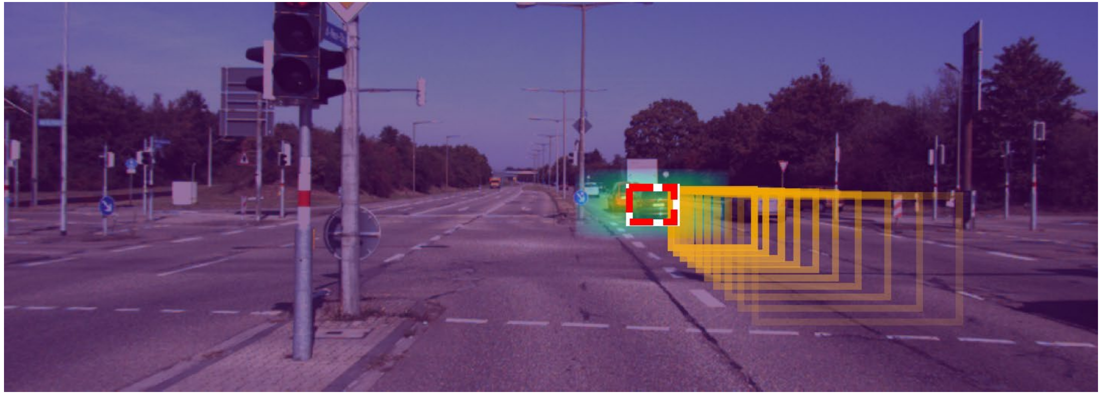
Robust Aleatoric Modeling for Future Vehicle Localization



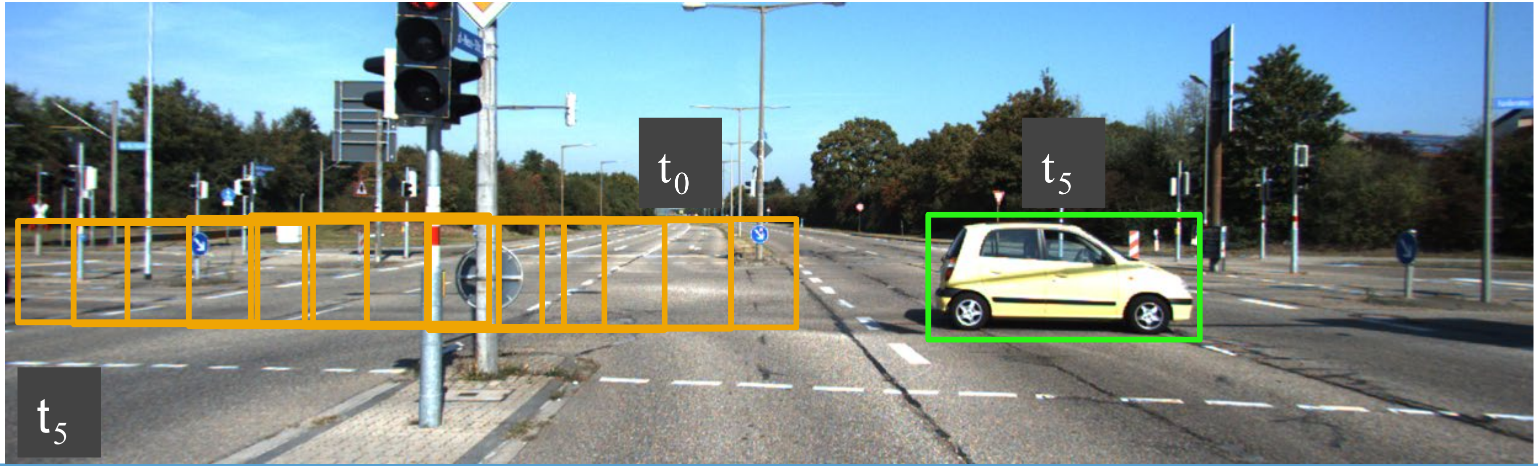
THE UNIVERSITY of NORTH CAROLINA at CHAPEL HILL

