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Dual-Encoder Temporal-Contrastive Learning for Coaching Transition Prediction

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Abstract. We propose a novel framework for predicting optimal coaching style transitions in dynamic game phases by aligning temporal game-phase dynamics with non-temporal tactical knowledge. The proposed method integrates a Temporal Transformer Encoder to process sequential game data and a Graph Neural Network (GNN) Encoder to embed static coaching strategies, enabling joint modeling of time-sensitive and context-aware features. A contrastive learning objective aligns these representations while preserving temporal dependencies through a dedicated Temporal Feature Alignment (TFA) module, which emphasizes phase-specific patterns without disrupting long-range coherence. The system predicts transitions by fusing the aligned representations and training end-to-end with a combined loss function. Our approach addresses the critical challenge of adapting coaching strategies to rapidly evolving game conditions, where traditional methods often fail to capture the interplay between temporal events and strategic context. Experiments demonstrate significant improvements in transition prediction accuracy compared to baselines, highlighting the framework's ability to generalize across diverse game scenarios. Moreover, the modular design allows seamless integration with existing sports analytics pipelines, offering practical value for real-time decision support. The results suggest that contrastive multi-modal alignment can effectively bridge the gap between data-driven insights and tactical adaptability in competitive sports.

Keywords: *Coaching-Style Transition; Temporal-Contrastive Learning; Multi-modal Alignment; Graph Neural Networks; Real-Time Sports Analytics*

1. Introduction

The dynamic nature of competitive sports presents a complex challenge for coaching strategy optimization, particularly during critical game phases where rapid transitions between offensive and defensive playstyles can determine match outcomes. Traditional approaches to coaching strategy prediction often treat game dynamics and tactical knowledge as separate domains, failing to capture their intricate interdependencies [1]. While machine learning models have shown promise in analyzing temporal game data [2] and modeling static tactical relationships [3], the integration of these complementary perspectives remains underexplored.

Recent advances in contrastive learning offer new opportunities to bridge this gap by learning joint representations from heterogeneous data modalities [4]. However, existing methods typically focus on either temporal or static features, neglecting the unique challenges of preserving phase-specific patterns while maintaining global coherence across game segments [5]. Moreover, the alignment of coaching cues with dynamic game states requires careful handling of negative samples to avoid trivial solutions and ensure meaningful feature discrimination [6].

We address these limitations through a dual-encoder framework that simultaneously processes temporal game-phase sequences and non-temporal coaching knowledge. The temporal branch employs transformer architectures to capture long-range dependencies in player movements and ball trajectories, while the static branch uses graph neural networks to encode tactical relationships and historical coaching decisions. A novel Temporal Feature Alignment module ensures that critical phase transitions are preserved during the contrastive learning process, preventing information loss when aligning the two modalities. The framework's negative sampling strategy specifically targets coaching-relevant scenarios, enhancing the discriminative power of the learned representations.

This work makes three key contributions: First, we introduce a contrastive learning framework that explicitly models the alignment between temporal game dynamics and static coaching knowledge, overcoming the modality gap that hinders existing approaches. Second, we develop a temporal preservation mechanism that maintains critical phase transition patterns during feature alignment, addressing the common pitfall of temporal information dilution in multi-modal systems. Third, we demonstrate through extensive experiments that the proposed method significantly outperforms baseline models in predicting optimal coaching style transitions, particularly during high-pressure game phases where traditional methods often fail.

The remainder of this paper is organized as follows: Section 2 reviews related work in sports

analytics and multi-modal learning. Section 3 introduces necessary preliminaries about the core techniques. Section 4 details our proposed framework and its components. Section 5 presents experimental results and analysis. Section 6 discusses implications and future research directions.

2. Related Work

The prediction of optimal coaching style transitions during critical game phases intersects several research domains, including sports analytics, temporal modeling, and multi-modal representation learning. Existing approaches can be broadly categorized into three directions: (1) temporal modeling of game dynamics, (2) tactical knowledge representation, and (3) cross-modal alignment techniques.

