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Cooperative Prediction of Vulnerable Road Users (VRUs)

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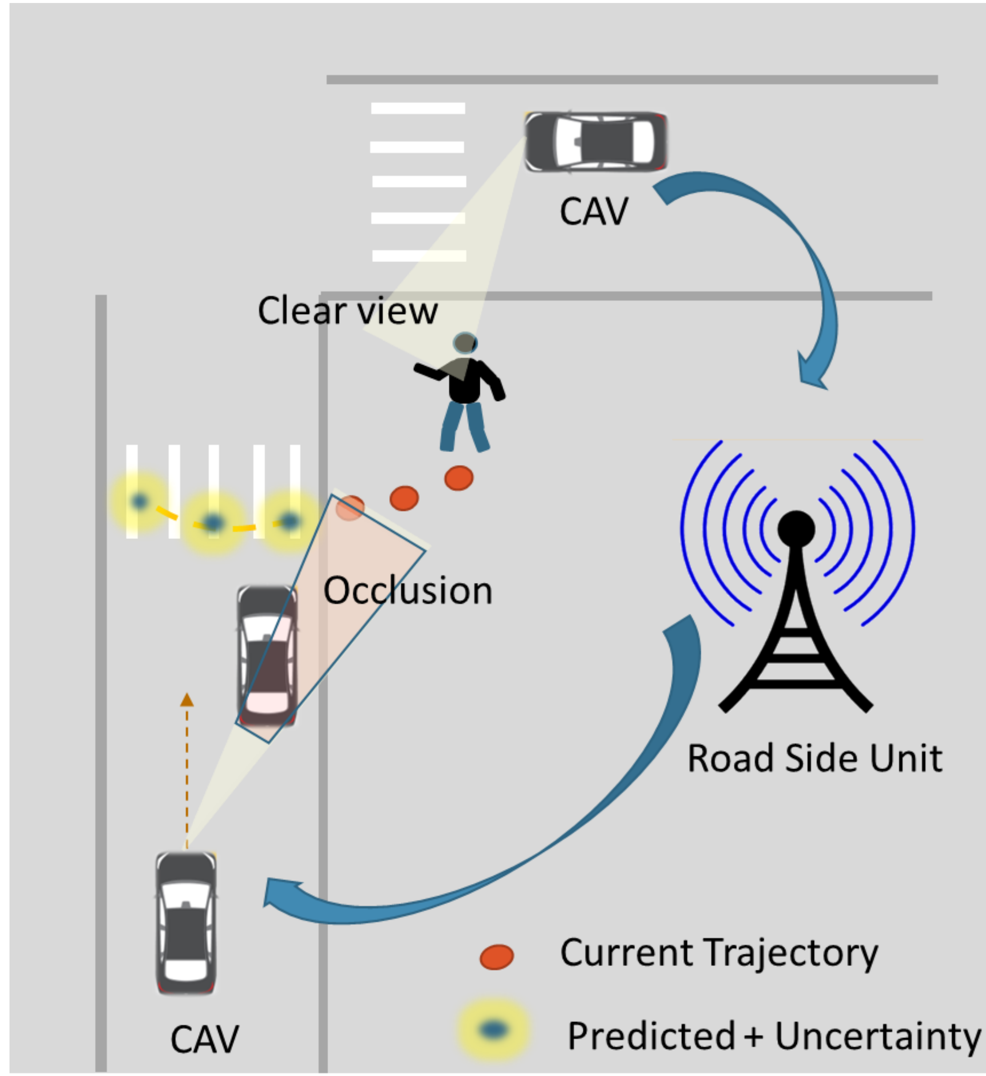
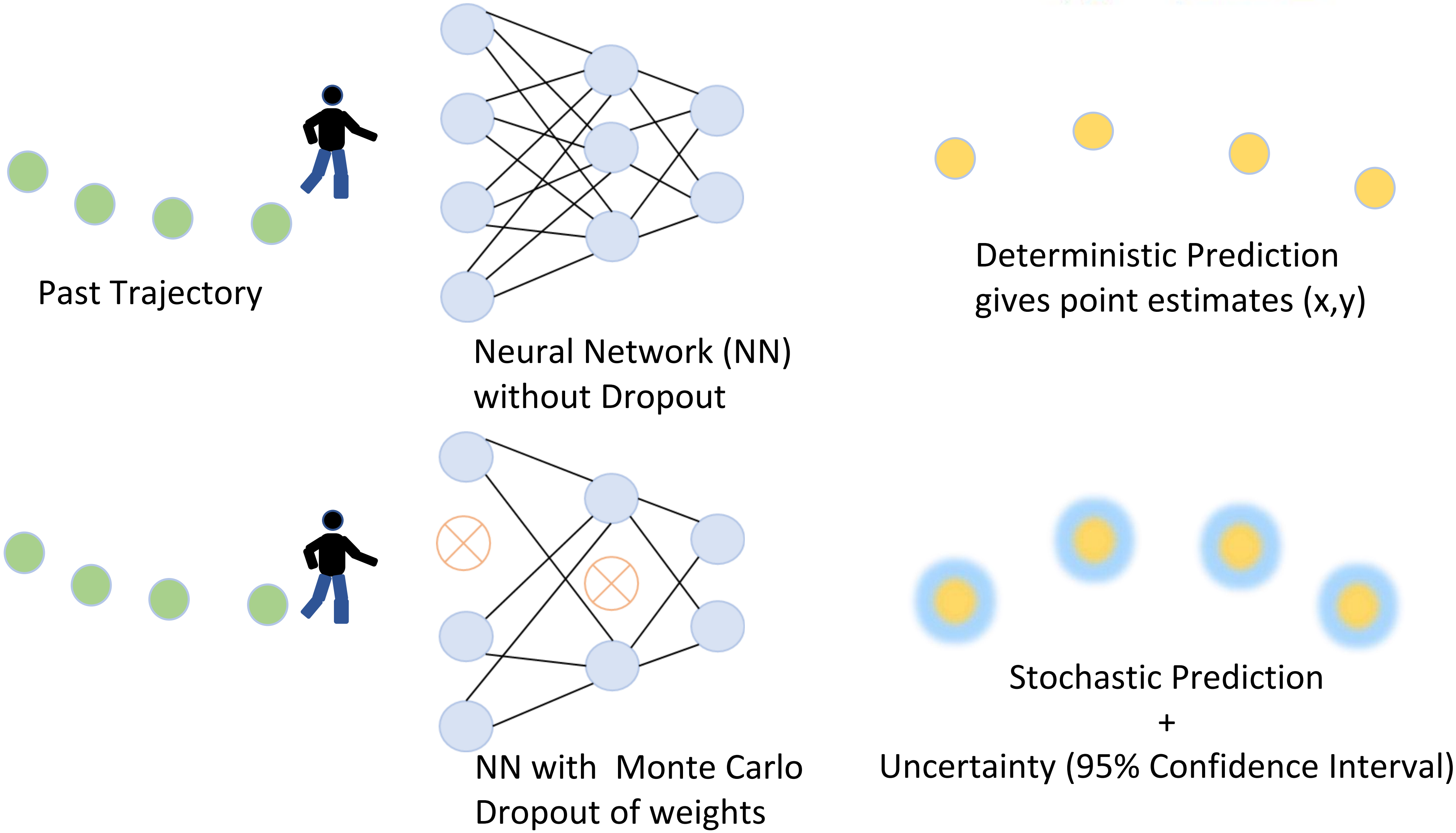
Goal: Uncertainty estimation of future pedestrian trajectory using Probabilistic method

