ROLE-SPECIFIC TRAJECTORY DECODERS FOR HETEROGENEOUS MULTI-AGENT PREDICTION

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ABSTRACT

Multi-agent trajectory prediction faces a fundamental challenge when agents exhibit heterogeneous behaviors: should models use shared parameters across all agents or provide specialized architectures for different agent types? I investigate this question in the context of team sports, where players in different roles exhibit systematically different movement patterns. I propose a hierarchical transformer with role-specific trajectory decoders that routes each agent to a specialized prediction model based on role, rather than using a single shared decoder. Through systematic ablation studies on NFL tracking data, I demonstrate that architectural specialization outperforms parameter sharing: my role-specific architecture achieves 32.3% improvement over a baseline transformer and 10.9% improvement over a single-decoder hierarchical baseline. Critically, gains concentrate along the dimension of greatest behavioral heterogeneity (15.1% improvement on longitudinal movement vs 1.7% degradation on lateral movement), validating my hypothesis that role-specific modeling captures position-appropriate movement patterns. This work provides empirical evidence that heterogeneous multi-agent systems benefit from architectural specialization when agent roles are known or inferable.

1 INTRODUCTION

Multi-agent trajectory prediction is a fundamental problem in autonomous systems, from self-driving vehicles to team sports analytics. A central modeling question is how to handle heterogeneous agent behaviors: should models use shared parameters across all agents, or provide specialized architectures for different agent types? Existing multi-agent architectures Alahi et al. (2016); Yuan et al. (2021) predominantly use shared decoders that apply identical parameters to all agents, implicitly assuming that parameter sharing provides sufficient capacity to capture diverse behaviors. However, when agents have fundamentally different roles—such as vehicles vs pedestrians in autonomous driving, or offensive vs defensive players in team sports—a single shared decoder must compromise between distinct movement patterns.

I investigate this question using NFL tracking data as a testbed. In team sports, players in different roles exhibit systematically different movement characteristics: wide receivers execute predetermined route patterns with high longitudinal velocity, defensive backs provide reactive coverage with more lateral movement, and quarterbacks make minimal adjustments within the pocket. I hypothesize that routing players to role-specific trajectory decoders will outperform parameter sharing by allowing each decoder to specialize for position-appropriate movement patterns, particularly along the dimension of greatest role differentiation.

To test this hypothesis, I develop a hierarchical transformer architecture with three role-specific decoders (offense, quarterback, defense) and conduct systematic ablation studies. I build four progressively improved models: (1) a baseline per-player transformer (3.90 yards RMSE), (2) attention pooling for adaptive frame weighting (3.05 yards), (3) hierarchical cross-player attention for interaction modeling (2.96 yards), and (4) role-specific decoders (2.64 yards). The role-specific architecture achieves 32.3% improvement over the baseline and 10.9% improvement over the single-decoder hierarchical model. Critically, gains concentrate along the longitudinal axis (15.1% improvement) while lateral accuracy slightly degrades (1.7%), confirming that specialization benefits align with the axis of greatest behavioral heterogeneity.

Contributions:

- Empirical evidence that architectural specialization via role-specific decoders outperforms parameter sharing in heterogeneous multi-agent trajectory prediction (32.3% improvement over baseline, 10.9% over single-decoder hierarchical).
- Demonstration that specialization gains concentrate along the dimension of greatest behavioral heterogeneity: 15.1% improvement on longitudinal movement (where roles differ most) vs 1.7% degradation on lateral movement.
- Systematic ablation study isolating the contributions of attention pooling (21.7%), cross-player attention (24.1%), and role-specific decoding (32.3%) in multi-agent sports prediction.

2 Related Work

Multi-agent trajectory prediction faces a fundamental challenge when agents exhibit heterogeneous behaviors. Alahi et al. Alahi et al. (2016) pioneered this field with Social LSTM, using spatial pooling for pedestrian interactions. More recent work applies similar concepts to sports Yeh et al. (2019); Honda et al. (2022); Brooks et al. (2022). Early approaches used LSTMs Hochreiter & Schmidhuber (1997) and graph neural networks Veličković et al. (2018); Li et al. (2021), but sequential processing and careful graph construction limit scalability.

