Traffic Analysis in Original Video Data of Ayalon Road

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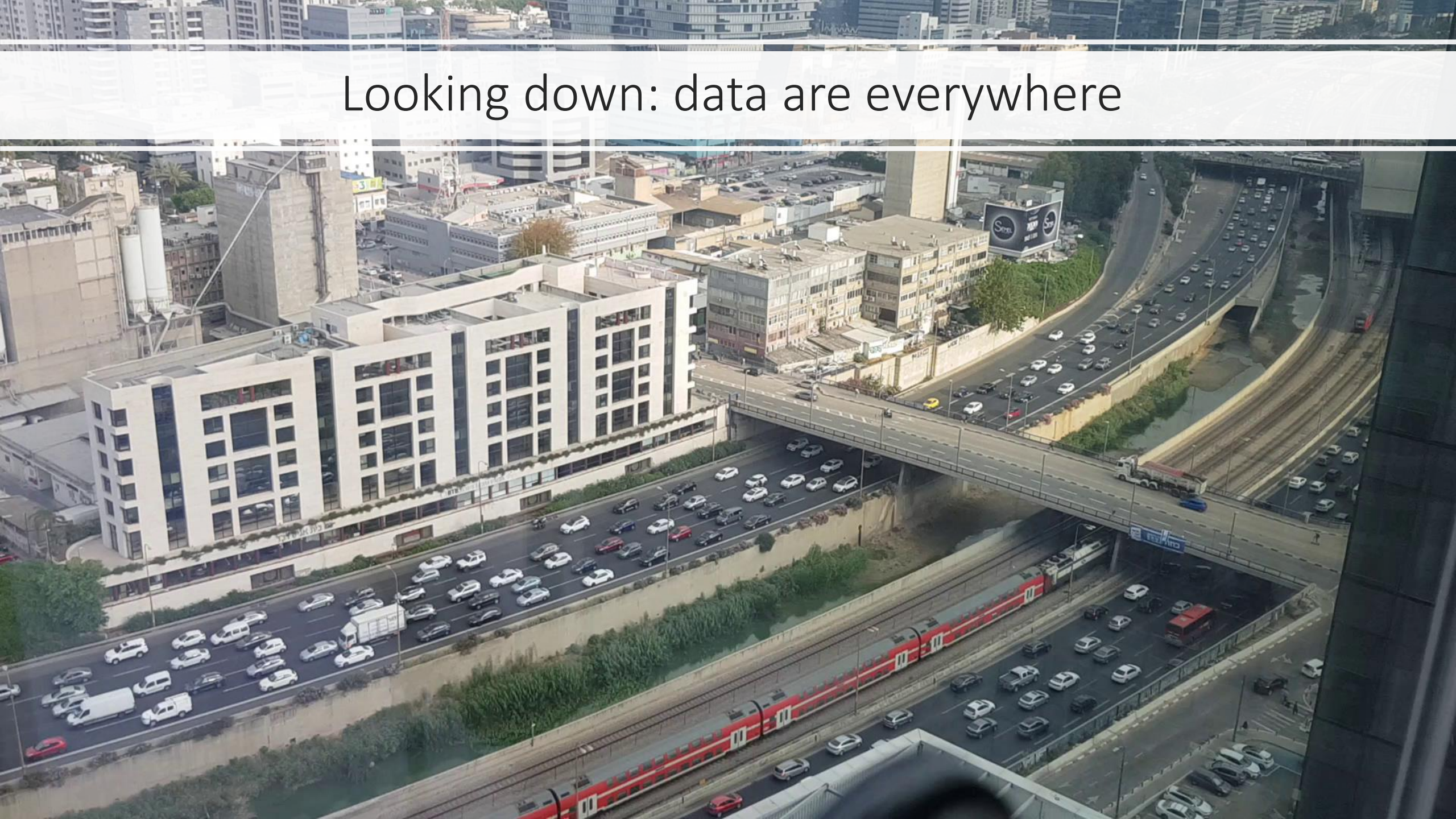
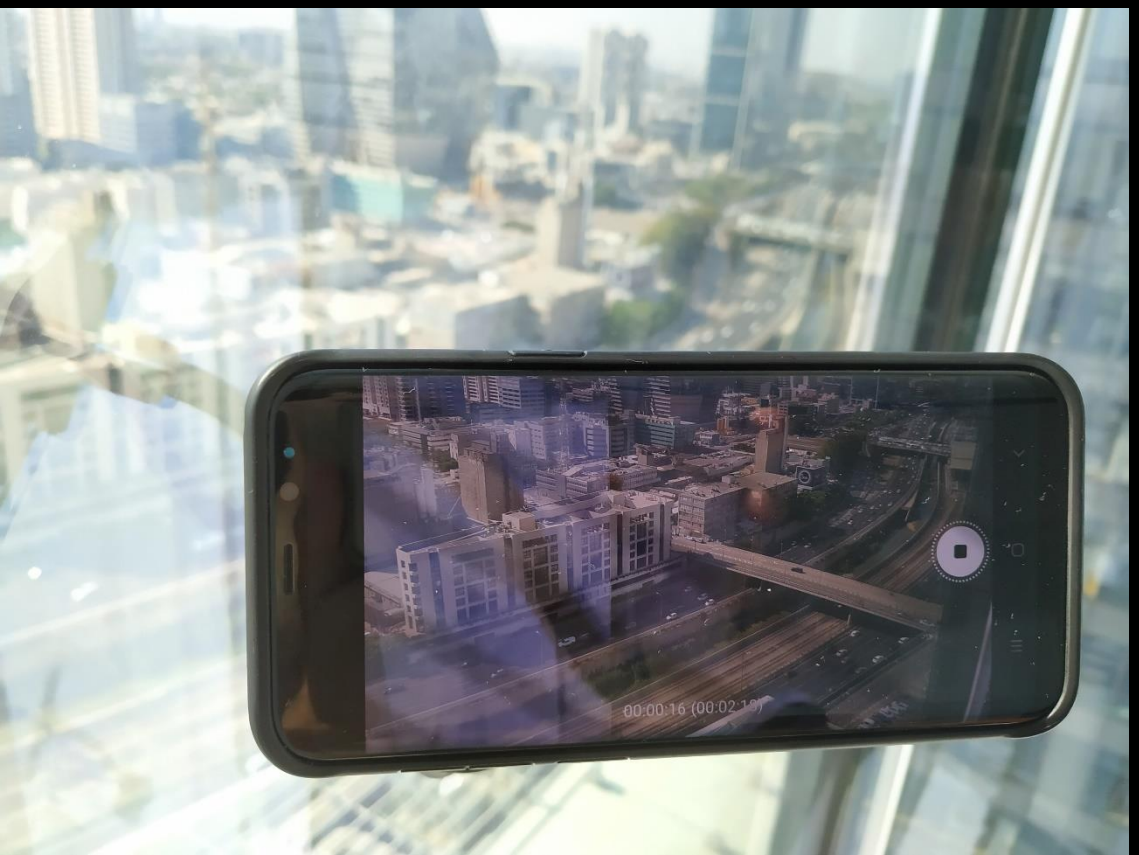
2019