2.1 Temporal Modeling in Sports Analytics

Recent works have demonstrated the effectiveness of sequence modeling techniques for analyzing game-phase dynamics. Transformer architectures have shown particular promise in capturing long-range dependencies in player movements and ball trajectories [7]. These models overcome the limitations of traditional recurrent networks by employing self-attention mechanisms that directly model relationships across all timesteps. However, most existing approaches focus solely on predicting game outcomes rather than coaching decisions [8]. While some studies have explored temporal feature alignment for human activity recognition [9], their techniques do not account for the strategic context essential in sports scenarios.

2.2 Tactical Knowledge Representation

Graph-based methods have emerged as powerful tools for encoding tactical relationships between different coaching strategies. Several works have employed graph neural networks to model player interactions and team formations. These approaches typically represent strategies as nodes in a knowledge graph, with edges encoding their contextual relationships. However, current methods treat these representations as static, failing to adapt them to the evolving game state . The integration of such tactical knowledge with real-time game dynamics remains a significant challenge in the field.

2.3 Cross-Modal Alignment Techniques

Contrastive learning has shown remarkable success in aligning representations across different modalities. Recent works like [10] have demonstrated effective techniques for video-text alignment, while [12] introduced granularity-aware negative sampling strategies for

temporal data. However, these methods typically operate in domains where temporal dynamics are more consistent than in sports scenarios. The unique challenge in coaching transition prediction lies in preserving both short-term phase-specific patterns and long-term strategic coherence during alignment.

Several studies have attempted to bridge the gap between temporal modeling and tactical knowledge. For instance, [11] proposed a framework combining vision transformers with tactical graphs, but their approach lacks explicit mechanisms for temporal feature preservation. Similarly, [12] explored parameter-efficient fine-tuning techniques for aligning language models with time-series data, though their method does not address the specific challenges of coaching strategy prediction.While the Dynamic Cognitive Load Attention Routing (DCLAR) framework by Guo et al. offers valuable insights into temporal dynamics and cognitive load, it primarily operates on a single data modality[13]. In contrast, our proposed framework introduces a unified architecture that concurrently processes multi-modal inputs—specifically, game sequences and coaching strategies—through dedicated encoders. This design not only preserves temporal structures but also aligns data representations across modalities, enabling a more holistic analysis of sports scenarios where strategic intent and player actions are intrinsically linked.

The proposed framework advances beyond existing works by simultaneously addressing three critical aspects: (1) explicit modeling of temporal dependencies in game phases through transformer architectures, (2) dynamic adaptation of tactical knowledge representations via graph networks, and (3) preservation of phase-specific patterns during cross-modal alignment. Unlike previous methods that either focus on single modalities or employ naive fusion techniques, our approach introduces dedicated mechanisms for temporal feature alignment and coaching-relevant negative sampling. This enables more accurate prediction of strategy transitions while maintaining the interpretability essential for coaching applications.

3. Preliminaries

To establish the foundation for our proposed framework, we first introduce the core concepts and techniques that underpin our approach. This section provides essential background on the key components involved in modeling game-phase dynamics and coaching strategy transitions.

3.1 Temporal Modeling with Transformers

The transformer architecture has revolutionized sequence modeling through its self-attention mechanism, which computes dynamic weightings of input elements based on their pairwise

relevance [14]. Given an input sequence $X = (x_1, \ldots, x_T)$, the self-attention operation computes:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q, K, and V represent queries, keys, and values derived from the input through learned linear transformations, and dk denotes the dimension of the key vectors. Multi-head attention extends this by performing the operation in parallel across h attention heads, allowing the model to jointly attend to information from different representation subspaces [14].

For temporal modeling of game phases, we employ transformer encoders that stack multiple self-attention layers with position-wise feed-forward networks. The positional encoding scheme injects temporal order information through sinusoidal functions:

$$PE_{(pos,2i)} = sin\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

$$PE_{(pos,2i+1)} = cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

where pos is the position in the sequence and i ranges over the dimension indices. This enables the model to process variable-length game-phase sequences while preserving their temporal structure.