CVPR

6/17/2019 Max Hudnell True Price Jan-Michael Frahm

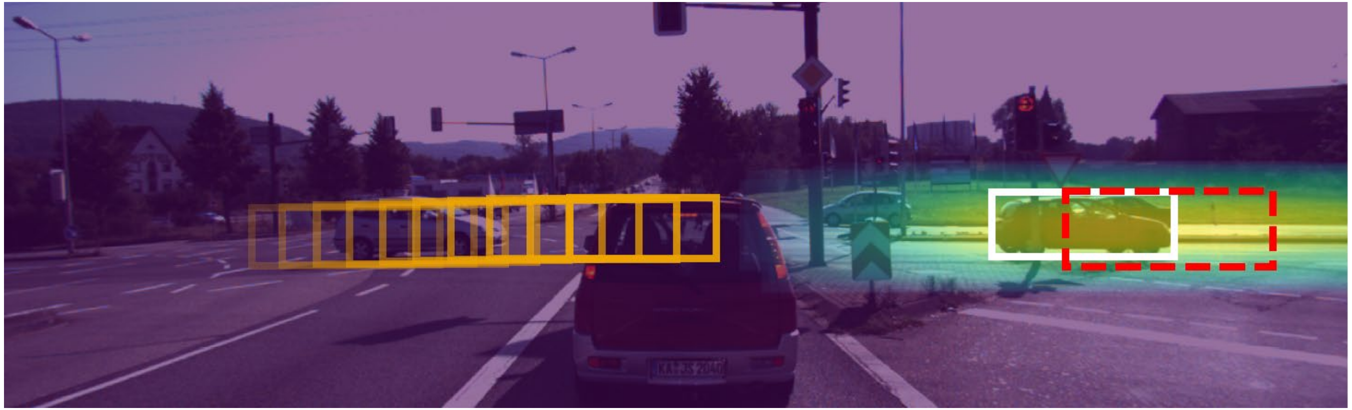
The Task

- What is (2D) future vehicle localization?
  - Localization – location and scale of object
  - => predicting where a vehicle is going to be



Our Goal

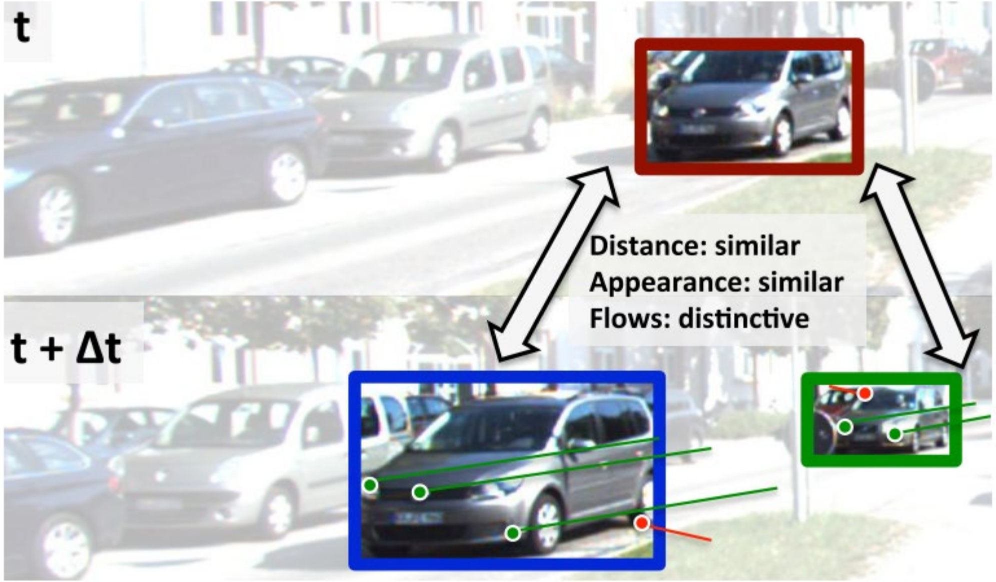
1. Predict where an object is likely to be
2. Produce an uncertainty estimate for our prediction



Related Work

- W. Choi *et al.* – Near-Online Multi-target Tracking with Aggregated Local Flow Descriptor
- Dueholm *et al.* – Trajectories and Maneuvers of Surrounding Vehicles with Panoramic Camera Arrays

