RallyGraph: Specialized Graph Encoding for Enhanced Volleyball Prediction

Rhys Tracy
rhystracy@cs.ucsb.edu
Departement of Computer Science, University of California, Santa Barbara
Santa Barbara, California, USA

Haotian Xia
haotianxia@cs.ucsb.edu
Departement of Computer Science, University of California, Santa Barbara
Santa Barbara, California, USA

Alex Rasla
alexrasla@engineering.ucsb.edu
Departement of Computer Science, University of California, Santa Barbara
Santa Barbara, California, USA

Yuan-Fang Wang
yfwang@cs.ucsb.edu
Departement of Computer Science, University of California, Santa Barbara
Santa Barbara, California, USA

Ambuj Singh
ambuj@cs.ucsb.edu
Departement of Computer Science, University of California, Santa Barbara
Santa Barbara, California, USA

Abstract

This study aims to enhance complex volleyball predictions, providing valuable insight for coaches and players. We present RallyGraph, a specialized graph encoding that enriches an existing volleyball dataset, adding contact-specific context without additional data collection. The application of Graph Neural Networks (GNNs) on this graph-embedded dataset markedly improves predictions for rally outcomes and set locations as compared to baseline models by yielding a more advanced analysis of the data. Lastly, we demonstrate the importance of choosing a model architecture that will better extract the important information for a given task. Ultimately, this study illuminates the strengths and weaknesses of graph encodings in sports analytics and will hopefully inspire future advancements in machine learning strategies for varied sports applications using graph-based encodings.

CCS Concepts

• **Computing methodologies → Machine learning**.

Keywords

datasets, neural networks, graph neural networks, natural language processing, sports data analysis

ACM Reference Format:
Rhys Tracy, Haotian Xia, Alex Rasla, Yuan-Fang Wang, and Ambuj Singh. 2018. RallyGraph: Specialized Graph Encoding for Enhanced Volleyball Prediction. In *Proceedings of KDD 2023 Workshop on Data Science and AI for Sports (DSAI4Sports '23).* ACM, New York, NY, USA, 5 pages. https://doi.org/XXXXXXX.XXXXXXX

DSAI4Sports '23, August 07, 2023, Long Beach, CA

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

As volleyball's popularity and level of play surge, a corresponding need for improved tactical analysis and game strategies has emerged which can be addressed with more sophisticated computational analytics. Concurrently, sports data analytics have garnered increasing attention, with numerous studies investigating game event predictions [17], team and player performance [4], sport development [12], and team performance analysis across various sports. For example, in the sports of Basketball [8], [19], [11], [9], [20], Soccer [17], [5], [14], [2], [13], and Baseball [15], [22], [18], [6], [10], [3], [1], numerous studies have analyzed game outcomes, player development, strategy identification, posture analysis, and injury risk assessment. However, Volleyball analytics remains relatively underexplored, with limited studies employing straightforward methodologies. Despite this, initial results have provided a promising baseline. To further these efforts, we introduce specialized encodings and models for volleyball analytics to improve upon current baseline approaches without requiring additional data.

2 Related Work

There have been a few recent datasets and studies for indoor volleyball [7], [21], but they are primarily focused toward computer vision and are not the most useful for tactical analysis or tracking in-depth game statistics since they are missing several important game variables. There has also been a recent beach volleyball dataset [21] that has been more useful for tactical analysis, but due to differences between beach volleyball and indoor volleyball–primarily the additional players and more strict positions in indoor volleyball–this dataset is limited solely to beach volleyball analysis. Lastly, a recent study [24] introducing a specialized indoor volleyball dataset has made a noticeable leap in the field.

Xia et al. [24] proposed a novel natural language approach to represent a volleyball rally as sequential rounds, each consisting of 1-4 contacts (pass, set, hit, block), and gathered an extensive dataset of NCAA and Professional men's volleyball games. This dataset enabled a deeper analysis of game statistics and showed promising results in previously unexplored tactical tasks using simple models. These tasks, valuable for both offensive and defensive strategy planning, included predicting rally winners, set locations, and hit types. However, the study had room for improvement, as it employed raw data and basic methods without exploring data encoding for performance enhancement. Our work addresses these limitations. Given the temporally sequenced nature of volleyball language, we have explored temporal graph-based encodings for this language and dataset.

