Predicting Events in MOBA Games: Dataset, Attribution, and Evaluation

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Abstract—The multiplayer online battle arena (MOBA) games have become increasingly popular in recent years. Consequently, many efforts have been devoted to providing pre-game or in-game predictions for them. However, these works are limited in the following two aspects: 1) the lack of sufficient in-game features; 2) the absence of interpretability in the prediction results. These two limitations greatly restrict the practical performance and industrial application of the current works. In this work, we collect and release a large-scale dataset containing rich in-game features for the popular MOBA game Honor of Kings. We then propose to predict four types of important events in an interpretable way by attributing the predictions to the input features using two gradient-based attribution methods: Integrated Gradients and SmoothGrad. To evaluate the explanatory power of different models and attribution methods, a fidelity-based evaluation metric is further proposed. Finally, we evaluate the accuracy and Fidelity of several competitive methods on the collected dataset to assess how well machines predict events in MOBA games.

I. INTRODUCTION

Nowadays, with the fast development of the gaming industry, electronic games are becoming increasingly popular, generating huge amounts of profit. Among all the genres of electronic games, MOBA games are one of the most popular and highest-grossing types, such as Defense of the Ancient II (DotA2), League of Legends (LoL), and Honor of Kings (HoK). Together, these three popular MOBA games have more than 300 million monthly active players globally and an even larger potential audience among the streaming media community. Along with MOBA games’ flourishing, much research has been done to predict the results before and during the games. These studies can be categorized into two types: pre-game predictions that predict the results of MOBA games before they begin [1], and in-game predictions that predict according to the in-game situations of the games [2].

In a sense, the in-game predictions are more significant and have broader application scenarios than the pre-game predictions. However, although some progress has been made, existing studies for in-game predictions are limited in the following two aspects. The first limitation is: the insufficiency of large-scale in-game data. Due to the difficulty in collecting in-game data, current datasets for MOBA game predictions contain only pre-game features [3] or limited types of in-game features such as “gold”, “experience”, and “death” [2]. Secondly, the use of non-interpretable models means the predictions of the current works are non-interpretable, which greatly limits their application. As one can see in Figure 1, the non-interpretable model used in LoL 2019 World Championship can only give the winning probabilities of the two teams (80% versus 20%), which is opaque to the audience. Hence, there is a need to generate human-interpretable predictions for MOBA games.

In this work, to facilitate the study of in-game predictions for MOBA games, we collect a large-scale dataset that contains in-game records with rich features extracted from the gamecore data (the back-end data of HoK) of 50,278 games. This dataset contains four types of label (prediction targets): “win”, “Tyrant”, “kill”, and “be-kill”, which are four of the most important events in HoK. Every second, we record more than 2,000 features. Within this dataset, one can easily train models...
to predict the important events of HoK.  

Given the game records as input, we further train two state-of-the-art (SOTA) sequence modeling networks, Long Short-Term Memory network (LSTM)\(^4\) and Transformer\(^5\), to predict the important events in HoK. However, as noted above, these well-known black-box networks are non-interpretable, so one cannot understand the reasons for their predictions. To mitigate this problem, we propose to apply two gradient-based attribution methods, Integrated Gradients (IG)\(^6\) and SmoothGrad (SG)\(^7\), to interpret the prediction result by attributing it to the top-contributed feature-dimensions. As reasoned by\(^6\) and\(^7\), with these methods we can determine which features primarily contribute to the current prediction result.

Although the attribution methods can interpret the predictions of deep neural networks, there is another issue in that it is difficult to evaluate the correctness of the attribution methods. In other words, we can hardly know how well they interpret the prediction results. So, inspired by the fidelity-based evaluation methods in Natural Language Processing\(^8\),\(^9\), we propose the Fidelity metric to evaluate the explanatory power of attribution methods and prediction models. The main idea of Fidelity is: when extracting the top-contributed feature-dimensions using an attribution method, if those extracted features have the potential to construct an optimal proxy model that agrees well with the original model on making a prediction, then this attribution method is good. In other words, we can evaluate the attribution results by measuring the consistency between the proxy model’s prediction results and the original model’s predictions: the more consistent these results are, the better the explanatory power of the attribution method will be. In experiments, the Fidelity metric proves that the IG method interprets better than the SG method in MOBA game event prediction tasks.

