Interpretable Goal-Based model for Vehicle Trajectory Prediction in Interactive Scenarios

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Objectives

- Understanding social interaction while predicting future trajectory in an urban environment is crucial for road safety in autonomous driving.

- Knowledge-based
  + Interpretable outputs
  - Limited performance

- Neural Networks (NN)
  + Better accuracy
  - Not interpretable

Key idea :
Combining the **interpretability** of a discrete choice model (DCM) with the **high accuracy** of a neural network-based model (NN) for **vehicle trajectory prediction.**

Problem Definition

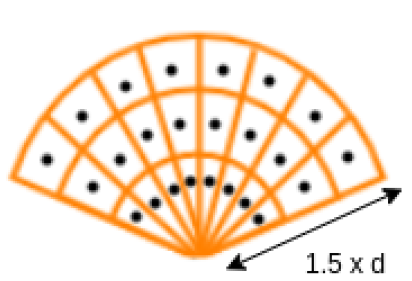
Inputs

- For agent i, its states from $t = 1$ to $t = t_{obs}$: $X_i^t = (x_i^t, y_i^t, v_i^t, a_i^t, \theta_i^t)$
- The potential goals coordinates
- The discrete choice model(DCM)

Outputs

- L future trajectories of the target agent T from time $t = t_{obs} + 1$ to $t = t_f$,
- The associated probabilities

Goal Set Representation



- **Directions** : polar angles
- **Longitudinal distance** : $d = t_f \times v$:
  - If fixed (f) : $v = 5.83\ m.s^{-1}$
  - If dynamic (d) : $v = v_T^{t_{obs}}\ m.s^{-1}$

Discrete Choice Models

Random Utility Maximization (RUM) theory : decision-maker aims at maximizing the utility relative to their choice of potential goal.

The **utility function** is composed of :

1. *occupancy* occ, occ^1: directions containing neighbours in the vicinity are less desirable.
2. *keep direction* dir : vehicles tend to maintain the same direction of motion.
3. *collision avoidance* col : when a neighbour vehicle's trajectory is head-on towards a potential goal, this goal becomes less desirable due to the chance of a collision.

We compare two DCM models :

1) DCM1 :

$$u_k(\mathrm{X}) = \beta_{dir} dir_k + \beta_{occ} occ_k + \beta_{col} col_k \tag{1}$$

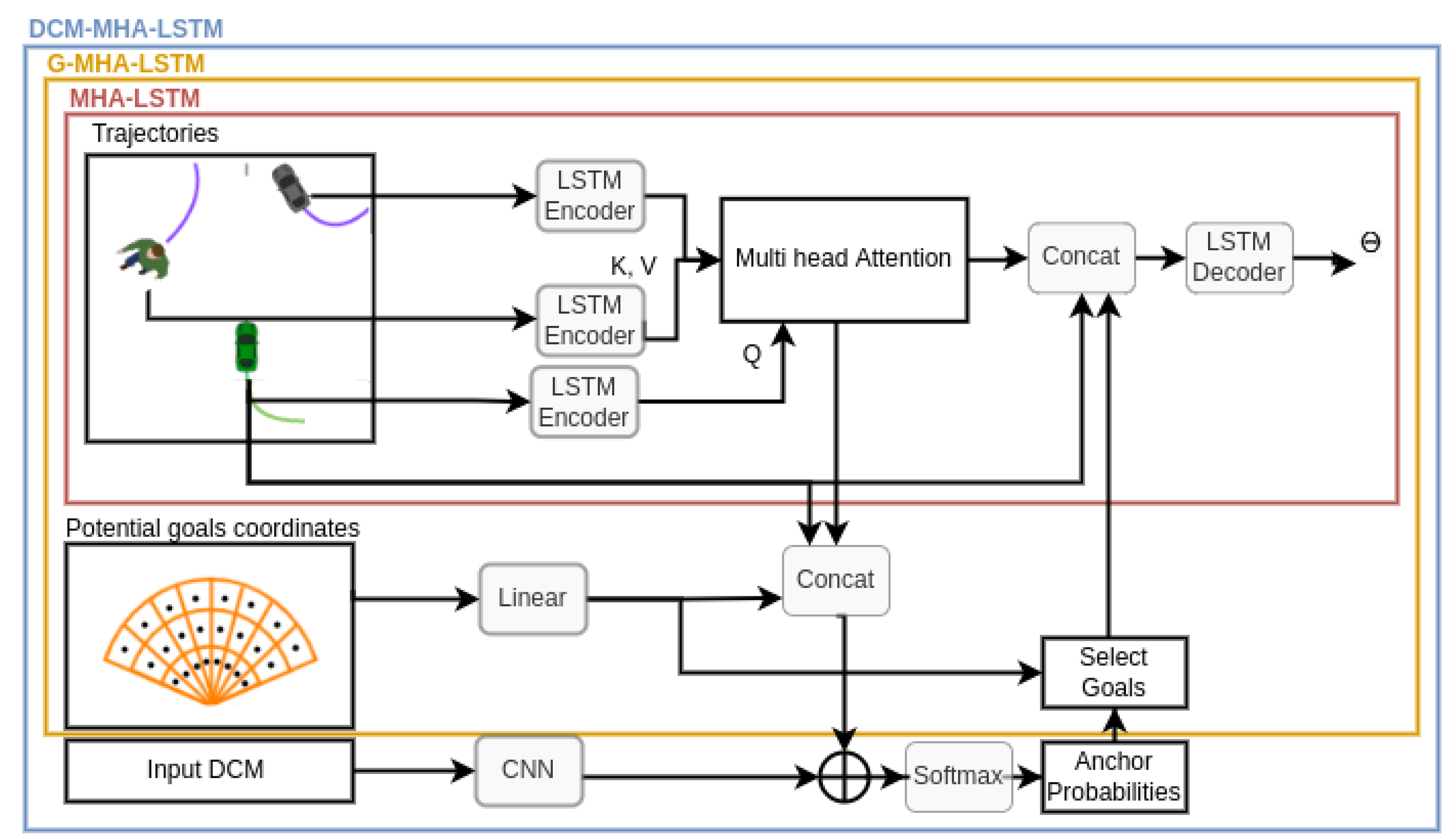
2) DCM2 :