Transformers Vaswani et al. (2017) address these limitations through parallel self-attention. Yuan et al. Yuan et al. (2021) developed AgentFormer, using separate attention for temporal and social dimensions. This hierarchical design—processing individual agent histories before modeling interactions—inspired my architecture. I adopt attentive pooling Lee et al. (2016) for adaptive frame weighting.

Research Gap. Existing architectures Alahi et al. (2016); Yuan et al. (2021) use a single shared decoder for all agents, implicitly assuming parameter sharing captures heterogeneous behaviors. This breaks down when agents have fundamentally different roles. Fernandez and Bornn Fernandez & Bornn (2019) observe that positions exhibit systematically different movement patterns in team sports, yet no prior work systematically investigates whether role-specific decoders outperform parameter sharing. I address this gap by comparing architectures on sports tracking data with well-defined role categories.

3 Problem Formulation

3.1 Heterogeneous Multi-Agent Trajectory Prediction

I formalize the problem as follows: given observation history $\{(x_{i,t}, v_{i,t}, a_{i,t})\}_{t=1}^{T_{obs}}$ for N agents with heterogeneous roles $r_i \in \mathcal{R}$, predict future trajectories $\{\hat{x}_{i,t}\}_{t=T_{obs}+1}^{T_{pred}}$ that minimize prediction error. The key challenge is that agents with different roles r_i exhibit systematically different motion dynamics. Standard approaches use a single shared decoder $D(\cdot)$ for all agents, while I propose role-specific decoders $\{D_r(\cdot)\}_{r\in\mathcal{R}}$ where each agent is routed to its corresponding decoder based on role.

Research Hypothesis: Architectural specialization via role-specific decoders will outperform parameter sharing when agents exhibit heterogeneous behaviors, with gains concentrated along the dimension of greatest role differentiation.

4 Proposed Method

4.1 Architecture Overview

My architecture uses a three-stage hierarchical design: (1) per-player temporal encoding to capture individual motion patterns, (2) cross-player spatial encoding to model agent interactions, and (3) role-specific trajectory generation. The key innovation is using *three separate* trajectory decoders—one each for offense, quarterback, and defense—rather than a single shared decoder. By routing each agent to a role-specific decoder based on position, I allow each decoder to specialize for position-appropriate movement patterns without parameter sharing constraints.

4.2 Model Architecture

Figure 1 illustrates the three-stage architecture:

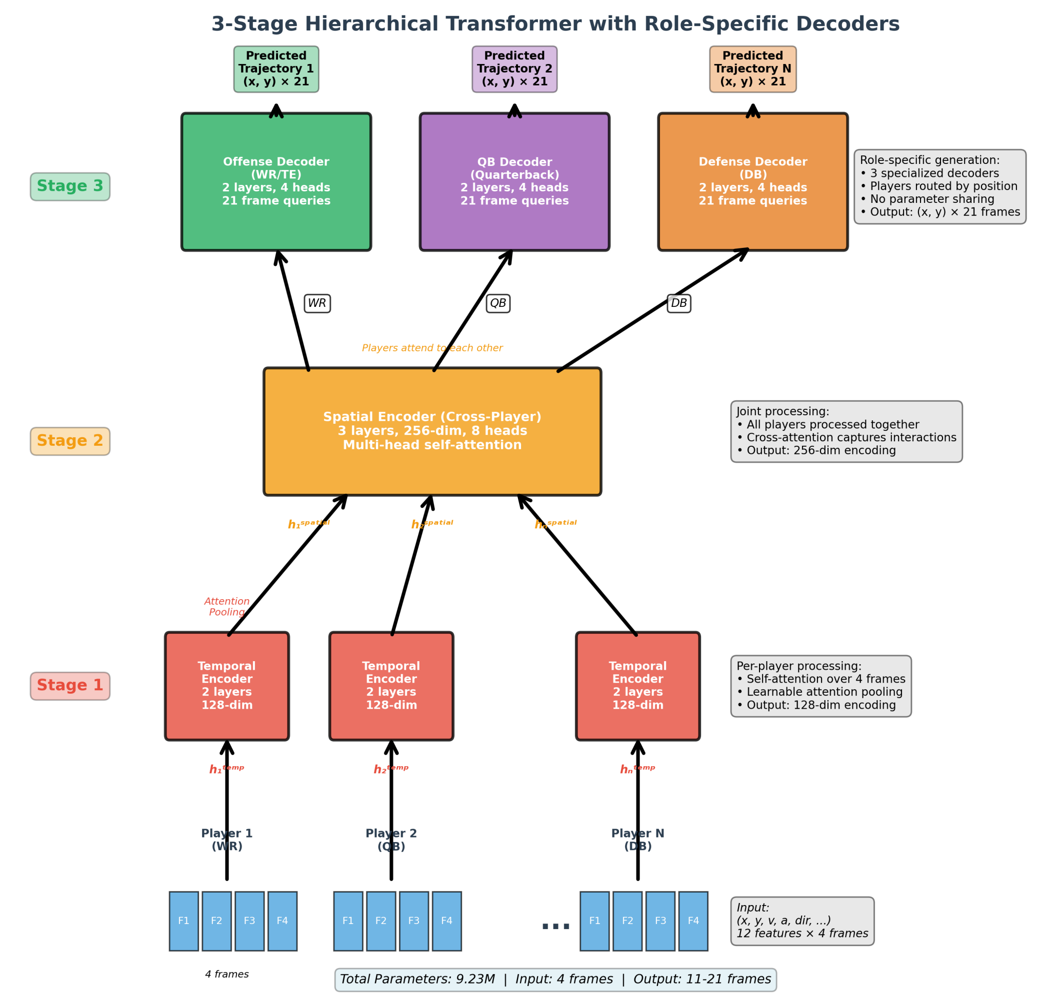

Figure 1: Three-stage hierarchical transformer with role-specific decoders. Stage 1 encodes each player's 4-frame history independently. Stage 2 models player interactions via cross-attention. Stage 3 routes players to role-specific trajectory decoders.

Stage 1 - Temporal Encoder: Each player's 4 input frames are processed independently by a 2-layer transformer encoder (128-dim, 4 heads) with learnable attention pooling, producing temporal encoding $h_i^{temp} \in \mathbb{R}^{128}$.

Stage 2 - Spatial Encoder: All players' temporal encodings are processed jointly by a 3-layer transformer encoder (256-dim, 8 heads). Multi-head self-attention captures player interactions, producing context-aware encoding $h_i^{spatial} \in \mathbb{R}^{256}$.

Stage 3 - Role-Specific Trajectory Decoders: Three separate 2-layer transformer decoders (4 heads each) generate trajectories for offense, quarterback, and defense. Players are routed to their corresponding decoder based on labeled role. Each decoder outputs (x, y) predictions with residual connections from the last observed position.

4.3 Implementation Details

Data Preprocessing. I extract 12 features per player per frame: position (x, y), velocity components $(v_x, v_y) = (s\cos(\text{dir}), s\sin(\text{dir}))$, acceleration components $(a_x, a_y) = (a\cos(\text{dir}), a\sin(\text{dir}))$, direction encoding $(\sin(\theta), \cos(\theta))$ to handle angular periodicity, and ball landing coordinates (x_{ball}, y_{ball}) to capture target information. Velocity and acceleration decomposition transforms speed and direction into Cartesian components aligned with prediction targets. Features are normalized using robust scaling (median centering with IQR scaling) to handle outliers in speed and acceleration distributions. The 4-frame input sequences are padded to a maximum of 10 players per play, with attention masking applied to ignore padding tokens during encoding.