Background

Looking down: data are everywhere

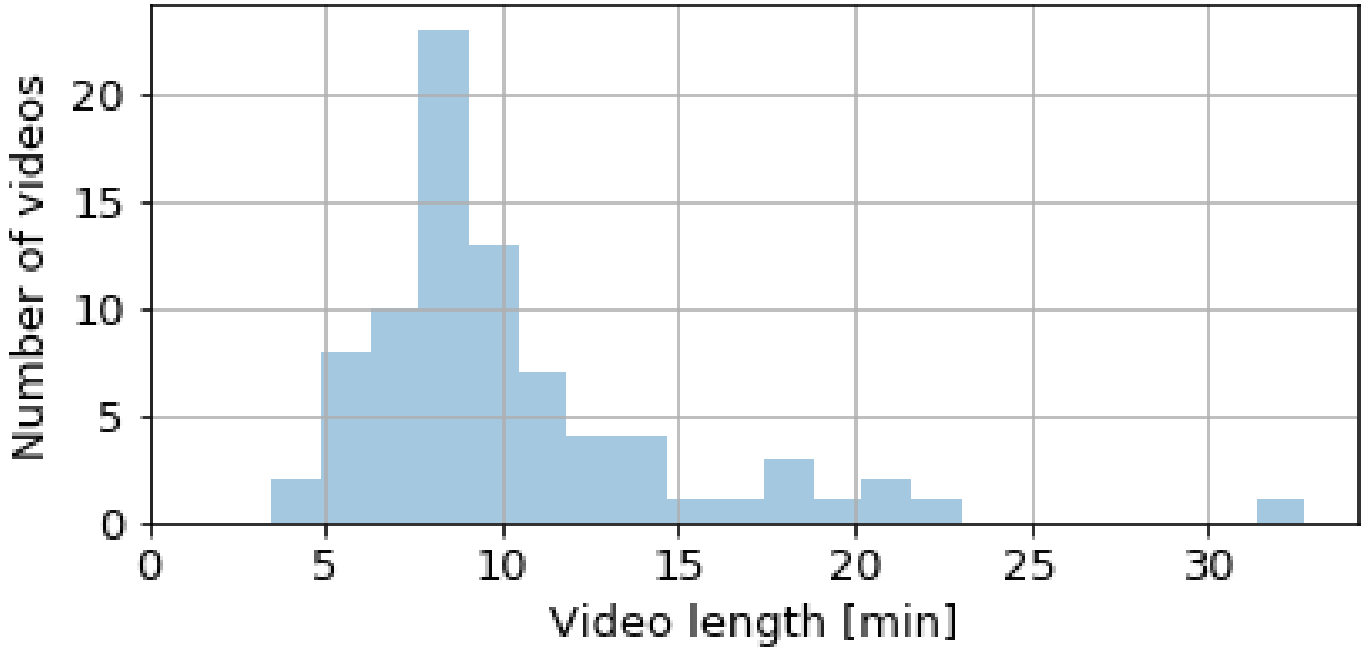


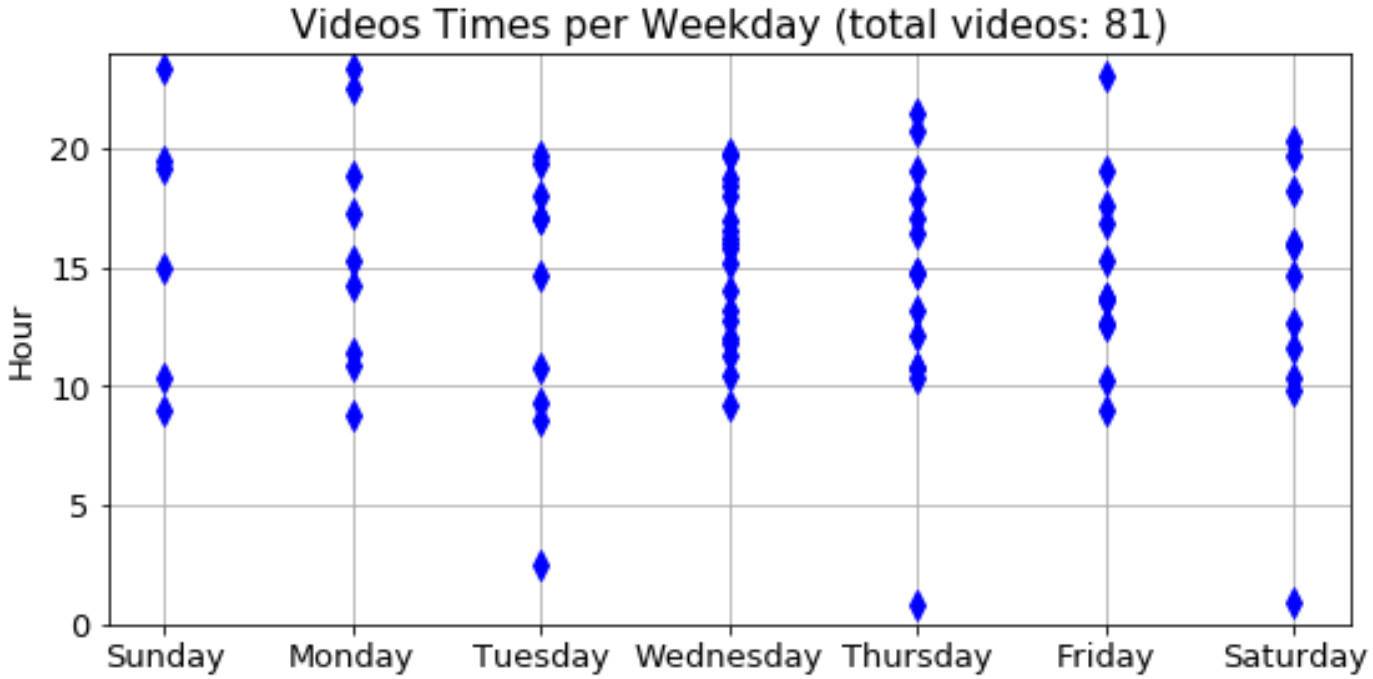
- Hyperlapse, x8 speed, Full-HD
- 120MB for 8 minutes