In summary, our contributions are three-fold: 1) We collect and release a large-scale MOBA game dataset containing rich in-game features of HoK, which may facilitate the future study of interpretable in-game prediction tasks for MOBA games. 2) We achieve interpretable event predictions with two SOTA sequence modeling networks and two SOTA gradient-based attribution methods. These works can serve as strong baselines for this task in future studies. 3) We evaluate the explanatory power of attribution methods and prediction models, proposing the Fidelity metric to quantitatively measure how well they interpret the prediction results.

### II. RELATED WORKS

#### A. MOBA Game Prediction

Studies on predicting MOBA games consist of pre-game and in-game predictions. Pre-game predictions focus on training prediction models based on pre-game features such as hero-selection\(^5\) and players’ historical records. Among these works,\(^1\) is the first to predict the DotA2 results before the games start.\(^10\) follows this work by combining the Genetic Algorithm with Logistic Regression (LR) and reports a higher prediction accuracy.\(^11\) proposes to build prediction models for DotA2 based on two different sets of training data: one comprising only the hero-selection information, and the other consisting of the full post-game data.\(^3\),\(^12\),\(^13\) further evaluate the performances of several machine learning methods for DotA2 win predictions, including Logistic Regression, Naive Bayes, GBDT, and other methods.\(^14\) proposes to improve pre-game DotA2 prediction using a better representation of hero-selection information.

Although much research has been done to perform pre-game predictions, in-game predictions are more informative and useful. Therefore, recent research focuses more on in-game MOBA game event predictions.\(^2\) first introduces three in-game features to achieve win predictions for DotA2.\(^15\) uses machine learning methods such as Logistic Regression and Decision Tree to predict the results of DotA2 using professional-level in-game data.\(^16\) proposes a two-stage model TSSTN to perform interpretable in-game predictions for HoK. However, this model can attribute the results to only six human-selected features such as “gold” and “heroes”. Moreover, their work achieves interpretability at the cost of accuracy, which undermines the performance. Value-based reinforcement learning methods\(^17\)–\(^20\) can also give in-game win predictions without interpretability.\(^21\),\(^22\) try to predict the results of LoL using multiple data collected from sensors and other hardware.

#### B. Gradient-Based Attribution Methods

In order to attribute the prediction of a deep network to its input features,\(^6\) proposes a gradient-based attribution method Integrated Gradients (IG). Two fundamental axioms, Sensitivity and Implementation Invariance, are also proposed to prove the correctness of IG. Following this work,\(^23\) applies IG to measure the word-importance for Neural Machine Translation.\(^24\) also applies IG to interpret the results of image-recognition networks.

\(^7\) proposes another gradient-based attribution method, SmoothGrad, to identify pixels that strongly influence the final decisions of image classifiers. By adding noise to the original image, we get a set of similar images. Then by averaging the gradients for each image to the image classifiers’ outputs, we can get a better sensitivity map (attribute result) of the original image to the classification result.

#### C. Fidelity Metric For Explanatory Power

The idea of “fidelity” is primarily used in the domain of Model Compression\(^25\),\(^26\) and Model Distillation\(^27\),\(^28\). Recently,\(^9\) proposes to utilize a similar concept of “faithfulness” to evaluate the interpretable methods for deep-learning based Nature Language Processing (NLP) models.\(^8\) further proposes a fidelity-based metric and its practical approximation method for Neural Machine Translation (NMT).
III. TASK AND DATASET

A. Prediction Tasks

We propose to predict four important events for HoK games: “win”, “Tyrant”, “kill”, and “be-kill”. These are four of the most important events in HoK and other MOBA games. The descriptions of these four events are as follows:

- **Win**: Predicting which team will win the game.
- **Tyrant**: Predicting which team will seize the Tyrant.
- **Kill**: Predicting who will be the next killer (the hero who kills the enemy).
- **Be-kill**: Predicting which hero will be killed next.

B. Events Extraction

To predict the four events mentioned above, we record the death information of all the heroes, monsters, and towers of 50,278 HoK games. The death information contains the death-frame (game-time), killer-information, hurt-information, and some other useful information, as shown in Figure 2. Then the task-labels can be extracted from this death information. It is worth noting that one may extract more potential events from the death information, such as towers’ destructions and the next optimal equipment.

C. Feature Extraction

In addition to the death information, we also record more than 2,000 in-game features every second of the games. We classify these features into five categories: “hero”, “global”, “monster”, “soldier”, and “tower”. An example of input features and events can be found in the appendix, and the whole dataset will be released after publication.

