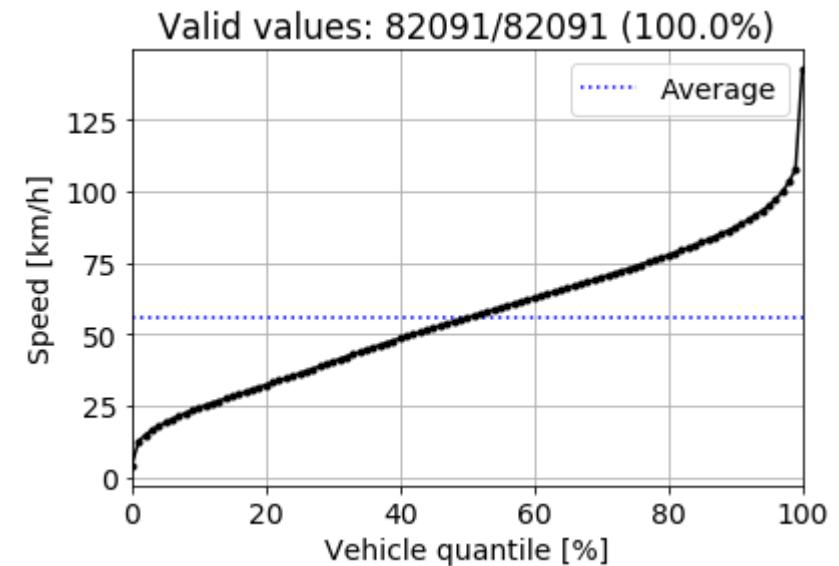
Vehicles speed distribution



143 km/h



3.9 km/h



More interesting frames



Sparsest frame (2 detected vehicles)

Densest frame (51 detected vehicles)