Collected data

- 81 videos X 8 minutes over 2 months



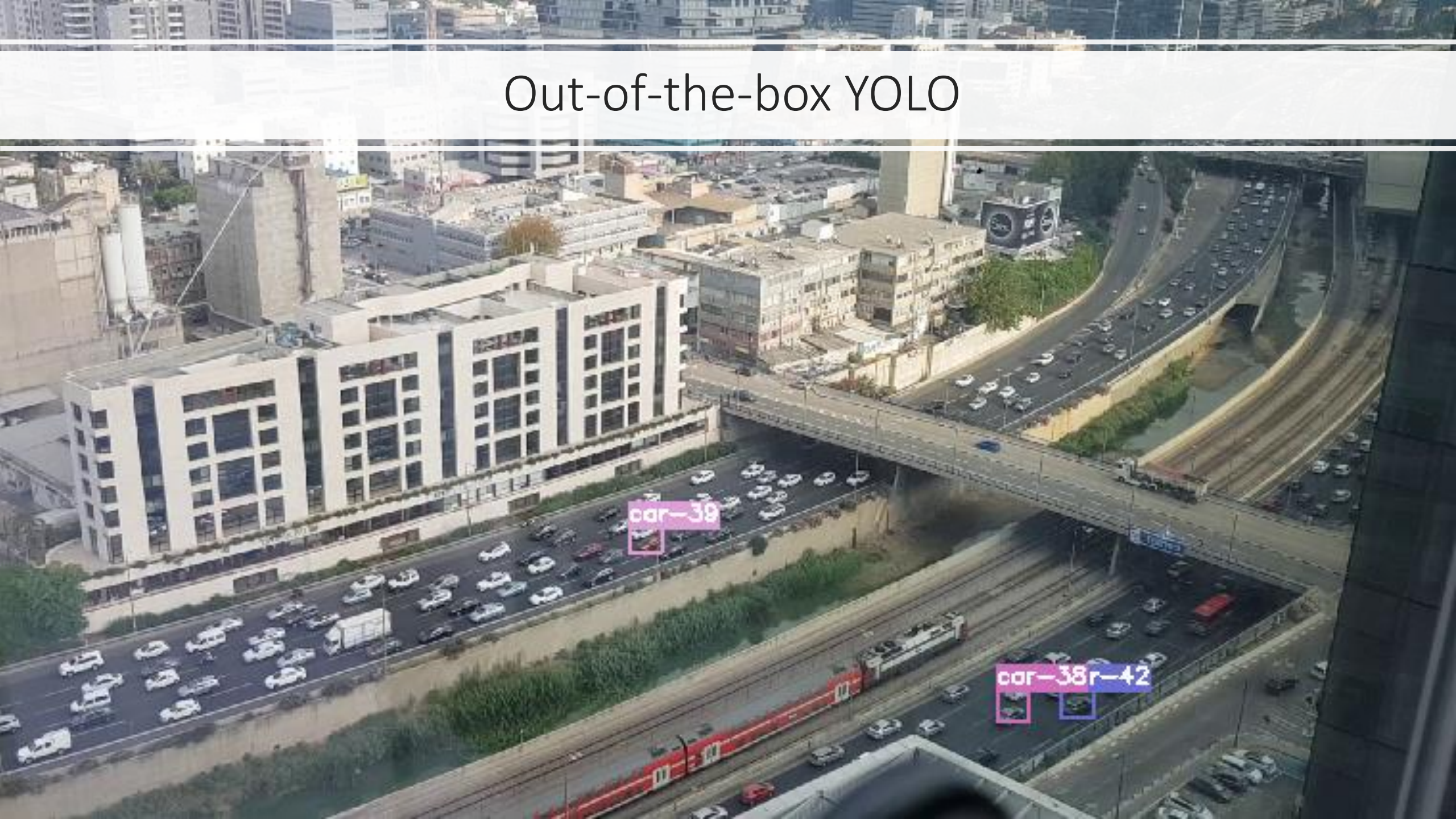


What we need

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

Detection

Out-of-the-box YOLO



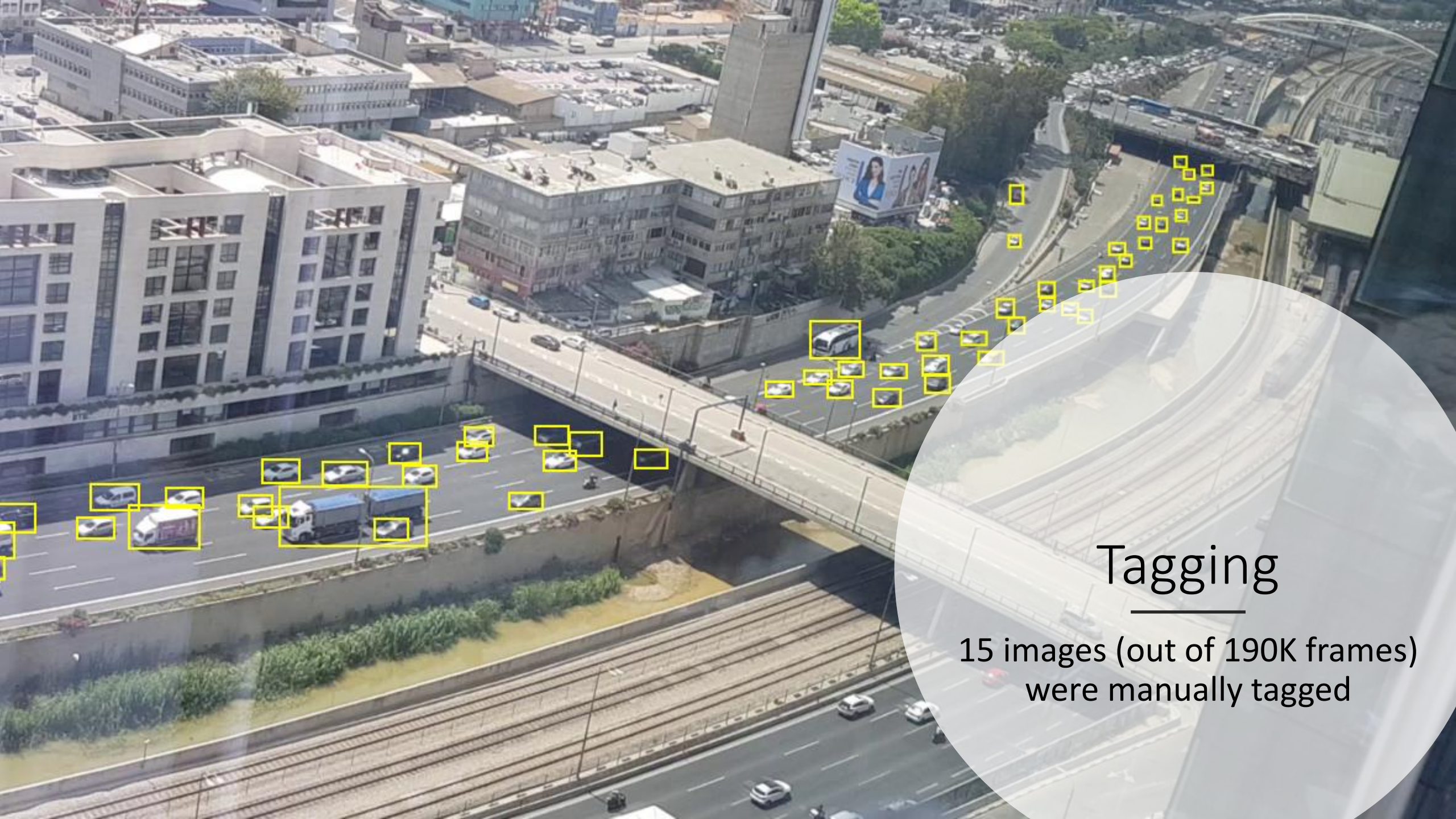
Out-of-the-box SSD (better with small, crowded objects)

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

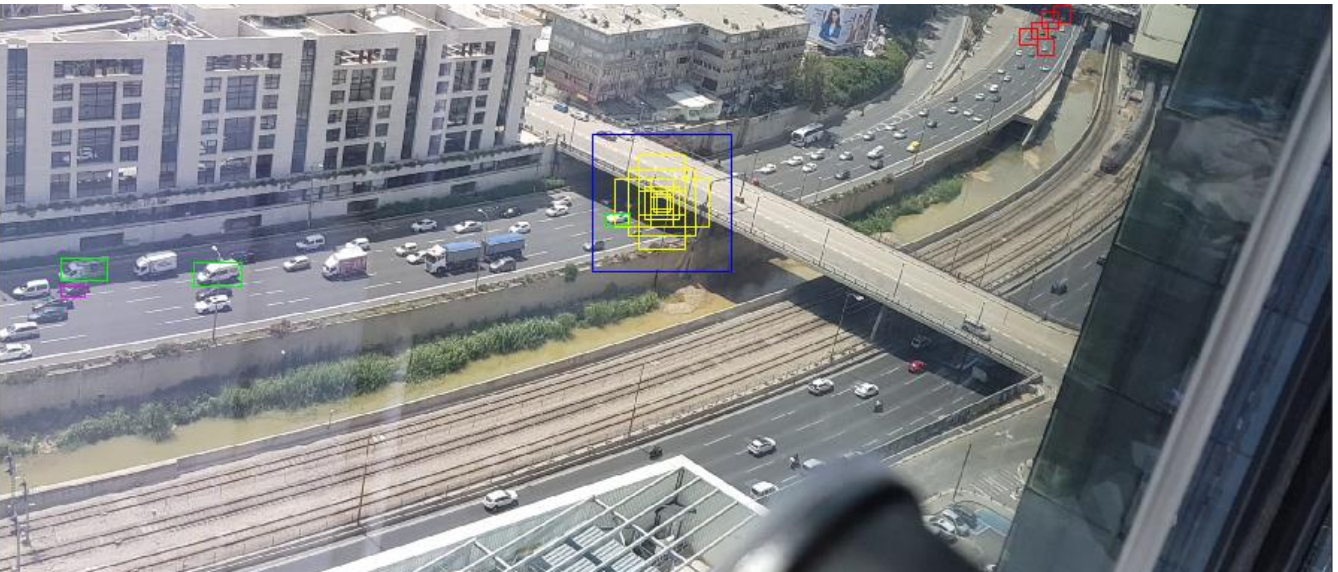


Tagging

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

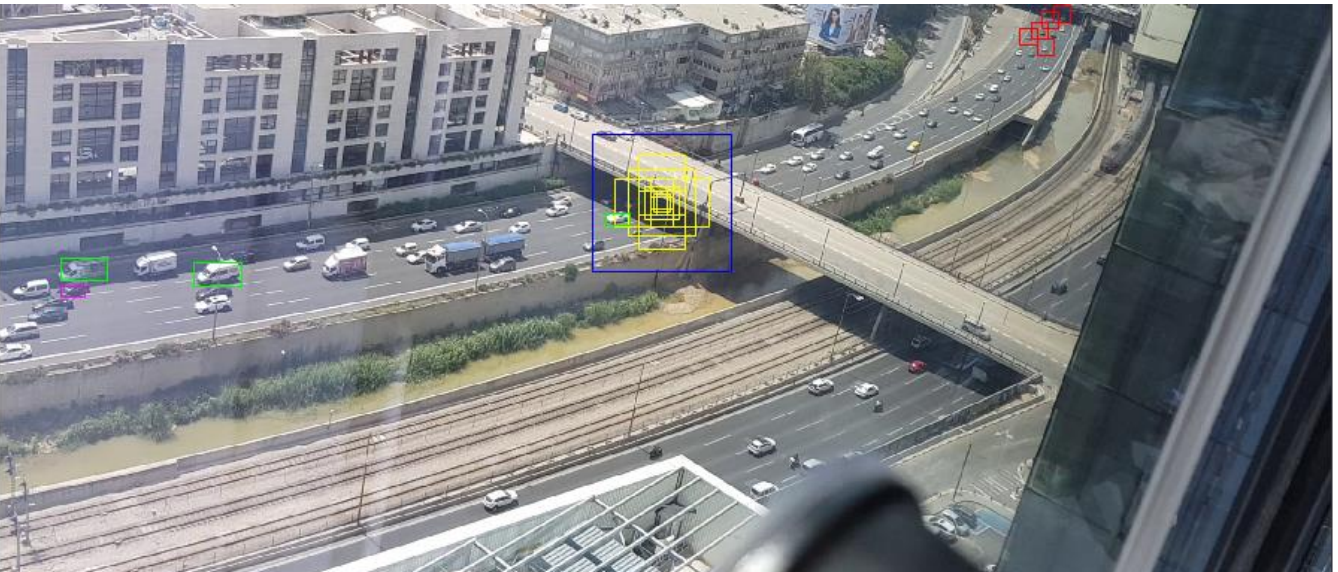
Tagged vehicles → network-compatible output

- 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***)