Graph-based encodings have proven effective in sports analysis for other sports, such as American football, basketball, and soccer. A recent study [23] introduced a sports-agnostic graph encoding to represent game-states, capturing intricate inter-player relationships otherwise ignored during model training. When applied to American football and the esports game Counter-Strike, this graph encoding reduced test loss by 20% and 9% respectively. Another study [25] utilized GNNs to predict future player locations and movements in multi-agent sports like basketball and soccer, integrating Variational Graph RNNs. The statistical player and ball distribution of their generative GNN model predictions surpassed the non-graph baseline. Additionally, the use of GNNs facilitated conditional predictions, such as how the players will move if A passes to B instead of C, providing valuable tactical insight.

Given that graphs well represent data from several different sports, graph encodings should enhance how volleyball data is represented. Specifically with the current leading dataset [24], a graph encoding could better associate variables to specific contacts in a 'ball round' and denote the temporal sequence of contacts without any additional data collection. Therefore, we propose using Graph Neural Networks and encoding volleyball round data into a graph structure to augment deep learning models' understanding of a volleyball rally.

3 RallyGraph Encoding

3.1 Underlying Data Representation

To analyze our graph encoding, it is crucial to first understand the information offered by the baseline dataset built off of in this study: the leading indoor volleyball dataset [24]. This dataset splits volleyball matches into a sequence of rallies and splits each rally into a sequence of rounds. Each round contains variables describing round information (team and round number), various locations of ball contacts, pass and set ratings, hit type used, blocking information, and serve type. All of this information—besides the two round level variables—relates to each individual contact. Pass contact location and pass rating relate to the pass contact, set rating and set location relate to the set contact, etc. All of this points to a contact-level encoding being an excellent option to analyze.

3.2 Encoding Methods

To accurately encode contact-specific variables and their temporal order in RallyGraph, we treat each contact as a graph node containing that contact's pertinent information. For instance, the 'set contact' node carries the setter location, set rating, and set destination variables, while the 'hit contact' node holds the hitter location and hit type variables. We represent the temporal sequence of contacts by connecting consecutive nodes with one-way edges. In a round consisting of a pass, a set, and a hit, one-way edges connect the pass node to the set node and the set node to the hit node. All edges bear equal weights without additional edge attributes. Though a simple graph encoding method, it fundamentally changes how a neural network will analyze the data.

3.3 Rally Outcome Prediction Task

Since the baseline rally outcome prediction task in the VREN paper [24] considers all information in a round (except the winning team and win/lose reason), we will use all the nodes for a given round to make a prediction. As such, we end up with a graph involving a pass node, then set node, then hit node, then block node. These graphs will involve the exact same information as is used in the baseline task, but will have a new graph encoding.

3.4 Set Location Prediction Task

The baseline set location prediction task in the VREN paper uses only the information in a round up to when the setter is about to set the ball. If we were to follow this same strategy, our encoding would involve only 2 nodes (pass and set nodes) in each graph, and–from our analysis–very small graph sizes yield poor GNN performance. However, we can address this by including the previous round's hit and block nodes if there exists a previous round in that rally. From further baseline testing, this additional information does not noticeably effect performance in any baseline model, so any performance changes with this task will be solely from the graph encoding. Therefore, for this task each graph involves the previous round's hit node (if it exists), the previous round's block node (if it exists), the current round's receive (pass) node, and the current round's set node only including information from before the setter contacts the ball—such as where the setter will set the ball from.

4 Methods

With the graph encodings ready, we next turn to the models we will test. To keep comparison consistent with the baseline, we will test a GCN to compare with CNN, a Graph GRU to compare with LSTM, and a Graph Transformer to compare with Transformer. To implement all of these models, we will use Spektral, a GNNs package built on Tensorflow and Keras. Since this package does not include a Graph Transformer Convolution layer, we implemented one modeled off of the Graph Transformer architecture introduced in Shi et al. [16] which has shown excellent results for Graph-based learning tasks. We used Tensorflow and Keras to build this Graph Transformer Convolution Layer off of the base MessagePassing layer available in Spektral. This Graph Transformer architecture performs self-attention on graph edges with queries embedded from the node features for the origin of the edge and keys and values embedded from the node features for the terminal of the edge. This architecture also includes gated residual connections between layers, a key factor making this architecture a Transformer.