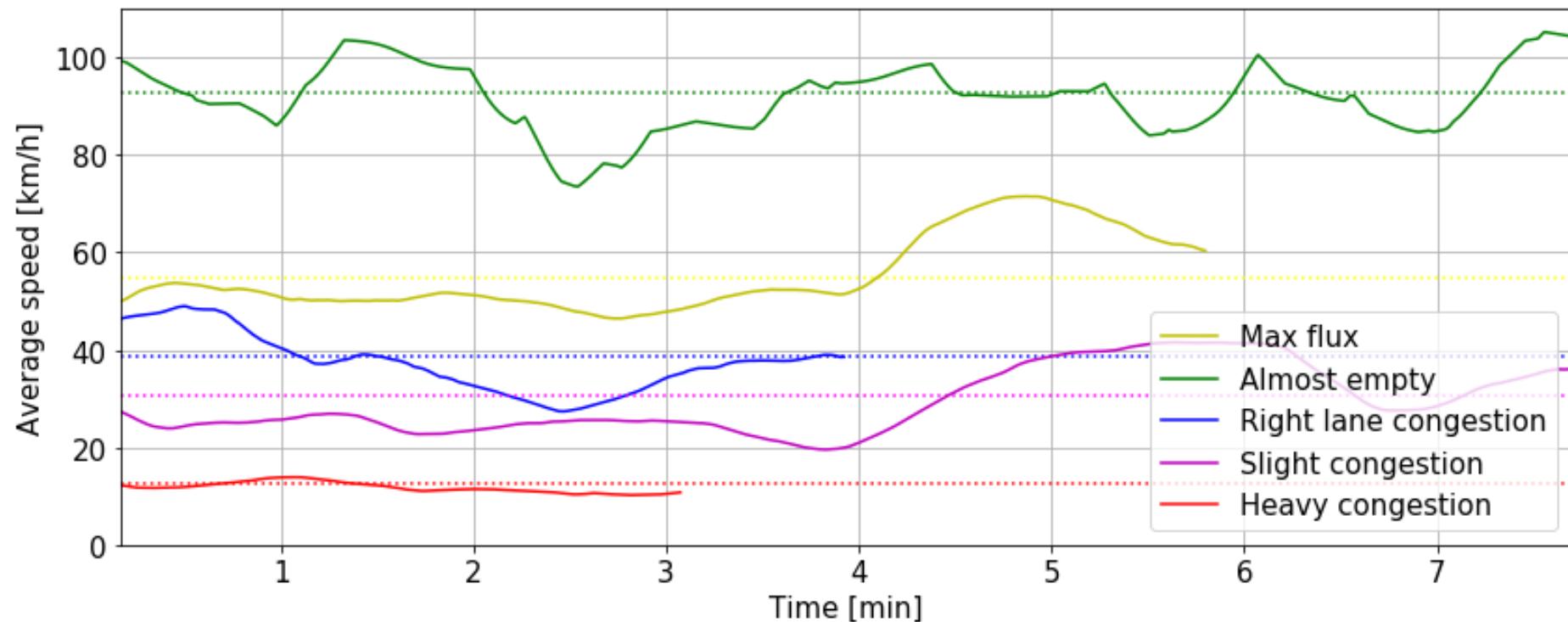


Unclear congestion on the left



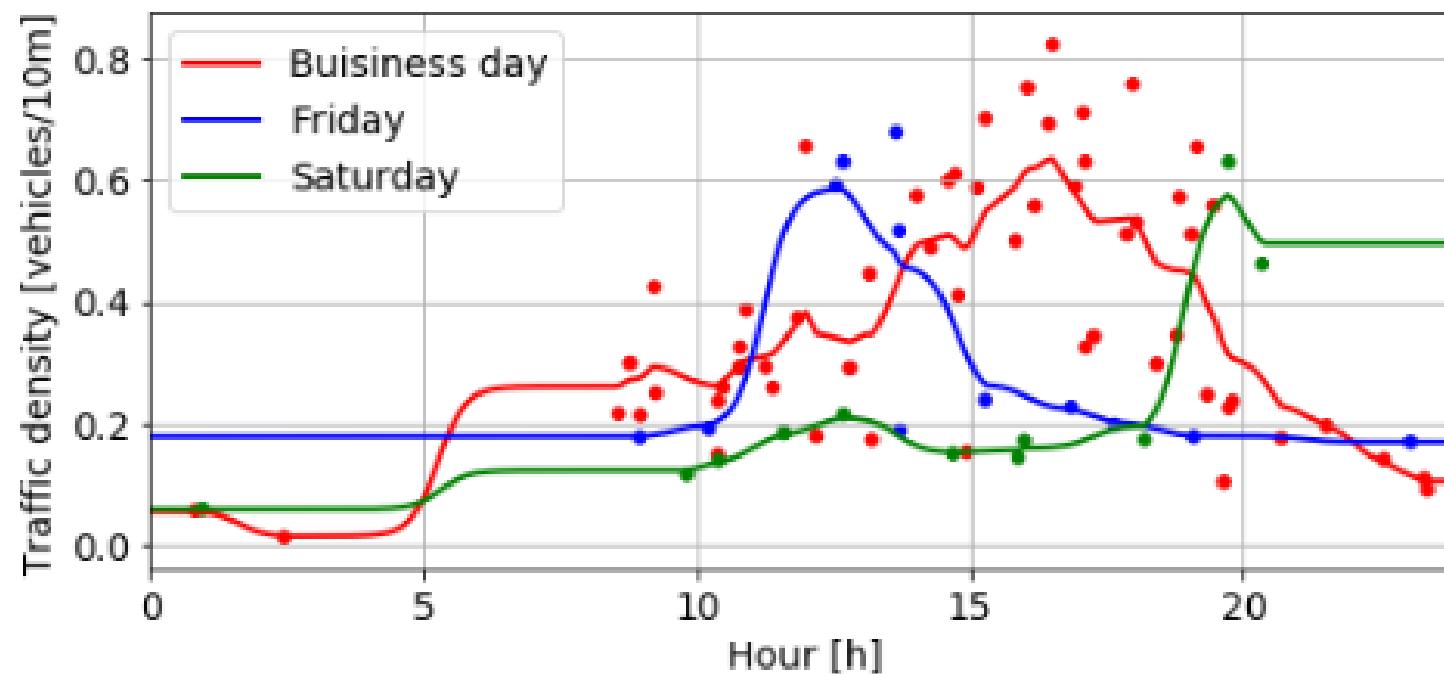
Speed trends within videos

- Stable compared to differences between videos



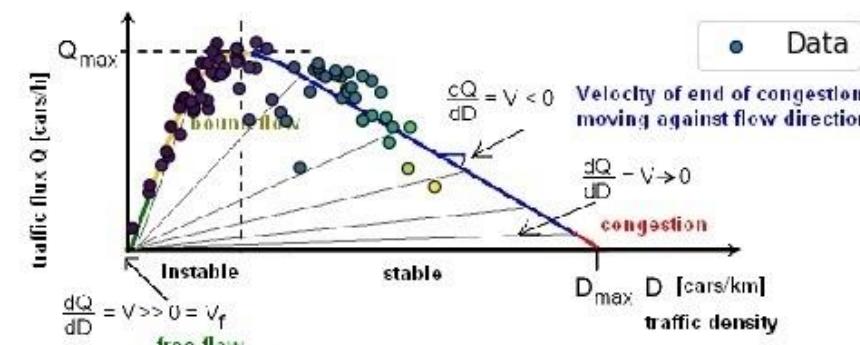
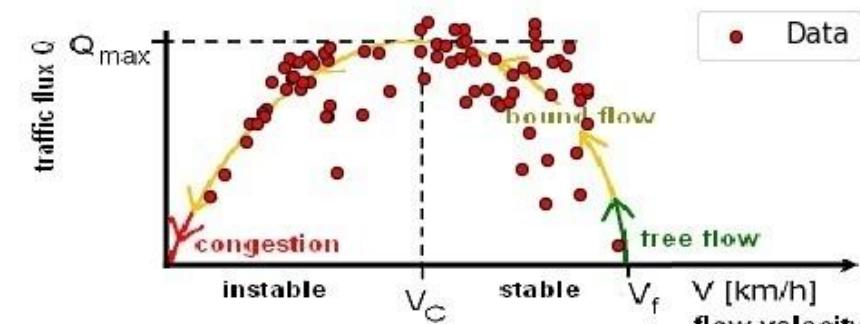
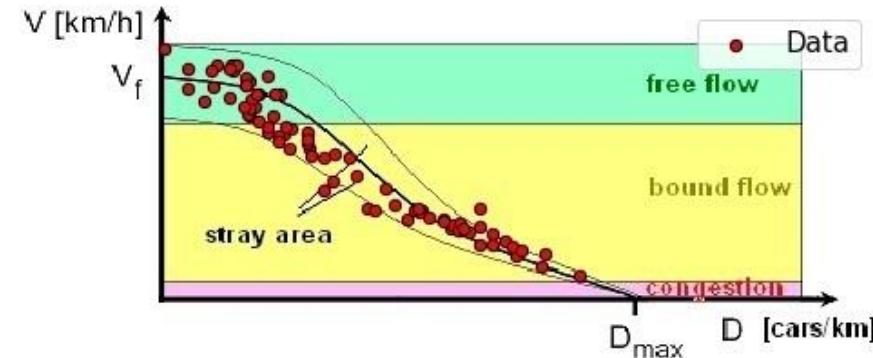
Traffic density over days and hours

- Rush hours:
 - Business days: 16:00-17:00
