Abstract

Multiplayer Online Battle Arena (MOBA) games have received increasing worldwide popularity recently. In such games, players compete in teams against each other by controlling selected game avatars, each of which is designed with different strengths and weaknesses. Intuitively, putting together game avatars that complement each other (synergy) and suppress those of opponents (opposition) would result in a stronger team. In-depth understanding of synergy and opposition relationships among game avatars benefits player in making decisions in game avatar drafting and gaining better prediction of match events. However, due to intricate design and complex interactions between game avatars, thorough understanding of their relationships is not a trivial task.

In this paper, we propose a latent variable model, namely Game Avatar Embedding (GAE), to learn avatars’ numerical representations which encode synergy and opposition relationships between pairs of avatars. The merits of our model are twofold: (1) the captured synergy and opposition relationships are sensible to experienced human players’ perception; (2) the learned numerical representations of game avatars allow many important downstream tasks, such as similar avatar search, match outcome prediction, and avatar pick recommender. To our best knowledge, no previous model is able to simultaneously support both features. Our quantitative and qualitative evaluations on real match data from three commercial MOBA games illustrate the benefits of our model.

Introduction

Multiplayer Online Battle Arena (MOBA) has been one of the most popular e-sports game types. For example, League of Legends (Riot Games), one of the most popular e-Sports, reportedly has 90 million accounts registered, 27 million unique daily players, and 7.5 million concurrent users at peak (Minotti 2016, Tassi 2016). In a MOBA game, 2 teams, composed of 5 player each, combat in a virtual environment. The goal is to beat the opposite team and destroy their base. Game avatars are often designed with a variety of attributes, skills, roles, etc., which is intended to provide players with choices and options so that every player can find a character that fits their preferences. Moreover, it is customary for avatars in such games to possess strength in one aspect, but weakness in others. As such, in order to win a match, it is well-known that players need to not only control their own game avatars well, but also need to select a game avatar that, together with other team members’ picks, forms a team that enhances skills and complements weaknesses of each other (synergy), while posing suppressing strengths over those in the opponent team (opposition). For example, in DOTA 2 (Valve Corporation), avatar Clockwerk has high synergy with Naix because Clockwerk can transport Naix to target enemy directly, increasing the limited mobility of Naix to hit enemy. Naix also delivers large damage to complement the limited attack by Clockwerk, making them an efficient fighting duo. In another example, avatar Anti-Mage’s mana burn skill reduces an opponent’s mana resource, making him a natural opposition to Medusa whose durable capability is completely relying on how much mana it has.

Comprehensive understanding of synergy and opposition relationships between game avatar enhances player awareness and experience in games. First, it allows players to make good decisions in drafting their team’s game avatars to maximize the chance of winning. Second, it improves the prediction of the match’s progress and final outcomes, which helps players in preparing for strategies in advance. Lastly, it helps players discover other game avatars that match their personal expertise or preferences. However, due to the intricate design and complex interactions among game avatars, thorough understanding of game avatars’ pros and cons and their relationships is not a trivial task to human players.

In order to model game avatars’ synergy and opposition relationships, we propose a latent variable model, called Game Avatar Embedding (GAE). GAE models game avatars as vectors in a low-dimensional space learned. We hypothesized that the probability function of a match outcome constitutes of pairwise synergy and opposition interactions formulated by game avatar vectors. Game avatar vectors and other model parameters are learned by gradient descent through maximizing the likelihood function of all observed match outcomes. Latent variable models (LVM) and embedding techniques have been shown to successfully capture characteristics of entities in texts (Mikolov et al. 2013).
we demonstrate the effectiveness of the model via quan-
tifying numerical representations of game avatars that can be
analyzed and utilized for many other
downstream applications. However, their method does not naturally derive mean-
ingful numerical representations of game avatars that can be
analyzed and utilized for many other downstream applica-
tions.

