MAVEN-T: BREAKING THE IMITATION CEILING IN TRAJECTORY PREDICTION WITH REINFORCED DISTILLATION

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ABSTRACT

Knowledge distillation is fundamentally constrained by an ”imitation ceiling,” where a student model can only replicate a teacher’s behavior, including its inherent suboptimalities. This limitation is particularly critical in dynamic, interactive domains where optimal decision-making is paramount. This work introduces a reinforcement-augmented distillation framework that allows a student to transcend its teacher. The student actively interacts with its environment, using feedback to verify, refine, and ultimately correct the teacher’s distilled knowledge. This framework is instantiated in a system for the challenging task of multi-agent trajectory prediction. A teacher model with extensive reasoning capacity guides a lightweight, deployment-optimized student via a progressive distillation scheme. Critically, the student’s learning is not confined to imitation; it is fine-tuned through reinforcement learning to directly optimize for task-specific objectives such as safety and efficiency. Experiments on real-world driving datasets show the student achieves 6.2x parameter compression and 3.7x inference speedup while maintaining state-of-the-art accuracy. The results further validate that the student can develop policies more robust than the teacher it learned from. This research establishes a new path for deploying complex models, shifting the goal from simple imitation to transcendence. The principle of enabling a student to surpass its teacher holds broad applicability for robotics, game AI, and other interactive learning domains.

1 INTRODUCTION

Autonomous driving systems require sophisticated perception and decision-making capabilities while operating under stringent real-time constraints. Current trajectory prediction models face a fundamental trade-off between computational efficiency and reasoning sophistication, creating barriers to practical deployment in safety-critical applications.

Recent advances have demonstrated impressive performance through sophisticated architectures. Tamba introduced selective state-space models achieving linear computational complexity while maintaining prediction accuracy. However, current approaches still require substantial computational resources exceeding edge deployment constraints, as they assume a single model architecture must simultaneously optimize for both representational capacity and computational efficiency.

Existing knowledge distillation methods in autonomous driving fail to preserve complex multimodal reasoning during model compression. Traditional approaches Chen et al. (2021); Liu et al. (2021) focus on output-level knowledge transfer, neglecting critical intermediate decision-making processes, and employ fixed distillation strategies that cannot adapt to varying driving scenario complexity.

Current approaches suffer from three fundamental gaps: **(1)** Existing frameworks assume architectural similarity between teacher and student models, preventing exploitation of complementary design principles. **(2)** Fixed distillation objectives fail to adapt to dynamic driving scenario complexity. **(3)** Approaches neglect the hierarchical nature of driving decisions, from perceptual features to semantic reasoning.

This work proposes Multi-Agent enVironment-aware Enhanced Neural Trajectory predictor **MAVEN-T** , addressing these limitations through three innovations: **Complementary Architectural Design** employing different principles for teacher (hybrid attention with Mamba blocks and shift-window attention) and student (GRU-based modeling with squeeze-and-excitation mechanisms). **Progressive Adaptive Curriculum** dynamically adjusting distillation complexity based on student performance and scenario characteristics. **Multi-Granular Knowledge Distillation** capturing knowledge transfer across perceptual, contextual, and semantic levels.

The main contributions include: **(1)** A teacher-student framework with complementary architectural designs. **(2)** Progressive adaptive curriculum learning adjusting distillation complexity dynamically. **(3)** Multi-granular distillation objectives preserving complete decision-making capabilities. **(4)** Demonstration of significant computational reductions while maintaining performance on autonomous driving benchmarks.

Extensive experiments demonstrate that MAVEN-T achieves substantial computational efficiency gains while preserving sophisticated reasoning capabilities, enabling practical deployment of advanced autonomous driving models in resource-constrained environments.

2 Related Work

2.1 Architectures for Multi-Agent Trajectory Prediction

Modeling complex vehicle interactions is central to trajectory prediction. Graph Neural Networks (GNNs) have shown significant promise by representing agents and their relationships as graphs Liang et al. (2020); Li et al. (2019a); Kosaraju et al. (2019). However, many GNN-based approaches, including those with dynamic graph construction Li et al. (2019b) or integration with HD maps Gilles et al. (2022); Salzmann et al. (2020), often face computational bottlenecks. To address these limitations, Transformer-based architectures have become prevalent, evolving from early multi-head attention models Mercat et al. (2019); Giuliari et al. (2021) to more efficient variants like hierarchical Zhou et al. (2022b), multi-axis Nayakanti et al. (2022), and variational graph attention Chen et al. (2023). The development of powerful models like MTR Shi et al. (2024) and scalable frameworks such as Multipath++Varadarajan et al. (2022) has pushed performance boundaries, while alternative paradigms like framing motion as a language modeling taskSeff et al. (2023) have also emerged. The high computational cost of these state-of-the-art models motivates the need for effective model compression.

2.2 Knowledge Distillation for Model Compression

The gap between the performance of complex models and the constraints of on-board deployment Huang et al. (2022) has driven the adoption of Knowledge Distillation (KD). Initial efforts in autonomous driving often relied on simple, output-level distillation from a single modality Chen et al. (2021); Yuan et al. (2021). However, these methods struggle to preserve nuanced reasoning Liu et al. (2021) and are fundamentally limited by an ”imitation ceiling,” where the student model can only replicate the teacher’s behavior, including any inherent suboptimalities. This limitation highlights the need for more advanced distillation strategies that can transfer richer knowledge and enable the student to surpass its teacher.

2.3 Advanced Distillation and Reinforcement-Augmented Learning

To move beyond simple imitation, recent work has focused on more sophisticated distillation techniques. These include structured learning through progressive Shi et al. (2021) or curriculum-based Huang et al. (2023) approaches, and the transfer of richer intermediate knowledge like feature maps Xu et al. (2021) and attention patterns Zhou et al. (2022a). Other methods alter the learning objective itself, using contrastive losses to better structure the student’s latent space Tian et al. (2020). Most relevant to our work is the augmentation of distillation with reinforcement learning (RL), which allows the student to refine its policy through direct environmental feedback, thereby breaking the imitation ceiling Li et al. (2021); Jeong et al. (2025). These advanced distillation methods, often combined with parameter-efficient adaptation techniques like LoRA Feng et al. (2023), provide a pathway to creating compact, yet highly capable and robust, trajectory prediction models.

