Appendix

A Anonymized Code

For an anonymized version of our code, please see: anonymous.4open.science/r/polysona

B Weight-Mixing Implementation

PyTorch-Style Forward Pass of Weight-Mixing Mixture-of-LoRA Layer

```
expert_alphas = router(...) # (b, num_experts)

expert_weight_A = (expert_alphas[..., None, None] * self.
    expert_weight_A[None]).sum(
     dim=1
)  # (b, r, in_features)
expert_weight_B = (expert_alphas[..., None, None] * self.
    expert_weight_B[None]).sum(
     dim=1
)  # (b, out_features, r)

output = torch.einsum(
     "bi,bri->br", x, expert_weight_A
)  # (b, in_features) @ (b, r, in_features) -> (b, r)
output = torch.einsum(
     "br,bor->bo", output, expert_weight_B
)  # (b, r) @ (b, out_features, r) -> (b, out_features)
output = self.dropout(output)  # (b, out_features)

output = F.linear(x, w0, b0) + output  # w0x + BAx + b0
```

C Style Consistency Metric Visualization

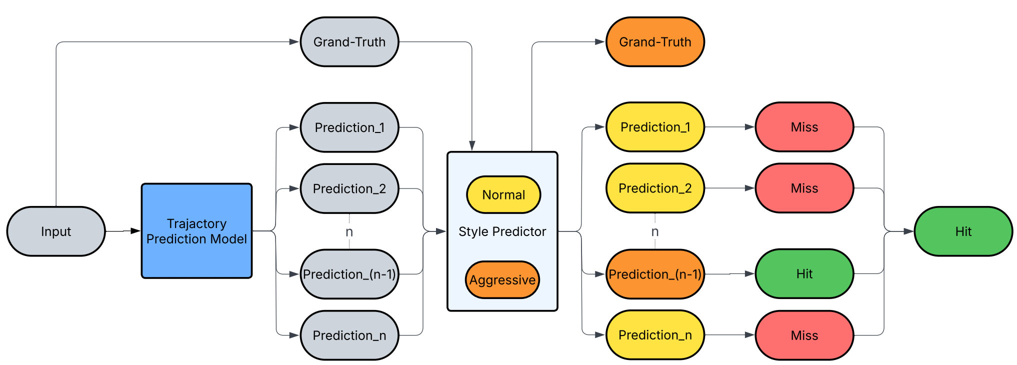


Figure 7: **Style Consistency Metric.** Given a driving scenario ("Input"), the black-box trajectory predictor generates n candidate futures ($\text{Prediction}_1, \ldots, \text{Prediction}_n$). A learned style predictor then assigns each candidate—and the true future ("Ground-Truth")—to one of two clusters (e.g. "Normal" vs. "Aggressive"). If at least one of the n predicted trajectories shares the same style label as the ground-truth, the sample is marked a *Hit*; otherwise it is a *Miss*. This hit/miss outcome directly measures whether the model's multi-modal outputs *cover* the driver's actual style, beyond conventional displacement errors.

D Style Consistency Metric

Extract kinematic static: For each trajectory τ, compute a feature vector

$$\phi(\tau) = \left[\bar{v},\ \bar{a},\ \bar{j}\right]^{\mathsf{T}} \in \mathbb{R}^d, \tag{8}$$

where $\bar{v}$, $\bar{a}$, and $\bar{j}$ are summary statistics (e.g. mean speed, peak acceleration, mean jerk)

Learn style clusters: Fit a Gaussian Mixture Model (GMM) with $k = 2$ on the set of all ground-truth kinematic embeddings in the evaluation set $\{\phi(\tau_n^*)\}_{n=1}^N$, yielding a cluster assignment function

$$C(\phi) \in \{\texttt{"normal"}, \texttt{"aggressive"}\}. \tag{9}$$

Normal and aggressive are assigned based on the mean speed of each cluster. A cluster with higher mean speed will be assigned as aggressive.