Although we focus on video game data in this paper, team formation analysis could help advance many other
domains, such as social networks (Lappas, Liu, and Terzi
2009), crowdsourcing (Rahman et al. 2015), Kittr (2010), Roy et al. 2015), and robotics
(Liemhetcharat and Veloso 2012). Existing works that also
use machine learning to learn characterization of team mem-
bers (Liemhetcharat and Veloso 2012) Rahman et al. 2015) are different than our work in that: (1) the dimensions of
team member characterization are often pre-defined and
fixed, such as a fixed set of skills, which requires manual ef-
forts and domain knowledge; (2) no opposition relationship
has been modeled.

MOBA Game Research
The rich design of MOBA games has attracted variety of
research to be conducted upon them. For example, team
formation analysis (Pobiedina et al. 2013a). Pobiedina et
al. 2013b; Neidhardt, Huang, and Contractor 2015; Kim
et al. 2016; Agarwala and Pearce 2014). skill decomposi-
tion (Chen et al. 2016), match outcome prediction and avatar
pick recommendation systems (Bhatthacharya and Sabik ).
They shed lights on real-world problems or facilitate build-
ing adaptive player experience (Nguyen, Chen, and El-Nasr
2015). Many of these tasks rely on processing vectors which
encode characteristics of game avatars. For example, in team
formation analysis, the calculation of team diversity is av-
eraged pairwise cosine distances between game avatars’
attribute vectors. Principal Component Analysis (Jolliffe
2002) and t-SNE (Maaten and Hinton 2008), two frequently
used dimension reduction techniques in clustering and vi-
sualization, are also based on entities’ vectors. Our GAE
model induces the vectors of game avatars encoding their
synergy and opposition relationships, which can facilitate
many downstream tasks that perform upon vectors.

LVMs and Embedding Models
LVMs/embedding models have been long studied in Natural
Language Processing (NLP) (Mikolov et al. 2013), graph
(Maaten and Hinton 2008), and recommendation system
(Koren, Bell, and Volinsky 2009). In this family of models,
entities are associated with vectors in a shared, continuous
low-dimensional space which encode entities’ characteris-
tics efficiently and effectively. We will use vectors and em-
bedding interchangeably to refer to the numerical represen-
tations of entities.

Some salient advantages of embedding models/LVMs are
as follows: 1. it requires little human labor for feature engi-
neering because entity vectors can be learned based on labels
or what are observed explicitly (e.g., links between nodes in a graph, user-item matrix, word sequences). 2. informa-
tion between entities can be shared more effectively dur-
ing the learning phase. For example, similar embeddings of
two similar words can be learned if they are often used and
occur in the similar contexts, even though they do not ap-
pear together. 3. learned vector representation can be reused
by many kinds of applications, such as sentiment analysis
(Maas et al. 2011) and data visualization (Maaten and Hinth-
ton 2008).

In our paper, game avatars are embedded as low-
dimensional vectors. Their values are learned (supervised)
through maximizing the winning probabilities (defined in Section 3) of all observed match outcomes. We will show in Performance Evaluation and Case Study that the learned game avatar embeddings indeed capture sensible team-related characteristics and allow for other downstream applications, such as similar avatar search and avatar pick recommendation. This cannot be achieved by previous methods such as Logistic Regression, Factorization Machine (Semenov et al. 2016) and Gradient Boosting Decision Tree (Friedman 2001) which simply predict match outcomes without a means to derive game avatar embeddings to be reused in other tasks.

Preliminary and Problem Definition
Suppose the training data is a match set \( M = \{M_1, M_2, \cdots, M_Z\} \) with \( Z \) matches. There are \( N \) unique game avatars appearing in total, denoted by \( A = \{A_1, A_2, \cdots, A_N\} \). We assume each match is competed between two teams, the red and the blue team. We use \( T_{z,r} = \{A_i\} \) and \( T_{z,b} = \{A_j\} \) to denote the sets of game avatars in the red team and the blue team in \( M_z \), respectively. Since we are studying 5-vs-5 MOBA games, we have for \( \forall z, |T_{z,r}| = 5 \) and \( |T_{z,b}| = 5 \). We use \( T = \{(T_{z,r}, T_{z,b})\}_{z=1,\cdots,Z} \) to denote all game avatar line-ups of \( M \).