 - Fridays: 12:00-13:00
 - Saturdays: 19:00-20:00



The Fundamental Traffic Diagram

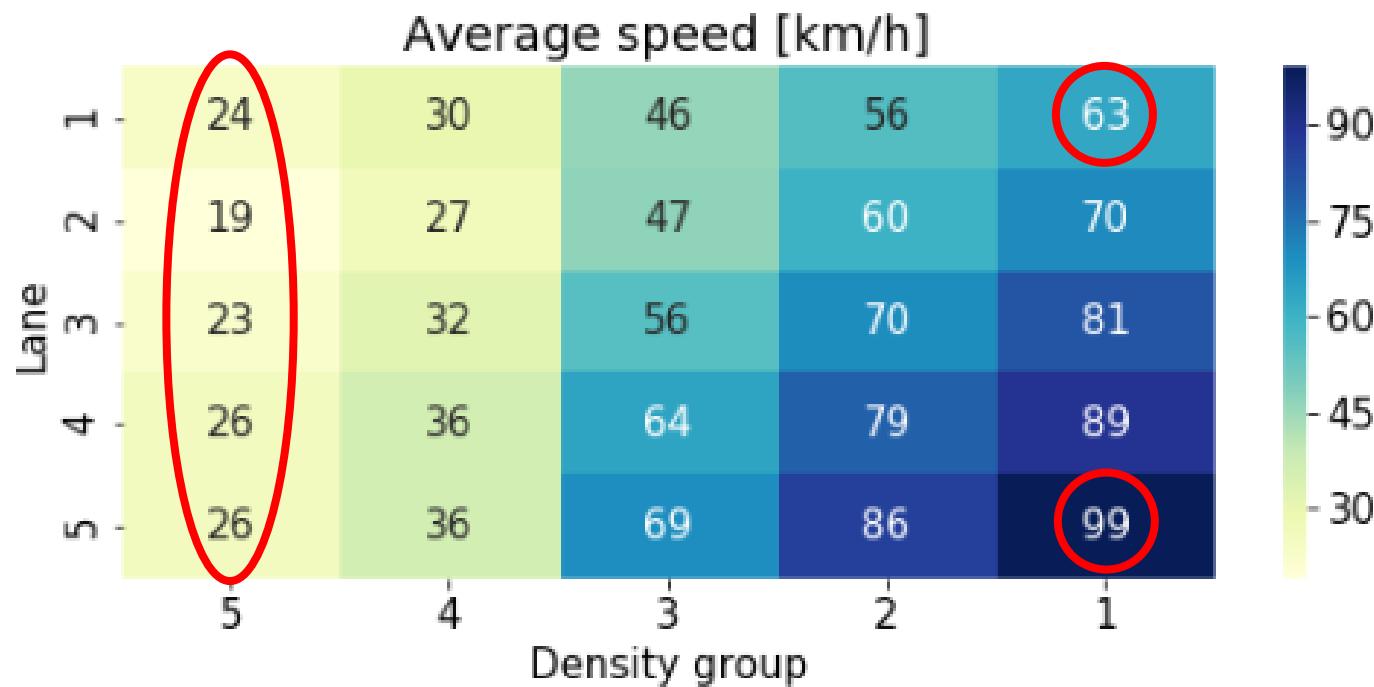
- Speed vs. density vs. flux
 - Original diagram by Ammoser et al.
- Data points **fit very well**
 - Clear separation between free-flow & congestion
- **Critical speed (max flux): $\sim 60 \text{ km/h}$**
- Flux vs. density outlier
 - Congestion on the right lane only