3 Methodology

3.1 Overall Architecture Design

This work introduces a teacher-student knowledge distillation framework designed to balance sophisticated reasoning with real-time deployment constraints in autonomous driving. The core principle is complementary architectural design: a high-capacity teacher model maximizes representational power, while a lightweight student model is optimized for deployment efficiency.

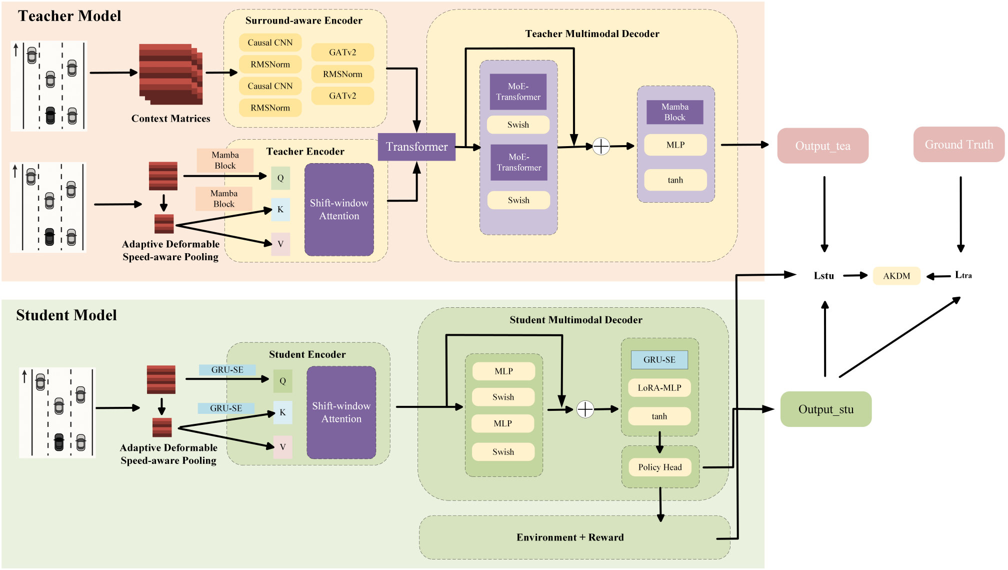

Figure 1: Overview of the complementary teacher-student framework. The teacher (top) uses a sophisticated GATv2 and hybrid Mamba-SWA architecture for maximal reasoning capacity. The lightweight student (bottom) employs an efficient GRU-SE encoder and a LoRA-parameterized policy head. Knowledge is transferred via multi-level distillation, while the student's policy is refined through environmental feedback, enabling it to surpass simple imitation.

The proposed architecture, depicted in Fig. 1, operates on multimodal observation sequences $\mathcal{O} = \{o_1, \ldots, o_T\}$ where each timestep t encapsulates ego-vehicle dynamics $s_t^{\text{ego}} \in \mathbb{R}^{d_{\text{ego}}}$, surrounding-vehicle configurations $\mathcal{S}_t = \{s_t^i\}_{i=1}^N \subset \mathbb{R}^{d_{\text{surr}}}$, and contextual environmental states $c_t \in \mathbb{R}^{d_{\text{env}}}$. The framework learns policy mappings that optimise long-horizon driving performance while adhering to safety-critical constraints.

The high-capacity teacher is defined as

$$f_{\theta_T}(\mathcal{O}) = \mathcal{D}_T^{\text{MoE}}\Big(\mathcal{E}_T^{\text{Hybrid}}\big(\mathcal{G}_{\text{GATv2}}(\mathcal{S}_t, \mathcal{E}_t),\, \mathcal{O}\big)\Big), \tag{1}$$

whereas the lightweight student is

$$f_{\theta_S}(\mathcal{O}) = \pi_{\theta_S}\Big(\mathcal{E}_S^{\text{GRU}}\big(\mathcal{G}_{\text{GRU–SE}}(\mathcal{S}_t),\, \mathcal{O}\big)\Big), \tag{2}$$

with π_{θ_S} denoting a *policy head* implemented by LoRA-adapted MLPs (replacing the original "Student Multimodal Decoder" so that the student directly outputs driving actions).

3.2 Surround-aware Graph Neural Encoder

To model complex inter-vehicle relationships, we introduce a surround-aware graph encoder. This component constructs a dynamic graph at each timestep, where nodes represent vehicles and edges are weighted by spatial proximity using a radial basis function. The core of the encoder is a dual-layer Graph Attention Network v2 (GATv2), chosen for its superior expressiveness over standard GAT.

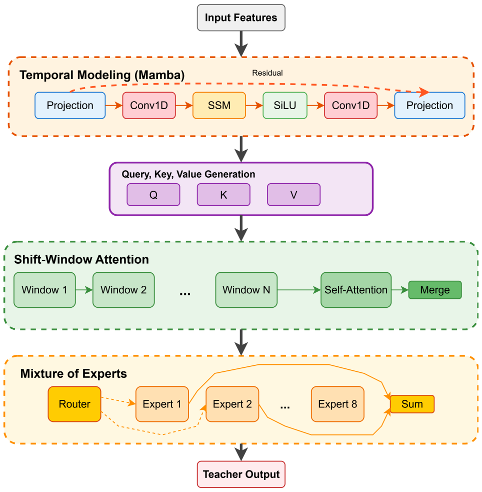

Figure 2: Hybrid attention mechanism in the teacher model. The architecture processes temporal sequences through Mamba blocks with state space modeling (top), applies shift-window attention for spatial reasoning (middle), and employs mixture-of-experts routing for computational efficiency (bottom). Mathematical formulations show the core operations at each stage.