Match outcomes are marked as \( O = \{o_1, o_2, \cdots, o_Z\} \). \( o_z \) means the red team wins over the blue team in \( M_z \), otherwise \( o_z = 0 \). We use \( p(o_z = 1) \) and \( p(o_z = 0) \) to denote the winning probability from the view of the red team and the blue team, respectively. Hence, \( p(o_z = 0) = 1 - p(o_z = 1) \).

Game Avatar Embedding Model
In this section, we will describe the proposed model, the learning process, as well as discuss its relationships with Factorization Machines, a related model.

Model Synergy and Opposition
Inspired by embedding methods which have managed to learn low-dimensional vectors to capture abundant attributes of entities, we propose to map characteristics of game avatars into a low-dimensional latent space. For a game avatar \( A_i \), its latent feature vector is denoted as \( a_i \in \mathbb{R}^K \). \( A \in \mathbb{R}^{N \times K} \) is the latent feature matrix such that \( A = \{a_i\} \).

We choose to use a bilinear model to model synergy and opposition relationships between pairs of avatars. The bilinear model allows us to separately learn game avatar embeddings, as well as the matrices that determine the extents of synergy and opposition across different dimensions of game avatar embeddings.

First, we introduce the intra-team synergy score function \( S(i,j) \), which calculates the level of synergy to which \( A_i \) exerts on \( A_j \) in the same team:

\[
S(i,j) = a_i^T \cdot P \cdot a_j = \sum_{m=1}^{K} \sum_{n=1}^{K} a_{im} \cdot p_{mn} \cdot a_{jn} \tag{1}
\]

\( P \in \mathbb{R}^{K \times K} \) is named synergy matrix. There are two ways to understand \( P \) intuitively:

1. one can think of \( a_i^T \cdot P = a'_i \) as converting \( A_i \)’s embedding into the dimensions that \( A_j \) looks for as a helpful teammate. Then, the higher the dot product is between \( a'_i \) and \( a_j \), the higher synergy the two game avatars can build.

2. alternatively, one can think that \( p_{mn} \) measures how much \( m \)-th dimension of \( a_i \) fits \( n \)-th dimension of \( a_j \) in terms of intra-team interaction.

Second, we define the inter-team opposition score function \( C(i,j) \), which quantifies the extent to which \( A_i \) counters \( A_j \) in the opposite team:

\[
C(i,j) = a_i^T \cdot Q \cdot a_j = \sum_{m=1}^{K} \sum_{n=1}^{K} a_{im} \cdot q_{mn} \cdot a_{jn} \tag{2}
\]

\( Q \in \mathbb{R}^{K \times K} \) is named opposition matrix. In a similar way to understand \( P, q_{mn} \) measures the influence on \( A_i \) countering \( A_j \) given their embeddings’ interaction on \( m \)-th and \( n \)-th dimension respectively.

Note that \( P \) and \( Q \) are not necessarily symmetric, as the level of opposition in which \( A_i \) suppress \( A_j \) could be different from that of \( A_j \) on \( A_i \).

In this model, we only capture pairwise relationships because they are much more prevalent. We also find advanced models such as Gradient Boosting Decision Trees (Friedman 2001) potentially considering more intricate relationships do not improve the match outcome prediction task on all the three datasets we study (See Section Performance Evaluation). Still, it is possible to extend GAE for higher order interactions by modeling them using tensors and tensor operations (Kolda and Bader 2009). We will explore this aspect in the future.

