Vehicle Interaction Learning

Xiaosong Jia

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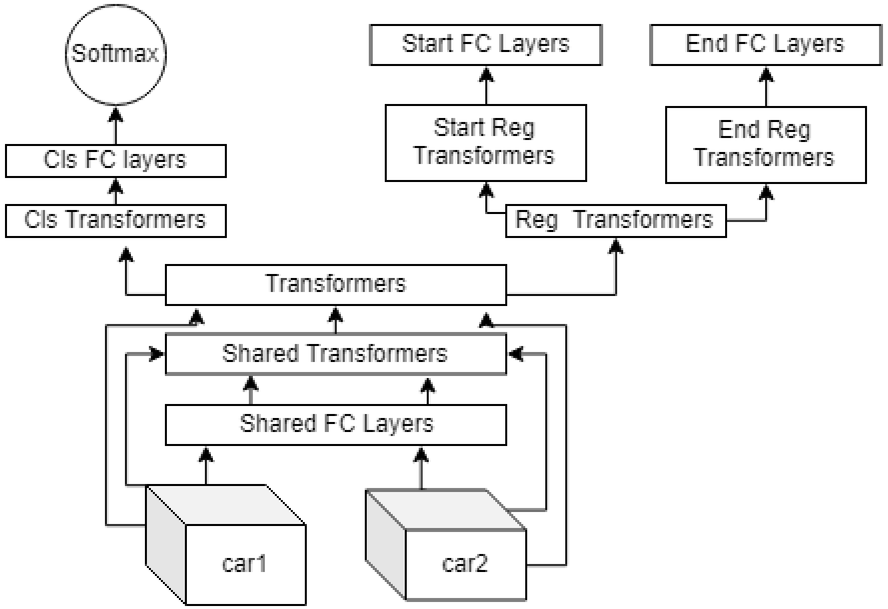
Additional Prior Information

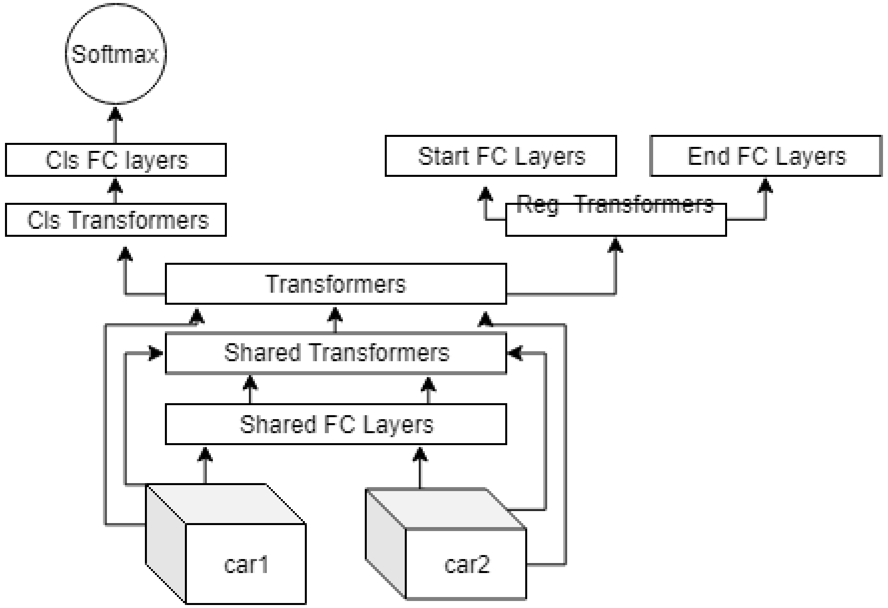
- Start < End
- Let the scores affect each other until the final output

- Similar Results for validation
- Improvements for transferring:

N->H: IoU6:72.0% Traj_cls: 89.7%

H->N: IoU6:72.3% Traj_cls: 87.1%





USA_Roundabout_FT

- Stop sign: <1s -> No interaction, >3s -> Exist interaction

Passing car's trajectory distance from stopping car less than 50 meters until 0

- TTC: <3s -> Exist interaction, >8s No interaction

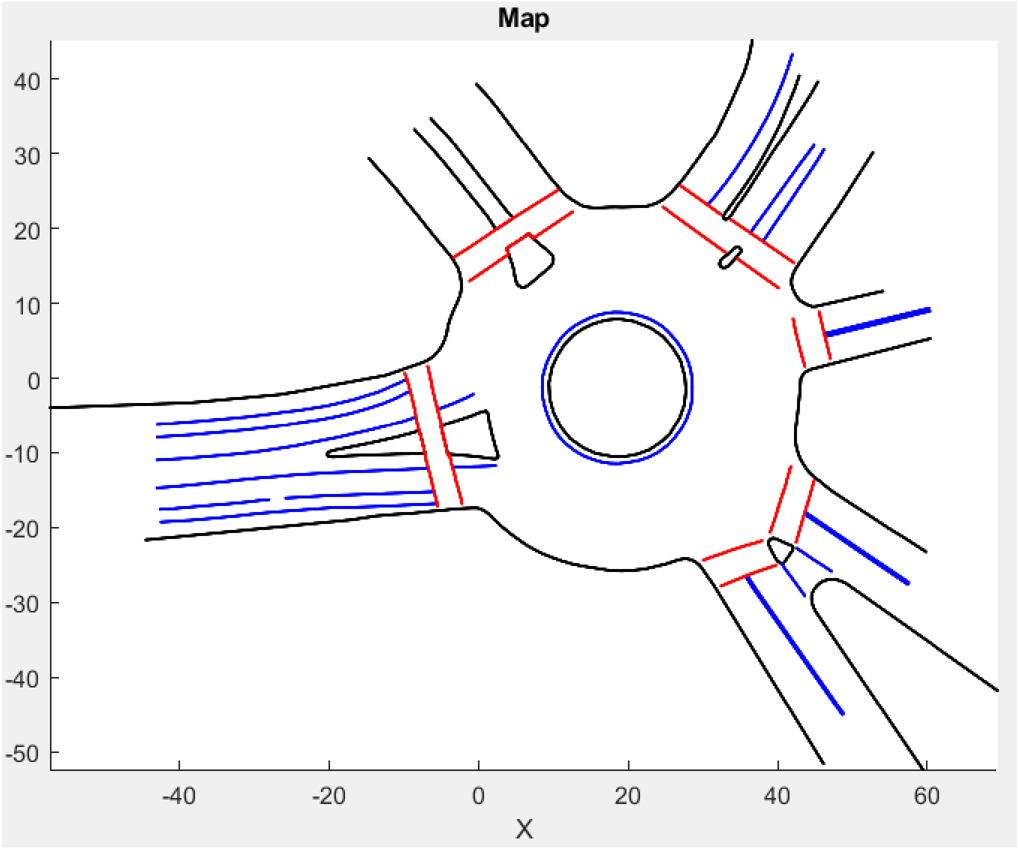
Both cars' trajectory distance less than 50 meters from collision point until one of the cars pass that point

- No TTC: No interaction

- Remove samples with interaction time >20s

Positive Sample: 5180 Negative Sample: 5238

	Positive	Negative
Stop Sign	3185	377
TTC	1669	515
Total	4954	892



USA_Roundabout_FT

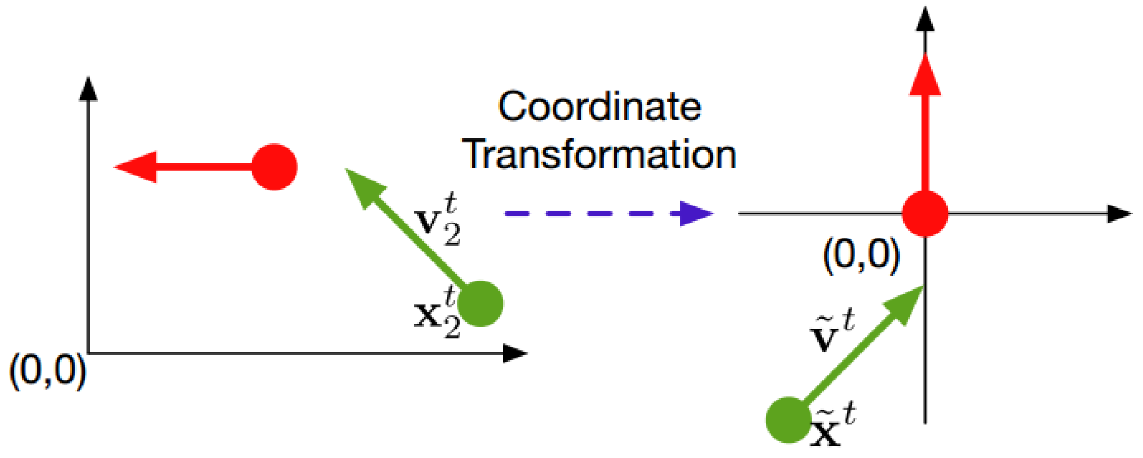
- Downsample: fps=5
- Clip: max_length = 20s