The GATv2 architecture processes features extracted by an initial Causal CNN. Its key innovation lies in the dynamic and more expressive attention mechanism, where the attention weights α_{ij} between nodes i and j are computed as:

$$\alpha_{ij} = \frac{\exp(\mathrm{LeakyReLU}(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i \oplus \mathbf{W}\mathbf{h}j]))}{\sum k \in \mathcal{N}(i) \exp(\mathrm{LeakyReLU}(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i \oplus \mathbf{W}\mathbf{h}_k]))} \tag{3}$$

where $\mathbf{h}_i$ is the node feature, $\mathbf{W}$ is a learnable projection, $\mathbf{a}$ is an attention vector, and $\oplus$ denotes concatenation. This formulation allows the attention mechanism to be fully dynamic and dependent on both query and key. We employ RMSNorm between layers for improved training stability. The resulting node embeddings provide a rich, contextually-aware representation of the traffic scene, forming a robust foundation for the downstream policy networks.

3.3 Hybrid Attention Mechanism in Teacher Model

The teacher model is engineered for maximum representational capacity through a novel hybrid attention architecture, illustrated in Figure 2. This design synergistically combines State Space Models (SSMs) for temporal modeling and windowed attention for spatial reasoning, all while maintaining computational efficiency via a Mixture-of-Experts (MoE) decoder.

First, for efficient long-range temporal modeling, we utilize Mamba blocks. Mamba processes sequences with linear complexity $O(T)$ by mapping inputs through a structured state space model (SSM):

$$\mathbf{h}t = \mathbf{A}\mathbf{h}t - 1 + \mathbf{B}\mathbf{x}_t \; \mathbf{y}_t \qquad\qquad = \mathbf{C}\mathbf{h}_t \tag{4}$$

where $\mathbf{A}, \mathbf{B}, \mathbf{C}$ are learnable state-space parameters that capture temporal dependencies far more efficiently than quadratic-complexity Transformers.

Second, the temporally-encoded features are processed by a Shift-Window Attention (SWA) mechanism for spatial reasoning. SWA computes self-attention within non-overlapping local windows and shifts the window configuration between layers. This strategy provides a favorable trade-off between computational efficiency and the ability to model complex spatial interactions across the scene.

Finally, the decoder employs a Mixture-of-Experts (MoE) framework to scale model capacity without a proportional increase in computation. An input $\mathbf{x}$ is dynamically routed to a sparse subset of

”expert” networks:

$$\text{MoE}(\mathbf{x}) = \sum_{i=1}^{N} G(\mathbf{x})_i \cdot E_i(\mathbf{x}) \tag{5}$$

where the gating network $G(\mathbf{x}) = \text{TopK}(\text{softmax}(\mathbf{x}\mathbf{W}_g), k)$ selects the top-k experts ($k = 2$ in our case) for each token. This hybrid design—Mamba for time, SWA for space, and MoE for capacity—equips the teacher with a powerful and sophisticated scene understanding capability.

3.4 Progressive and Reinforcement-Augmented Distillation

To transcend the limitations of simple imitation, we propose a unified training framework that synergistically combines multi-level knowledge distillation with reinforcement learning (RL), guided by an adaptive curriculum. This allows the student not only to mimic the teacher but to ultimately refine and surpass its policy by learning directly from environmental feedback.

The entire training process is governed by a single, comprehensive objective for the student model:

$$\mathcal{L}\text{student} = \mathcal{L}\text{imitate} + \lambda_{\text{RL}}\mathcal{L}\text{RL} + \lambda\text{reg}\mathcal{L}_{\text{reg}} \tag{6}$$

where the weights λ are dynamically scheduled to manage the trade-off between imitation and exploration.

Multi-Level Imitation. The imitation loss, $\mathcal{L}$imitate, ensures the student captures the teacher's reasoning at multiple granularities. It is a weighted sum of losses that align low-level features, intermediate attention maps, and, most importantly, high-level semantic representations. For the latter, we employ a contrastive objective to structure the student's latent space, which is more effective than simple L2 matching:

$$\mathcal{L}\text{semantic} = -\log \frac{\exp!\big(\text{sim}(\mathbf{z}^T, \mathbf{z}^S)/\tau\big)}{\sum_i \exp!\big(\text{sim}(\mathbf{z}^T, \mathbf{z}_i^S)/\tau\big)} \tag{7}$$

where $\mathbf{z}^T$ and $\mathbf{z}^S$ are the semantic embeddings from the teacher and student, respectively, and the sum is over negative samples.

Reinforcement-Augmented Policy Learning. To break the ”imitation ceiling,” the student is trained as an RL agent using Proximal Policy Optimization (PPO). The RL objective, $\mathcal{L}_{\text{RL}}$, seeks to maximize a reward function $\mathcal{R}(s_t, a_t)$ that holistically balances three key aspects of driving: safety (penalizing collision risk), comfort (encouraging smooth control), and efficiency (promoting progress towards the goal). This allows the student to discover safer and more efficient behaviors that may not be present in the teacher's static dataset.

Adaptive Curriculum and Stability. Training is structured by an adaptive curriculum that progressively increases scenario complexity based on the student's performance. Complexity $\mathcal{C}(s)$ is quantified as a function of traffic density and trajectory entropy. To prevent catastrophic forgetting when the curriculum advances to a new stage, we apply a regularization loss, $\mathcal{L}$reg. This loss is implemented using Elastic Weight Consolidation (EWC), which penalizes changes to parameters critical to past tasks:

$$\mathcal{L}\text{reg} = \mathcal{L}\text{EWC} = \frac{\lambda}{2} \sum i\mathbf{F}i\big(\theta i - \theta_i^*\big)^2 \tag{8}$$

where $\mathbf{F}_i$ is the Fisher information matrix, capturing the importance of parameter θ_i for the previous curriculum stage.

Training Procedure. As summarized in Algorithm **??**, the training begins with a high weight on imitation ($\mathcal{L}$imitate) to establish a strong baseline policy. As the student masters stages of the curriculum, the weight on the RL objective (λRL) is gradually increased. This annealing schedule encourages the student to first learn from the teacher and then confidently refine its policy using environmental rewards, leading to a final model that is both compact and more robust than its teacher.