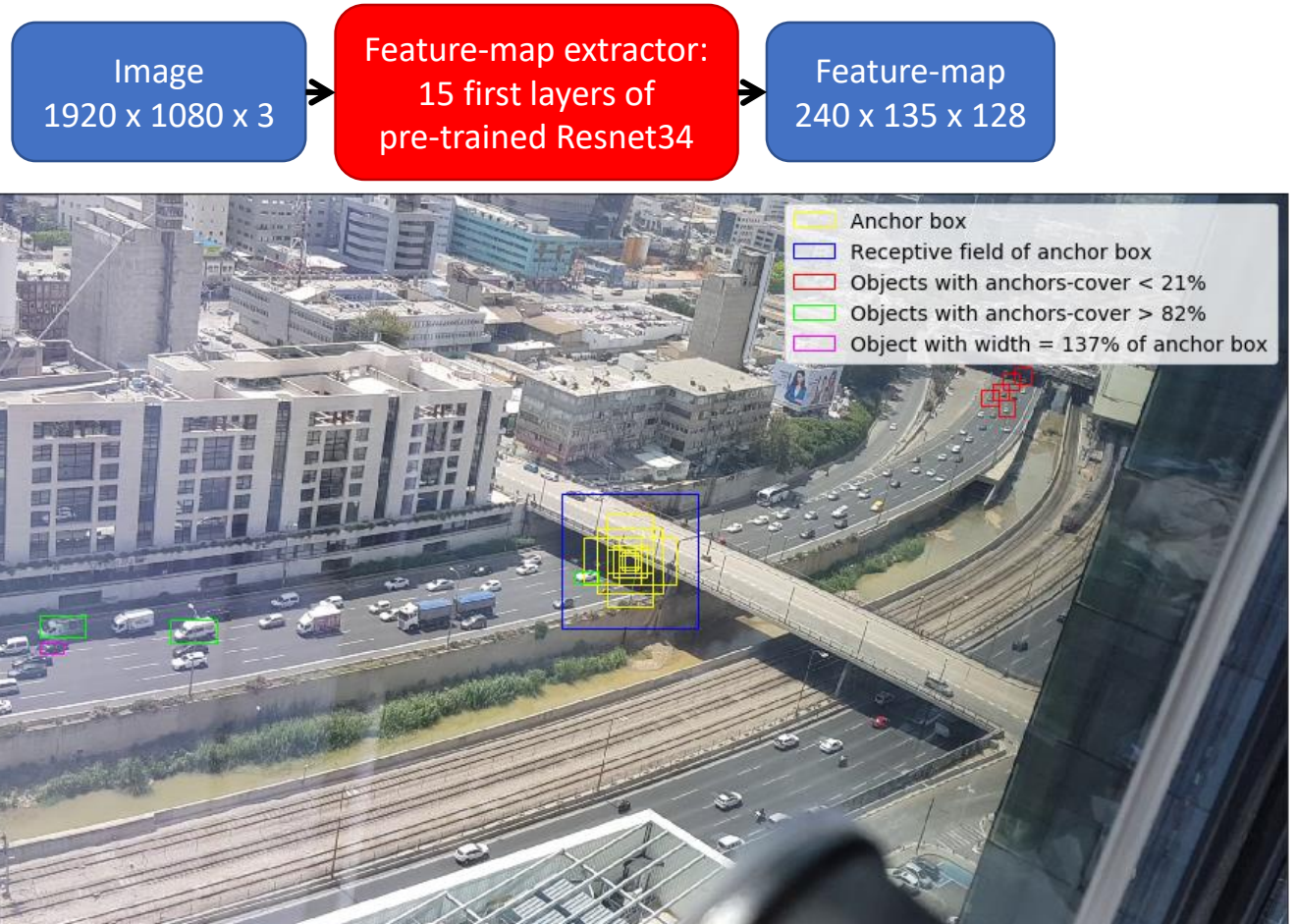


Tagged vehicles → network-compatible output

- 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



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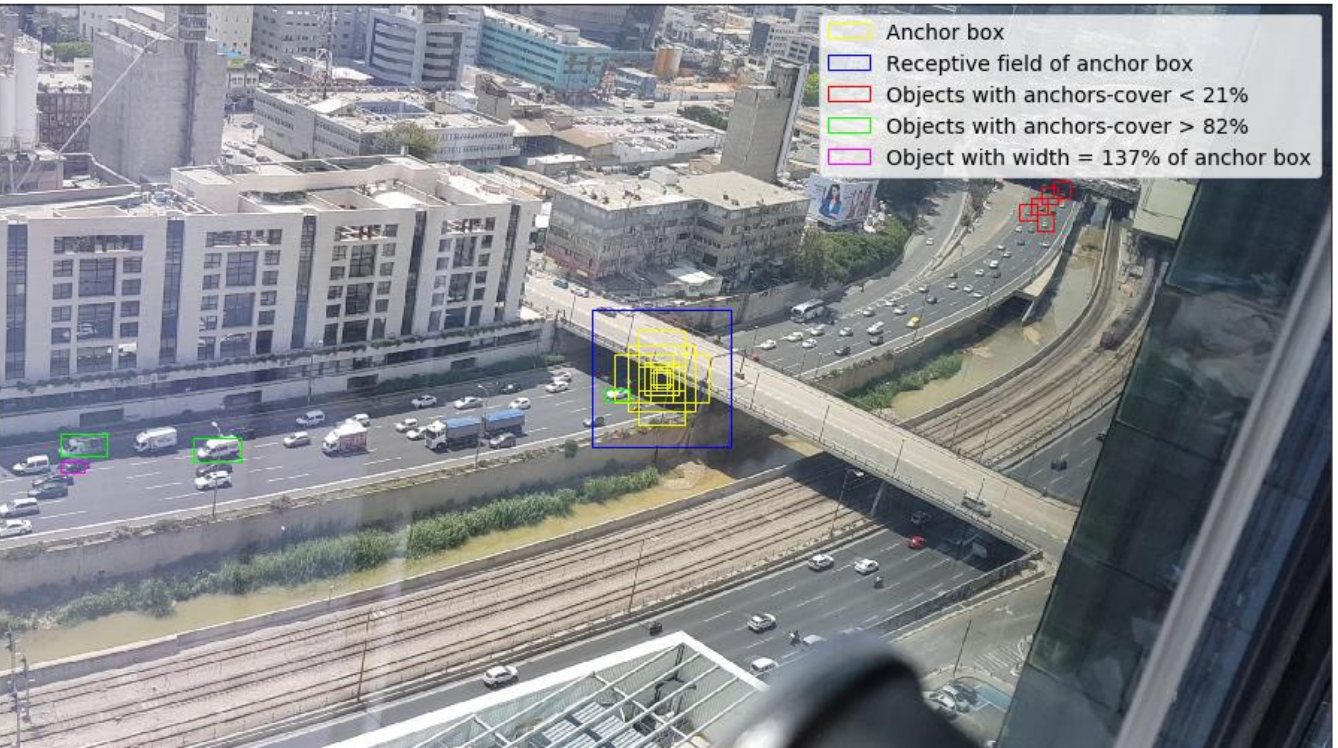

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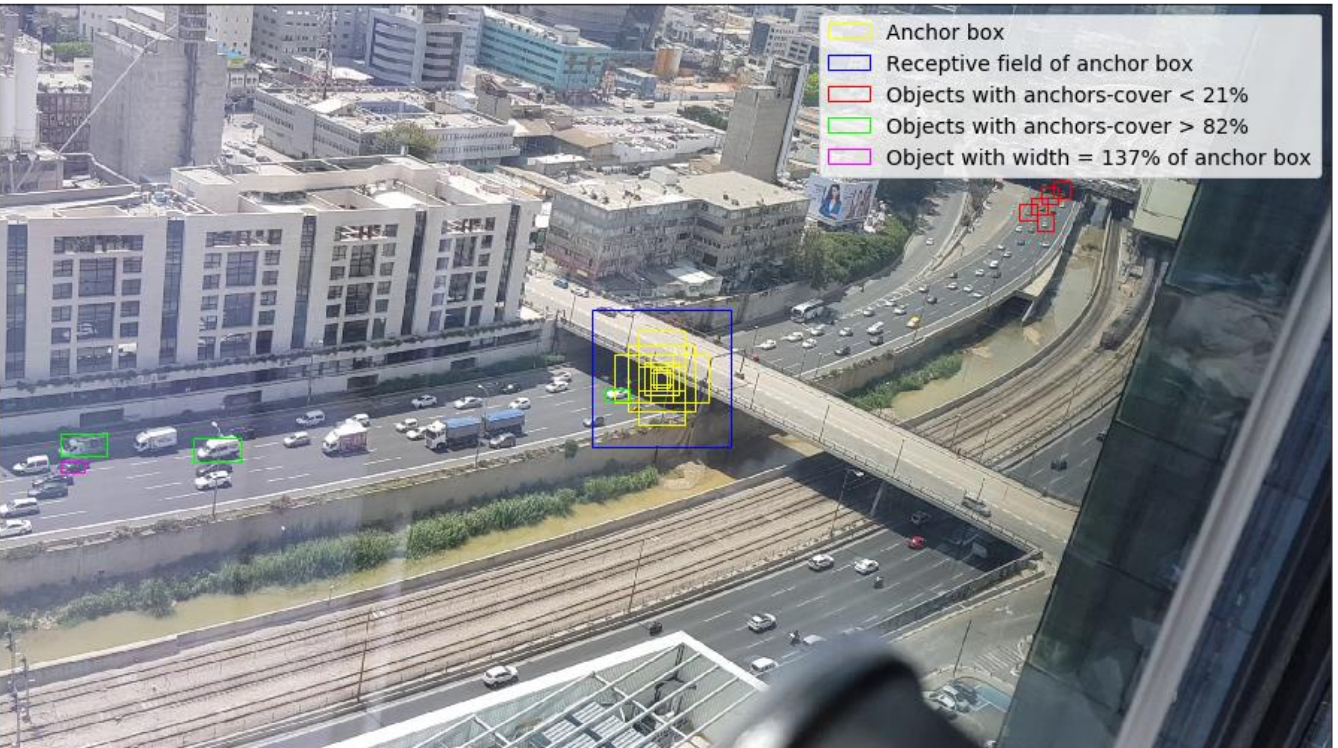
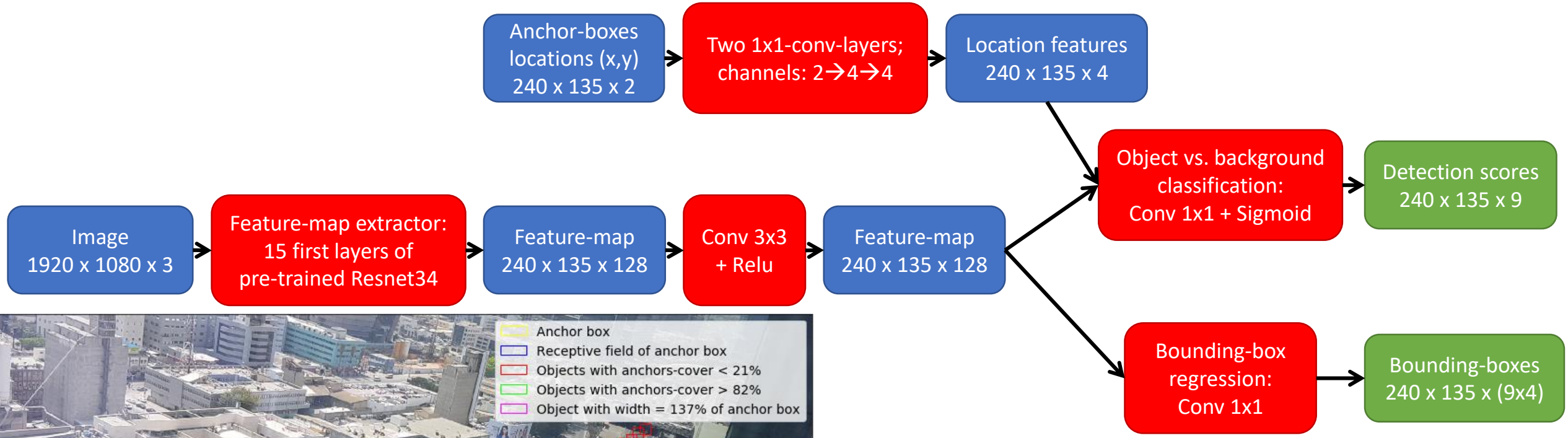
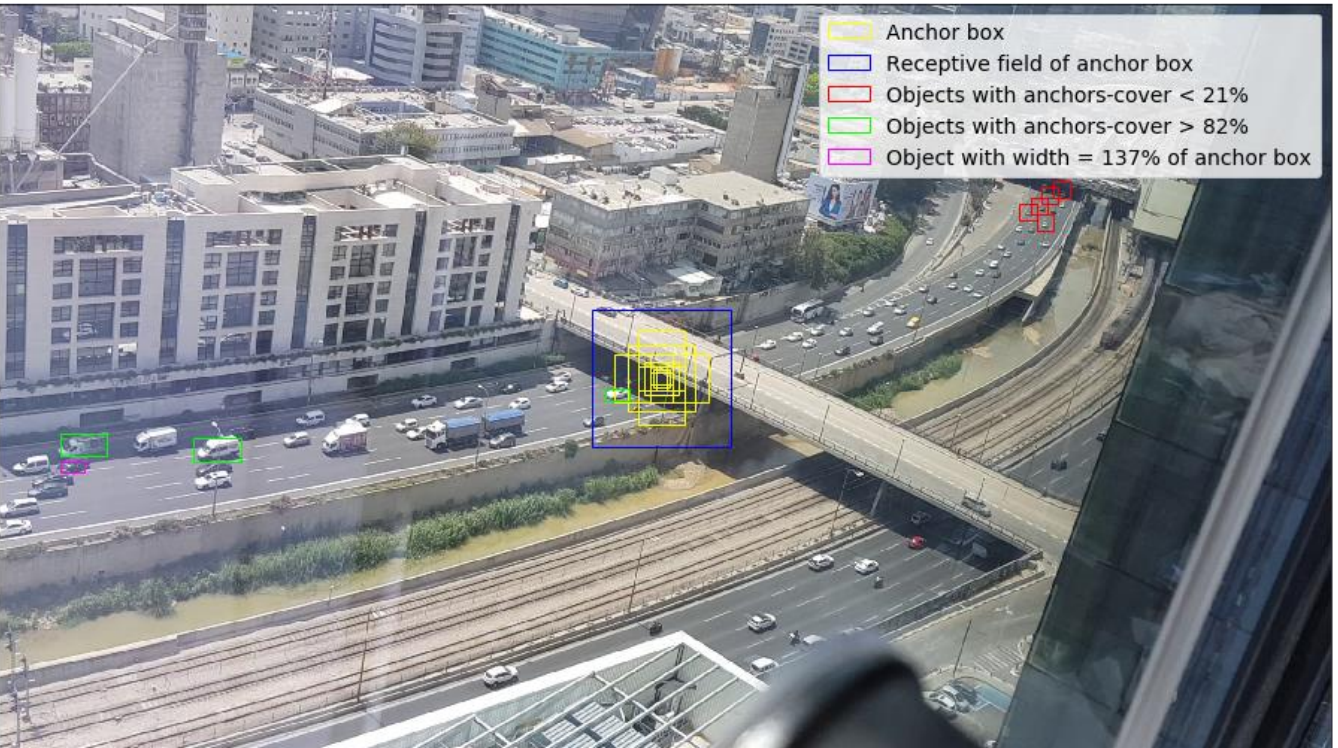