$$u_k(\mathrm{X}) = \beta_{dir} dir_k + \beta_{occ^1} occ_k^1 \tag{2}$$

For occ, we consider the position of the neighbors at time t_{obs}.

For occ^1, we consider their predicted position at time t_f using a Constant velocity model.

Model Architecture



Training

Ouputs : means and variances $\Theta_l^t = (\mu_l^t, \Sigma_l^t)$ of Gaussian distributions.
The **loss functions** are :

- $L_{reg} = -\min_l \sum_{t=t_{obs}+1}^{t_{obs}+t_f} log(\mathcal{N}(y^t|\mu_l^t;\Sigma_l^t)))$,
- $L_{score} = -\sum_{l=1}^{L} \delta_{l*}(l) log(P_l)$, where δ is a function equal to 1 if $l = l*$ and 0 otherwise,
- $L_{cls} = -\sum_{k=1}^{K} \delta_{k*}(k) log(p_k)$, where p_k is the probability associated with the potential goal k, δ is a function equal to 1 if $k = k*$ and 0 otherwise, k_*^t is the index of the potential goal most closely matching the endpoint of the ground truth trajectory.

Estimation of β

Model	β_{dir}	β_{col}	β_{occ}	β_{occ^1}
DCM1-MHA-LSTM (f)	-2.3	-0.3	0.2	-
DCM2-MHA-LSTM (f)	-2.4	-	-	-0.1

- β_{dir} < 0 : vehicles tend to keep their direction,
- β_{occ} > 0 : vehicles tend to prefer nearby spatial zones crowded by agents (counter intuitive). This can be interpreted as in situations where a lot of agents are moving toward the same destination,
- β_{occ^1} < 0 : vehicles tend to avoid occupied zones,
- β_{col} < 0 : vehicles tend to avoid zones where there are potential colliders.

Comparison of Methods

Comparison of different methods on the INTERACTION validation set (3 secs horizon)

Model	$MinADE_6$	$MinFDE_6$	$Coll-II$
MHA-LSTM	0.23	0.69	6.1 %
G-MHA-LSTM (f)	0.21	0.58	1.5 %
G-MHA-LSTM (d)	0.22	0.63	1.9 %
ODCM1-MHA-LSTM (f)	0.20	0.58	1.4 %
ODCM1-MHA-LSTM (d)	0.24	0.68	**1.0** %
ODCM2-MHA-LSTM (f)	0.24	0.67	1.2 %
ODCM2-MHA-LSTM (d)	0.31	0.81	1.3 %
DCM1-MHA-LSTM (f)	**0.19**	**0.57**	1.4 %
DCM1-MHA-LSTM (d)	0.20	0.60	1.4 %
DCM2-MHA-LSTM (f)	0.21	0.57	1.2%
DCM2-MHA-LSTM (d)	0.22	0.61	1.1 %