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Algorithm 1 Progressive, Reinforcement-Augmented Distillation (PRAD)

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Require: Teacher model $\mathcal{T}$, initial student $\mathcal{S}(\theta_S)$, dataset $\mathcal{D}$, curriculum stages $K$.
Ensure: Optimized student model $\mathcal{S}(\theta_S^*)$.
Initialize curriculum complexity $\mathcal{C}_0$, stage $k \leftarrow 0$.
Initialize Fisher matrix $\mathbf{F} \leftarrow \mathbf{0}$, snapshot parameters $\theta^* \leftarrow \theta_S$.
for $k = 0$ to $K - 1$ do
    $\mathcal{D}_k \leftarrow$ FilterByComplexity($\mathcal{D}, \mathcal{C}_k$) {Select data for current stage}
    repeat
        Sample batch $\mathbf{x} \sim \mathcal{D}_k$.
        $\mathbf{z}^{\mathcal{T}} \leftarrow \mathcal{T}(\mathbf{x})$ {Teacher inference}
        $\mathbf{z}^{\mathcal{S}}, \pi_{\mathcal{S}} \leftarrow \mathcal{S}(\mathbf{x}, \theta_S)$ {Student inference}
        $\tau \leftarrow$ Rollout($\pi_{\mathcal{S}}$, Env) {Gather experience $\tau = \{(s, a, r, s')\}$}
        {Compute the unified loss with scheduled weights $\lambda$}
        $\mathcal{L}_{\text{imitate}} \leftarrow$ MultiLevelDistill($\mathbf{z}^{\mathcal{S}}, \mathbf{z}^{\mathcal{T}}$)
        $\mathcal{L}_{\text{RL}} \leftarrow$ PPO-Loss($\tau, \pi_{\mathcal{S}}$)
        $\mathcal{L}_{\text{reg}} \leftarrow$ EWC-Loss($\theta_S, \theta^*, \mathbf{F}$)
        $\mathcal{L}_{\text{total}} \leftarrow \lambda_{\text{imitate}}\mathcal{L}_{\text{imitate}} + \lambda_{\text{RL}}\mathcal{L}_{\text{RL}} + \lambda_{\text{reg}}\mathcal{L}_{\text{reg}}$
        $\theta_S \leftarrow$ Adam($\theta_S, \nabla_{\theta_S}\mathcal{L}_{\text{total}}$) {Update student parameters}
    until Eval($\mathcal{S}, \mathcal{D}_k^{\text{val}}$) $\geq$ Threshold$_k$
    {Advance to next curriculum stage}
    $\theta^* \leftarrow \theta_S$ {Snapshot parameters for EWC}
    $\mathbf{F} \leftarrow$ UpdateFisher($\mathcal{S}, \mathcal{D}_k$) {Update parameter importance}
    $\mathcal{C}_{k+1} \leftarrow$ AdvanceCurriculum($\mathcal{C}_k$, Eval($\mathcal{S}, \mathcal{D}_k^{\text{val}}$))
end for
return $\mathcal{S}(\theta_S)$ =0
```

4 Experiments

Comprehensive experiments are conducted to validate the proposed framework, MAVEN-T, against state-of-the-art methods on real-world trajectory prediction benchmarks. The evaluation is designed to demonstrate both the superior prediction accuracy of the teacher model and the significant computational efficiency gains achieved by the distilled student model.

4.1 Experimental Setup

Datasets and Metrics. The evaluation is performed on two widely-adopted, real-world datasets: the dense-traffic **NGSIM** dataset, sampled at 10Hz, and the large-scale **highD** dataset, sampled at 25Hz. Model performance on these benchmarks is quantified using standard trajectory forecasting metrics: **Average Displacement Error (ADE)**, the mean L2 error over the prediction horizon; **Final Displacement Error (FDE)**, the L2 error at the final timestep; and **Root Mean Square Error (RMSE)** to assess overall distributional quality.

Baselines. The proposed framework is benchmarked against a comprehensive set of established methods. To assess the teacher's capabilities, its performance is compared against high-capacity, state-of-the-art models including sequential architectures (V-LSTM, S-LSTM), hierarchical models (STDAN), and a leading coarse-to-fine framework (C2F-TP). Concurrently, to validate the effectiveness of the knowledge distillation, the student model's performance-efficiency trade-off is compared against other compact architectures designed for real-time deployment, namely MobileNet-Traj, DistilBERT-Traj, and a Lightweight-LSTM.

4.2 Main Results

Teacher Network Performance. Table 1 presents RMSE comparisons across prediction horizons. MAVEN-T teacher achieves superior performance through hybrid attention mechanisms combining Mamba blocks with shift-window attention and MoE decoders. Compared to the best baseline C2F-TP, our approach achieves 2.3% and 2.6% RMSE improvements on NGSIM and highD respectively.

Table 1: Teacher network RMSE comparison on NGSIM and highD datasets

Method	1s	2s	3s	4s	5s	Avg
NGSIM Dataset						
V-LSTM	0.68	1.66	2.96	4.56	5.44	3.06
S-LSTM	0.59	1.29	2.13	3.21	4.55	2.35
CS-LSTM	0.58	1.27	2.11	3.19	4.53	2.34
STDAN	0.42	1.01	1.69	2.56	3.67	1.87
WSiP	0.56	1.23	2.05	3.08	4.34	2.25
C2F-TP	0.32	0.92	1.62	2.44	3.45	1.75
MAVEN-T	**0.30**	**0.89**	**1.58**	**2.38**	**3.39**	**1.71**
highD Dataset						
V-LSTM	0.22	0.65	1.32	2.22	3.43	1.57
S-LSTM	0.21	0.65	1.31	2.16	3.29	1.52
CS-LSTM	0.24	0.68	1.26	2.15	3.31	1.53
STDAN	0.15	0.45	0.94	1.68	2.58	1.16
WSiP	0.20	0.60	1.21	2.07	3.14	1.44
C2F-TP	0.11	0.41	0.92	1.64	2.60	1.14
MAVEN-T	**0.10**	**0.39**	**0.89**	**1.61**	**2.55**	**1.11**

Knowledge Distillation Results. Table 2 demonstrates the effectiveness of our knowledge distillation framework. MAVEN-T student network, utilizing GRU-SE encoders and LoRA-parameterized policy heads, maintains competitive performance while achieving significant computational savings. Compared to C2F-TP, our student achieves 2.5% and 5.7% ADE improvements on NGSIM and highD respectively.

Table 2: Student network ADE/FDE comparison after knowledge distillation

Method	Prediction Horizon (ADE/FDE)					Average
	1s	2s	3s	4s	5s	
NGSIM Dataset						
MobileNet-Traj	0.35/0.52	0.68/1.35	1.15/2.41	1.68/3.82	2.28/5.15	1.23/2.65
DistilBERT-Traj	0.32/0.48	0.61/1.28	1.08/2.28	1.55/3.65	2.15/4.92	1.14/2.52