	Sample_len_avg	Label_len_avg
HighD	57.0 frames	14.5 frames
NGSIM	80.2 frames	14.8 frames
FT	58.2 frames	35.6 frames

	IoU0.6 Acc	IoU0.9 Acc	Traj Cls Acc
HighD	97.0%	34.7%	99.4%
NGSIM	85.4%	26.0%	90.1%
FT	94.3%	71.4%	91.3%

Relative Motion Features [Tianmin et.al. TOPICS 2018]

- At each time step, calculate the relative motion given a reference agent.
- Features: $[\tilde{\mathbf{x}}^{t\top}, \tilde{\mathbf{v}}^{t\top}, \mathbf{v}_1^{t\top}, \tilde{\mathbf{x}}^{t\top}\tilde{\mathbf{v}}^{t}, \|\tilde{\mathbf{x}}^{t}\|, \|\tilde{\mathbf{v}}^{t}\|, \|\mathbf{v}_1^{t}\|]$
- Rotation Invariance + Eliminate Absolute Coordinate
- Augmentations: both vehicles should be reference agent



	Absolute Features			Relative Features		
	IoU0.6	IoU0.9	Traj Cls	IoU0.6	IoU0.9	Traj Cls
HighD	97.0%	34.7%	99.4%	91.9%	30.3%	97.7%
NGSIM	85.4%	26.0%	90.1%	79.1%	18.7%	88.1%
FT	94.3%	71.4%	91.3%	91.4%	61.3%	88.0%

Semi-supervised Learning

- Use only 250 positive samples + 125 negative samples + 125 random negative samples

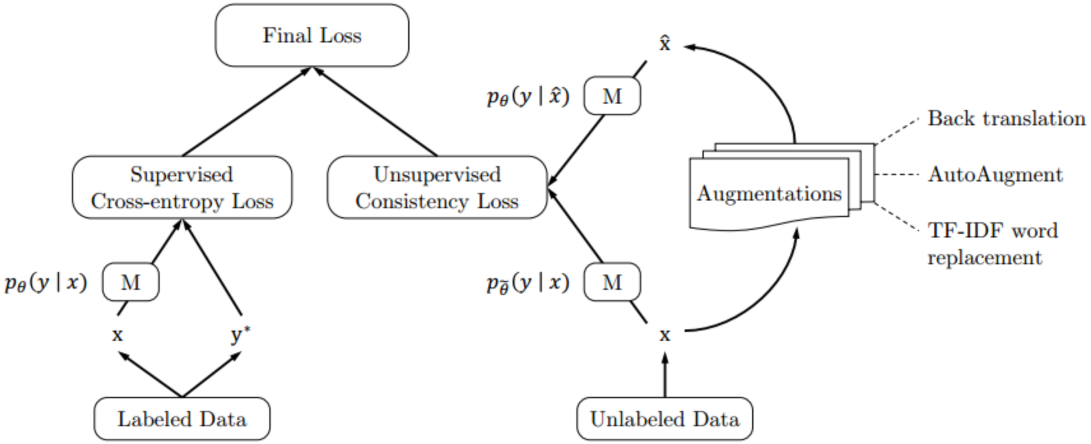
	All data			250+125+125			Fine Tune 250+125+125		
	IoU0.6	IoU0.9	Traj Cls	IoU0.6	IoU0.9	Traj Cls	IoU0.6	IoU0.9	Traj Cls
HighD (10011)	97.0%	34.7%	99.4%	76.9%	16.3%	92.4%	86.8%	23.6%	93.7%
NGSIM (5319)	85.4%	26.0%	90.1%	52.5%	7.4%	84.0%	76.4%	16.3%	89.1%