- Object tracking
- Utilize bounding box predictions
  - Linear and quadratic



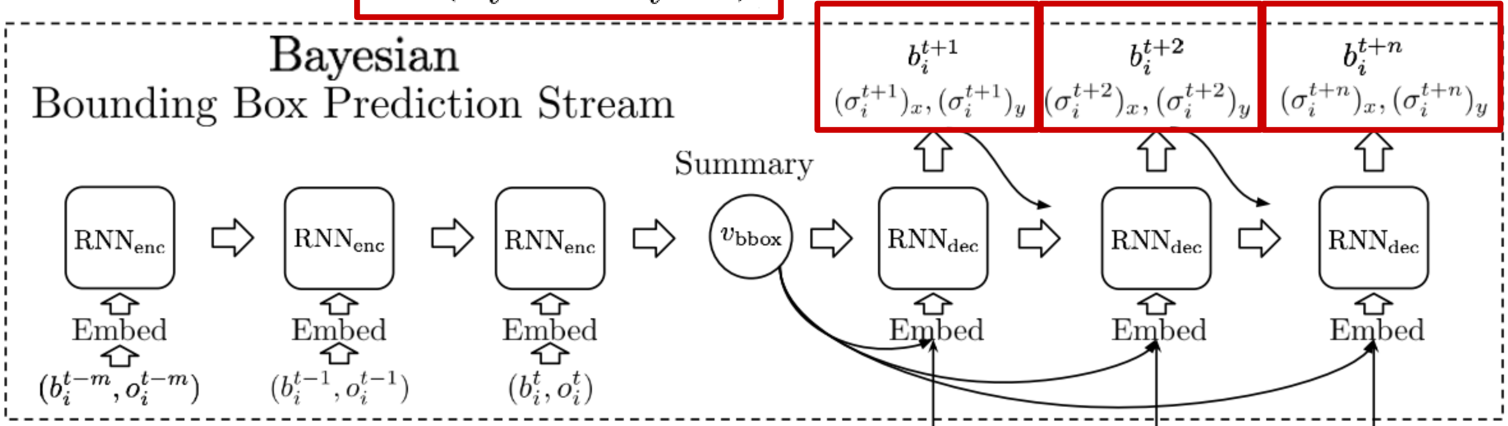
Related Work

Long-Term On-Board Prediction of People in Traffic Scenes under Uncertainty

- A. Bhattacharyya *et al.,* CVPR 2018
- RNN
- Gaussian uncertainty

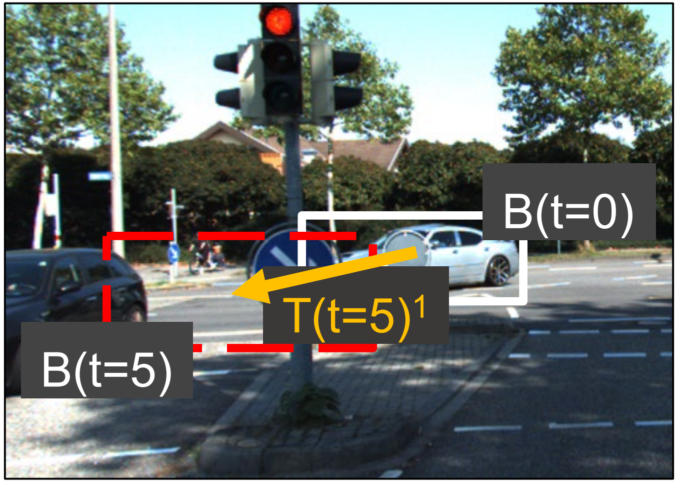
Last Observation: t **Prediction: $t + 5$**

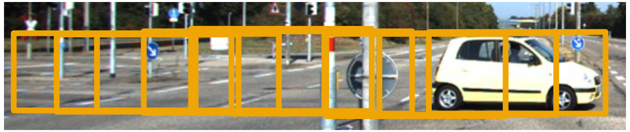
$$\mathcal{N}(b_i^{t+n}, \Sigma_i^{t+n})$$



Method

$$B_i = [x_i, y_i, w_i, h_i]$$





$$\mathbf{B} = \{B_{-n+1}, B_{-n+2}, \ldots, B_0\}$$

Input layer (size=4*n*)