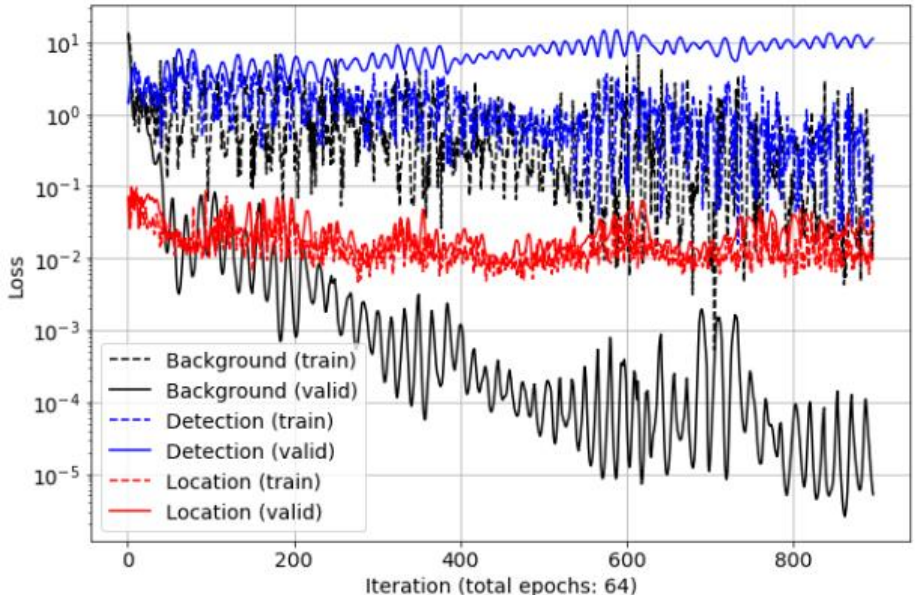
Network architecture





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*

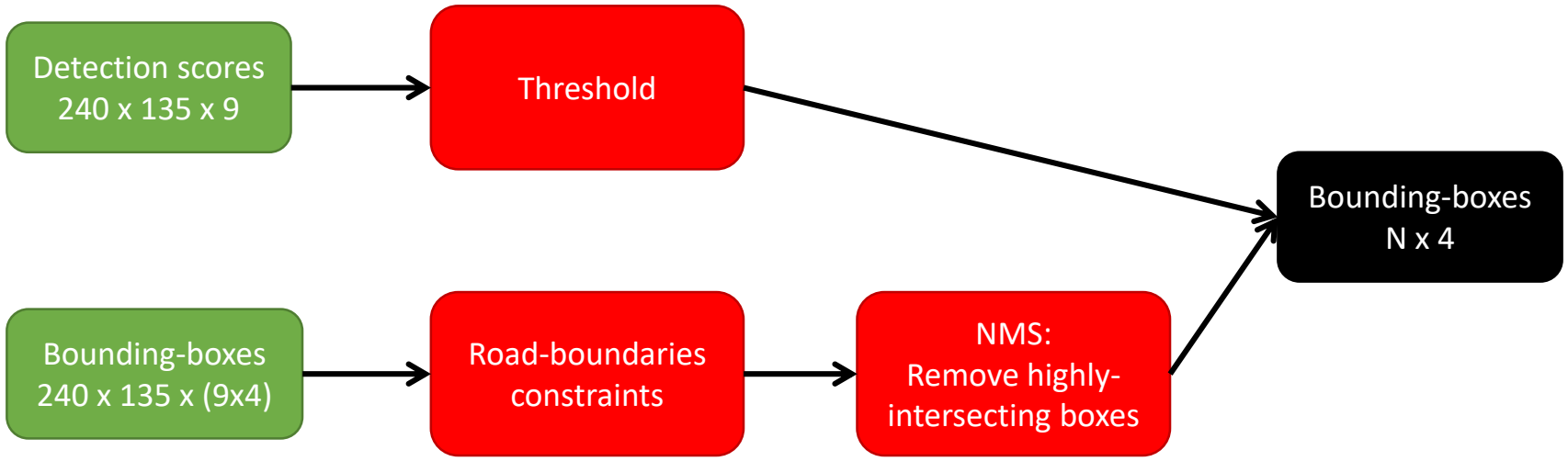
3 training images

Middle of training (15 training images)