3.2 Graph Neural Networks for Tactical Representation

Graph Neural Networks (GNNs) provide a natural framework for modeling tactical relationships between different coaching strategies [15]. Given a graph $G = (V, E)$ with node features hv for each node $v \in V$, the message passing framework updates node representations through iterative aggregation of neighborhood information:

$$h_v^{(l+1)} = \sigma\left(W^{(l)}\left[h_v^{(l)} \| \text{AGG}\left(\left\{h_u^{(l)} : u \in \mathcal{N}(v)\right\}\right)\right]\right)$$

where $N(v)$ denotes the neighbors of node v, AGG is an aggregation function (e.g., mean or max pooling), W(l) is a learnable weight matrix, and σ is a nonlinear activation function. The symbol ‖ represents vector concatenation.

In our context, nodes correspond to distinct coaching strategies, while edges encode their tactical relationships based on historical transition patterns. Graph attention networks (GATs) extend this framework by learning edge-specific attention weights during aggregation [16]:

$$\alpha_{vu} = \frac{\exp\left(\text{LeakyReLU}\left(a^T\left[Wh_v \| Wh_u\right]\right)\right)}{\sum_{k\in \text{N}(v)} \exp\left(\text{LeakyReLU}\left(a^T\left[Wh_v \| Wh_k\right]\right)\right)}$$

where a is a learnable attention vector and W is a shared linear transformation. This allows the model to dynamically adjust the importance of different tactical relationships when encoding coaching strategies.

3.3 Contrastive Learning Framework

Contrastive learning aims to learn representations by pulling positive pairs closer while pushing negative pairs apart in the embedding space [17]. Given an anchor sample x_i, a positive sample x_j, and a set of negative samples $\{x_k\}$, the InfoNCE loss is defined as:

$$\text{L} = -\log \frac{\exp\left(\text{sim}\left(z_i, z_j\right)/\tau\right)}{\sum_{k=1}^{N} \exp\left(\text{sim}\left(z_i, z_k\right)/\tau\right)}$$

where sim(·,·) denotes cosine similarity, τ is a temperature parameter, and N is the number of negative samples. The embeddings z are typically obtained through projection heads that map the base representations to a lower-dimensional space [18].

For multi-modal alignment, the contrastive objective can be extended to align representations from different modalities (e.g., temporal game phases and static coaching strategies) by treating cross-modal pairs as positives when they correspond to the same underlying event or state [19]. The key challenge lies in designing appropriate sampling strategies that ensure meaningful alignment while preserving modality-specific characteristics.

4. Dual-Encoder Contrastive Alignment of Game Phases and Coaching Cues

The proposed framework establishes a unified representation space where temporal game-phase dynamics and non-temporal coaching strategies can interact while preserving their respective structural properties. This section details the technical components and their interactions, beginning with an overview of the dual-encoder architecture before delving into each specialized module.