- Future state estimation due to occlusion is often difficult.
- Deterministic state prediction lacks robustness.
- VRU state information transferred via V2V or V2I communication.
- Ego CAV vehicle predicts future trajectory with uncertainty based on information.



Method: Probabilistic Prediction with weight dropout



Architecture: Neural Network models for Bayesian Inference

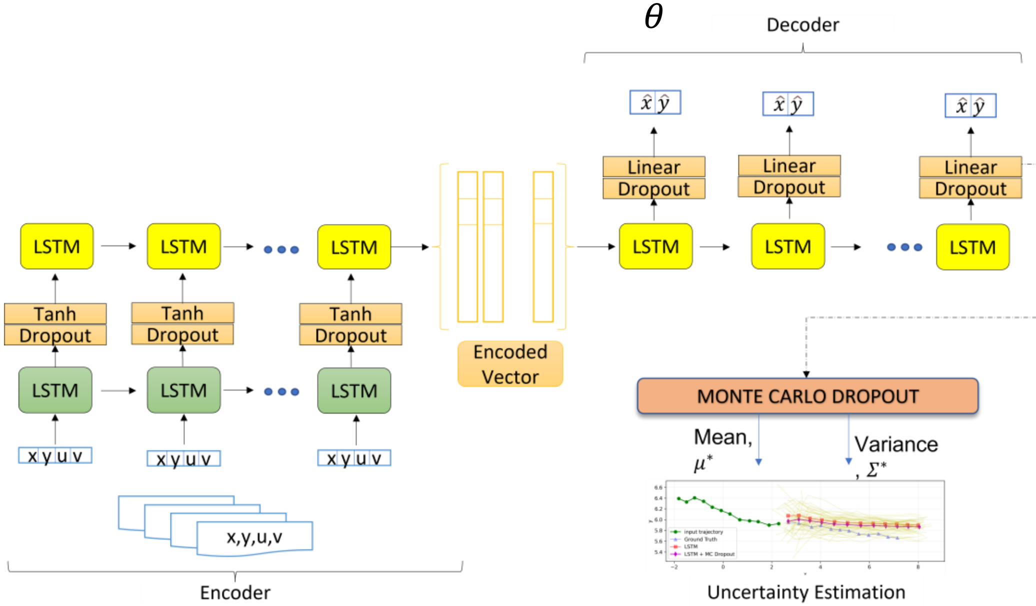
- Compared three neural network models; LSTM, 1D-CNN and CNN-LSTM for both deterministic as well as probabilistic prediction using MC dropout of weights.

- Prediction of future state (deterministic)/states (probabilistic), y^* based on test sample, x^* :

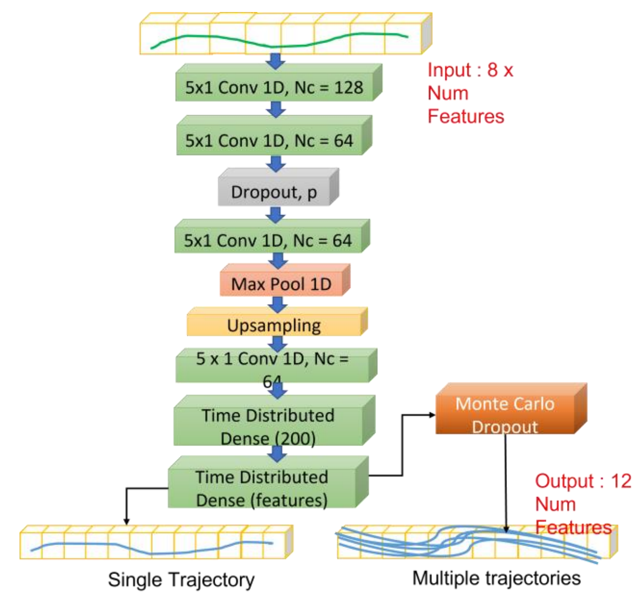
Training : Bayes Rule, $$P(\theta|X,Y) = \frac{P(X,Y|\theta)P(\theta)}{P(X,Y)}$$

Testing : $$p(y^*|x^*,X,Y) = \int_{\theta} p(y^*|x^*,\theta')p(\theta'|X,Y)\,d\theta'$$

X,Y : Train Data,
θ : *weights*



(a) Long Short-Term Memory (LSTM)



(b) Convolutional Neural Network (CNN)

Results: Probabilistic Prediction outperforms deterministic output

Performance metrics:

a) Average Displacement Error (ADE): Mean of Euclidean distance between predicted and ground truth points.

b) Final Displacement Error (FDE): Euclidean distance between the final point of estimated and ground truth trajectory

- Tested on two publicly available pedestrian datasets with five scenes.
  ETH dataset: ETH and Hotel scene
  UNIVERSITY dataset: ZARA1, ZARA2 UNIV

- Mean predicted path of probabilistic models was closer to ground truth with lower average ADE/FDE compared to deterministic prediction.