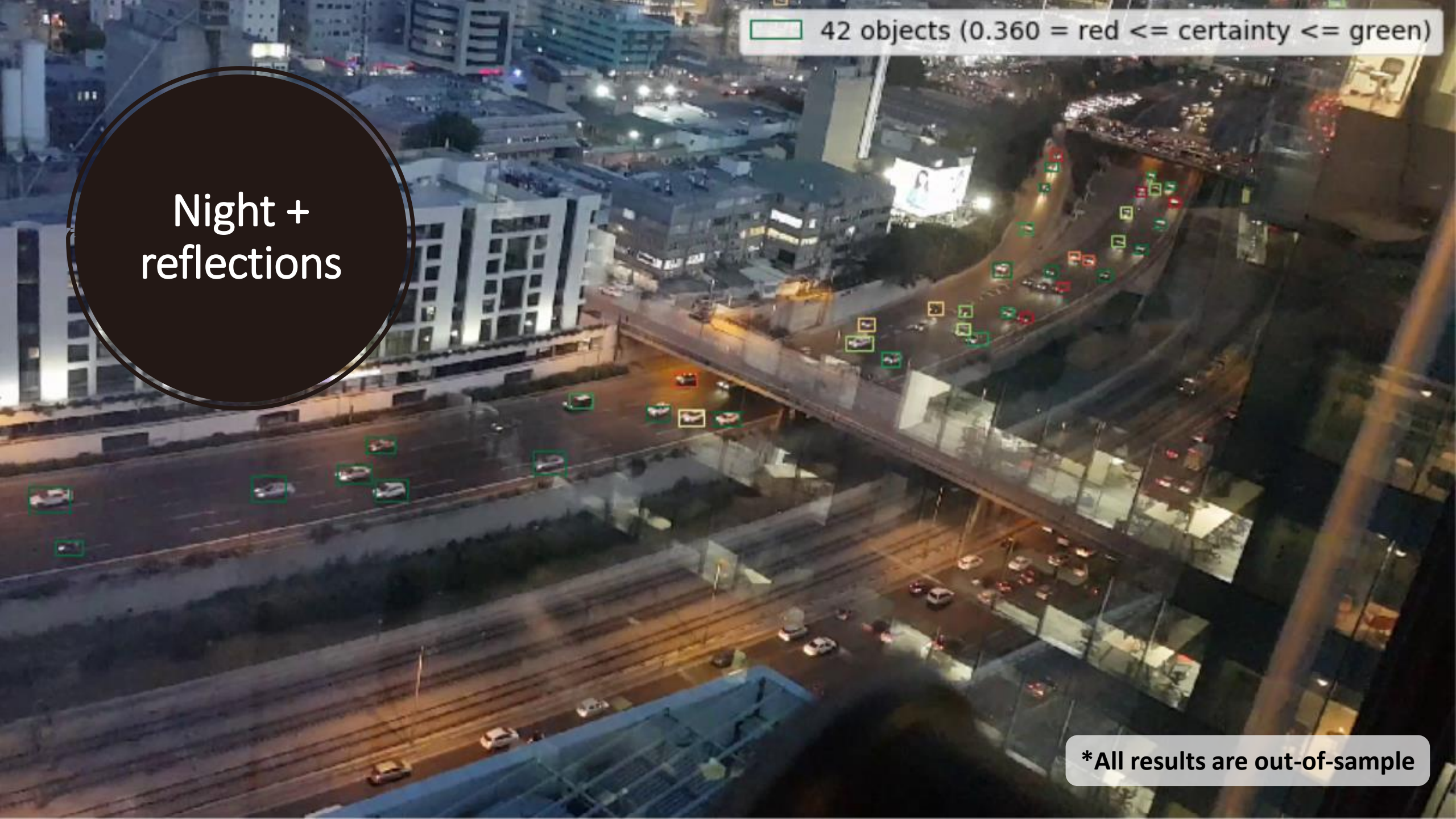
Middle of training

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


70 objects (0.318 = red <= certainty <= green
Protest
*All results are out-of-sample

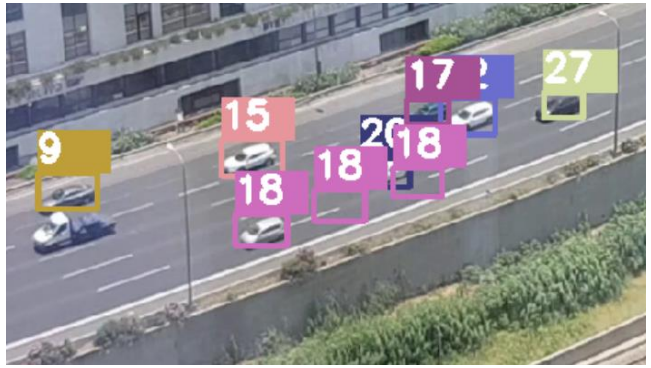

22 objects (0.379 = red <= certainty <= green)
Shavuot
*All results are out-of-sample

Tracking

SORT: Simple, Online and Realtime Tracking

- New detections ↔ "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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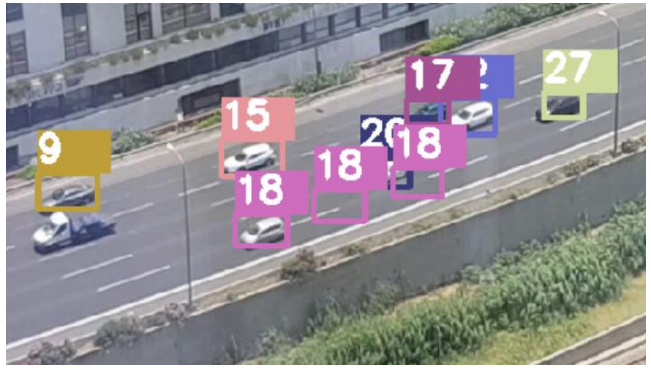
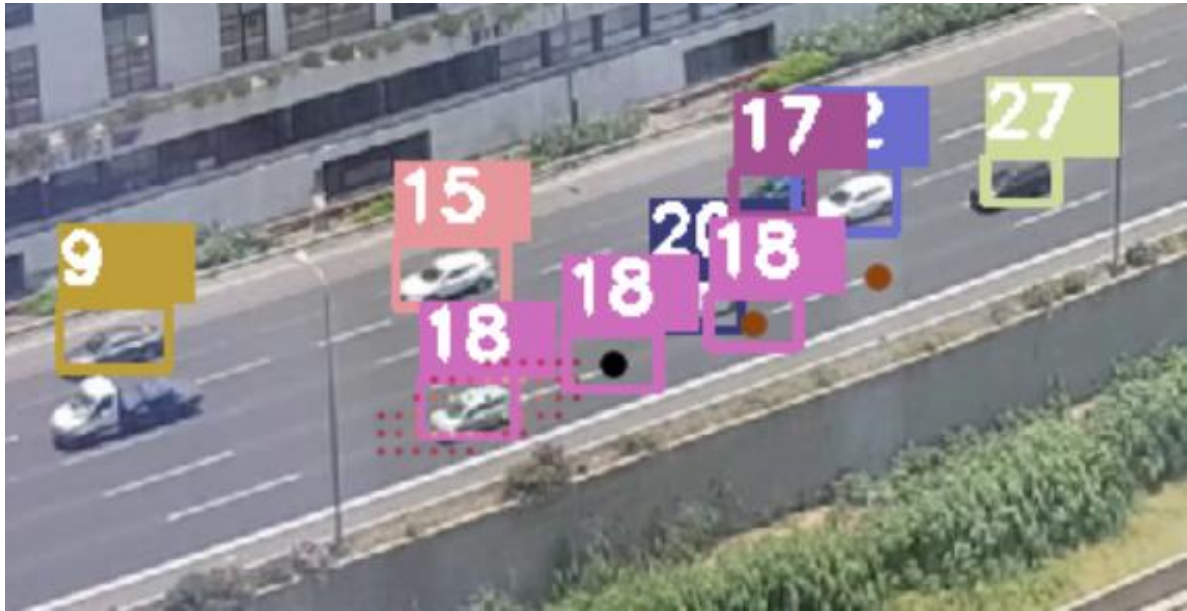


What the customer had in mind

- 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?

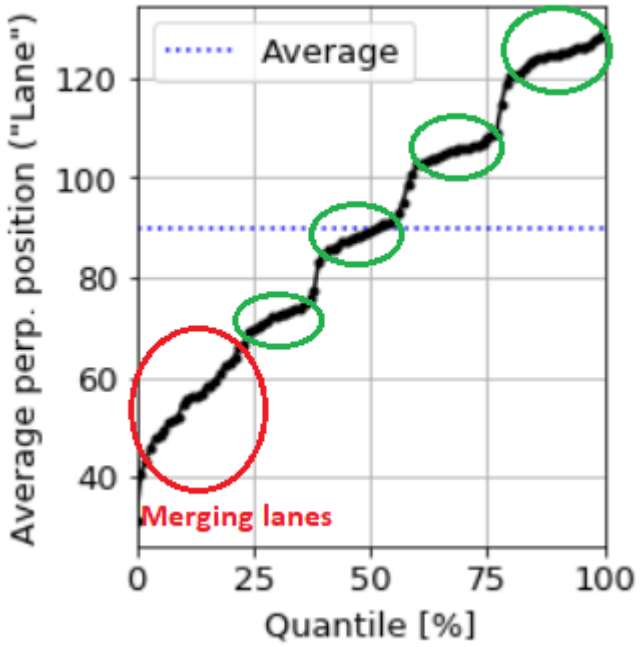
KF-based objects assignment

- 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** = $U^T \cdot \begin{pmatrix} 10^2 & 0 \\ 0 & 2^2 \end{pmatrix} \cdot U$ $\quad (U \coloneqq (u1, u2))$
  - ⇒ **Likelihood (any location | predicted location, covariance)**
- [New detections ↔ tracks] assigned by likelihood

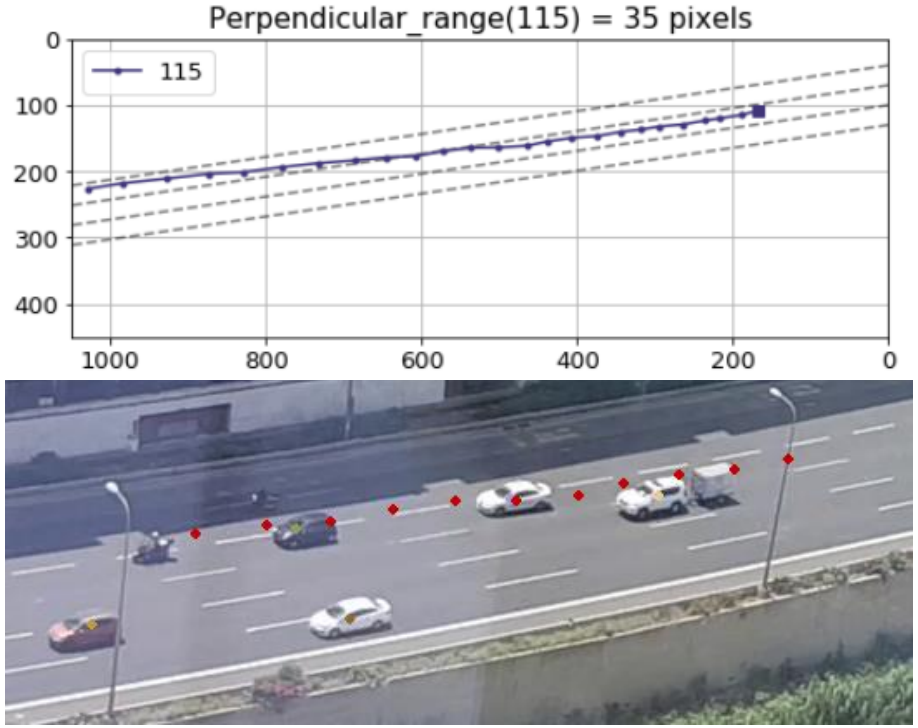


Does it work?