Training Methodology. I train using AdamW Loshchilov & Hutter (2019) with learning rate $5{\times}10^{-5}$, weight decay 0.01, and cosine annealing over 50 epochs (batch size 16). The loss function is masked MSE that applies per-frame weights only to valid output frames (11–21 frames depending on play length), preventing the model from learning padding artifacts. I follow a systematic ablation approach, developing four progressive architectures: (1) Baseline per-player transformer (3.90 yards RMSE), (2) + attention pooling for adaptive temporal aggregation (3.05 yards), (3) + hierarchical cross-player attention for interaction modeling (2.96 yards), (4) + role-specific trajectory decoders (2.64 yards). Each model is trained independently to convergence. Implementation uses PyTorch 2.0 on CPU, with the final role-specific model containing 9.23M parameters.

5 Experiments

5.1 Experimental Setup

I evaluate my hypothesis using the NFL Big Data Bowl 2026 dataset, which provides tracking data from passing plays during the 2023 NFL season. For each play, the input consists of 4 frames ($T_{obs} = 4$) of tracking data (positions, velocities, accelerations, directions) for approximately 9 players, along with the ball landing location. The prediction target is (x, y) positions for $T_{pred} =$ 11–21 frames (variable length). The field coordinates span 120 yards (longitudinal, X-axis) by 53.3 yards (lateral, Y-axis).

The dataset contains three primary role categories: (1) *Offense* (wide receivers, tight ends) who execute predetermined routes with high longitudinal velocity, (2) *Quarterbacks* who make minimal pocket adjustments, and (3) *Defense* (defensive backs) who provide reactive coverage with more lateral movement. This role structure provides a controlled testbed for evaluating architectural specialization vs parameter sharing.

I use Week 1 data for training (819 plays, 2,679 player trajectories) and Week 2 for validation (850 plays, 2,758 trajectories). The evaluation metric is RMSE between predicted and actual positions across all frames and players.

5.2 Ablation Study

Table 1 and Figure 2 show systematic improvement across four iterations. Role-specific decoders achieve 2.64 yards RMSE with particularly strong X-axis gains (15.1%), validating my hypothesis.

Table 1: Prediction performance across model iterations. Role-specific decoders achieve best overall RMSE (2.64 yards), with 15.1% X-axis improvement demonstrating the value of role-specific modeling.

Model	**RMSE ↓**	**X-RMSE ↓**	**Y-RMSE ↓**	**MAE ↓**
Baseline	3.90	4.65	2.96	2.13
+ Attention Pooling	3.05	3.48	2.56	1.71
+ Hierarchical	2.96	3.67	2.02	2.13
+ Role-Specific	**2.64**	**3.11**	2.06	**1.88**
Improvement vs Baseline	-32.3%	-33.1%	-30.4%	-11.7%
Improvement vs Hierarchical	-10.9%	**-15.1%**	+1.7%	-11.5%

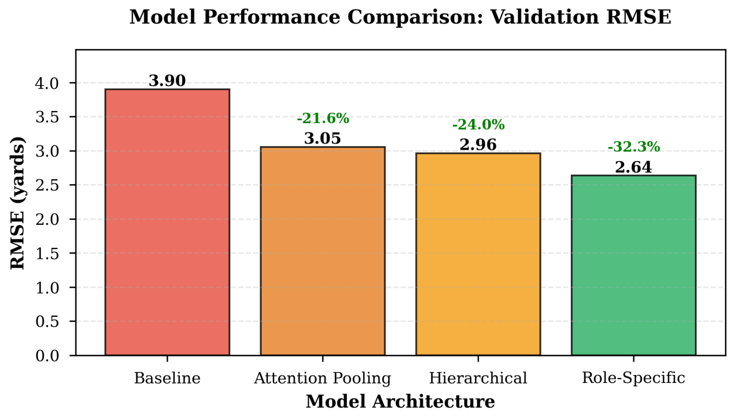

Figure 2: Model performance progression across ablation studies. Each architectural enhancement provides systematic improvement, with role-specific decoders achieving 32.3% improvement over baseline.