- **Hero** As shown in Figure 3, hero-features contain the information of the ten heroes in the game, including the hero’s ID (name), camp, level, kill-count, assist-count, death-count, skills’ information, and many other features.
- **Global** Global features describe the game’s overall situations, including the game-time, number of two camps’ alive heroes, money-amount, and number of alive towers. An example of global features is shown in Figure 4.
- **Monster** Monster-features contain the information of up to 27 monsters (Tyrant is one of them), including the monster’s health-points (hp), alive-or-not status, location, attack, and monster-type, as shown in Figure 5.
- **Soldier** As shown in Figure 6, soldier-features cover the information of up to 82 soldiers. Features in this category include the soldiers’ camp, location, hp, alive-or-not status, soldier-type, and attack.
- **Tower** Tower-features contain the information of two camps’ 22 towers, including the tower’s attack-range, location, camp, distance to heroes, hp, tower-type, and attack. An illustration is shown in Figure 7.

IV. PREDICTION

In this section, we first encode all the categorical features in the dataset into one-hot vectors, then concatenate them with other numerical features as the input vectors. Given the encoded input feature, we train two SOTA sequence modeling networks, LSTM and Transformer, to predict the occurrences of the aforementioned events.

A. Input Feature

Some of the in-game features in the collected dataset are categorical, such as hero-ID, skill-ID, and NPC-type. To better represent these categorical features, we encode them to one-hot vectors. As for the numerical features such as gold-difference and kill-difference, we normalize them to real values ranging in $[0, 1]$. After preprocessing, all the vectors and variables will be concatenated into a 5,885-dimension vector. To capture the sequential characteristics of the input data, we choose the consecutive $l$-seconds’ data as input, which means that the data up to game-time $t$ will be represented.
by $X = [x^{t-l+1}, \ldots, x^T]$. For “Tyrant”, “kill”, and “be-kill” tasks, we choose the training data at $S$ seconds-intervals before the events’ happening time (using the data from game-time $t-l+1\to t$ to predict the event at $t+S$); for “win” task, we set some fixed time-intervals, and choose the game records at these intervals as the training data.

B. Prediction Model

To capture the time-sequential characteristics of the games, we use SOTA sequence modeling networks such as LSTM [4] and Transformer [5] to perform the prediction tasks. A fully-connected layer is used to make the final predictions for the four tasks, as shown in Figure 8.

V. Attribution Method

In order to find the underlying reasons for the prediction models’ results, we utilize two gradient-based attribution methods, Integrated Gradients (IG) [6] and SmoothGrad (SG) [7], to interpret the event predictions by attributing the prediction to the input features for MOBA games. Assume that the output of the prediction network is $P(y|X)$ where

\[
\begin{align*}
F(X): & \text{prediction results} \\
P(y|X): & \text{predicted distribution}
\end{align*}
\]

Specifically, let $x^t = [x^1, \ldots, x^T]$ be the input vector at game-time $t$ and let $X = [x^{t-l+1}, \ldots, x^T]$ be the $l$-second sequential input up to game-time $t$. Assume that $F$ is a prediction model and $P(y|X)$ is its output. We set $X'$, which has the same dimension as $X$, to be the baseline, with all its elements to be 0. Then the IG of $X$ is defined by the integral of gradient from $X'$ to $X$ in the straight-line path:

\[
IG_{i,j} = \int_{0}^{1} \frac{\partial P(y|\hat{X})}{\partial x_{i,j}} \hat{x} = x' + \alpha(x - x')
\]

where $IG_{i,j}$ represents the contribution of feature-dimension $j$ to the prediction in $x'$.

However, this theoretical formulation of IG is inconvenient for practical applications due to the existence of the path-integral. A practical approximation of Equation (1) can then be formulated by:

\[
IG_{i,j} \approx \frac{X_{i,j} - X'_{i,j}}{\text{steps}} \sum_{k=1}^{\text{steps}} \frac{\partial P(y|\hat{X})}{\partial x_{i,j}} | \hat{x} = x' + \frac{\alpha}{\text{steps}}(x - x')
\]

where $\text{steps}$ is the number of steps that evenly distribute from the baseline $X'$ to the input $X$. The larger $\text{steps}$ we choose, the better approximation of IG we will get. In practice, $\text{steps}$ ranging from 100 to 300 results in good enough approximations and reasonable efficiency [6].