Assign styles to predictions: For each sample n, let $\{\hat{\tau}_{n,i}\}_{i=1}^6$ be the six predicted trajectories. Define

$$s_n^* = C\big(\phi(\tau_n^*)\big), \quad s_{n,i} = C\big(\phi(\hat{\tau}_{n,i})\big). \tag{10}$$

Define hit/miss: A *hit* occurs if at least one predicted style matches the ground-truth style:

$$\mathrm{Hit}_n = \{\exists\, i \ :\ s_{n,i} = s_n^*\}, \quad \mathrm{Miss}_n = 1 - Hit_n. \tag{11}$$

Style Consistency Rate (SCR): The overall metric is

$$\mathrm{SCR} = 1 - \frac{1}{N}\sum_{n=1}^{N} \mathrm{Miss}_n, \tag{12}$$

which reflects the fraction of samples for which the model predicts at least one trajectory whose kinematic cluster matches the driver's true style.

By construction, the SCR goes beyond pure spatial accuracy: it measures whether the model "covers" the driver's true style among its multi-modal outputs. A style-agnostic predictor may achieve low ADE/FDE by clustering its modes around average behavior, but will incur a high miss rate on aggressive samples. In contrast, a style-aware model—conditioned on inferred driving-style embeddings—should include at least one candidate trajectory whose kinematics align with the true style, yielding a higher SCR. In our experiments (see Appendix **??**), augmenting the trajectory model with style embeddings substantially reduces the miss rate on aggressive drivers, demonstrating the metric's ability to reveal improvements that ADE/FDE alone cannot capture.

E How does the model reason? Taking a look at the saliency maps.

To gain insight into which input features the model attends when forecasting agent trajectories, we compute saliency maps by measuring the sensitivity of the most likely predicted trajectory with respect to each input feature. Formally, let $X = \{A_{\text{in}}, M_{\text{in}}\}$ denote the concatenation of historical object trajectories A_{in} and map polylines M_{in}. If $\hat{p}_\tau$ is the probability of trajectory τ, then let $\hat{\tau}^* = \arg\max_\tau \hat{p}_\tau$ be the most likely predicted trajectory after a forward pass from a model. Then, we compute the gradient

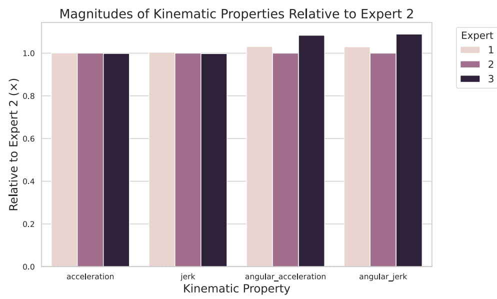
$$\nabla_X \hat{\tau}^* = \frac{\partial \hat{\tau}^*}{\partial X}$$

via back-propagation, and form the saliency map

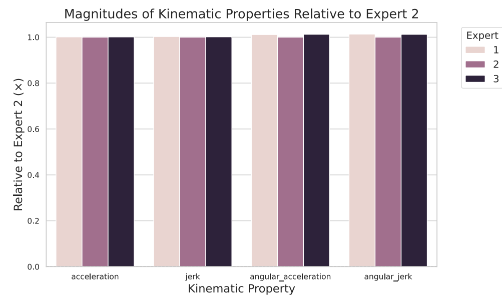
$$S(X) = \log(\|\nabla_X \hat{\tau}^*\|_2 + 1).$$

We use logarithmic scaling above to better display nuances in smaller gradient magnitudes. For visualizing this saliency map, we render the map polylines and the agents' historical trajectories colored using $S(X)$. Warmer colors highlight map segments or agent trajectories that the model deems more important for predicting future trajectories. Likewise, lighter colors highlight areas of less importance. Each agent vehicle is also colored on the same scale based on the maximum saliency value of its historical trajectory. We generate this visualization for both the MTR+Actions baseline model and the Ours+MoV model.