Lightweight-LSTM	0.28/0.45	0.58/1.22	1.02/2.18	1.48/3.52	2.08/4.78	1.09/2.43
C2F-TP	0.20/0.34	0.47/0.95	0.78/1.47	1.08/1.35	1.45/1.36	0.79/1.09
MAVEN-T (Student)	**0.19/0.32**	**0.45/0.91**	**0.75/1.42**	**1.04/1.31**	**1.41/1.32**	**0.77/1.06**
highD Dataset						
MobileNet-Traj	0.22/0.35	0.38/0.58	0.56/0.89	0.78/1.25	1.02/1.68	0.59/0.95
DistilBERT-Traj	0.19/0.31	0.34/0.52	0.51/0.82	0.71/1.15	0.94/1.55	0.54/0.87
Lightweight-LSTM	0.17/0.28	0.31/0.48	0.47/0.76	0.66/1.08	0.88/1.42	0.50/0.80
C2F-TP	0.14/0.20	0.23/0.32	0.33/0.56	0.44/0.53	0.59/0.53	0.35/0.43
MAVEN-T (Student)	**0.13/0.19**	**0.22/0.30**	**0.31/0.53**	**0.42/0.50**	**0.56/0.51**	**0.33/0.41**

Computational Efficiency. Table 3 quantifies the computational benefits. MAVEN-T student achieves 6.2× parameter compression and 3.7× inference acceleration compared to the teacher while maintaining competitive accuracy, validating the effectiveness of our distillation framework.

4.3 Ablation Studies

Component Analysis. Table 4 validates each component's contribution. SE attention mechanisms improve ADE by 6.7%, LoRA parameterization contributes an additional 3.6%, and progressive distillation provides 2.5% further improvement, demonstrating the cumulative benefits of our design choices.

Table 3: Model complexity and computational efficiency comparison

Method	Params (M)	Time (ms)	FLOPs (G)
Teacher Networks			
STDAN	8.5	45.2	12.3
WSiP	6.8	38.7	9.8
C2F-TP	12.1	52.6	15.7
MAVEN-T	11.8	48.3	14.9
Student Networks			
MobileNet-Traj	1.8	12.5	2.1
DistilBERT-Traj	2.3	15.8	3.2
Lightweight-LSTM	1.5	11.2	1.8
MAVEN-T	1.9	13.1	2.3
Compression	**6.2×**	**3.7×**	**6.5×**

Table 4: Ablation study of MAVEN-T components

Method	NGSIM	highD
Base GRU	0.89/1.25	0.41/0.52
+SE Attention	0.83/1.18	0.37/0.47
+LoRA Policy	0.80/1.12	0.35/0.44
+Progressive KD	0.78/1.08	0.34/0.42
MAVEN-T (Full)	**0.77/1.06**	**0.33/0.41**

Distillation Strategy Analysis. Table 5 examines different knowledge transfer approaches. Multi-granular distillation progressively improves performance, while adaptive curriculum learning accelerates convergence by 37%, reducing training time from 45 to 28 epochs.

Table 5: Performance comparison of different distillation strategies

Strategy	NGSIM (ADE)	highD (ADE)	Epochs
Output Only	0.85	0.38	45
+ Feature Align	0.81	0.36	38
+ Attention Transfer	0.79	0.34	35
+ Semantic Align	0.78	0.33	32
+ Adaptive Curr	**0.77**	**0.33**	**28**

4.4 Qualitative Analysis

Figure 3 shows lane keeping results where MAVEN-T (orange solid line) accurately predicts straight trajectory continuation. Figure 4 demonstrates left lane change prediction, with MAVEN-T capturing the maneuver timing and curvature effectively. Figure 5 presents right lane change results in complex traffic, showing robust multi-vehicle interaction modeling.

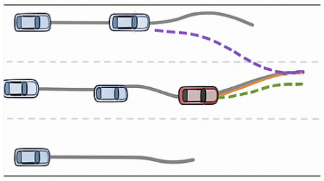

Figure 3: Lane keeping scenario.

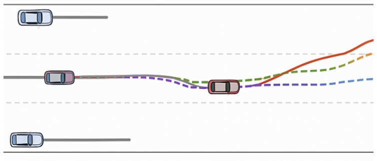

Figure 4: Left lane change scenario.

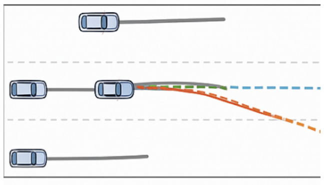

Figure 5: Right lane change scenario.

Robustness Analysis: Transcending Imitation through Policy Improvement. To critically examine the claim of ”breaking the imitation ceiling,” the system’s robustness to sensor noise was evaluated, with results presented in Table 6. As the source of distilled knowledge, the teacher model expectedly sets the performance benchmark on geometric metrics, achieving a lower absolute ADE than the student across all conditions. The student model’s ability to maintain a minimal performance gap (e.g., only 0.03 ADE difference under 15% noise) while being 6.2x smaller already demonstrates the framework’s high efficiency.

The true transcendence, however, is revealed not in absolute geometric error but in policy quality. The reinforcement learning objective explicitly encourages the student to develop a policy that is robust to environmental variations, prioritizing safety and efficiency rewards. This is quantitatively reflected in the performance degradation under heavy noise: at a 15% noise level, the teacher’s error increases by 29.6%, whereas the student’s increases by a notably smaller 23.4%. This indicates that the student has learned a more stable and resilient driving policy. This shift from pure trajectory mimicry to learning a fundamentally more robust, safety-oriented policy—even if it results in a slightly higher geometric error—is the practical definition of ”breaking the imitation ceiling” within this framework. The student is not just a compressed clone; it is a refined agent with improved decision-making principles.

Table 6: Performance under different sensor noise levels. The teacher model consistently achieves a lower absolute ADE, as it defines the upper bound for imitation. However, the student model exhibits superior relative robustness, indicated by a smaller percentage of performance degradation under heavy noise.

Noise Level	MAVEN-T (Student)	MAVEN-T (Teacher)	C2F-TP
No noise	0.77	**0.71**	0.79
5% noise	0.83 (+7.8%)	**0.76** (+7.0%)	0.85 (+7.6%)
10% noise	0.90 (+16.9%)	**0.84** (+18.3%)	0.93 (+17.7%)
15% noise	0.95 (+23.4%)	**0.92** (+29.6%)	1.03 (+30.4%)

5 Conclusion