Lower ADE/ FDE is better

		ETH	HOTEL	ZARA1	ZARA2	UNIV	AVERAGE
	S-LSTM [12]	1.09/2.35	0.79/1.76	0.47/1.00	0.56/1.17	0.67/1.40	0.72/1.54
	SGAN [32]	0.87/1.62	0.67/1.37	0.35/0.68	0.42/0.84	0.76/1.52	0.61/1.21
	Sophie [33]	0.70/1.43	0.76/1.67	0.30/0.63	0.38/0.78	0.54/1.24	0.54/1.15
	Social-BiGAT [34]	0.69/1.29	0.49/1.01	**0.30/0.62**	**0.36/0.75**	0.55/1.32	0.48/1.00
Deterministic	LSTM	0.54/0.94	0.33/0.46	0.51/0.96	0.53/0.96	0.75/0.93	0.53/0.85
	1D CNN	0.71/0.90	0.71/1.04	0.75/1.02	0.86/1.16	0.95/1.24	0.79/1.07
	CNN-LSTM	0.68/1.11	0.98/1.29	0.73/0.99	0.95/1.27	0.87/1.11	0.84/1.15
Probabilistic	LSTM + MC	0.55/0.94	**0.32/0.45**	0.51/0.96	0.54/0.96	0.59/0.84	**0.50/0.83**
	1D CNN + MC	0.69/0.84	0.58/0.79	0.73/0.99	0.85/1.15	0.71/0.85	0.71/0.92
	CNN-LSTM + MC	**0.48/0.82**	**0.3/0.48**	0.50/0.83	0.77/1.12	**0.53/0.86**	**0.51/0.82**

Ablation Study: Effect of Dropout Probability and Long-term prediction horizon

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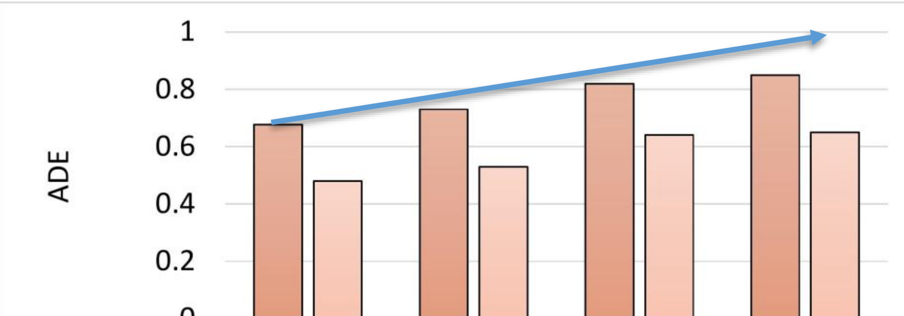
I. Dropout Probability (p)

- Stochastic dropout of weights with probability p.
- For p = 0.2 , 0.3 , 0.4 , 0.5. p = 0.3 implies 30% of weights are randomly dropped during each test inference.



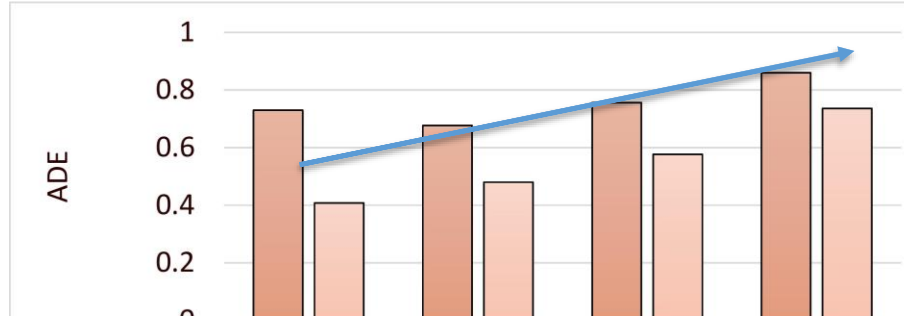
	0.2	0.3	0.4	0.5
CNN-LSTM	0.677	0.73	0.82	0.849
MC	0.48	0.53	0.64	0.65

Fig. ADE with dropout probability, p for CNN-LSTM

- ADE increased with dropout probability, p.
- Mean of probabilistic prediction (MC) has lower ADE compared to deterministic (CNN-LSTM).