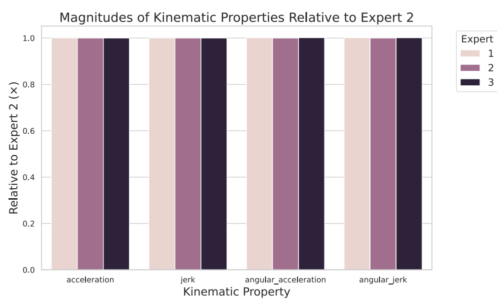
F Additional Visualizations for Relative Kinematics by Expert



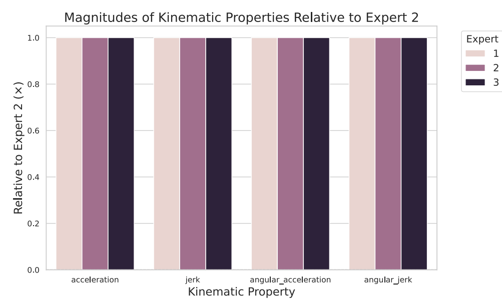
(a) C-Poly



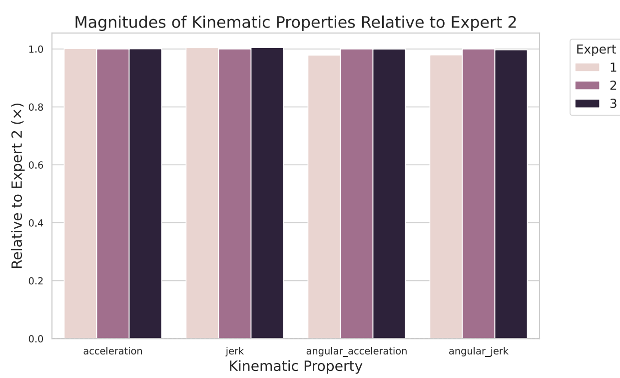
(b) HyperFormer



(c) Polytropon



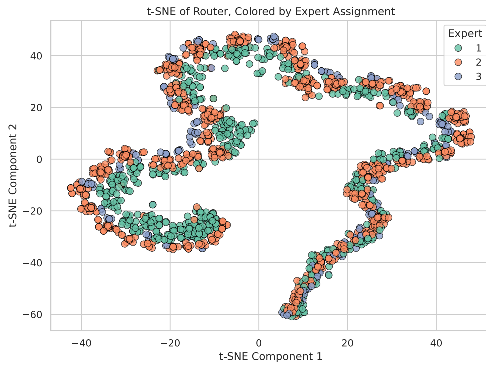
(d) MoV



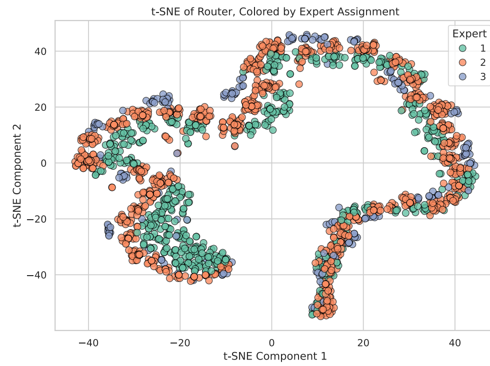
(e) CAT

Figure 8: **Kinematic magnitude comparisons for all variants of our approach.** Experiments run with seed 0 are plotted.

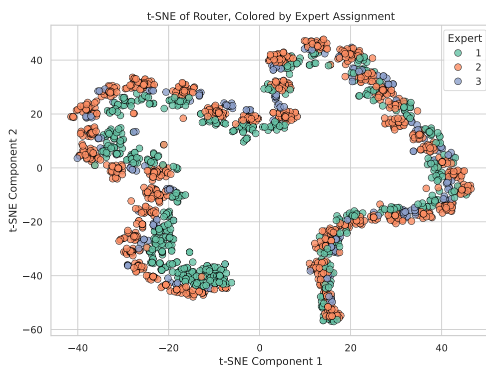
G Additional t-SNE plots for Router Embeddings by Expert