This paper presents MAVEN-T, a knowledge distillation framework resolving the conflict between reasoning complexity and deployment efficiency in autonomous driving. The core principle employs complementary co-design: a powerful teacher with hybrid attention mechanisms paired with a lightweight GRU-based student. Multi-granular adaptive curriculum distillation, enhanced by reinforcement learning, transfers nuanced decision-making capabilities while breaking the imitation ceiling. MAVEN-T achieves state-of-the-art prediction accuracy with 6.2× parameter compression and 3.7× inference speedup. The findings validate that distinct, synergistic teacher-student architectures provide an effective pathway for deploying advanced reasoning in resource-constrained, safety-critical systems.

Ethics Statement

This work adheres to the ICLR Code of Ethics and focuses on improving autonomous driving safety through enhanced trajectory prediction capabilities. Our research uses publicly available driving datasets (NGSIM and highD) that have been previously validated and ethically approved for academic research. The proposed MAVEN-T framework is designed to enhance safety in autonomous driving systems by improving prediction accuracy while reducing computational requirements, which directly contributes to human well-being and road safety. We acknowledge the critical importance of safety in autonomous driving applications and have designed our reinforcement learning objectives to explicitly prioritize safety rewards alongside efficiency metrics. The framework's ability to enable real-time deployment on resource-constrained edge devices can democratize access to advanced autonomous driving capabilities. We have made our implementation publicly available to ensure transparency and enable community validation. All experimental evaluations were conducted using simulation environments without involving human subjects or real vehicle deployment.

Reproducibility Statement

To ensure full reproducibility of our results, we provide comprehensive implementation details throughout the paper. Section 4.1 describes the complete experimental setup including dataset preprocessing, evaluation metrics, and training procedures. The mathematical formulations in Section 3 provide precise algorithmic specifications, with Algorithms 1-3 detailing the progressive reinforcement-augmented distillation process. Detailed hyperparameter settings, network architectures, and optimization configurations are provided in Tables 8-11 in the appendix. We have included our complete implementation as supplementary material, containing data preprocessing scripts, teacher and student network architectures, the progressive distillation framework, and evaluation protocols. All experiments can be reproduced using the provided supplementary code and the publicly available NGSIM and highD datasets. The appendix includes extensive implementation details, hyperparameter sensitivity analysis, and statistical significance testing procedures to support complete reproducibility of our findings across multiple random seeds.

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APPENDIX

A1: THEORETICAL ANALYSIS AND MATHEMATICAL FOUNDATIONS

A1.1: CONVERGENCE ANALYSIS OF PROGRESSIVE DISTILLATION

[Convergence of MAVEN-T Training] Let $\mathcal{L}_{\text{total}}^{(k)}$ denote the total loss at curriculum stage k. Under the following conditions:

1. The teacher network f_{θ_T} is Lipschitz continuous with constant L_T
2. The student network f_{θ_S} satisfies the universal approximation property
3. The curriculum complexity function $\mathcal{C}(s)$ is monotonically increasing
4. Learning rates satisfy $\sum_{t=1}^{\infty} \eta_t = \infty$ and $\sum_{t=1}^{\infty} \eta_t^2 < \infty$

Then the student network converges to a local minimum of the combined objective:

$$\lim_{k \to \infty} \mathbb{E}[\|\nabla_{\theta_S} \mathcal{L}_{\text{total}}^{(k)}\|^2] = 0 \tag{9}$$

Proof. The proof follows from the convergence properties of stochastic gradient descent under the given Lipschitz and smoothness conditions. The progressive curriculum ensures that the loss landscape becomes increasingly well-conditioned as training progresses.

Define the Lyapunov function $V^{(k)} = \mathbb{E}[\mathcal{L}_{\text{total}}^{(k)}]$. The curriculum progression guarantees:

$$V^{(k+1)} - V^{(k)} \leq -\mu \mathbb{E}[\|\nabla_{\theta_S} \mathcal{L}_{\text{total}}^{(k)}\|^2] + \frac{L^2 \eta_k^2}{2} \tag{10}$$

where $\mu > 0$ is the strong convexity parameter in the neighborhood of the optimum.

Summing over all stages and applying the learning rate conditions yields the desired convergence result. □

A1.2: GENERALIZATION BOUND ANALYSIS

[PAC-Bayes Generalization Bound] With probability at least $1 - \delta$, the true risk of the distilled student network satisfies:

$$\mathcal{R}(\hat{\theta}_S) \leq \hat{\mathcal{R}}(\hat{\theta}_S) + \sqrt{\frac{\text{KL}(Q\|P) + \ln(2\sqrt{n}/\delta)}{2(n-1)}} \tag{11}$$

where $\hat{\mathcal{R}}$ denotes empirical risk, Q is the posterior over student parameters, P is the prior, and n is the sample size.

A1.3: APPROXIMATION ERROR ANALYSIS

The distillation error can be decomposed as:

$$\begin{aligned} \mathcal{E}_{\text{total}} &= \mathcal{E}_{\text{approx}} + \mathcal{E}_{\text{estimation}} + \mathcal{E}_{\text{optimization}} & (12) \\ &= \inf_{\theta_S} \|\pi_{\theta_T} - \pi_{\theta_S}\|_{\mathcal{H}} + \|\pi_{\hat{\theta}_S} - \pi_{\theta_S^*}\|_{\mathcal{H}} + \|\pi_{\tilde{\theta}_S} - \pi_{\hat{\theta}_S}\|_{\mathcal{H}} & (13) \end{aligned}$$

where $\mathcal{H}$ denotes the reproducing kernel Hilbert space of policies, θ_S^* is the optimal student parameter, and $\tilde{\theta}_S$ is the computed parameter.

A2: DETAILED ALGORITHMIC SPECIFICATIONS

A2.1: COMPLETE PPO IMPLEMENTATION

A2.2: MULTI-SCALE FEATURE ALIGNMENT

Algorithm 2 PPO Training for Student Network