- Adding DCM decreases collisions, fixed representation (f) gives better results.
- Ours : DCM1-MHA-LSTM (f)

Comparison with the state-of-the-art

Comparison models without map

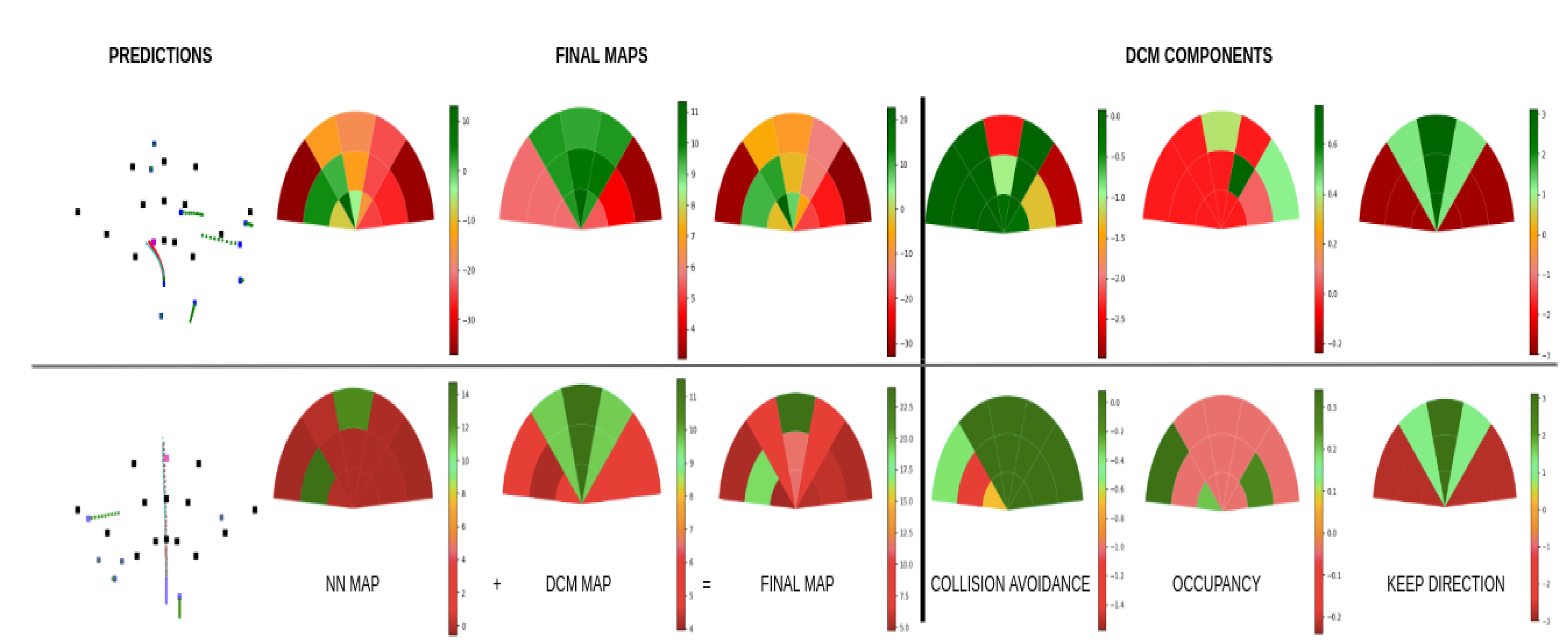
Model	$MinADE_6$	$MinFDE_6$
DESIRE	0.32	0.88
Multipath	0.30	0.99
Ours	**0.19**	**0.58**

Comparison models with map

Model	$MinADE_6$	$MinFDE_6$
SAN	0.10	0.29
TNT	0.21	0.67
ITRA	0.17	0.49
ReCoG	0.19	0.66
Ours	**0.19**	**0.58**

- Competitive results against state-of-the-art models.
- Unlike any of these methods our method provides interpretability.

Interpretable Outputs



- (Un)favourable potential goals are shown in green (red).
- First row : the *NN map* influences the most the final decision.
- Second row : the decision is influenced by *keep direction* and *collision avoidance*.