Semi-supervised learning

- UDA (2019-07 Google, CMU)

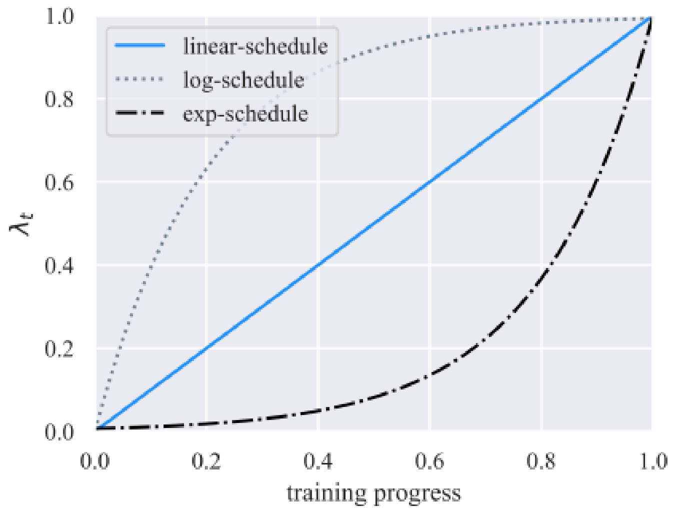
$$\min_{\theta} \mathcal{J} = \mathbb{E}_{x,y^* \in L} \left[p_\theta(y^* \mid x) \right] + \lambda \mathcal{J}_{\text{UDA}}(\theta)$$

$$\min_{\theta} \mathcal{J}_{\text{UDA}}(\theta) = \mathbb{E}_{x \in U} \mathbb{E}_{\hat{x} \sim q(\hat{x} \mid x)} \left[\mathcal{D}_{\text{KL}} \left(p_{\tilde{\theta}}(y \mid x) \,\|\, p_\theta(y \mid \hat{x}) \right) \right]$$



Traj cls confidence > threshold -> force the start/end regression similar

Semi-supervised learning



- Training Signal Annealing (labeled):

For traj_cls √

For reg

- Confidence-based masking (unlabeled): mask out examples that the current model is not confident about

For traj_cls √

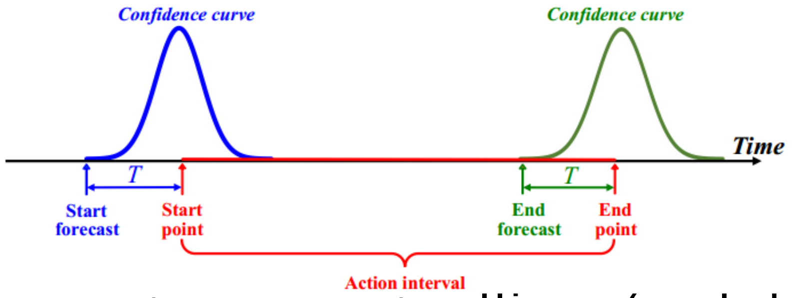
For reg

Semi-supervised learning

- Entropy Minimalization (unlabeled): regularizes the predicted distribution on augmented examples $p_\theta(y|x')$ to have a low entropy.

For traj_cls √

For reg

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[0.056 0.089 0.135 0.198 0.278 0.375 0.487 0.607 0.726 0.835 0.923 0.98
 1.    0.98  0.923 0.835 0.726 0.607 0.487 0.375 0.278 0.198 0.135 0.089
 0.056]
```

- Softmax temperature controlling (unlabeled): A lower temperature corresponds to a sharper distribution.

For traj_cls √

For reg

$$\mathrm{Softmax}(l(\bar{x})/\tau)$$

Failed Trying

- Regression loss -> Classification Loss (Softmax over all the frames)
- Sparse Positive Signal -> assign higher weights to positive samples
- Values heavily depends on length -> temperature

Temperature not low enough -> large weights, overfitting

Temperature too low -> extreme gradients

- Results: hard to tune; slow to converge; worse results

Future work

- Single source domain + target domain unlabeled data
- Single source domain + small number of target domain labeled data
- Multiple source domains
- Multiple source domains + target domain unlabeled data
- Multiple source domains + small number of target domain labeled data