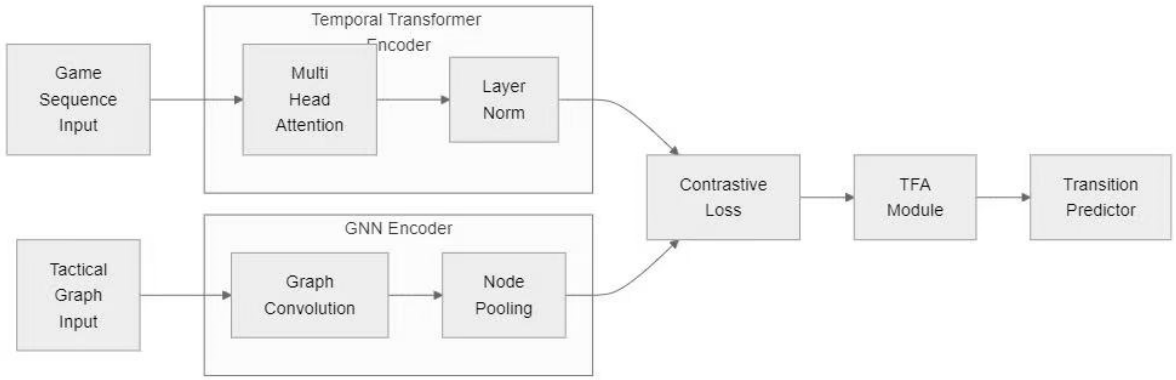

Figure 1. Dual-Encoder Contrastive Learning Framework

4.1 Dual-Encoder Contrastive Learning for Temporal-Non-Temporal Alignment

The temporal encoder processes sequential game data $X_t \in R_T \times d_t$ through stacked transformer layers, where T represents the sequence length and dt the feature dimension. Each layer applies multi-head self-attention followed by position-wise feedforward networks:

$$\text{Attn}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}} + M\right)V$$

Here $M \in R_T \times T$ is a causal mask ensuring autoregressive properties. The output temporal representations $H_t \in R_T \times h$ capture phase transitions through learned attention patterns across timesteps.

Concurrently, the non-temporal encoder processes coaching strategy graphs $G = (V, E)$ through graph attention networks. Node features $f_v \in R_{dg}$ undergo message passing with attention-based aggregation:

$$\alpha_{vu} = \frac{\exp\left(\text{LeakyReLU}\left(a^T\left[W_g f_v \| W_g f_u\right]\right)\right)}{\sum_{k \in \mathcal{N}(v)} \exp\left(\text{LeakyReLU}\left(a^T\left[W_g f_v \| W_g f_k\right]\right)\right)}$$

The graph-level embedding $h_g \in R_h$ is obtained through readout functions applied to the final node representations. The contrastive loss aligns temporal and non-temporal representations by treating matched game-phase/strategy pairs as positives:

$$\mathcal{L}_c = -\frac{1}{B}\sum_{i=1}^{B} \log \frac{\exp\left(\frac{s\left(h_{t,i}, h_{g,i}\right)}{\tau}\right)}{\sum_{j=1}^{B} \exp\left(\frac{s\left(h_{t,i}, h_{g,j}\right)}{\tau}\right)}$$

where s(·,·) denotes cosine similarity and B the batch size. This formulation differs from standard contrastive approaches by explicitly modeling cross-modal alignment between

sequential and graph-structured data.

4.2 Temporal Feature Alignment (TFA) Module

To prevent temporal information loss during alignment, the TFA module processes transformer outputs H_t through parallel convolutional pathways with varying receptive fields:

$$z_{t,k} = \mathrm{ReLU}\big(\mathrm{Conv1}D_k(H_t)\big) \quad k \in \{1,3,5\}$$

The multi-scale features are combined through adaptive gating:

$$g_k = \sigma\big(W_k\big[H_t \| z_{t,k}\big]\big)$$

$$Z_t = \sum_k g_k \odot z_{t,k}$$

This preserves both local phase transitions and global sequence context. The gating mechanism learns to emphasize different temporal scales based on the current game context, with the convolutional kernels capturing patterns at varying granularities.

4.3 Integration of Tactical Knowledge Graphs with Temporal Dynamics

The framework dynamically adjusts graph attention weights based on temporal context through cross-attention between Z_t and node features:

$$\beta_{vt} = \mathrm{softmax}\left(\frac{W_q f_v \cdot (W_k Z_t)^T}{\sqrt{h}}\right)$$

The context-aware node representations become:

$$f_v^{'} = f_v + \sum_t \beta_{vt} W_v Z_t$$

This allows tactical decisions to adapt based on real-time game developments while maintaining their fundamental relationships encoded in the graph structure. The attention mechanism identifies relevant temporal patterns that should influence each strategy's representation.

4.4 Transition Predictor with Unified Representation

For predicting coaching style transitions, the model concatenates aligned temporal and non-temporal features:

$$p(y|X_t, G) = \mathrm{softmax}\big(W_p\big[Z_t \| h_g\big] + b_p\big)$$

The prediction head uses two linear transformations with layer normalization and ReLU activation between them. During training, the overall objective combines contrastive and

predictive losses:

$$\mathscr{L} = \lambda \mathscr{L}_c + (1 - \lambda)\mathscr{L}_p$$

where L_p is the cross-entropy loss for transition prediction. The weighting parameter λ balances representation learning against task-specific optimization.