Model Winning Probability
Next, we propose to model a winning outcome as the linear breakdown of the individual biases, as well as their intra-team and inter-team interactions, of game avatars from the two teams involved. Individual biases represent game avatars’ intrinsic control difficulty that affects match outcomes, denoted as \( b = \{b_1, b_2, \cdots, b_N\} \). Hence, the winning outcome \( p(o = 1) \) of a match \( M_z \) is defined as follows:

\[
p(o_z = 1) = \sigma\left(\sum_{i \in T_{z,r}} b_i - \sum_{j \in T_{z,b}} b_j + \sum_{i,j \in T_{z,r}} S(i,j) - \sum_{i,j \in T_{z,b}} S(i,j) + \sum_{i,j \in T} C(i,j) - C(j,i)\right) \tag{3}
\]

where \( \sigma(\cdot) \) is sigmoid function \( \frac{1}{1 + \exp(-x)} \).

The input of the sigmoid function is the sum of the differences of: (1) individual biases towards winning, (2) synergy strength inside the team, and (3) opposition intensity against the opponent team. The latter two differences depend on traversing all valid pairs of game avatars within the same team or across the two teams. The larger the differences are,
the closer \( p(o_2 = 1) \) is to 1 meaning the advantageous team is more likely to win.

Note that in our formulation, players’ individual skill levels are not accounted for in the winning outcome’s probability. This is reasonable, since the data we collected is from highly selective ranked matches. Most commercial MOBA games have proprietary matchmaking systems to ensure that only sufficiently experienced players with similar skill levels are allowed to compete in ranked matches (the type of matches we study). Therefore, the chance of results being skewed by data from incompetent players is low.

**Objective Function and Learning**

Assuming that each match is independent, the overall likelihood function is:

\[
p(O, T | A, P, Q, b) = \prod_{z=1}^{Z} p(o_z = 1) \alpha z p(o_z = 0)^{1-\alpha z}
\]

(4)

The objective function is to minimize the negative log likelihood w.r.t \( \Theta = \{A, P, Q, b\} \):

\[
J(\Theta) = -\frac{1}{Z} \sum_{z=1}^{Z} (o_z \log p(o_z = 1) + (1 - o_z) \log p(o_z = 0))
\]

(5)

For parameter learning, we use AdaGrad (Duchi, Hazan, and Singer 2011) to update parameters based on a small batch of matches in each iteration.

**Relation to Factorization Machine Model**

GAE has a close relationship with 2-way factorization machine (FM) (Rendle 2010), which has been applied in (Semenov et al. 2016) to predict match outcomes of the same kind of games. In (Semenov et al. 2016), for a match \( M_z \), the feature vector \( x_z \in \{0, 1\}^{2N} \) is a binary vector indicating which five avatars appear in the red and blue team respectively:

\[
x_{zi} = \begin{cases} 
1, & \text{if } i \leq N \text{ and avatar } i \text{ was in the red team} \\
0, & \text{otherwise}
\end{cases}
\]

(6)

and FM models a winning probability by additionally exploring pairwise interactions between non-zero features:

\[
p(o_2 = 1) = \sigma \left( \sum_{i \in T_r, r} c_i + \sum_{j \in T_b, b} c_j + \sum_{i,j \in T_r, r} < v_i, v_j > + \sum_{i,j \in T_b, b} < v_i, v_j > + \sum_{i \in T_r, r} \sum_{j \in T_r, r} < v_i, v_i > \right)
\]

(7)

where \( c_i \in \mathbb{R} \) and \( v_i \in \mathbb{R}^K \) for \( \forall i = 1, \cdots, 2N \) are first-order and second-order parameters, and \( < \cdot, \cdot > \) is dot product operation. Therefore, each avatar \( A_i \) is associated with a quartet of parameters \((c_i, c_i+\cdot, v_i, v_i+\cdot)\).