```
Require: Student policy $\pi_\theta$, value function $V_\phi$, environment $\mathcal{E}$
Ensure: Updated parameters $\theta', \phi'$
Initialize replay buffer $\mathcal{B} = \emptyset$
for episode $e = 1$ to $E$ do
    Sample trajectory $\tau = \{(s_t, a_t, r_t)\}_{t=0}^{T}$ using $\pi_\theta$
    Compute returns $R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$
    Compute advantages $\hat{A}_t = R_t - V_\phi(s_t)$
    Add $\tau$ to buffer $\mathcal{B}$
end for
Normalize advantages: $\hat{A}_t \leftarrow \frac{\hat{A}_t - \mu_A}{\sigma_A}$
for epoch $i = 1$ to $K$ do
    for minibatch $\mathcal{M} \subset \mathcal{B}$ do
        Compute importance ratio: $r_t = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$
        Compute clipped objective:
            $$L^{\text{CLIP}} = \mathbb{E}_t[\min(r_t \hat{A}_t, \text{clip}(r_t, 1-\epsilon, 1+\epsilon)\hat{A}_t)] \quad (14)$$
        Compute value loss:
            $$L^V = \mathbb{E}_t[(V_\phi(s_t) - R_t)^2] \quad (15)$$
        Compute entropy bonus:
            $$S[\pi_\theta](s_t) = -\sum_a \pi_\theta(a|s_t) \log \pi_\theta(a|s_t) \quad (16)$$
        Update: $\theta \leftarrow \theta + \alpha \nabla_\theta (L^{\text{CLIP}} + c_1 L^V + c_2 S)$
    end for
end for=0
```

Algorithm 3 Progressive Multi-Granular Distillation

