Team YHY at CoachAI Badminton Challenge 2023: ShuttleNet application for turn-based sequence prediction

Longxing Tan[1] , **Hongying Yue**[2] ,
[1]Beihang University
[2]Renmin University of China
tanlongxing@gmail.com, yuehongyingyhy@163.com

Abstract

The utilization of machine learning in sports analysis has gained significant importance in recent times. In this report, we present the application of ShuttleNet, a transformer-based model, to predict turn-based strokes in badminton for the CoachAI 2023 Track 2 challenge. Through optimization techniques and the implementation of turn-based post-processing for location prediction, our solution got the 4th place in the competition. Code is available at github.com/LongxingTan/Data-competitions/tree/master/ijcai-badminton

1 Introduction

Sports analysis has become a valuable tool for improving player performance across various disciplines [Richter *et al.*, 2021]. The CoachAI Badminton Challenge 2023 Track2, focuses on predicting future turn-based strokes in badminton. The challenge presents an opportunity to create a sequence model that effectively captures patterns within player sequences and adversarial sequences.

Our team YHY ranked in the 4th place in the final leaderboard, with 1.97 cross entropy loss and 0.68 MAE loss. We perform the best in landing location predictions.

1.1 Data and task

The training data, known as ShuttleSet22 [Wang *et al.*, 2023], comprises 44 unique matches, 35 unique players, and a total of 2268 rallies. Each rally involves predicting the future type and location from the earliest observed 4 strokes.

The label distribution is presented in Figure 1. Notably, the x and y locations are predominantly concentrated in the center area. As for stroke type classification, there are 10 different types, but imbalanced.

For evaluating model performance, two metrics are utilized. The first metric is the average cross-entropy loss for the type prediction, while the second metric is the mean absolute error loss for the location prediction. The final score is obtained by averaging these two values, considering both the classification and regression tasks.

2 Detailed solution

The task can be considered as a multiple and variable steps prediction. We treat it as a single-step prediction like the decoder inference in the transformer [Vaswani *et al.*, 2017]. In each step, the training sample is 0 $\sim$ n-1 step, and the label is 1 $\sim$ n step. While inference, each step will predict the next stroke value and add it to training data for further prediction until the last step [Sutskever *et al.*, 2014]. The overall solution is mainly based on the ShuttleNet [Wang *et al.*, 2022].

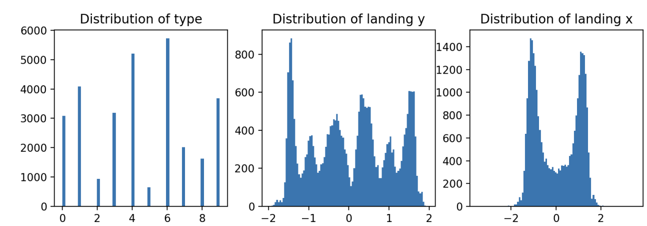

Figure 1: Data distribution

2.1 Sample

For local validation, we split the train data based on match IDs since the validation and test data mostly come from different matches. Specifically, we used rallies with a match ID less than 36 for training the model, and the remaining rallies were utilized as validation data.

To further enhance test performance, we have the option to use all available data to train a global model for inference. This approach allows the model to learn from a larger and more diverse dataset, potentially leading to improved predictions during testing.

2.2 Model

As mentioned, our prediction model is ShuttleNet, which features a novel structure designed to capture turn-based sequence information. The primary architecture is based on the transformer with an encoder-decoder module. The encoder part consists of three layers of self-attention blocks, while the decoder has three layers of self-attention and cross-attention blocks, as illustrated in Figure 2.