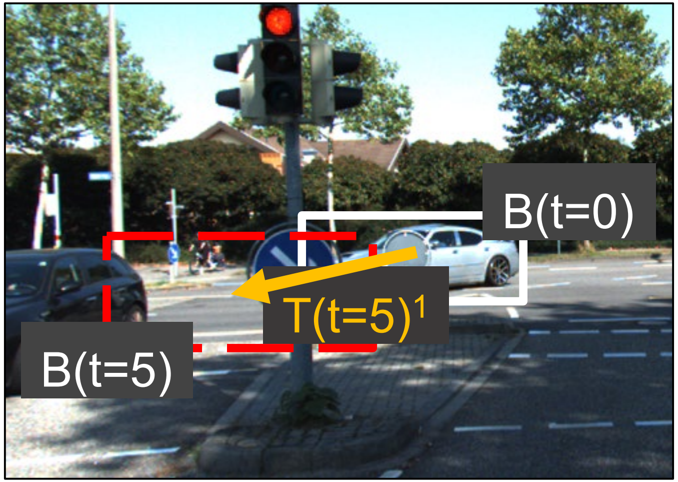
Output layer

$$T(t) = [T_x(t), T_y(t), T_w(t), T_h(t)]$$

[1]R. Girshick (2013), Rich Feature Hierarchies

Method

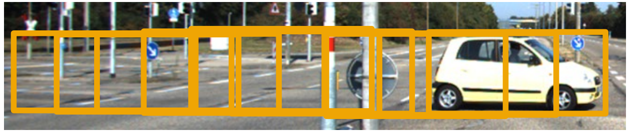
$$B_i = [x_i, y_i, w_i, h_i]$$

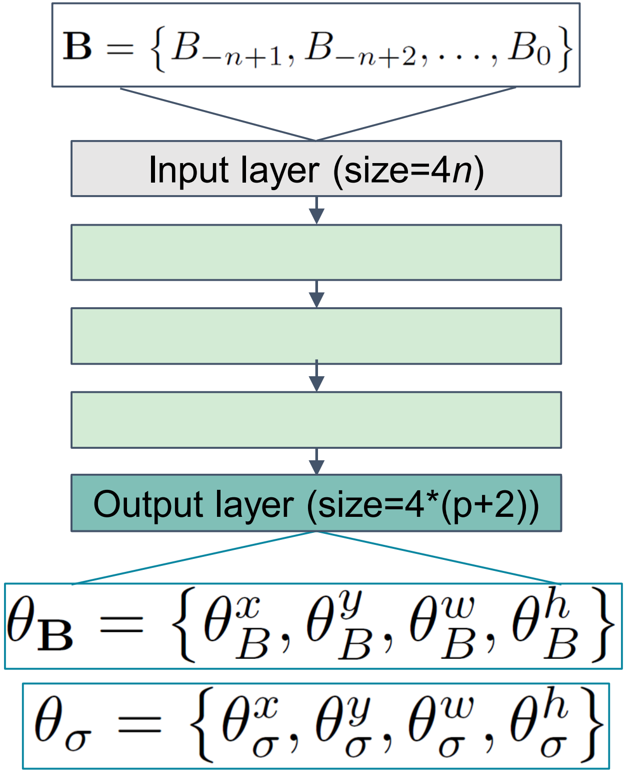


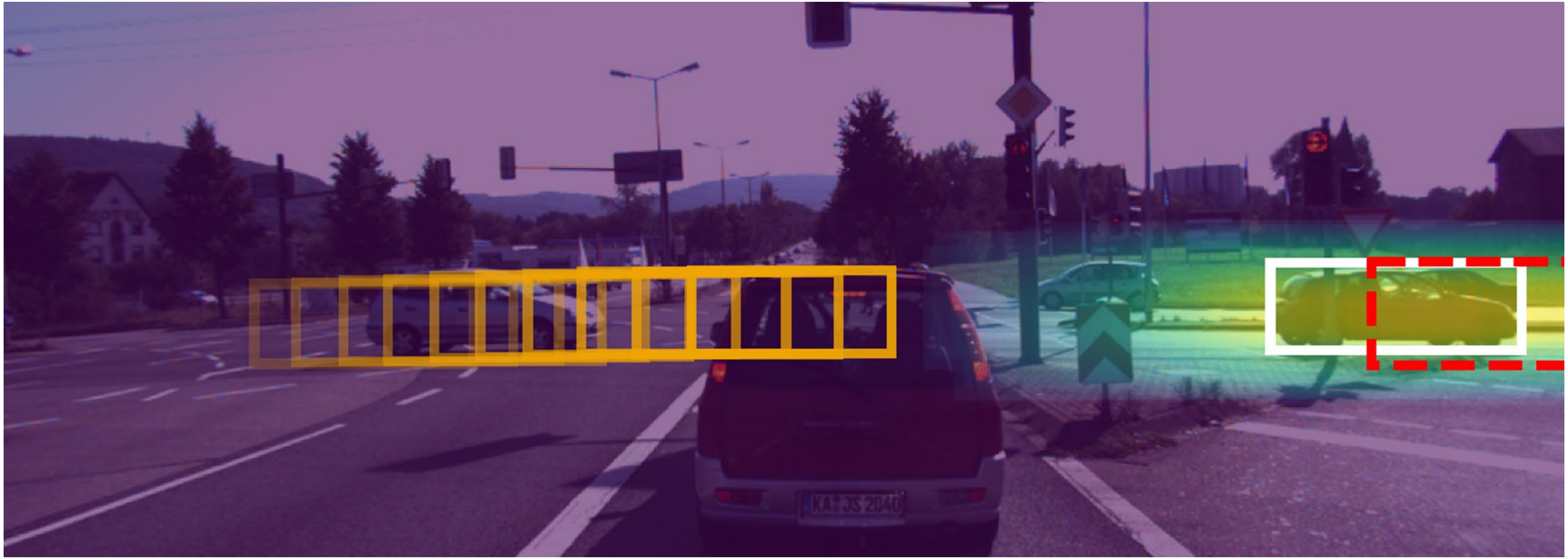
- Build polynomial from coefficients:

$$T_d(t; \theta_B^d) = \sum_{i=1}^{p} \theta_B^{d(i)} t^i.$$

$$\sigma_d(t; \theta_\sigma^d) = |\theta_\sigma^{d(1)} t| + |\theta_\sigma^{d(0)}|$$

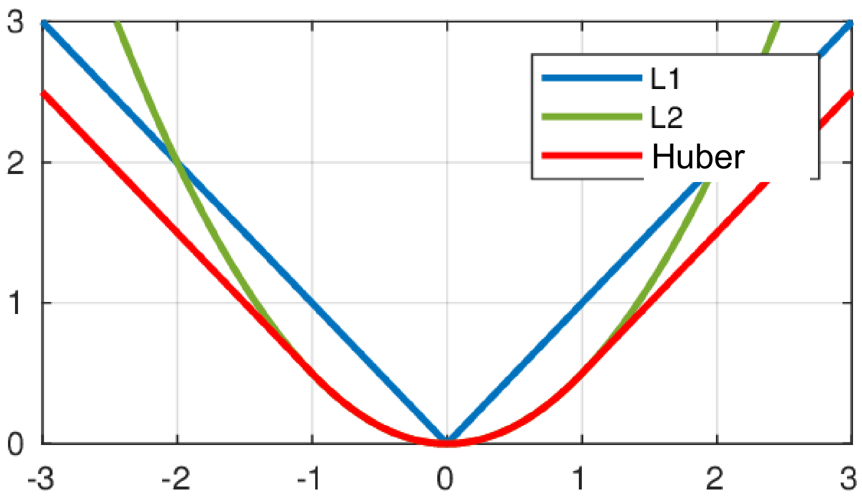






Training for Confidence

- Formulating a Huber distribution



- Used for bounding box regression[1]

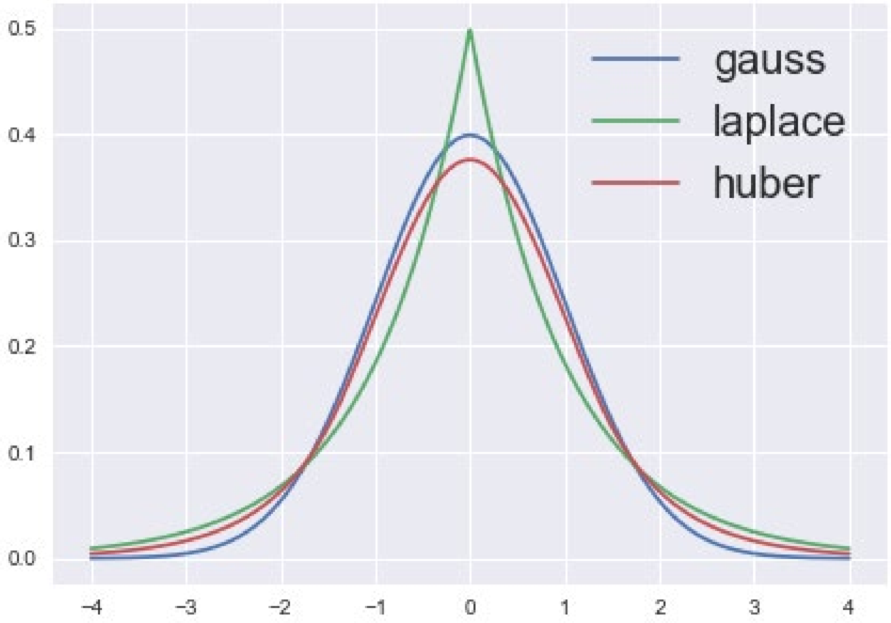
Huber loss:

$$H(\hat{x}, x) = \begin{cases} \frac{1}{2}\left(\hat{x} - x\right)^2 & \text{if } |\hat{x} - x| < \tau \\ \tau|\hat{x} - x| - \frac{1}{2}\tau^2 & \text{otherwise,} \end{cases}$$