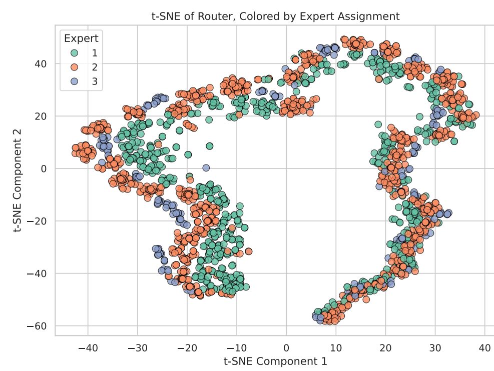
(a) C-Poly



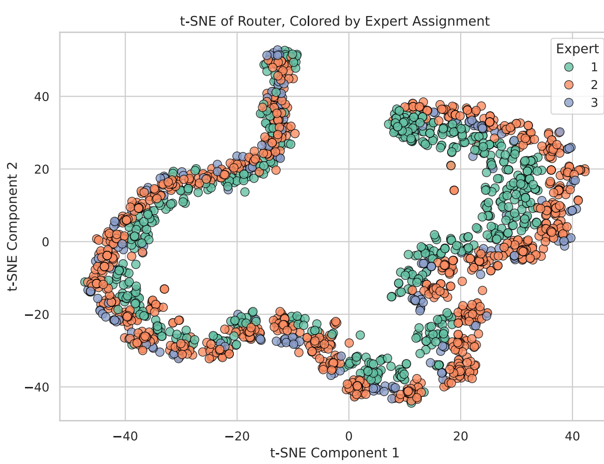
(b) HyperFormer



(c) Polytropon



(d) MoV



(e) CAT

Figure 9: **t-SNE visualization of router embeddings for all variants of our approach.** Experiments run with seed 0 are plotted.

H Baseline MTR Model Hyperparameters

Table 5: Hyperparameters used for training the MTR baseline model.

Hyperparameter	**Value**
Context Encoder	
NAME	MTREncoder
NUM_OF_ATTN_NEIGHBORS	7
NUM_INPUT_ATTR_AGENT	39
NUM_INPUT_ATTR_MAP	29
NUM_CHANNEL_IN_MLP_AGENT	256
NUM_CHANNEL_IN_MLP_MAP	64
NUM_LAYER_IN_MLP_AGENT	3
NUM_LAYER_IN_MLP_MAP	5
NUM_LAYER_IN_PRE_MLP_MAP	3
D_MODEL	256
NUM_ATTN_LAYERS	6
NUM_ATTN_HEAD	8
DROPOUT_OF_ATTN	0.1
USE_LOCAL_ATTN	True
Motion Decoder	
NAME	MTRDecoder
NUM_MOTION_MODES	6
D_MODEL	512
NUM_DECODER_LAYERS	6
NUM_ATTN_HEAD	8
MAP_D_MODEL	256
DROPOUT_OF_ATTN	0.1
NUM_BASE_MAP_POLYLINES	256
NUM_WAYPOINT_MAP_POLYLINES	128
LOSS_WEIGHTS.cls	1.0
LOSS_WEIGHTS.reg	1.0
LOSS_WEIGHTS.vel	0.5
NMS_DIST_THRESH	2.5
Training	
max_epochs	40
learning_rate	0.0001
learning_rate_sched	[22, 24, 26, 28]
optimizer	AdamW
scheduler	lambdaLR
grad_clip_norm	1000.0
weight_decay	0.01
lr_decay	0.5
lr_clip	0.000001
WEIGHT_DECAY	0.01
train_batch_size	64
eval_batch_size	64
Data	
max_num_agents	64
map_range	100
max_num_roads	768
max_points_per_lane	20
manually_split_lane	True
point_sampled_interval	1
num_points_each_polyline	20
vector_break_dist_thresh	1.0
predict_actions	True

I PolySona Model Hyperparameters

Table 6: Hyperparameters used for training the PolySona models. Rows highlighted in yellow indicate differences from the baseline MTR configuration.