Source: Hendrik Ammoser, Faculty of Transport and Traffic Sciences, Dresden, Germany

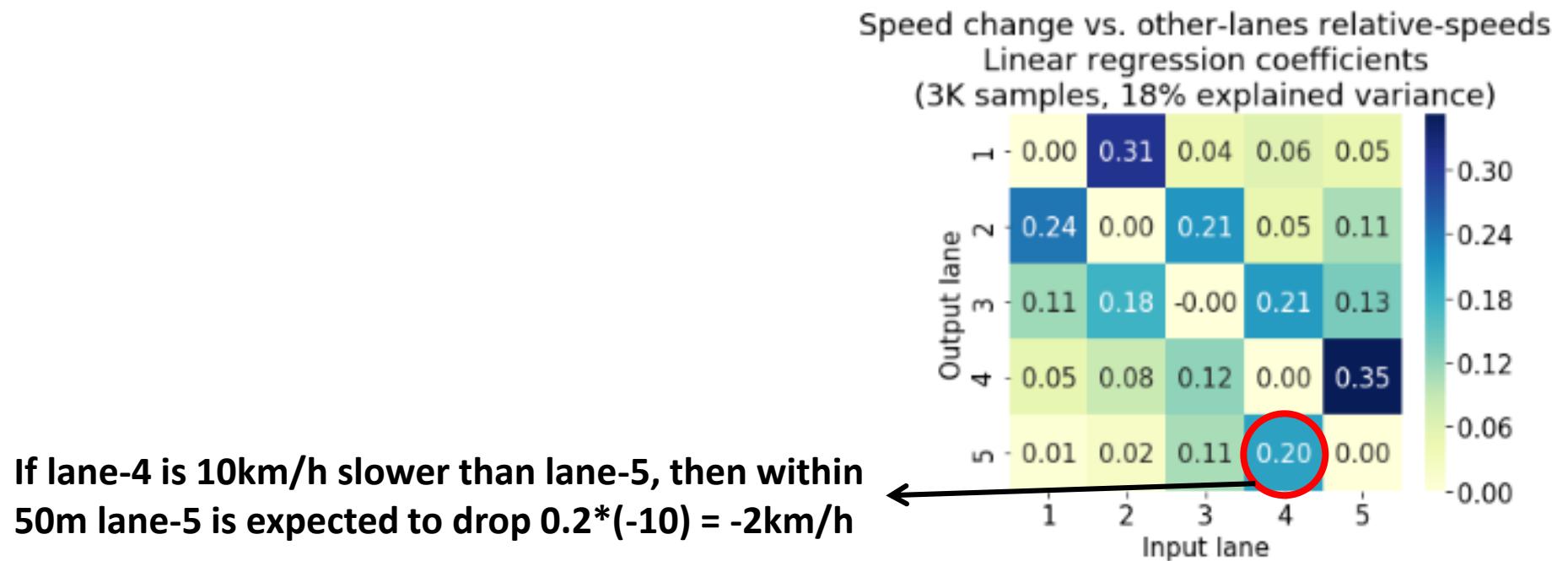
Speed vs. lane

- Left lanes are faster – in particular in free-flow



Can a driver trust currently-faster lanes?

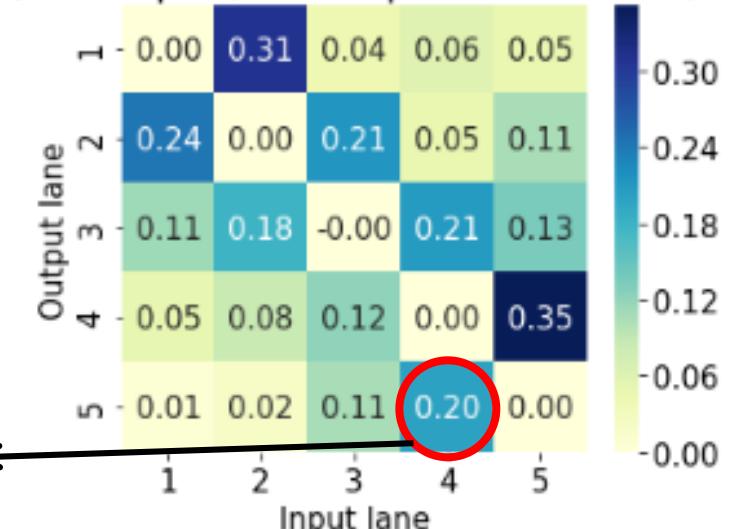
- I drive and the lanes around me move faster – will they keep moving faster?
 - **Output:** prediction of speed-changes in current lane within 50m
 - **Input:** speed differences of adjacent lanes – linearly-explain 18% of the changes out-of-sample



Can a driver trust currently-faster lanes?