To facilitate prediction based on player habits, we embed the player ID, shot type, and landing location into the same

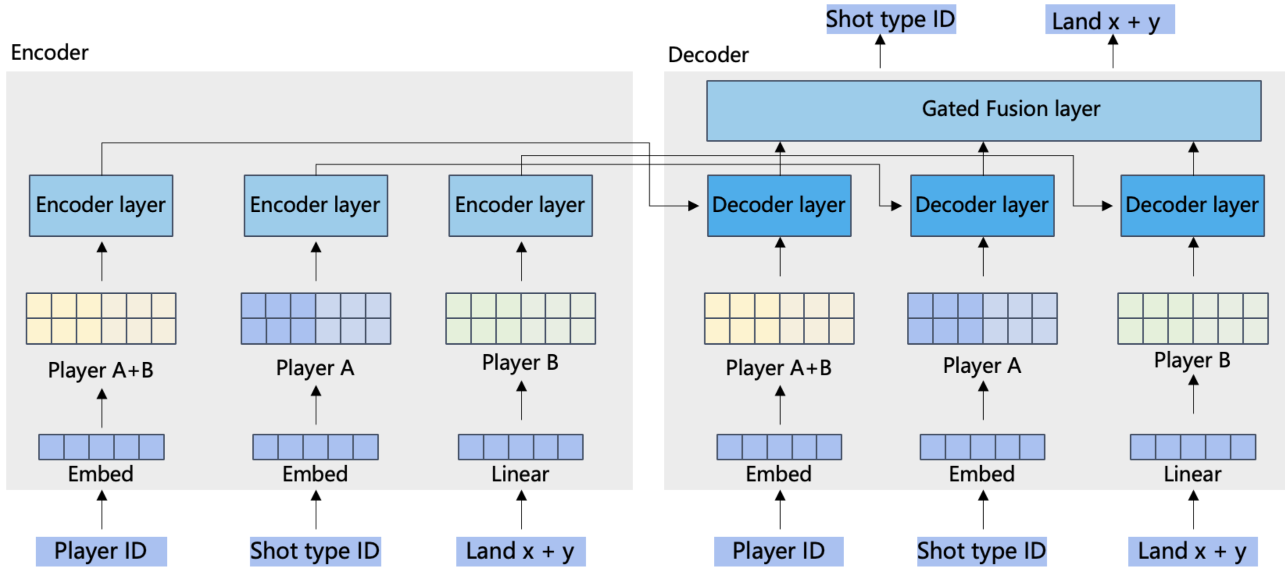

Figure 2: model structure

Table 1: Model configuration

Hyper-parameters	Value
Encoder sequence lengths	4
Predict sequence lengths	66
Number of encoder layers	3
Attention hidden sizes	64
Number of attention heads	2
Attention drop out rate	0
Feed forward layer hidden sizes	64
Feed forward layer dropout rate	0

shape as the model input. The embedding layers are followed by a pre-processing layer that separates player properties. Additionally, the attention layer is modified to handle both player information and adversarial information effectively. The model must be capable of reflecting the intricate relationship between shot types and landing positions. ShuttleNet incorporates various attention modules, such as player A type and location attention, as well as player A's attention with player B. These attention modules allow the model to better understand the turn-based sequence.

For detailed model configuration, please refer to Table 1. Notably, we increased the attention hidden sizes from 32 to 64 and made modifications to other default parameters to enhance model performance.

Additionally, we set the loss weight to achieve a better balance between the classification loss and regression loss. Specifically, we multiply the shot type loss by a factor of 1.1 to improve this balance. The training parameters configuration is presented in Table 2.

Table 2: Training configuration

Training parameters	Value
Batch sizes	32
Training epochs	165
Learning rate	0.0001
Optimizer	Adam

2.3 Post-processing

In badminton competitions, the landing location y of the shuttlecock should alternate between player A's field and player B's field. This means that the prediction results for "y" should also alternate between positive and negative values until the last stroke. However, the last stroke can be different, and the length of the rally can be considered as valuable information to improve the score. Unfortunately, we cannot use this leaky information in real scenarios, so it is not used for the final submission.

To address this, we attempted to add a signal flag to allow the model to learn this behavior by itself. However, it did not yield as good results as simply adjusting it through post-processing, as most cases were predicted correctly. In the post-processing step, we decide the positive or negative landing location of "y" based on the initial stroke. The post-processing checks if the predicted "y" location signal matches the initial stroke or not. Thanks to the global attention and local attention mechanisms designed in ShuttleNet, most of the prediction signals are correct. In cases where the prediction is incorrect, we adjust the signal accordingly. For these samples, if the positive or negative "y" location is incorrect, the value is clipped to be less than 1.5. This post-processing step helps us achieve the best location prediction results.

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