[1]R. Girshick (2015), Fast R-CNN

Training for Confidence

- Formulating a Huber distribution



Gaussian pdf:

$$f(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Laplace pdf:

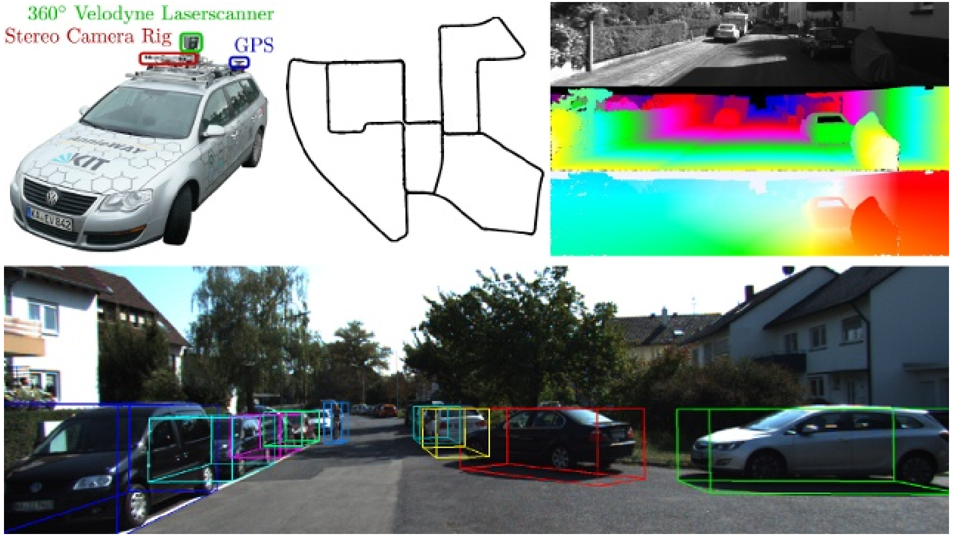
$$f(x \mid \mu, b) = \frac{1}{2b} \exp\left(-\frac{|x-\mu|}{b}\right)$$

Huber pdf:

$$p(\hat{x}|x,\sigma) = \begin{cases} \frac{1}{c} \exp\left(-\frac{(\hat{x}-x)^2}{2\sigma^2}\right) & \text{if } |\hat{x}-x| < \tau \\ \frac{1}{c} \exp\left(-\frac{\tau}{\sigma^2}|\hat{x}-x| + \frac{\tau^2}{2\sigma^2}\right) & \text{otherwise,} \end{cases}$$

Experiments: Dataset

- KITTI “Raw” dataset
  - 38 videos of various scenes
- Sample creation:
  - Isolate 20 continuous frames for tracked objects
    - Use first 10 as ‘prior’ input
    - Next 10 frames are targets

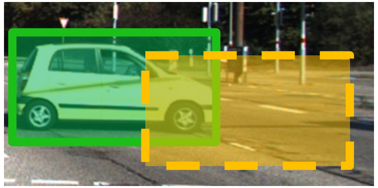


Experiments: Evaluating the mean

		All					Hard				
		DE		ADE	IoU		DE		ADE	IoU	
Loss	Func.	+0.5s	+1.0s		+0.5s	+1.0s	+0.5s	+1.0s		+0.5s	+1.0s
–	constant	32.06	72.15	36.98	0.498	0.339	44.23	102.40	51.62	0.326	0.128
–	linear	14.61	39.51	17.95	0.663	0.464	23.14	63.27	28.56	0.492	0.219
L1	$p = 6$	12.81	29.05	14.78	0.697	0.564	17.06	38.06	19.56	0.607	0.475
L2	$p = 6$	15.13	37.43	18.12	0.671	0.521	20.90	51.97	25.02	0.563	0.394
Huber	$p = 6$	12.58	29.18	14.72	0.708	0.584	16.18	36.76	18.76	0.622	0.488
Huber	RNN	14.01	31.37	16.12	0.686	0.570	19.62	44.63	22.71	0.577	0.442

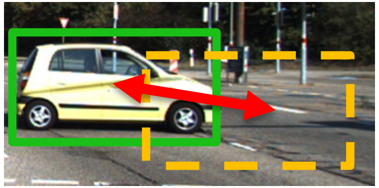
Metrics:

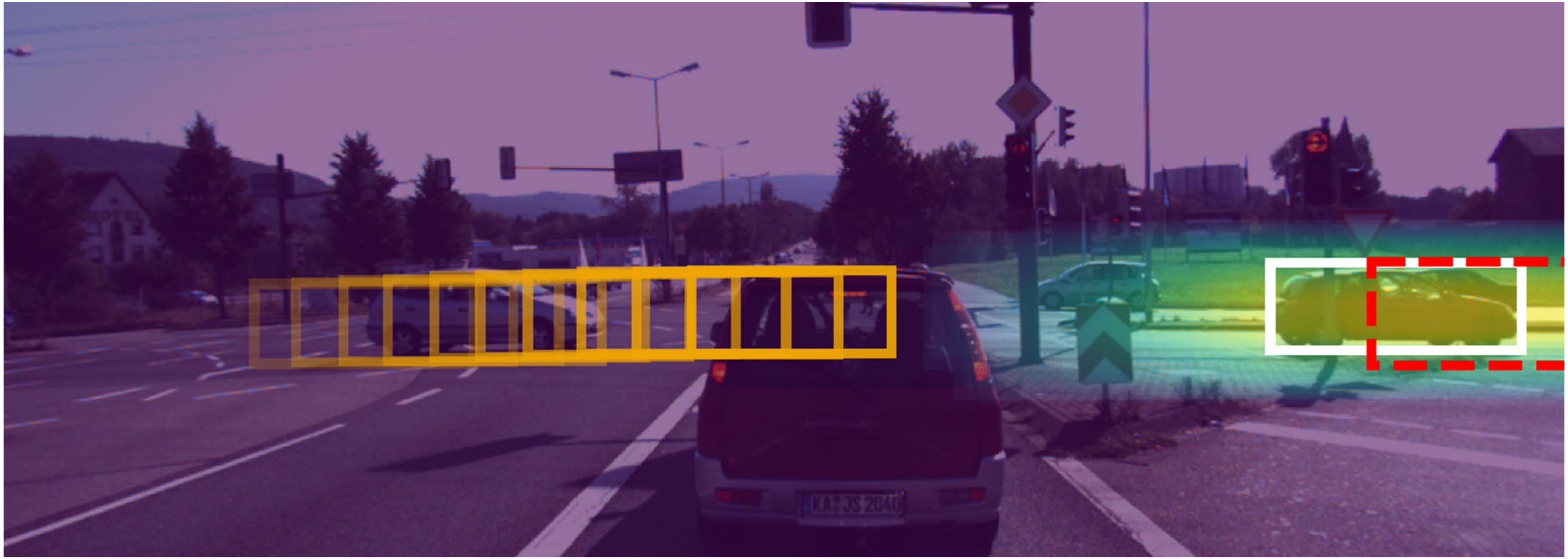
- Intersection over Union (IoU):