- I drive and the lanes around me move faster – will they keep moving faster?
 - **Output:** prediction of speed-changes in current lane within 50m
 - **Input:** speed differences of adjacent lanes – linearly-explain 18% of the changes out-of-sample
 - Within 50m, my speed is expected to move 20-30% towards the adjacent speeds
 - More than 50% of the speed-difference between lanes diminishes within 50m
- Note:
 - Only videos of congestions
 - Memoryless model (can't know historical speeds as the driver observed them up the road)

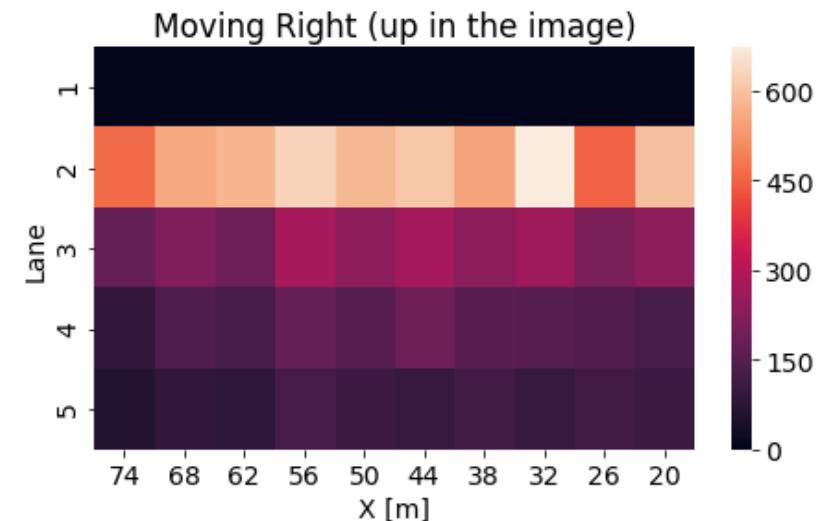
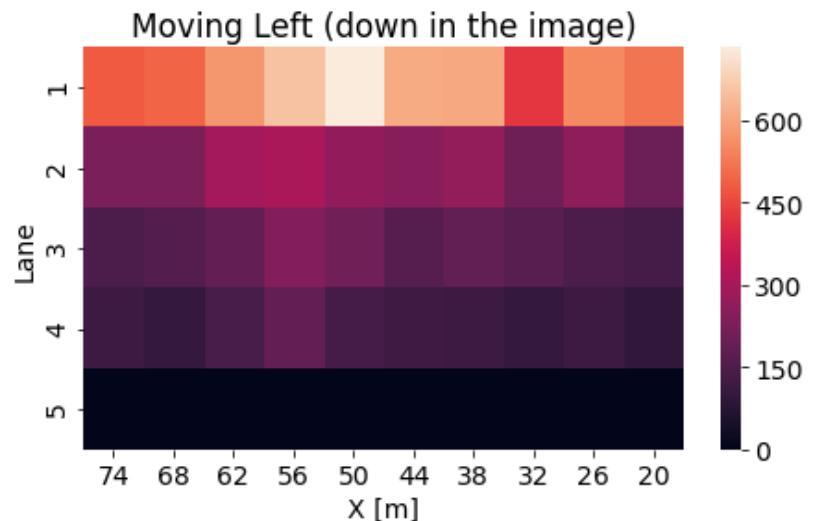
Speed change vs. other-lanes relative-speeds
Linear regression coefficients
(3K samples, 18% explained variance)



If lane-4 is 10km/h slower than lane-5, then within 50m lane-5 is expected to drop $0.2 * (-10) = -2\text{km/h}$