B. SmoothGrad

SmoothGrad is also a gradient-based attribution method, first proposed by [7], which can be utilized to attribute the prediction to the input features for MOBA games. Assume that the output of the prediction network is $P(y|X)$ where
same feature will be processed by the same FC layer for the fully-connected (FC) layers. Input dimensions belonging to the hero-ID and skill-ID will be transformed using several parallel 2,001 dimensions, in which numerical features will be directly dimensions will first be mapped into embedding vectors of vectors first. As Figure 9 shows, the input vector of 5,885 we need to transform the original input into embedding C. Embedding tion \( \sigma \) represents the zero-mean Gaussian noise with standard devia-
to the model’s output \( j \)
where \( \phi \) is the attribution method, \( Tr \) and \( T \) are the original training and testing sets upon which \( F \) is trained and tested, and \( W_\phi^k \) represents the new testing set containing instances that keep the top-k contributed feature-dimensions selected by \( \phi \) for instances of \( T \).

### VI. Fidelity Metric

“Fidelity” is the concept of keeping part of the input and assessing how much information can be retrieved, which is recently formulated to evaluate the explanation methods in NLP [8], [9]. In this section, we propose a fidelity-based metric that measures the explanatory power of models and attribution methods in our MOBA game prediction tasks. As shown in Algorithm [1] with attribution method \( \phi \), we can attribute the prediction results of model \( F \) to \( k \) top-contributed feature-dimensions. Then we attempt to evaluate how well these attributed features represent the input. Specifically, we only preserve the top-k contributed feature-dimensions for each training or testing instance and replace other dimensions with zero. In this way, we get new sets of training and testing dataset \( V_\phi^k \) and \( W_\phi^k \) from the original sets \( Tr \) and \( T \). Then, an optimal proxy model \( Q \), which has the same architecture with \( F \), can be trained using the new training set \( V_\phi^k \). Finally, the Fidelity of attribution method \( \phi \) on model \( F \) can be computed as follows:

\[
Fidelity_{F,\phi}(F, \phi) = \frac{\text{Accuracy}(Q(X) = y|X, y \in W_\phi^k)}{\text{Accuracy}(F(X) = y|X, y \in W_\phi^k)},
\]

(4)
in which \( F \) is the original prediction model, \( Q \) is the proxy model, \( \phi \) is the attribution method, \( Tr \) and \( T \) are the original training and testing sets upon which \( F \) is trained and tested, and \( W_\phi^k \) represents the new testing set containing instances that keep the top-k contributed feature-dimensions selected by \( \phi \) for instances of \( T \).

### VII. Experiments

#### A. Experimental Settings

We conduct experiments on the dataset mentioned above. We set 5,000 games from the dataset as the validation set and another 5,000 games as the testing set. The rest 40,278 games are the training set.

The sequence-length \( l \) of the sequential input \( X = [x^{i+1}, \ldots, x^l]^T \) is 5. For “Tyrant”, “kill”, and “be-kill” tasks, we choose the input data at \( S \) seconds-intervals before the events’ happening time, where \( S \in \{5, 10, 15, 20\} \). For “win” task, we choose the input data every 60 seconds from the beginning of each game. We also assess the accuracy of the “win” task at different game-times, ranging from 40.0-seconds (the beginning of the games) to 20.0-minutes.

#### B. Prediction Models

1) LSTM: We use bidirectional LSTM with two recurrent layers. The probability of dropout is 0.2. The size of the hidden state is 128. After the LSTM, we use a 256-dimension fully-connected layer and a \( \tanh \) function to compute the class-scores \( P(y|X) \).

2) Transformer: The numbers of layers and attention heads are 2 and 8, respectively. We set the dropout probability of the Transformer to be 0.1 and the embedding dimensions to be 256. After the Transformer, a 256-dimension FC layer and \( \tanh \) function are used to compute \( P(y|X) \).
TABLE I: Accuracy of LSTM and Transformer for the four tasks at different intervals before the events’ happening.

| Task   | Model     | Accuracy      |
|--------|-----------|---------------|
| Tyrant | LSTM      | 0.930 0.910 0.871 0.834 |
|        | Transformer | 0.934 0.916 0.880 0.841 |
| win    | LSTM      | 0.221 0.206 0.184 0.175 |
|        | Transformer | 0.230 0.216 0.189 0.179 |
| kill   | LSTM      | 0.278 0.207 0.160 0.143 |
|        | Transformer | 0.319 0.228 0.175 0.149 |
| be-kill| LSTM      | 0.230 0.216 0.189 0.179 |
|        | Transformer | 0.278 0.207 0.160 0.143 |

C. Attribution Methods

We compare the “explanatory power” of two attribution methods, **Integrated Gradients** (IG) and **SmoothGrad** (SG), on two prediction models (LSTM and Transformer) and four tasks (“Tyrant”, “win”, “kill”, and “be-kill”). For each task, we use the attribution methods to find the top-\(k\) contributed feature-dimensions in the input, where \(k \in \{100, 10, 5, 1\}\). Specifically, since our input is time-sequential, we average the IG/SG of the input among the time-dimension of the input \(X\), then choose the top-\(k\) dimensions of the averaged IG/SG to be the top-contributed feature-dimensions.