Vehicles distribution among lanes



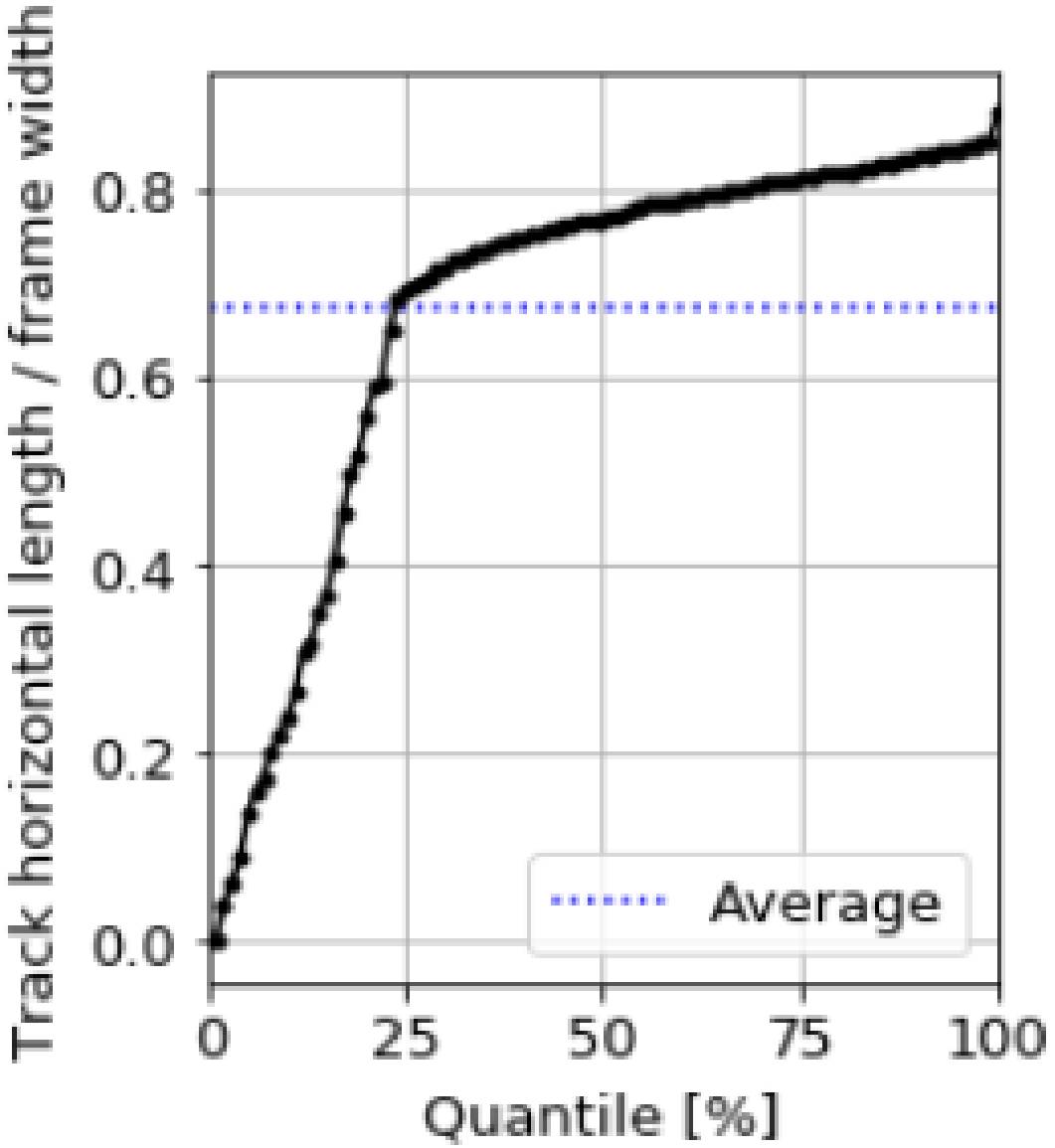
Detected lane transition



Track over gaps w/o detection

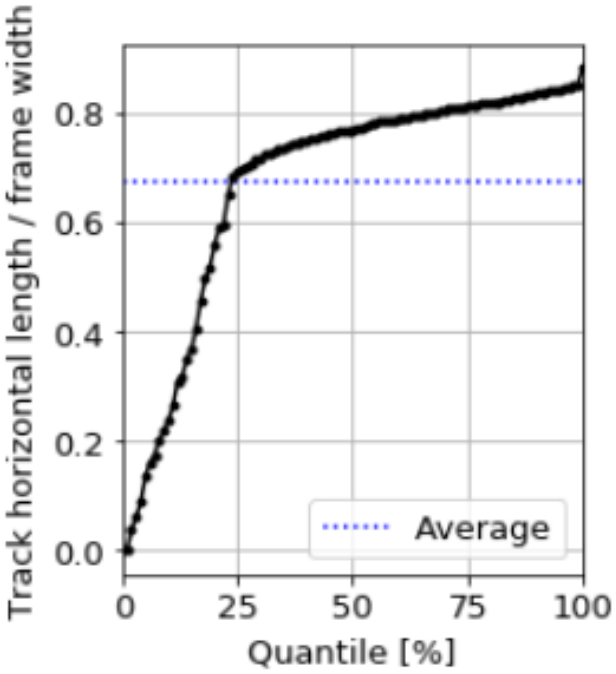
Does it work?