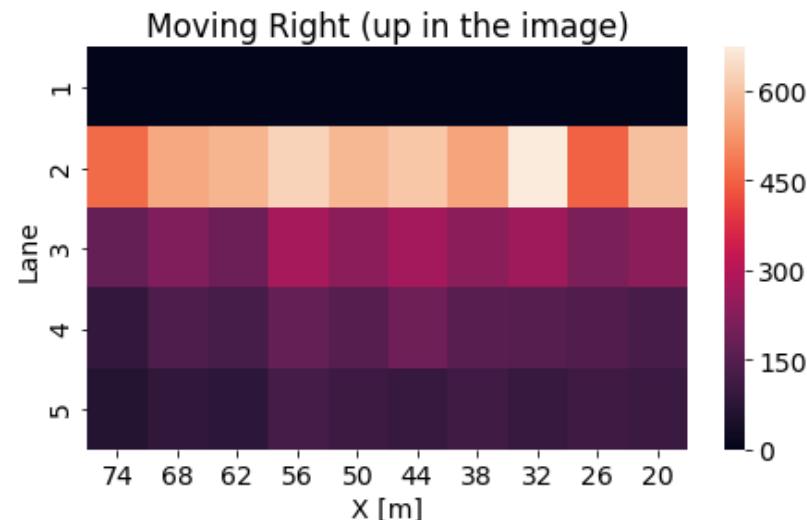
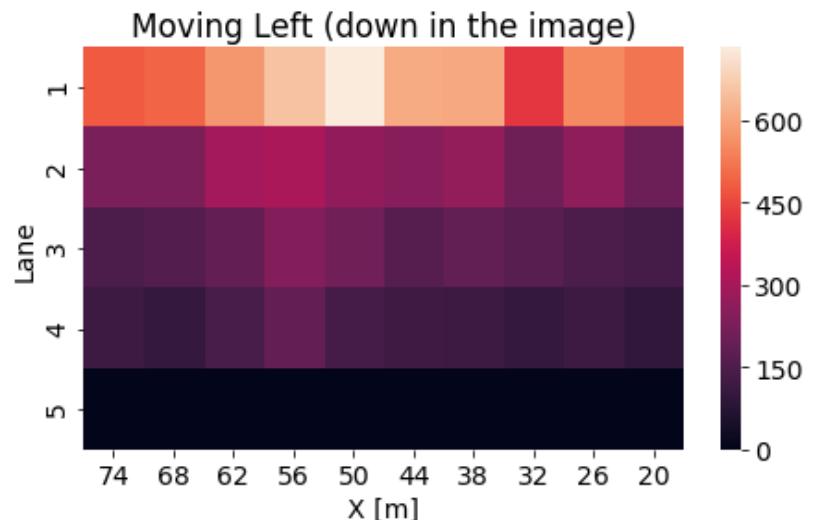
Lane transitions

- 24K lane-transitions detected over 60m of road
- Mostly in the right – near the entries & exits