II. Time Horizon (T_f)

- Quantify uncertainty in states for long term forecast.
- Considered future prediction horizon, T_f = 3.2 , 4.8 , 6.4 , 8 secs



	T =3.2	T=4.8	T =6.4	T =8
CNN-LSTM	0.73	0.677	0.756	0.86
MC	0.408	0.48	0.577	0.736

Fig. ADE with time horizon, T_f for CNN-LSTM

- ADE increased with Prediction horizon, T_f.
- It shows uncertainty grows with time.
- Mean of probabilistic prediction (MC) has lower ADE.

Results: Estimated Trajectory with confidence Interval

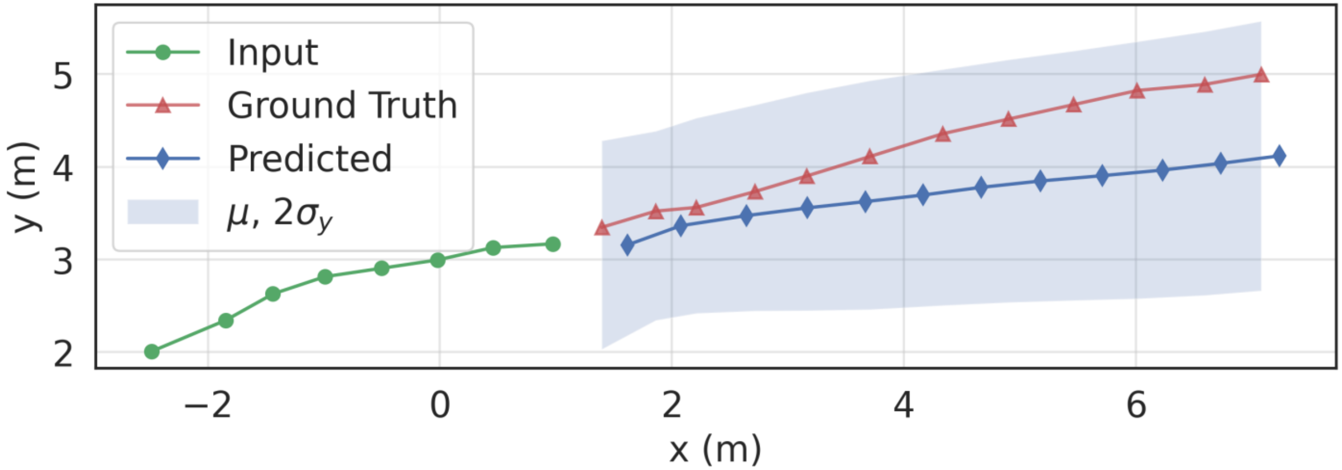
- Neural Network is called N times where weights are dropped with probability, p for each pass generating a distribution of N predicted trajectories with:

- Based on 95% Confidence interval, 80% of test trajectories contain the ground truth.

- In future, perception/state uncertainty will be used for uncertainty propagation .

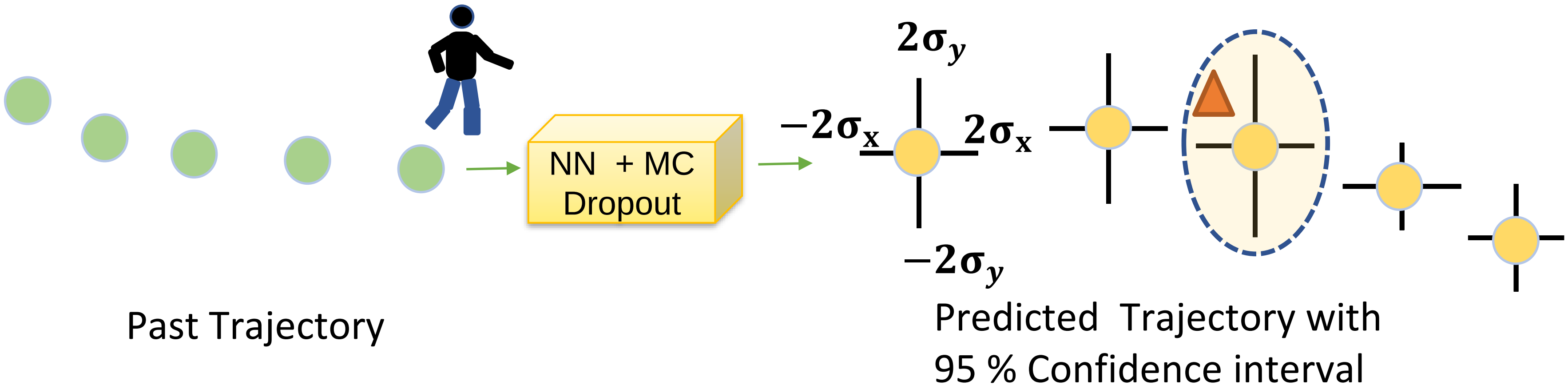
Mean, $\bar{y} = \frac{1}{N}\sum_{n=1}^{N} y^*(n)$