- 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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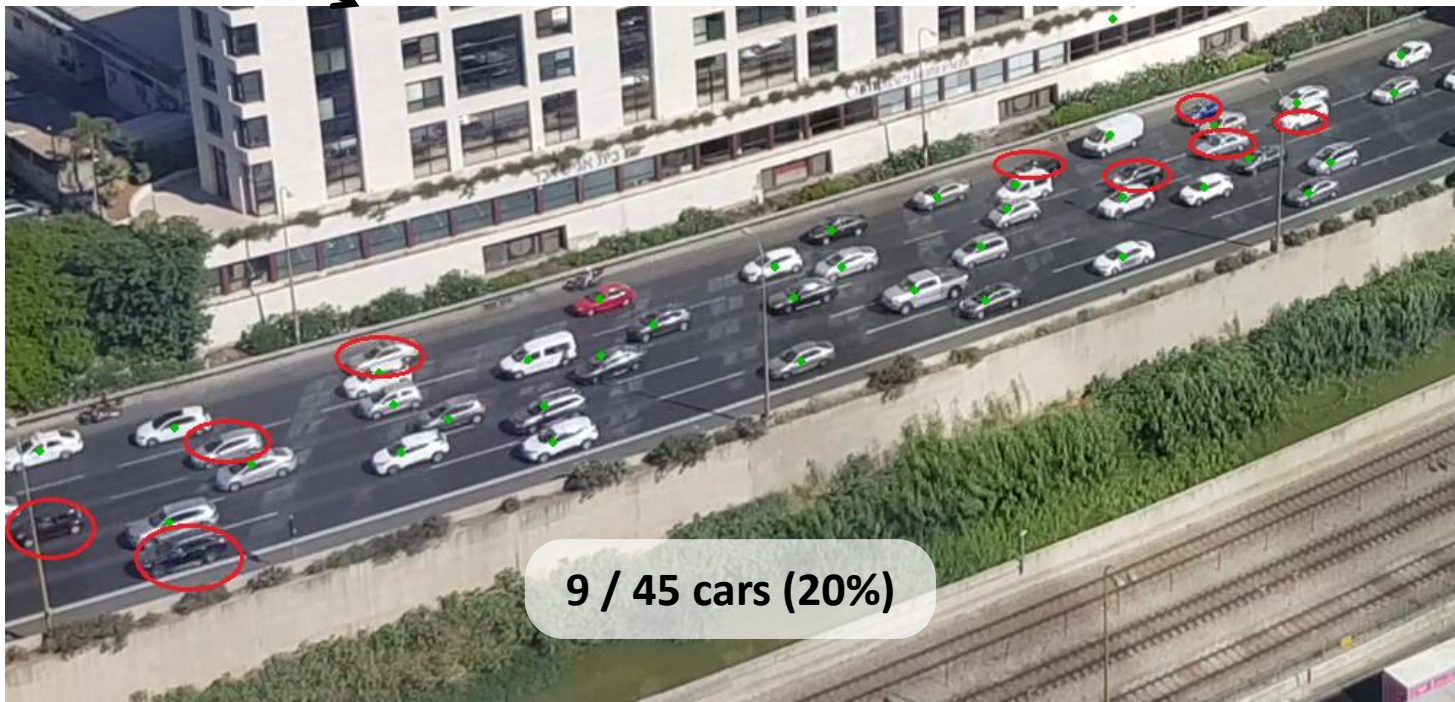
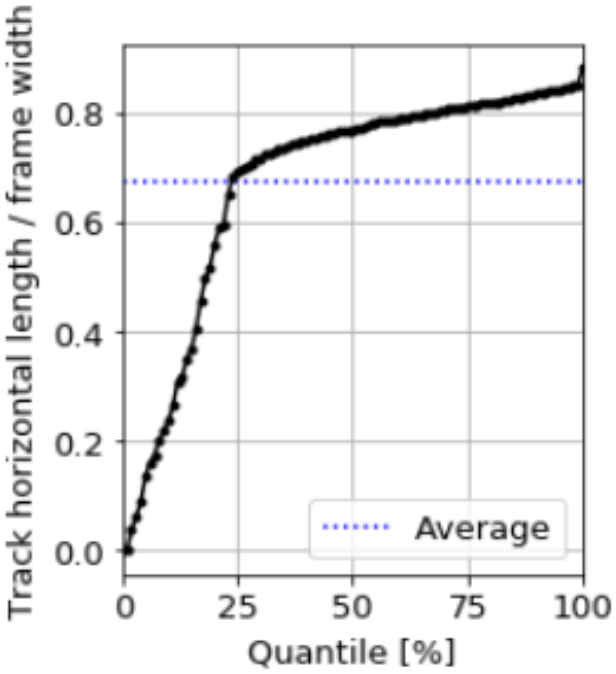
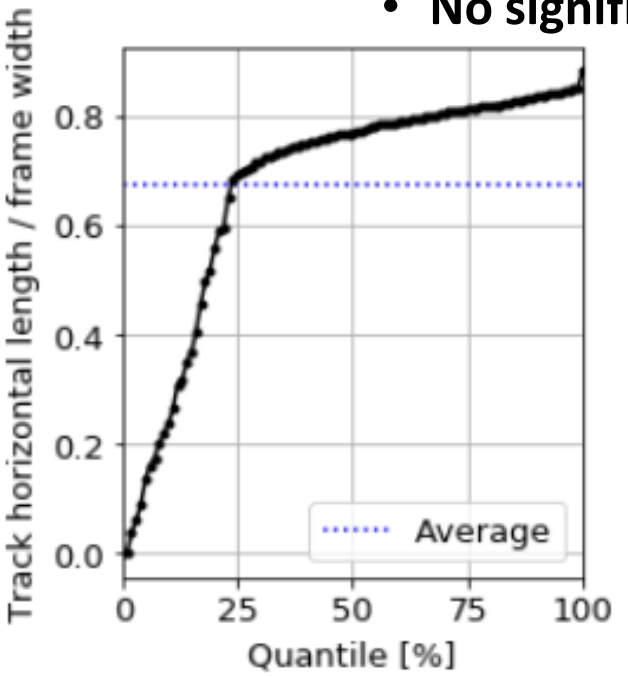
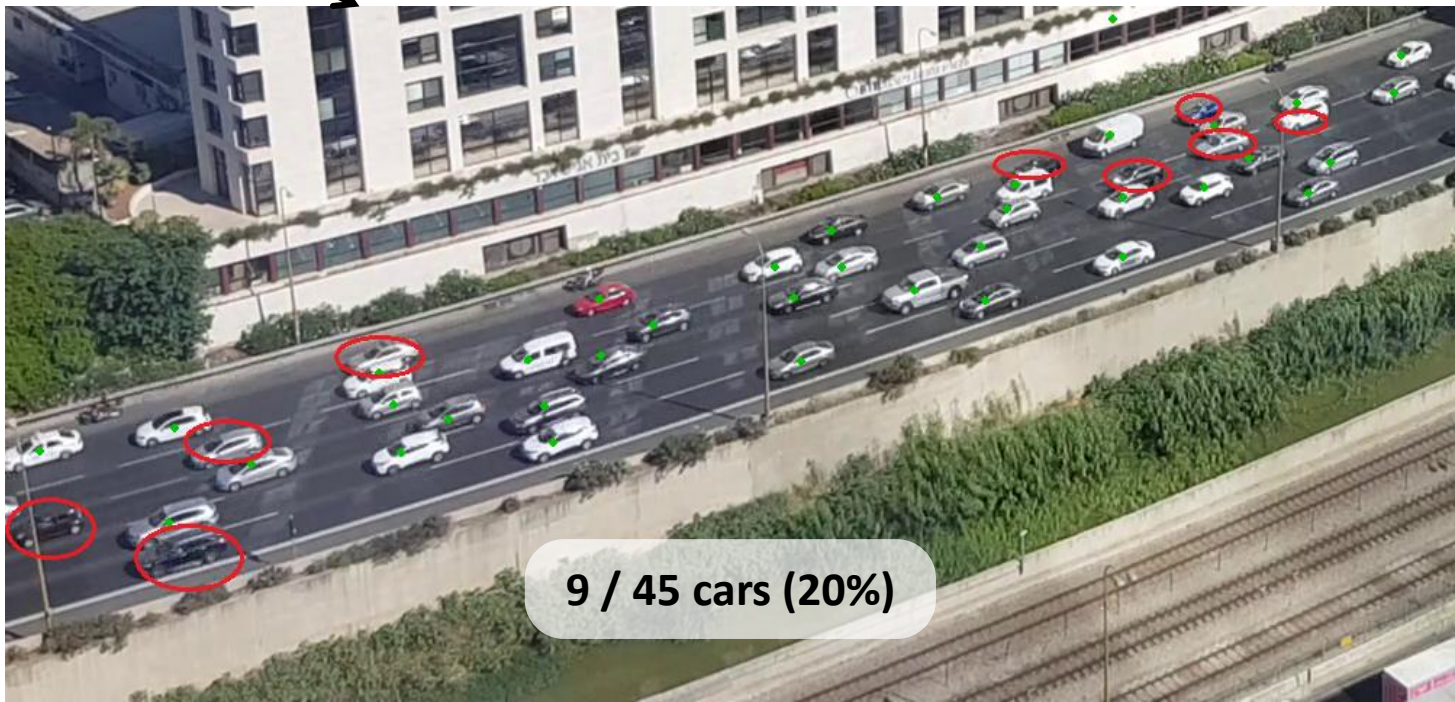




Does it work?

- Do we track the whole path?
  - Fake tracks: false detections
  - Failed tracks: missing detections, hidings
  - **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 structures

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

TODO show p2m transformation

Data structures

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

* Can be concatenated over all videos

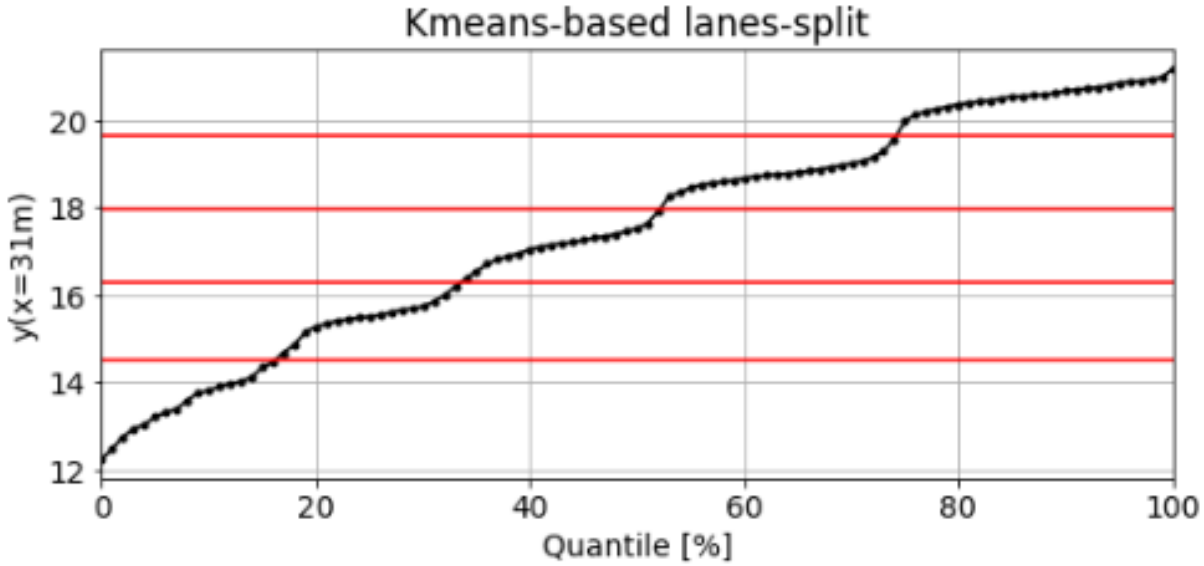
TODO show p2m transformation

Data structures

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 quantiles 10,30,50,70,90 as initial centers)

* Can be concatenated over all videos

TODO show p2m transformation



Summary

Main contributions

- 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
- TODO analysis contribution

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

Future 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)
  - TODO think of something more interesting...
- 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:
  - TODO

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


Thank you