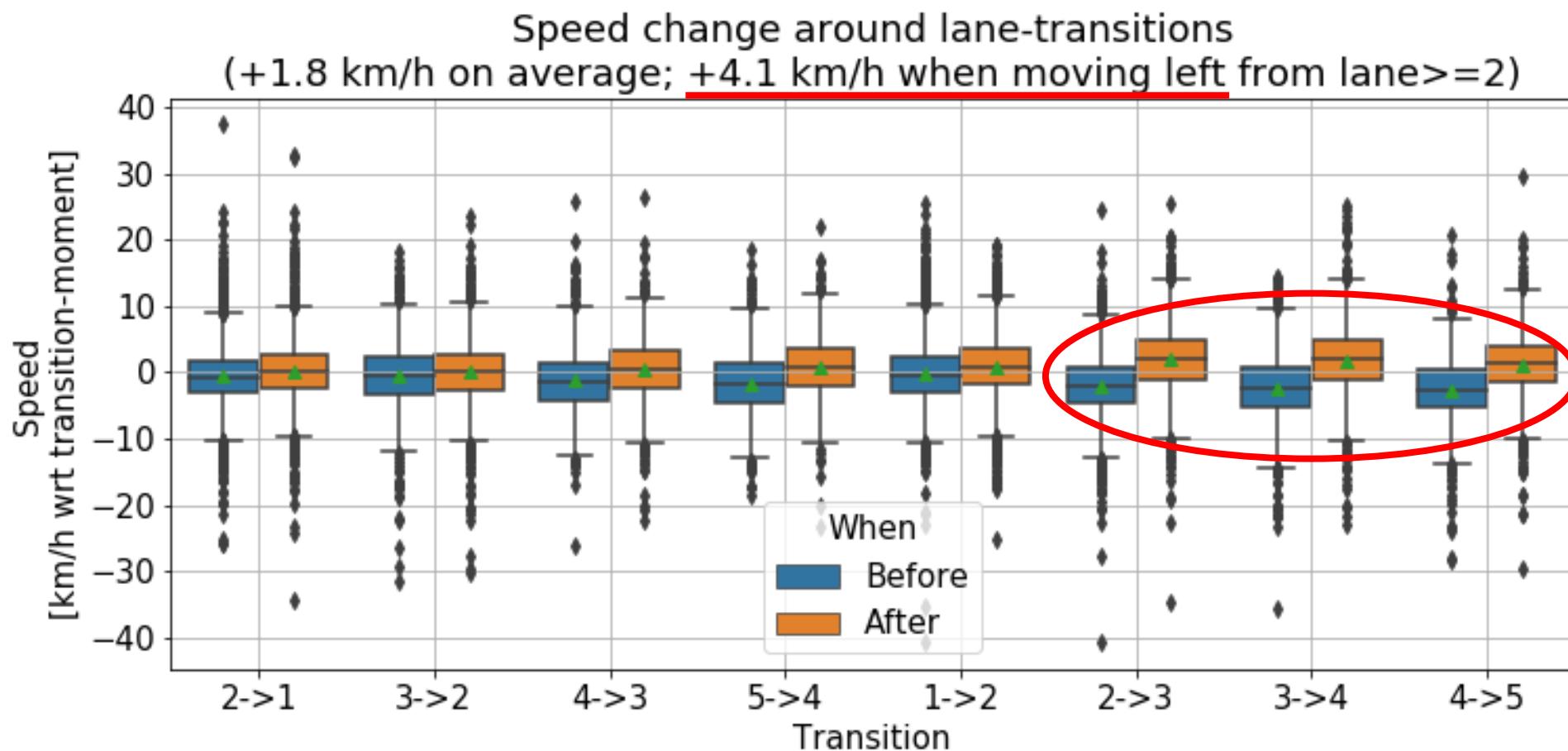
Lane transitions

- 24K lane-transitions detected over 60m of road
- Mostly in the right – near the entries & exits
- Manual sanity check: **5/10 FP transitions** 😞
 - Close to edge of a lane (e.g. high vehicles)
 - Tracking confusions on dense traffic
- 12K true transitions / 82K vehicles = **transition per 7 vehicles**



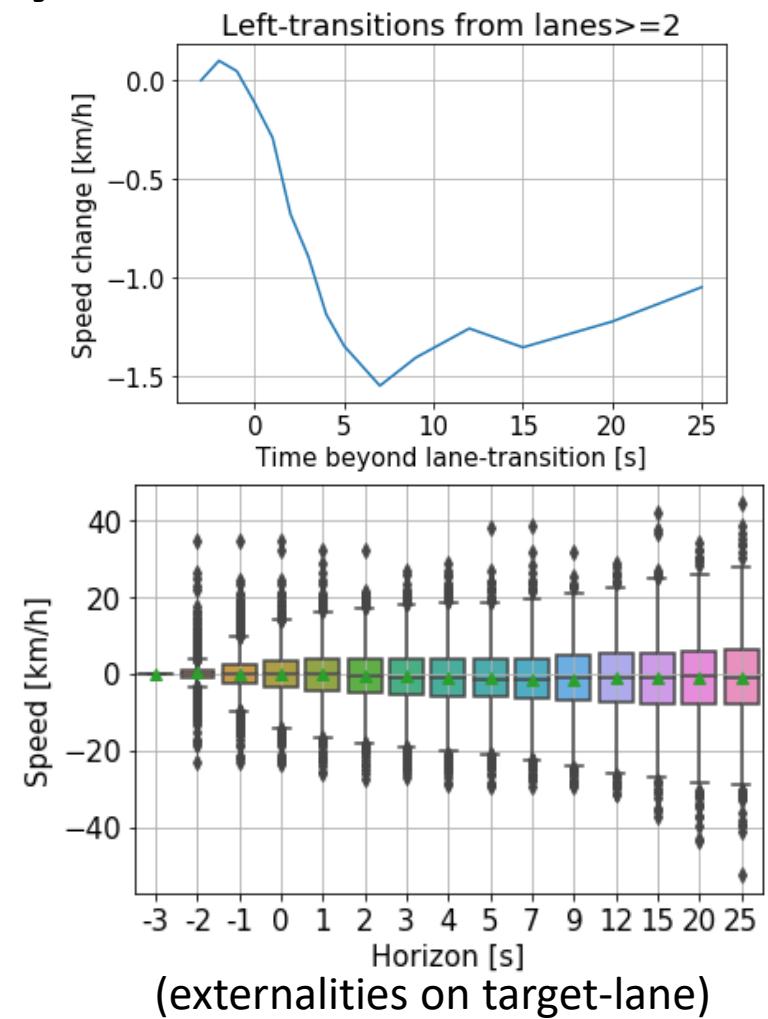
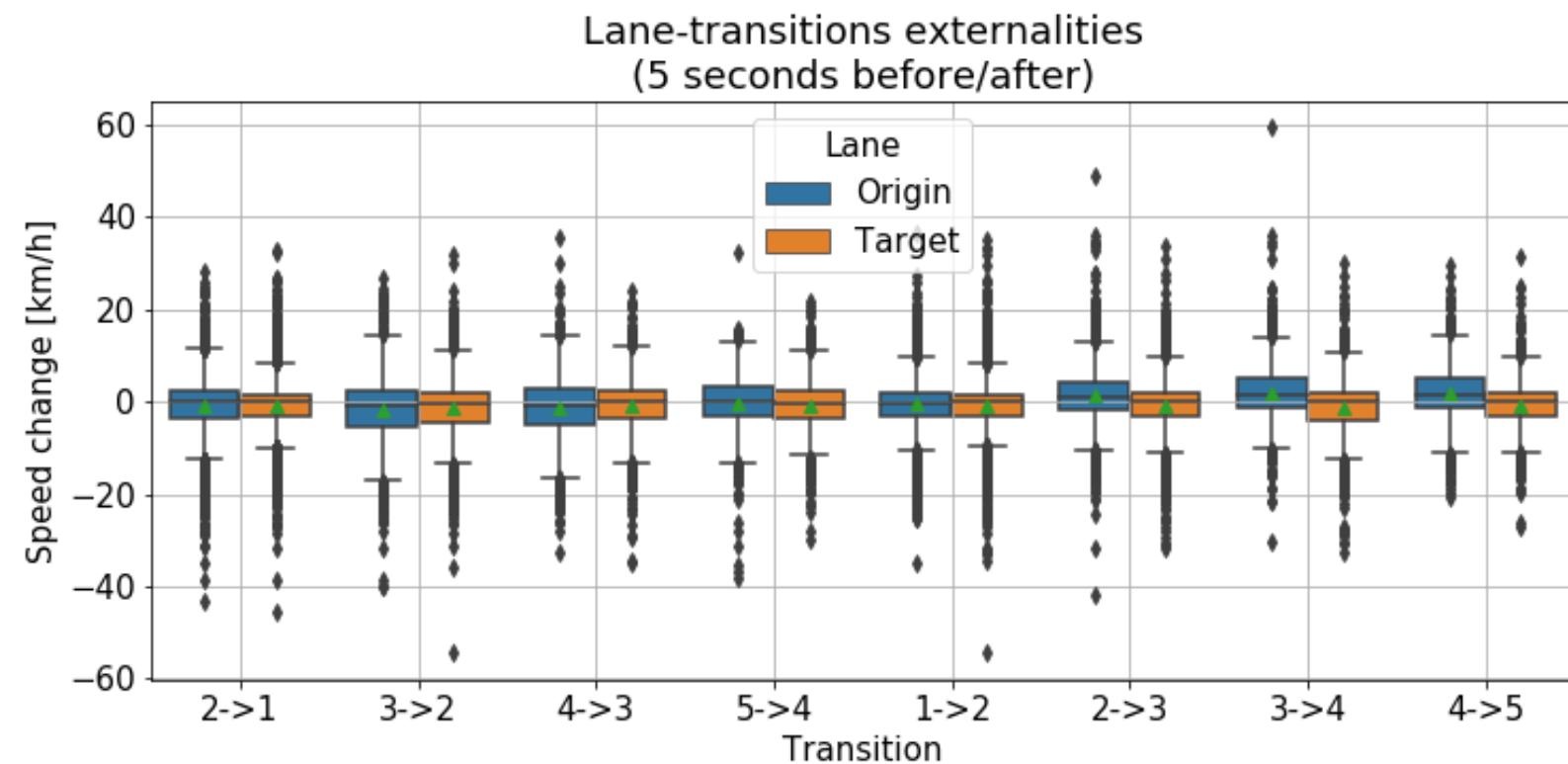
Lane transitions