For rally outcome prediction, all three GNN structures were evaluated. However, for other tasks, only Transformer and CNN/GCN architectures were employed due to RNNs' limitations. GCN included one Graph Convolution Layer, a graph global pooling layer, and three dense layers. The Graph GRU contained a Gated Graph Convolution Layer with a GRU Gate, a graph global pooling layer, and two dense layers. The Graph Transformer comprised one custom Graph Transformer Convolution Layer, a graph global pooling

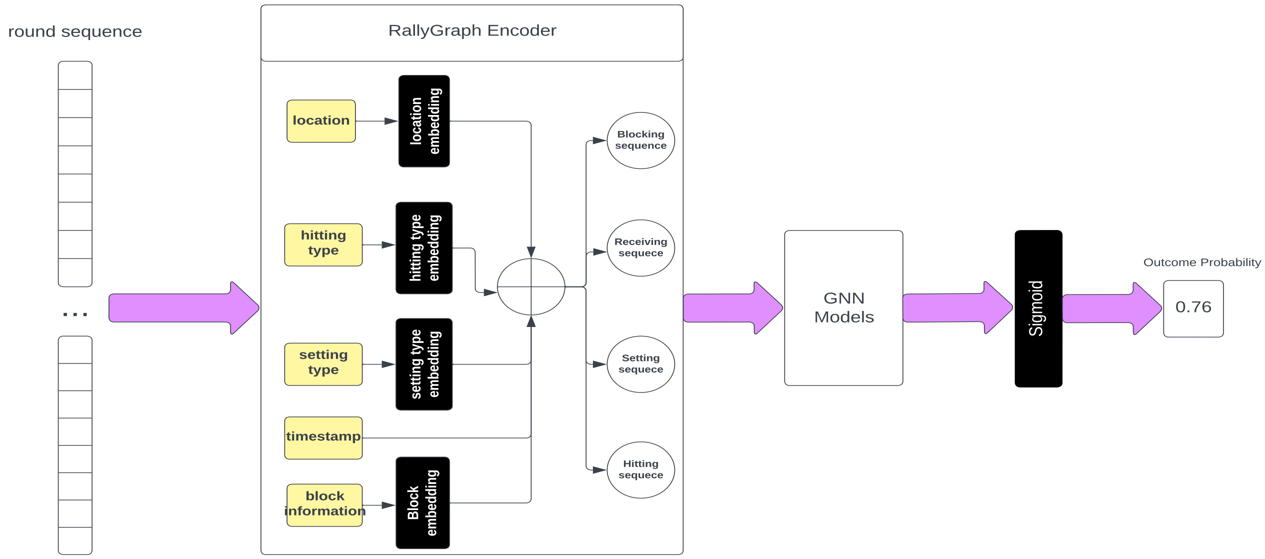

Figure 1: Our framework for taking raw round sequence data, encoding to RallyGraph format, then making a rally outcome prediction with GNN models

layer, and two dense layers. The loss function and metrics used for training, validation, and testing varied depending on the task.

5 Results and Analysis

Our findings demonstrate that the RallyGraph encodings significantly improved model performances across NCAA and Professional games and consistently standardized performance between the two levels of play. This is in contrast to inconsistent baseline performance between NCAA and Pro play due to differences in play level and consistency. For instance, baseline models were better at predicting rally outcomes in professional games, owing to less randomness and higher mental strength of the more skilled pro players. The opposite was the case with the set location task being better predicted in NCAA games, as professional setters exhibit more skill and unpredictability. However, graph encodings minimized the performance gap between NCAA and Professional games by clarifying the underlying volleyball data relationships that may be harder for the models to capture under different scenarios thus the relationships become equally clear in both levels of play.