Dot productions in Eqn. [7] can be re-written in the vector-matrix product form that is similar to Eqn. [1] and Eqn. [2]. For each \( A_i \), we can set \( v_i = U_i u_i \) and \( v_i+\cdot = V_i u_i \), where \( U_i \) and \( V_i \) are two matrices that linearly transform the same base \( u_i \). \( u_i \) can be seen as the equivalence of \( a_i \) in GAE, a vector capturing characteristics of \( A_i \). Therefore, each pairwise term in Eqn. [7] can be written as:

\[
< v_i, v_j > = U_i^T (U_i^T u_j) u_j
\]

(8)

\[
< v_i+\cdot, v_j+\cdot > = U_i^T (V_i^T V_j) u_j
\]

(9)

\[
< v_i, v_j+\cdot > = U_i^T (U_i^T V_j) u_j
\]

(10)

FM and GAE both attempt to estimate second-order interactions through the embedding/factorization technique. Therefore, they both inherit the advantages of the factorization technique that all pairs of co-occurrences can help the learning of any particular pair of interaction. Since the hierarchy of both models is the linear summation of first-order biases and second-order interactions, FM and GAE are expected to have similar classification performance in match outcome prediction. However, for FM, it is unclear how to determine \( U_i \) and \( V_i \) for \( \forall i \). On the contrast, GAE by design can learn game avatar embedding and synergy and opposition matrices at the same time, which enables practitioners to reuse game avatar embedding for other downstream tasks.

**Performance Evaluation**

We evaluate the utility of GAE using datasets collected from three commercial MOBA games, namely Defense of the Ancients (DOTA2), Heroes of Newerth (HoN), and Heroes of the Storms (HotS). All data is from 5-vs-5 matches that pit ten random players in two teams against each other. No major game update affecting the mechanics of the games occurred during the data collection phase. All three games employ matchmaking systems that select only players of similar skill levels when assembling a match. All the three datasets have roughly balanced winning outcomes for both the red and blue teams. Statistics of the three datasets is shown in Table [II].

The HotS match data was downloaded from a third-party game log website [1] all the matches happened during the last month of 2016. The HoN dataset was collected by (Suznjevic, Matijasevic, and Konfic 2015), which contains matches played between December 20, 2014 from April 29, 2015. Finally, for DOTA 2, we use the original data set collected between February 11, 2016 to March 2, 2016 by Semenov et al. (Semenov et al. 2016), and extract a subset of matches played by gamers with similar skill levels (i.e., normal level).

**Experiment Setup and Results**

There are two experiments designed to assess the effectiveness of GAE. The first is conducted as a numerical evaluation in terms of outcome prediction, while the second evaluates GAE’s interpretability using human experts, as compared to other state-of-the-art methods.

[1] https://www.hotslogs.com/InfoAPI
Table 1: Statistics of datasets

|                  | HotS  | HoN   | DOTA2 |
|------------------|-------|-------|-------|
| # of Matches     | 1,814,066 | 1,101,046 | 3,056,596 |
| # of Avatars     | 58    | 126   | 111   |

Table 2: Outcome prediction AUC on test datasets; (*) indicate where GAE outperforms with p-values < 0.001.

| Models  | HotS  | HoN   | DOTA2 |
|---------|-------|-------|-------|
| LR      | 0.6095* | 0.6115* | 0.6875* |
| GBDT    | 0.6375* | 0.6144* | 0.7014* |
| FM      | 0.6440  | 0.6154* | 0.7143  |
| GAE     | 0.6437  | 0.6220  | 0.7143  |

Outcome Prediction Results

First, we evaluate the match outcome prediction performance of GAE against well-known baselines, including Logistic Regression (LR), Gradient Boosting Decision Trees (GBDT), and 2-way Factorization Machine (FM). For each game dataset, we adopt a 10-fold cross-validation procedure with train:validate:test ratio set to be 8:1:1. In each fold, a model with different configurations of hyperparameters (e.g., regularization penalty, the number of trees, the dimension of latent space, etc.) is trained on the train dataset and the best hyperparameters is determined according to the classification performance on the validation dataset. The classification performance of the model with the best hyperparameters on the test dataset will be recorded as the final measurement of its classification strength. For GAE, we use Eqn. 3 to predict outcomes on test datasets. For baseline models, Eqn. 6 is used to construct feature vectors, similar to how it is done in previous works. The area under ROC Curve (AUC) is used as the classification performance measurement. Ten test AUC are recorded during the 10-fold cross-validation for each model (LR, GBDT, FM and GAE) such that classification performance can be compared using paired t-test (with confidence level 0.001).