1) **Integrated Gradients**: We apply Equation (2) to realize IG, and choose the dividing steps to be \(steps = 100\).

2) **SmoothGrad**: We apply Equation (3) to realize SG with \(steps = 100\), and set the standard derivation \(\sigma\) of Gaussian noise for the \(i\)-th dimension of \(X\) to be \(0.15 \cdot (\max(X_i) - \min(X_i))\).\(^1\)

D. Evaluation Metrics

1) **Accuracy**: We use the prediction accuracy as the evaluation metric for the aforementioned two prediction models for the four tasks.

2) **Fidelity**: We evaluate the explanatory power of different pairs of attribution method (IG and SG) and prediction model (LSTM and Transformer) with the Fidelity metric using Equation (4) and Algorithm 1. We conduct these experiments by preserving the top-\(k\) contributed feature-dimensions, where \(k \in \{100, 10, 5, 1\}\).

VIII. RESULTS AND ANALYSIS

A. Prediction Accuracy

Table I indicates that the two models achieve close accuracy, while Transformer is slightly more accurate. For “Tyrant”, “kill”, and “be-kill” tasks, the prediction accuracy decreases when the prediction interval \(S\) increases (from 5.0-seconds to 20.0-seconds), which is logical since it is easier to predict an event in the near future than one in the distant future. For example, if the Tyrant is killed at game-time \(t\)-seconds, then at “\(t - 5\)”-seconds we are almost sure the team that has an advantage will seize the Tyrant, while at “\(t - 20\)”-seconds the future situations are not that clear.

\(^1\)We do not fine-tune this parameter too much because the result is not sensitive to the value of \(\sigma\).

From Table I we can also conclude that “Tyrant” prediction is the most accurate one and “win” prediction is the next, while “kill” and “be-kill” predictions are less accurate. The underlying reasons are as follows: 1) “Tyrant” and “win” are binary-classification tasks, while there are ten labels for “kill” and “be-kill”. 2) It is much easier to predict the macro-scale events (such as which team will seize the Tyrant and which team will win) than to predict the micro-scale events (which hero exactly will be killed or kill others) since there is too much uncertainty and variability for micro-scale events. Experiments also show that predictions for “be-kill” tasks are more accurate in the near future (within 10 seconds), while “kill” predictions are more accurate in the distant future (longer than 10 seconds). A possible explanation for this phenomenon is as follows: In the near future, it is easier to predict who will be killed by checking whose situation is the worst, while there might be several possible candidate killers, making it relatively harder to predict which one of them exactly will be the killer. However, situations will definitely change in the distant future, such as 20 seconds later. Therefore, we no longer sure which hero will be in the worst situation then, while it is relatively more accurate to predict which hero will be the potential killer by checking who is the most powerful one.

We further test the accuracy of the two models at different game-times for the “win” task to investigate the nature of outcomes for MOBA games. As shown in Figure 10, the prediction accuracy of both models first increases as the games progress, then declines in the late-game stages (after 12.5-minutes of game-play). This phenomenon happens due to the following reasons: 1) In the early-game stages (before 12.5-minutes), the games become more predictable as time goes on because the leading team will accumulate its advantages in gold, level, and equipment. 2) In the late-game stages (after 12.5-minutes), the level and equipment of both teams reach a maximum. Therefore, games are increasingly affected by uncertainty, such as players’ accidental mistakes, and therefore are harder to predict.
TABLE II: Fidelity of different pairs of attribution methods and prediction models for the four prediction tasks.