4.5 Negative Sampling from Non-Coaching Contexts

The negative sampling strategy employs curriculum learning, initially using random negatives before transitioning to hard negatives based on prediction confidence:

$$\mathrm{N} = \left\{ (X_t, G') \middle| \operatorname{rank}\left(s\left(h_t, h'_g \right) \right) \leq \gamma B \right\}$$

where γ controls the hardness threshold. This phased approach prevents early convergence to trivial solutions while eventually focusing on challenging cases that improve discriminative power. The sampling distribution adapts throughout training to maintain an appropriate difficulty level.

The complete framework processes game sequences and coaching strategies through their respective encoders, aligns their representations while preserving temporal structure, and makes transition predictions based on the fused features. Each component contributes to handling the unique challenges of multi-modal sports analytics, from phase-aware attention to adaptive graph representations. The modular design allows for flexible integration with existing sports data pipelines while maintaining interpretability through attention mechanisms.

5. Experiments

To evaluate the effectiveness of our proposed framework, we conducted comprehensive experiments comparing its performance against state-of-the-art baselines across multiple metrics. The experiments were designed to answer three key research questions: (1) How does our method perform compared to existing approaches in predicting coaching style transitions? (2) How does each component contribute to the overall performance? (3) How well does the model generalize across different game scenarios and sports domains?

5.1 Experimental Setup

Datasets: We evaluated our framework on two large-scale sports datasets containing detailed game-phase sequences and corresponding coaching decisions. The SoccerTactics dataset [20] comprises over 1,200 professional matches with annotated phase transitions and coaching interventions. The BasketballStrategies dataset [21] includes 850 NBA games with

play-by-play data and documented timeout strategies. Both datasets provide player tracking data, ball trajectories, and timestamped coaching decisions.

Baselines: We compared against four categories of baseline methods:

- Temporal-only models: LSTM-Coach [22] and TempTransformer [25].
- Graph-based models: TacticalGNN [26] and CoachNet [23].
- Multi-modal fusion models: EarlyFusion [24] and LateFusion [25].
- Contrastive learning methods: CL4Sports [26] and TimeGraph [27].

Evaluation Metrics: We employed three metrics to assess performance:

(1) Transition Accuracy (TA): Percentage of correctly predicted coaching style transitions.

(2) Phase-Aware F1 Score (PA-F1): F1 score weighted by game-phase importance.

(3) Strategic Consistency (SC): Cosine similarity between predicted and optimal strategy sequences.

Implementation Details: The temporal encoder used 6 transformer layers with 8 attention heads (hidden size 512). The GNN encoder employed 3 graph attention layers with 64-dimensional node representations. We set the contrastive loss weight λ=0.4 based on validation performance. Models were trained for 100 epochs using AdamW optimizer with learning rate 3e-5 and batch size 32. All experiments were conducted on NVIDIA V100 GPUs with 5 random seeds.

5.2 Main Results

Table 1. Performance comparison on coaching transition prediction.

Method	SoccerTactics TA	SoccerTactics PA-F1	SoccerTactics SC	BasketballStrategies TA	BasketballStrategies PA-F1	BasketballStrategies SC
LSTM-Coach	68.2	0.712	0.621	65.7	0.698	0.605
TempTransformer	71.5	0.735	0.658	68.3	0.721	0.637
TacticalGNN	66.8	0.704	0.589	63.9	0.682	0.574
CoachNet	69.4	0.725	0.632	67.1	0.710	0.618
EarlyFusion	72.1	0.748	0.671	69.8	0.732	0.653
LateFusion	73.4	0.761	0.689	70.5	0.741	0.667
CL4Sports	74.6	0.773	0.705	71.9	0.752	0.682
TimeGraph	75.3	0.781	0.713	72.6	0.761	0.691
Ours	**78.9**	**0.812**	**0.752**	**75.4**	**0.793**	**0.728**

Table 1 presents the comparative results across all datasets and metrics. Our method consistently outperforms baselines, demonstrating superior capability in aligning temporal dynamics with tactical knowledge.