5.3 Directional Error Analysis

Figure 3 shows the role-specific model achieves 15.1% improvement on X-axis (longitudinal) predictions while showing minor degradation (1.7%) on Y-axis (lateral). This asymmetry validates my hypothesis: gains concentrate along the dimension of greatest behavioral heterogeneity, where offensive forward routes and defensive lateral coverage differ most.

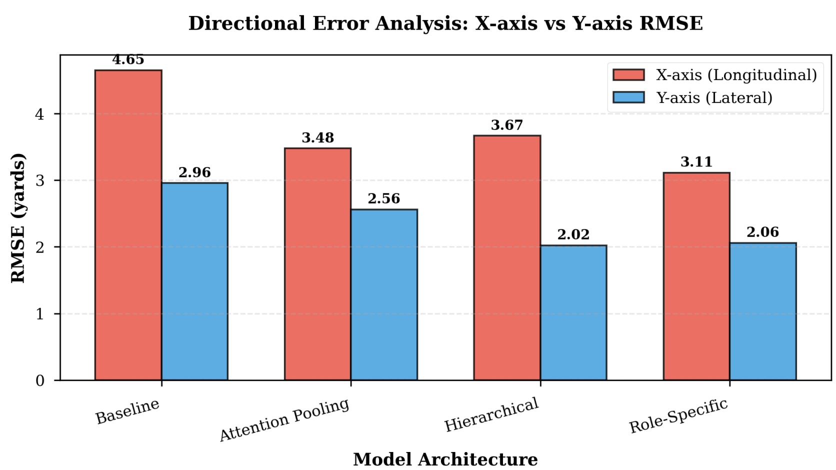

Figure 3: Directional error analysis comparing hierarchical and role-specific models. Role-specific decoders achieve 15.1% improvement on X-axis (longitudinal) movement where behavioral heterogeneity is greatest, with minor Y-axis degradation (1.7%).

5.4 Role-Specific Performance

Table 2 shows per-role accuracy. The offense decoder achieves best performance (2.37 yards RMSE) as predetermined routes are more predictable than reactive defensive coverage (2.74 yards), validating that each decoder learns role-appropriate movement patterns.

Table 2: Prediction accuracy by player role.

Role	RMSE ↓	X-RMSE ↓	Y-RMSE ↓	Count
Offense (WR/TE)	**2.37**	2.80	1.85	9,306
Defense (DB)	2.74	3.23	2.14	22,874
Overall	**2.64**	3.11	2.06	32,180

6 Discussion

Generalizability: The core insight—architectural specialization outperforms parameter sharing for heterogeneous agents—extends beyond sports to autonomous driving (vehicles vs pedestrians), multi-robot systems, and warehouse automation. Requirements are (1) known or inferable agent roles and (2) role-specific behavioral patterns.

Limitations: My model requires labeled agent roles and contains 9.23M parameters (86% more than single-decoder baseline), increasing memory requirements, though 10.9% accuracy improvement justifies this trade-off. The dataset contains approximately 9 players per scenario.

Future Work: Extensions include probabilistic prediction, learned role discovery, graph neural networks Brooks et al. (2022); Li et al. (2021) for explicit agent relationships, and temporal attention for timing-dependent behaviors Perin et al. (2022).

7 Conclusion

I investigated whether architectural specialization via role-specific decoders outperforms parameter sharing in heterogeneous multi-agent trajectory prediction. Through systematic ablation studies on NFL tracking data, I demonstrated that routing agents to specialized decoders based on role achieves 32.3% improvement over a baseline transformer and 10.9% improvement over a single-decoder hierarchical baseline. Critically, gains concentrate along the dimension of greatest behavioral heterogeneity: 15.1% improvement on longitudinal movement (where offensive and defensive roles differ most) versus 1.7% degradation on lateral movement. This asymmetry directly validates my hypothesis that role-specific modeling captures position-appropriate movement patterns without parameter sharing constraints. This work provides empirical evidence that heterogeneous multi-agent systems benefit from architectural specialization when agent roles exhibit systematically different behavioral dynamics, with applications extending to autonomous driving, multi-robot systems, and other domains with heterogeneous agent populations.

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