5.1 Rally Outcome Prediction Results

In the rally outcome prediction task, as per Table 1, our graph encodings and GNNs significantly outperformed the baseline. Both GCN and Graph GRU significantly improved NCAA and Pro testing games performance in all metrics except brier score. Graph Transformer showed considerable improvement in NCAA performance and a slight boost in Pro performance in all metrics except brier score. These improvements suggest that our graph encoding provides a more detailed rally representation, leading to more nuanced and superior predictions. Since baseline Transformers do an excellent job at analyzing the relationships between different variables with their attention mechanism, they don't benefit as much from the graph encoding. However, Graph Transformer performed notably better on the NCAA game, implying that the lower play level of the NCAA games made identifying underlying relationships challenging, but the graph encoding clarified these relationships and thus standardized performance across both play levels.

Table 1: Rally outcome prediction task performance of each model on college-level games & professional games. There are significant improvements among all three models compared to the baseline performance. The Graph Transformer gives the best result.

Level of game	Model	Binary Accuracy(%)	AUC	Brier Score	Mean Absolute Error
college	Transformer*	74.38	0.82	0.18	0.34
	CNN*	69.06	0.75	0.20	0.40
	LSTM*	65.91	0.75	0.21	0.41
	Graph Transformer	81.15	0.87	0.15	0.27
	Graph GRU	77.81	0.86	0.33	0.31
	GCN	78.20	0.86	0.20	0.30
professional	Transformer*	80.00	0.85	0.16	0.32
	CNN*	71.59	0.76	0.20	0.39
	LSTM*	70.06	0.75	0.20	0.40
	Graph Transformer	81.15	0.87	0.16	0.27
	Graph GRU	77.83	0.86	0.29	0.31
	GCN	78.20	0.86	0.17	0.30

* model prediction results from VREN [24].

5.2 Set Location Prediction Results

The set location prediction task also witnessed considerable improvements with our graph encoding, as illustrated in Table 2. Interestingly, a base CNN outperformed the baseline Transformer (the only model tested in VREN [24]), with the GCN further enhancing the CNN's performance. The Graph Transformer similarly displayed a performance improvement over the baseline Transformer. These improvements have led us to a deeper understanding of the factors influencing a setter's decision to set the ball. Given that setters attempt to introduce as much randomness as possible in their set location choices, simpler models tend to perform better. Thus the CNN model offered a 2-3% performance enhancement over the baseline Transformer—a significant difference in a difficult-to-predict task—and the GCN demonstrated similar improvement over the Graph Transformer.

Table 2: Categorical Accuracy for setting location prediction in both professional and college level games. All three models are improved compared to the baseline result

Level of game	Model	Categorical Accuracy(%)
college	Transformer*	54.65
	GCN	59.10
	CNN	57.43
	Graph Transformer	56.57
professional	Transformer*	51.65
	GCN	59.10
	CNN	53.30
	Graph Transformer	56.57

* model prediction results from VREN [24].

While the graph encoding did improve set prediction performance, the enhancement was not as substantial as in the rally outcome prediction task. Though this may be due in part to the increased difficulty of the set prediction task, it may also suggest that contact-by-contact information may be less useful for this task. The superior performance of convolution models over transformer models also would suggest that the setter's choice depends less on contact-by-contact information. Instead, simpler data (such as the setter's court location, pass rating, etc.) likely hold more influence over the setter's decision, and a simpler convolution model can extract this information more effectively. This hypothesis also aligns with volleyball experts' views on the factors influencing set location during a rally.

Another conclusion from this task's results is that there might be other important information for predicting a setter's choice—such as how rushed a setter is and the height of the pass—that is not included in the current dataset.

6 Conclusion and Future Work

We present a novel graph encoding, RallyGraph, to enrich volleyball data context, significantly improving prediction task performance. While not universally applicable, these results highlight the potential of graph encoding in sports analytics and hopefully inspire improvements across machine learning applications. We also emphasize the importance of model architecture selection to optimize data utilization, noting that simpler models may perform better in certain tasks. These insights have enhanced our understanding of volleyball rally dynamics and offered valuable input for game strategy development. In future studies, we hope to gather more sophisticated data than explored in this study and analyze other encoding formats to potentially further enhance predictive results.

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