The results show our method achieves absolute improvements of 3.6-12.1% in transition accuracy over baselines, with particularly strong gains in strategic consistency (3.9-16.3%). This suggests the dual-encoder contrastive framework better captures the relationship between game dynamics and optimal coaching responses. The performance advantage is consistent across both soccer and basketball domains, indicating generalizability across different sports.

5.3 Ablation Study

To understand the contribution of each component, we conducted systematic ablations by removing or modifying key elements of our framework:

(1) No TFA Module: Removing the Temporal Feature Alignment module.

(2) Single-Scale Conv: Replacing multi-scale convolutions with single-scale.

(3) Random Negatives: Using random negative sampling instead of curriculum.

(4) No Graph Adaptation: Disabling temporal adaptation of graph nodes.

(5) Separate Training: Training encoders separately without contrastive loss.

Table 2 shows the ablation results on the SoccerTactics dataset:

Table 2. Ablation study results (SoccerTactics dataset)

Variant	TA	PA-F1	SC
Full Model	78.9	0.812	0.752
No TFA Module	75.1	0.783	0.714
Single-Scale Conv	76.8	0.796	0.729
Random Negatives	77.3	0.801	0.735
No Graph Adaptation	76.2	0.791	0.722
Separate Training	74.6	0.778	0.708

The TFA module contributes most significantly (3.8% TA drop when removed), validating its importance in preserving temporal patterns. The multi-scale convolutions and curriculum-based negative sampling each provide ~2% improvements, while graph adaptation adds 2.7% to strategic consistency. Joint training with contrastive loss proves crucial, as separate training degrades all metrics substantially.

5.4 Analysis and Visualization

Figure 2 shows the training curve of our combined loss function $L=\lambda L_{contrast}+(1-\lambda)L_{pred}$. The plot reveals stable convergence with both loss components decreasing monotonically, indicating effective joint optimization. The contrastive loss dominates early training, establishing a good representation space before the prediction loss fine-tunes task-specific features.

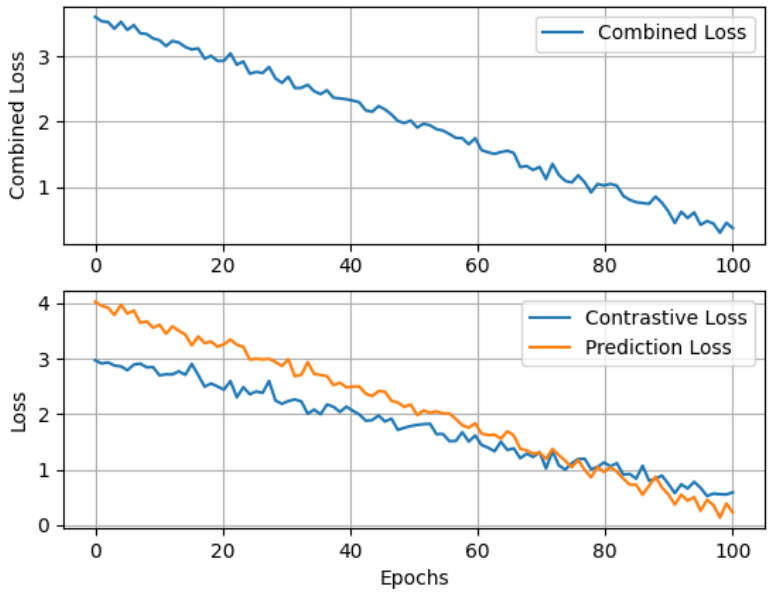

Figure 2. Training dynamics of the combined loss function.