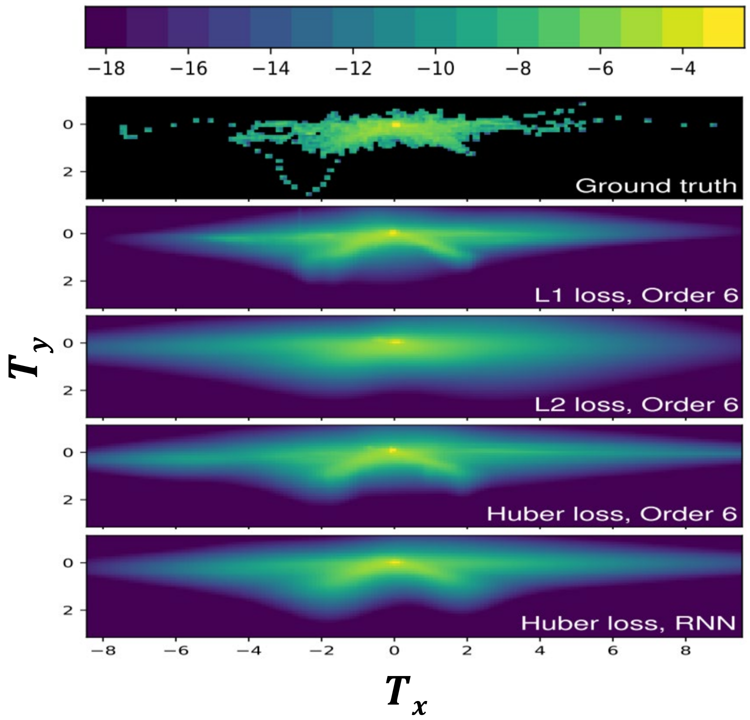
$$\frac{|A \cap B|}{|A \cup B|}$$

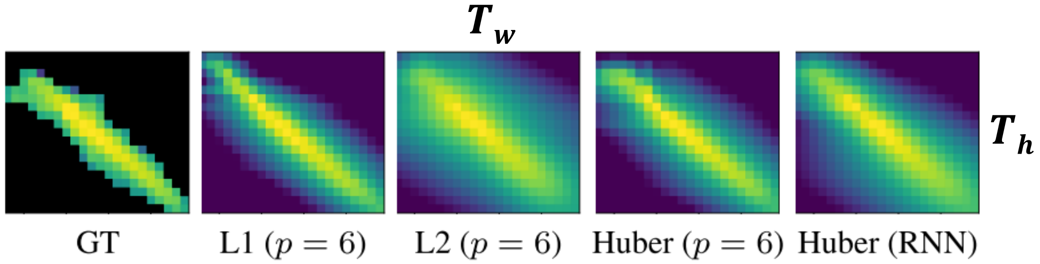
- Displacement Error (DE):





Experiments: Evaluating uncertainty





Config.	L1	L2	Huber	Huber (RNN)
$\mathcal{H}^2(\mathcal{T}, \hat{\mathcal{T}})$	0.568	0.607	0.562	0.562

Bin entire test set

Metric:

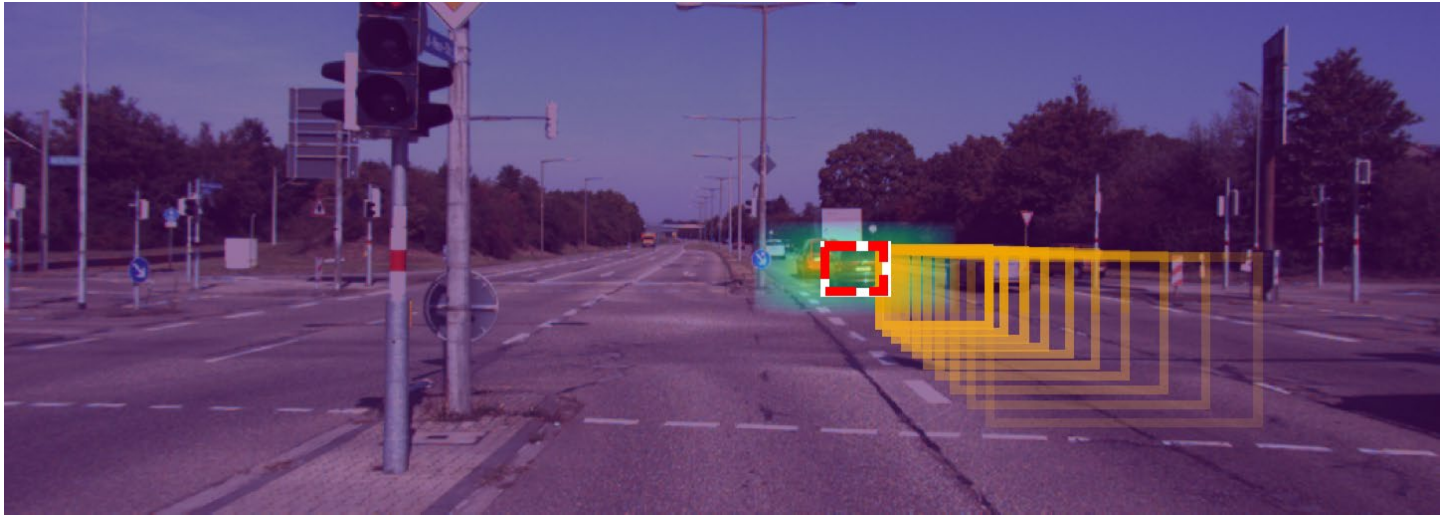
- Squared Hellinger Distance:

$$\mathcal{H}^2(\mathcal{T}, \hat{\mathcal{T}}) = \frac{1}{2}||\sqrt{\mathcal{T}} - \sqrt{\hat{\mathcal{T}}}||_2^2$$

Future Work

$$\sigma(t) = [\sigma_x(t), \sigma_y(t), \sigma_w(t), \sigma_h(t)]$$

- Model uncertainty as a joint distribution
- Integrate with object tracking



Thank you!

Questions?

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