- Transition is **usually followed by speed increase** (of the same vehicle)



Lane transitions

- Externalities (effect on other vehicles) are **too noisy** to be studied



Summary

Main contributions

- Demonstration of home-made applied traffic research
- Original dataset of traffic in a major road
- Detection
 - Small, crowded objects in noisy images
 - Trainable from little data
- Tracking
 - Fast-moving objects in low frame-rate videos
 - Robustness to missing detections
- Analysis
 - Validation of the *Fundamental Traffic Diagram*
 - Critical speed (max flux) – 60 km/h
 - Initial understanding of lane-transitions effects

Methodological insights (nothing surprising...)

- Data are everywhere
- **Draw/plot/print everything:** it's often not what you expected
- **Transfer learning** is insanely powerful
- **Sampling** may be crucial for training
- Have a **pipeline** for anything useful – you'll always run it again
- **Running time profiling:** many unexpected computational pitfalls

Possible extensions

- Data:
 - Tag before & after Hashalom interchange
- Detection:
 - Tag more data from "difficult" videos
 - Further tuning of hyper-params & architecture
 - Further output filtering (e.g. stricter manual constraints)
- Tracking:
 - Exploit size in addition to location
 - Non-linearly-additive models instead of KF:
 - Model parameters in meters (not pixels) – requiring location-dependent noise matrix
 - Large negative acceleration is more probable in higher speeds and in direction of motion
 - “Deep SORT”: exploit visual info
- Analysis:
 - ARIMA models for traffic speed or density
 - Effects of additional or removed lanes

References

- [Project repo in GitHub](#)
- [VGG Image Annotator](#) / Abhishek Dutta et al., Oxford
- [Guide to build Faster RCNN in PyTorch](#) / Fractal research group
- [Object detection and tracking in PyTorch](#) / Chris Fotache
- [Simple Online and Realtime Tracking](#) / Alex Bewley et al.
- [Kalman Filter](#) / Wikipedia
- [The Fundamental Traffic Diagram](#) / Wikipedia



Thank you