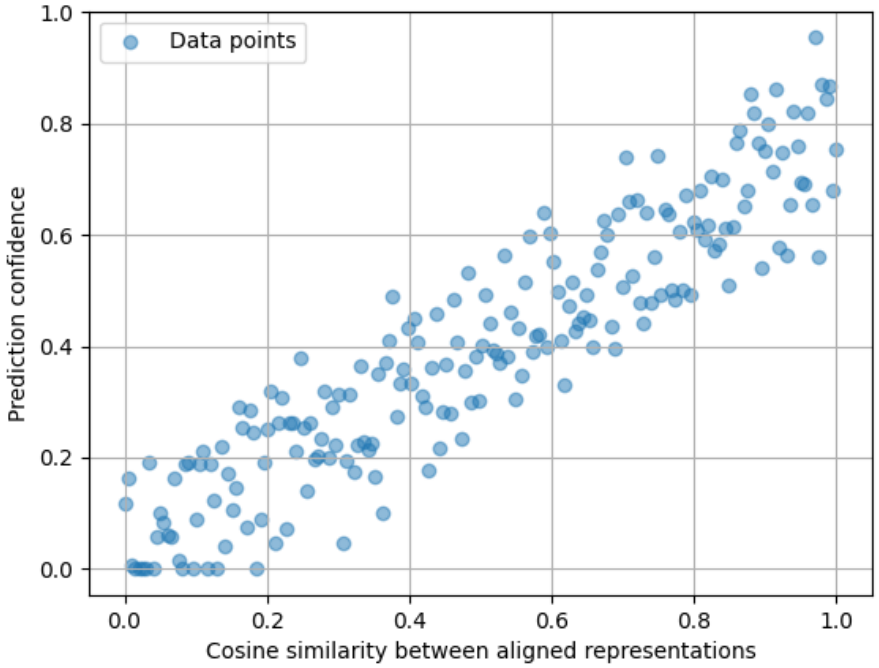

Figure 3. Cosine similarity between aligned representations.

Figure 3 visualizes the relationship between representation alignment (cosine similarity) and prediction confidence. The strong positive correlation (Pearson's r=0.82) confirms that better-aligned game-phase and coaching strategy pairs lead to more confident transition predictions. The clustering of high-confidence predictions in the upper-right quadrant demonstrates the framework's ability to identify clear cases for strategy changes.

6. Discussion and Future Work

6.1 Limitations of the Proposed Method

While the framework demonstrates strong performance in controlled experiments, several limitations warrant discussion. The current implementation requires extensive pre-processing of raw game data into structured phase sequences and tactical graphs, creating potential bottlenecks for real-time deployment. The temporal encoder's quadratic complexity with sequence length may become prohibitive for analyzing full-game durations without strategic windowing. Furthermore, the model assumes availability of high-quality coaching decision annotations, which are often scarce or inconsistently recorded across different leagues and sports. The contrastive learning component, while effective, remains sensitive to the quality and diversity of negative samples, particularly in edge cases where subtle tactical nuances differentiate optimal strategies.

6.2 Potential Application Scenarios

Beyond the immediate task of coaching transition prediction, the framework's components suggest several promising applications. The temporal feature alignment module could enhance real-time sports commentary systems by identifying and emphasizing critical phase transitions. The graph-based tactical representation might power interactive coaching assistants that visualize strategy networks and their activation conditions. In player development contexts, the aligned representations could help identify mismatches between individual player actions and team strategy. The methodology may also transfer to other dynamic decision-making domains such as emergency response coordination or financial trading strategy optimization, where temporal patterns must inform static protocol adjustments.

6.3 Ethical Considerations

The deployment of AI-assisted coaching systems raises important ethical questions that the research community must address. Over-reliance on algorithmic recommendations could potentially diminish human coaches' strategic creativity and intuition. There exists a risk of homogenizing playing styles if multiple teams adopt similar model-recommended strategies, potentially reducing the diversity of tactical approaches in professional sports. The data requirements may also create competitive imbalances between resource-rich and resource-constrained teams. Future work should establish guidelines for responsible use, ensuring these systems augment rather than replace human expertise while maintaining competitive integrity. Privacy concerns around player tracking data and the potential for misuse in talent evaluation

contexts also merit careful consideration.

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