Variance, $\Sigma_{y^*} = \frac{1}{N}\sum_{n=1}^{N} (y^*(n) - \bar{y})^2$

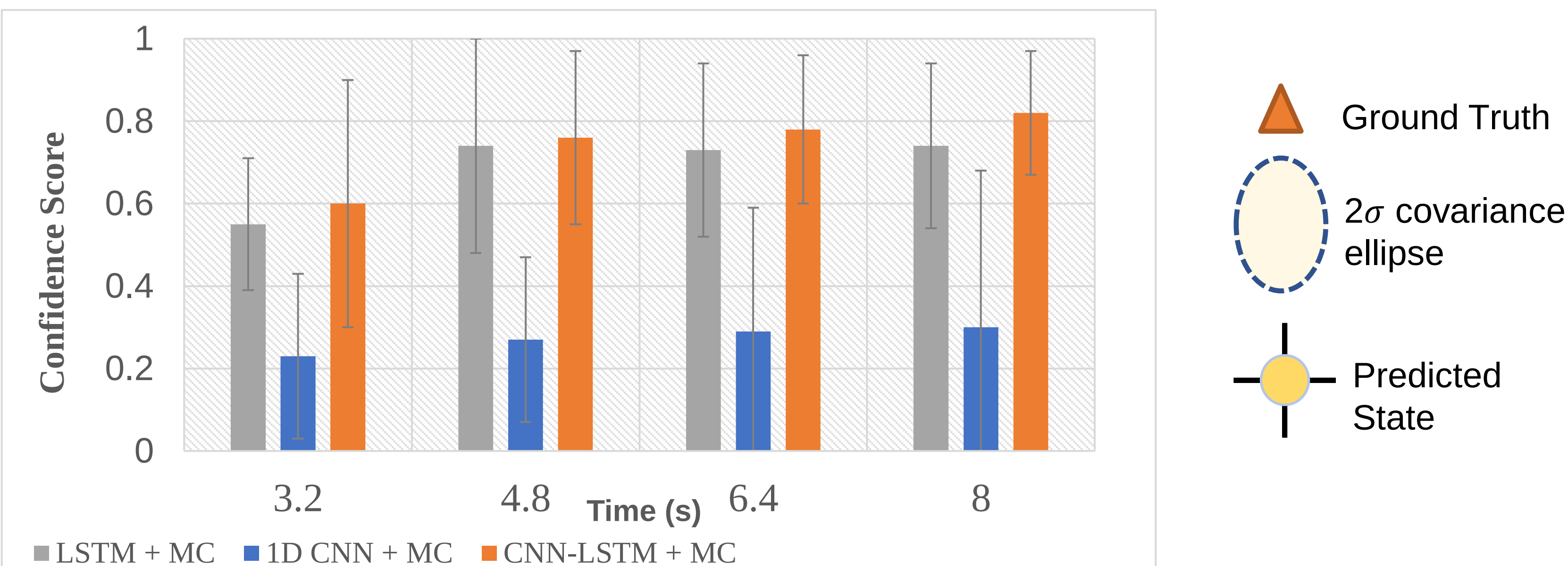


A. Nayak, A. Eskandarian and Z. Doerzaph, "Uncertainty Estimation of Pedestrian Future Trajectory Using Bayesian Approximation," in *IEEE Open Journal of Intelligent Transportation Systems*, vol. 3, pp. 617-630, 2022, doi: 10.1109/OJITS.2022.3205504.

Results: Confidence Score



Confidence Score: Whether the ground truth lies within 95% of predicted confidence interval



Plot shows percentage of Ground truth lying within 2σ covariance ellipse for ETH dataset.