Hyperparameter	Value
Context Encoder	
NAME	MTREncoder
NUM_OF_ATTN_NEIGHBORS	7
NUM_INPUT_ATTR_AGENT	39
NUM_INPUT_ATTR_MAP	29
NUM_CHANNEL_IN_MLP_AGENT	256
NUM_CHANNEL_IN_MLP_MAP	64
NUM_LAYER_IN_MLP_AGENT	3
NUM_LAYER_IN_MLP_MAP	5
NUM_LAYER_IN_PRE_MLP_MAP	3
D_MODEL	256
NUM_ATTN_LAYERS	6
NUM_ATTN_HEAD	8
DROPOUT_OF_ATTN	0.1
USE_LOCAL_ATTN	True
Motion Decoder	
NAME	PolySonaDecoder
NUM_MOTION_MODES	6
INTENTION_POINTS_FILE	`cluster_64_center_dict_6s.pkl`
D_MODEL	512
NUM_DECODER_LAYERS	6
NUM_ATTN_HEAD	8
MAP_D_MODEL	256
DROPOUT_OF_ATTN	0.1
NUM_BASE_MAP_POLYLINES	256
NUM_WAYPOINT_MAP_POLYLINES	128
LOSS_WEIGHTS.cls	1.0
LOSS_WEIGHTS.reg	1.0
LOSS_WEIGHTS.vel	0.5
NMS_DIST_THRESH	1.0
Training	
max_epochs	10
learning_rate	0.001
learning_rate_sched	[22, 24, 26, 28]
optimizer	AdamW
scheduler	polynomialLR (power=2)
grad_clip_norm	1000.0
weight_decay	0.00
lr_decay	0.5
lr_clip	0.000001
train_batch_size	256
eval_batch_size	256
predict_actions	True
lora_rank	4
freeze_encoder	True
freeze_decoder	True
attention_only	False
num_personas	3
prior	[0.3, 0.6, 0.1]
λ_{recon}	50
λ_{KL}	50
λ_{entropy}	25
seed	0 / 1 / 2
Data	
max_num_agents	64
map_range	100
max_num_roads	768
max_points_per_lane	20
manually_split_lane	True
point_sampled_interval	1
num_points_each_polyline	20
vector_break_dist_thresh	1.0

J Impact of Rank on Performance

Table 7: **Comparison of Ours+CAT Across Different Ranks.**

Rank	brierFDE↓	minADE↓	minFDE↓	MissRate↓
2	2.1593	0.8573	1.7059	0.3151
4	2.1607	0.8624	1.7041	0.3171
8	2.1578	0.8578	1.7042	0.3120
16	2.1668	0.8610	1.7102	0.3151

Table 8: **Comparison of Ours+CAT Across Different Ranks, Grouped by Kalman Difficulty and TDBM Driving Styles.**

	Kalman Difficulty			TDBM Driving Styles			
Rank	Easy	Medium	Hard	Timid	Careful	Reckless	Threatening
2	0.8120	1.1675	3.9875	0.8903	0.8865	0.8577	0.8172
4	0.8188	1.1678	2.4978	0.8793	0.8477	0.8655	0.8161
8	0.8130	1.1641	3.9882	0.8913	0.9833	0.8581	0.8183
16	0.8149	1.1758	4.2696	0.8944	0.8858	0.8613	0.8225

K Standard Deviation Table

Table 9: **Standard Deviation of Trajectory Prediction Benchmark Performance Comparisons.**

Method	brierFDE↓	minADE↓	minFDE↓	MissRate↓
Ours+Polytropon [25]	0.0004	0.0004	0.0004	0.0009
Ours+C-Poly [29]	0.0026	0.0011	0.0025	0.0003
Ours+HyperFormer [14]	0.0017	0.0004	0.0017	0.0010
Ours+CAT [26]	0.0019	0.0012	0.0018	0.0010
Ours+MoV [37]	0.0010	0.0007	0.0010	0.0004

Table 10: **Standard Deviation of minADE Comparison by Kalman Difficulty and TDBM Driving Style groups.**

	Kalman Difficulty			TDBM Driving Styles			
Method	Easy	Medium	Hard	Timid	Careful	Reckless	Threatening
Ours+PolyTropon [37]	0.0003	0.0032	0.0040	0.0005	0.0038	0.0004	0.0005
Ours+C-Poly [29]	0.0013	0.0003	0.0146	0.0009	0.0286	0.0012	0.0011
Ours+HyperFormer [14]	0.0006	0.0013	0.0060	0.0006	0.0330	0.0004	0.0007
Ours+CAT [26]	0.0012	0.0051	0.0682	0.0014	0.0340	0.0012	0.0012
Ours+MoV [37]	0.0007	0.0006	0.0041	0.0008	0.0026	0.0007	0.0006