| Task  | Attribution Model | Fidelity |
|-------|-------------------|----------|
|       | Top 100 | Top 10 | Top 5 | Top 1 |
| Tyrant | 5.0sec | IG+LSTM | 0.942 | 0.862 | 0.822 | 0.726 |
|       |        | SG+LSTM | 0.956 | 0.816 | 0.778 | 0.653 |
|       |        | IG+Transformer | 0.968 | 0.885 | 0.811 | 0.611 |
|       |        | SG+Transformer | 0.970 | 0.840 | 0.800 | 0.632 |
| win   | IG+LSTM | 0.908 | 0.814 | 0.799 | 0.715 |
|       | SG+LSTM | 0.897 | 0.825 | 0.762 | 0.656 |
|       | IG+Transformer | 0.950 | 0.891 | 0.866 | 0.800 |
|       | SG+Transformer | 0.938 | 0.872 | 0.834 | 0.622 |
| kill  | IG+LSTM | 0.329 | 0.207 | 0.201 | 0.161 |
|       | SG+LSTM | 0.311 | 0.218 | 0.189 | 0.178 |
|       | IG+Transformer | 0.460 | 0.357 | 0.313 | 0.184 |
|       | SG+Transformer | 0.384 | 0.175 | 0.159 | 0.177 |
| be-kill | IG+LSTM | 0.293 | 0.177 | 0.157 | 0.148 |
|       | SG+LSTM | 0.296 | 0.171 | 0.172 | 0.157 |
|       | IG+Transformer | 0.346 | 0.268 | 0.259 | 0.193 |
|       | SG+Transformer | 0.363 | 0.244 | 0.244 | 0.179 |

B. Fidelity

Fidelity of different attribution methods (IG and SG) and prediction models (LSTM and Transformer) with respect to \( k \) top-contributed feature-dimensions \( (k \in \{100, 10, 5, 1\}) \) is shown in Table III. With a few exceptions, IG and Transformer achieve the highest Fidelity for “win”, “kill”, and “be-kill” tasks. Fidelity decreases when the number of top-contributed feature-dimensions \( k \) changes from 100 to 1, because when we preserve fewer features, less information of the game can be retrieved.

Experiments show that the Fidelity for “Tyrant” and “win” tasks is higher than the Fidelity for “kill” and “be-kill” tasks. One reason is that the first two tasks are binary classification tasks and the last two tasks are ten-label classification tasks. Therefore, the Fidelity (defined by the accuracy of the proxy model) of “Tyrant” and “win” is higher. The other reason is that to predict which team will win or seize the Tyrant, we mainly rely on a small number of critical features (such as gold-difference and Tyrant’s distances to heroes); however, to predict which hero will be the next killer or be-killed one, we need to consider more factors, such as hero-skil information, hero-level, locations, hp, and many other important features.

C. Parameters

We further conduct an additional experiment to evaluate the effect of the choice of \( \text{steps} \) on the final Fidelity result. We assess the Fidelity of different \( \text{steps} \) values of IG and SG for the “win” prediction task with Transformer as the prediction model. From Table III, we can see that there is little change in Fidelity for \( \text{steps} \) ranging in \([10, 500]\), which indicates that Fidelity is not sensitive to the choice of \( \text{steps} \).

D. Case Study

A case study is given in which the two teams are fighting for the Tyrant. As Figure 11 shows, Transformer predicts that the red team will get the Tyrant with probability 86%, and IG further attributes the prediction result to five reasons: 1) Distances between the Tyrant and the heroes: the red team’s heroes are closer to the Tyrant and therefore have a better chance of killing the Tyrant. 2) Hero-3 has died: hero-3 belongs to the blue team, so the blue team has a disadvantage. 3) Gold difference and 4) Kill-count difference: the blue team has a disadvantage in terms of gold difference and kill-count difference. 5) The skill-3 (ultimate skill) of hero-1 is of a low level: this skill is essential for group fighting, so hero-1’s team (blue team) is not capable of seizing the Tyrant. Eventually, the red team indeed kills the Tyrant.

IX. Conclusions

In this paper, we attempt to address two main issues for in-game MOBA events: 1) insufficient in-game features and 2) lack of interpretability. We first collect and release a large-scale HoK dataset containing rich in-game features. To predict four important events (“Tyrant”, “win”, “kill”, and “be-kill”) of HoK in an interpretable manner, we train two sequence modeling networks (LSTM and Transformer) based on the collected dataset and adopt two attribution methods, Integrated Gradients and SmoothGrad, to give human-interpretable explanations of the prediction results. In addition, a fidelity-based metric is proposed to evaluate the explanatory power of the attribution methods and prediction models. Experiments show that LSTM and Transformer suit well the prediction tasks in terms of accuracy, and Integrated Gradients outperforms SmoothGrad in terms of the Fidelity metric in our scenarios.

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