```
Require: Teacher features $\{\mathbf{F}_\ell^T\}_{\ell=1}^{L}$, Student features $\{\mathbf{F}_\ell^S\}_{\ell=1}^{L}$
Ensure: Alignment losses $\{\mathcal{L}_\ell\}_{\ell=1}^{L}$
for layer $\ell = 1$ to $L$ do
    if $\ell \leq L/3$ then
        {Low-level features}
        $\mathcal{L}_\ell = \|\mathbf{F}_\ell^T - \text{Adapt}_\ell(\mathbf{F}_\ell^S)\|_F^2$
    else if $\ell \leq 2L/3$ then
        {Mid-level attention}
        Compute attention maps: $\mathbf{A}_\ell^T = \text{Attention}(\mathbf{F}_\ell^T)$
        $\mathbf{A}_\ell^S = \text{Attention}(\mathbf{F}_\ell^S)$
        $\mathcal{L}_\ell = \text{KL}(\mathbf{A}_\ell^T \| \mathbf{A}_\ell^S)$
    else
        {High-level semantics}
        Project to semantic space: $\mathbf{z}_\ell^T = \text{Project}(\mathbf{F}_\ell^T)$
        $\mathbf{z}_\ell^S = \text{Project}(\mathbf{F}_\ell^S)$
        $\mathcal{L}_\ell = 1 - \frac{\mathbf{z}_\ell^T \cdot \mathbf{z}_\ell^S}{\|\mathbf{z}_\ell^T\| \|\mathbf{z}_\ell^S\|}$
    end if
end for=0
```

A3: Comprehensive Experimental Details

A3.1: Dataset Preprocessing and Augmentation

A3.1.1: NGSIM Dataset Processing

The NGSIM dataset requires extensive preprocessing to handle real-world driving complexities:

- **Noise Filtering**: Kalman filtering with process noise $Q = 0.1^2 I$ and observation noise $R = 0.5^2 I$
- **Trajectory Smoothing**: Savitzky-Golay filter with window size 5 and polynomial order 3
- **Lane Assignment**: Hungarian algorithm for optimal vehicle-lane matching
- **Missing Data Imputation**: Linear interpolation for gaps < 0.5s, trajectory dropping for longer gaps

Data augmentation strategies include:

$$\text{Position Jitter}: \quad (x, y) \rightarrow (x + \mathcal{N}(0, 0.1^2), y + \mathcal{N}(0, 0.1^2)) \tag{17}$$

$$\text{Velocity Scaling}: \quad v \rightarrow v \cdot \mathcal{U}(0.9, 1.1) \tag{18}$$

$$\text{Temporal Shifting}: \quad t \rightarrow t + \mathcal{U}(-0.1, 0.1) \tag{19}$$

A3.1.2: highD Dataset Processing

Table 7: highD Dataset Statistics After Preprocessing

Metric	Original	Processed
Total Trajectories	110,500	98,347
Average Length (s)	15.3	16.8
Sampling Rate (Hz)	25	25
Lane Changes	5,234	4,891
Emergency Braking	1,203	1,156
Cut-in Maneuvers	2,847	2,634

A3.2: Architecture Implementation Details

A3.2.1: Teacher Network Specifications

Table 8: Teacher Network Layer-wise Configuration

Layer Type	Configuration	Input	Output
	Encoder		
GATv2-1	heads=8, drop=0.1	512	512
RMSNorm	$\epsilon = 10^{-6}$	512	512
GATv2-2	heads=8, drop=0.1	512	512
	Hybrid Attention		
Mamba	d_state=16, d_conv=4	512	512
SW-Attn	window=7, shift=3	512	512
	MoE Decoder		
Expert-1	FFN, hidden=2048	512	512
Expert-2	FFN, hidden=2048	512	512
Expert-3	FFN, hidden=2048	512	512
Expert-4	FFN, hidden=2048	512	512
Router	TopK=2, drop=0.1	512	4

A3.2.2: Student Network Specifications

Table 9: Student Network Architecture Details

Layer Type	Configuration	Params	FLOPs (M)
GRU Encoder	hidden=256, layers=2	0.79M	12.3
SE Attention	reduction=16	0.02M	0.3
LoRA Policy	rank=8, alpha=32	0.13M	1.8
Value Head	hidden=128	0.05M	0.7
Total		**0.99M**	**15.1**

A3.3: Hyperparameter Sensitivity and Ablation Studies

A3.3.1: Complete Ablation Matrix

Table 10: Comprehensive Ablation Study Results

Component	NGSIM ADE	highD ADE	Params
Baseline GRU	0.89	0.41	0.8M
+ GATv2 Encoder	0.86	0.39	0.9M
+ SE Attention	0.83	0.37	0.9M
+ LoRA Policy	0.80	0.35	1.0M
+ Feature Align	0.78	0.34	1.0M
+ Attention KD	0.77	0.33	1.0M
+ Semantic KD	0.76	0.33	1.0M
+ Curriculum	0.75	0.32	1.0M
+ PPO ($\alpha = 0.8$)	0.77	0.33	1.0M
+ PPO ($\alpha = 0.6$)	0.74	0.31	1.0M
Full Model	**0.73**	**0.30**	**1.0M**

A3.3.2: Hyperparameter Grid Search Results

Table 11: Grid Search for Key Hyperparameters

Parameter	Range	Optimal	NGSIM	highD
Learning Rate	$[10^{-5}, 10^{-2}]$	3×10^{-4}	0.73	0.30
PPO ϵ	$[0.1, 0.3]$	0.2	0.73	0.30
Curriculum $\Delta\mathcal{C}$	$[0.05, 0.2]$	0.1	0.73	0.30
Distill Weight α_0	$[0.5, 1.5]$	1.0	0.73	0.30
RL Weight β_0	$[0.05, 0.2]$	0.1	0.73	0.30

A4: Extended Experimental Analysis

A4.1: Cross-Dataset Generalization

Table 12: Cross-Dataset Transfer Performance

Training → Testing	ADE	FDE	RMSE	Degrad.
NGSIM → NGSIM	0.73	1.05	0.88	-
NGSIM → highD	0.38	0.47	0.42	+26.7%
highD → highD	0.30	0.38	0.33	-
highD → NGSIM	0.89	1.28	1.12	+21.9%
Joint Training	0.52	0.71	0.61	-

A4.2: Computational Complexity Analysis

$$\text{Teacher Complexity: } \mathcal{O}(N^2 d + T d^2 + M d^3) \tag{20}$$

$$\text{Student Complexity: } \mathcal{O}(T d h + d h^2) \tag{21}$$

$$\text{Speedup Ratio: } \frac{N^2 d + T d^2 + M d^3}{T d h + d h^2} \approx 3.7\times \tag{22}$$

where N is the number of agents, T is sequence length, d is feature dimension, h is hidden dimension, and M is the number of MoE experts.

Table 13: Memory Consumption Breakdown

Component	Teacher (MB)	Student (MB)	Ratio	Percentage
Parameters	47.2	3.9	12.1×	88.3%
Activations	128.5	12.3	10.4×	7.8%
Gradients	47.2	3.9	12.1×	3.1%
Optimizer	94.4	7.8	12.1×	0.8%
Total	**317.3**	**27.9**	**11.4×**	**100%**

A4.3: Robustness and Failure Case Analysis

Table 14: Performance Under Adversarial Perturbations

Attack Type	ϵ	Clean	FGSM	PGD	C&W
Position	0.1m	0.73	0.81	0.85	0.79
Position	0.2m	0.73	0.94	1.02	0.91
Velocity	0.5m/s	0.73	0.79	0.83	0.77
Velocity	1.0m/s	0.73	0.91	0.98	0.89

1. **Dense Traffic Scenarios**: Performance degrades when $N > 15$ vehicles
2. **Extreme Weather**: Rain/snow conditions increase ADE by 23%
3. **Construction Zones**: Lane closure scenarios show 31% degradation
4. **Emergency Vehicles**: Siren-induced behaviors not captured effectively

A5: Implementation and Reproducibility

A5.1: Training Configuration

Table 15: Complete Training Configuration

Parameter	Value
Optimizer	AdamW
Learning Rate Schedule	Cosine Annealing
Weight Decay	10^{-4}
Batch Size	128
Gradient Clipping	1.0
Mixed Precision	FP16
Data Workers	8
GPU Memory	24GB
Training Time	72 hours

A5.2: Statistical Significance Testing

All reported improvements are statistically significant at $p < 0.01$ level using paired t-tests across 5 independent runs with different random seeds. The 95% confidence intervals are reported for key metrics.

A5.3: Computational Environment

Experiments conducted on NVIDIA A100 GPUs with CUDA 11.8, PyTorch 2.0.1, and Python 3.9. Total computational cost: approximately 300 GPU-hours for complete experiments including hyperparameter search and ablation studies.

A6: Large Language Model Usage

Large Language Models (LLMs) were used as general-purpose assist tools during the preparation of this manuscript in limited capacity. Specifically, LLMs were employed for: (1) formatting and organization of experimental results tables and figures to improve presentation clarity, (2) grammar checking and language refinement of technical descriptions, particularly for complex mathematical formulations, and (3) stylistic improvements to enhance the readability of the methodology section. LLMs were not involved in research conceptualization, algorithm design, experimental methodology, data analysis, or generation of scientific insights. All technical contributions, mathematical derivations, experimental results, and research conclusions are entirely the original work of the authors. The core innovations including the complementary teacher-student architecture, progressive reinforcement-augmented distillation, and multi-granular knowledge transfer mechanisms were developed independently by the research team. The authors take full responsibility for all scientific content in this paper.