Table 2 reports the classification performances of all models in match outcome prediction. The paired t-tests showed that GAE has significantly higher test AUC than other models except GAE vs. FM in HotS and DOTA2.

We observe that LR has the worst classification AUC in all three games. That is not surprising because LR does not model interactions between avatars. This verifies that there do exist team synergy and opposition between game avatars. GBDT is a tree-based model that could handle interactions among more than two game avatars. However, it achieves statistically worse results than GAE. This demonstrates: (1) the strength of embedding methods in effectively encoding meaningful information of pairwise synergy and opposition relationships in a low-dimensional space; (2) much more data might be needed for GBDT to fully capture more complicated relationships. When GAE and FM are tuned with a proper number of latent space dimensions $K$, they achieve comparable AUC in HotS and DOTA2. This verified our expectation in Section Relation to Factorization Machine Model that GAE and FM should have similar outcome prediction performance because they both rely on factorization techniques to quantify pairwise interactions. However, the exception is HoN where GAE is statistically significantly better than FM in HoN and GAE appears to have smaller improvement over LR than in other games. We will investigate the characteristics of HoN compared to other MOBA games in the future. Overall, GAE predicted match outcomes well and robustly.

Human Evaluation

Second, we would like to validate how sensible GAE results are as compared to the experts’, i.e., human players’, judgment. We ask human players to rate pairs of game avatars in terms of similarity, synergy and opposition. Intuitively, if a model’s scores are highly correlated with human ratings, we conclude that such model generates sensible results. Since recruitment of knowledgeable players is a relatively expensive task, we only evaluate on the DOTA2 dataset. Based on a pilot test of three DOTA2 players, 60 pairs are selected which have clear similarity, synergy and opposition relationships (20 pairs for each kind of relationship). For example, the 20 similarity evaluation pairs include both very similar as well as very different pairs of game avatars because either kind is expected to be evaluated consistently by subjects.

When using GAE to evaluate the pairs, the similarity is determined by cosine similarity between the learned game avatar embeddings. The synergy is determined by $S(i,j) + S(j,i)$ and the opposition by the absolute value of $C(i,j) - C(j,i)$ for any pair of game avatars $A_i$ and $A_j$. Note that besides GAE, we are not aware of any approach that can handle similarity, synergy, and opposition queries all in a single model. FMs can naturally answer synergy and opposition queries; more specifically, two avatars’ synergy and opposition levels can be obtained using the left hand side of Eqn. 8 and Eqn. 10 respectively. However, they are not designed for similarity search, so we created an ad-hoc baseline method to compute avatars’ similarity based on the cosine similarity between the respective rows of a win-ratio matrix $W \in \mathbb{R}^{N \times 2N}$, constructed as:

$$W_{i,j} = \frac{\text{# of matches } (A_i, A_j) \text{ win}}{\text{# of matches } (A_i, A_j) \text{ from the same team}}$$ (11)

http://scikit-learn.org/  
https://github.com/dmlc/xgboost  
https://github.com/ibayer/fastFM
\[
W_{i,j+N} = \frac{\text{# of matches } A_i \text{ wins over } A_j}{\text{# of matches } A_i, A_j \text{ from the opposite teams}}
\]

(12)

To collect human ratings, we created a survey asking subjects to rate on a 5-point Likert scale the level of similarity, synergy or opposition on the 60 pairs, with 1 as “not at all” and 5 as “very much”, and asked ten similarly skillful DOTA2 players to provide their ratings. We produce Pearson’s \( r \) between human ratings and GAE/baseline scores on the 20 pairs in each kind of relationship.

We compared the correlations (using Pearson’s \( r \)) between human ratings and those by GAE and the baseline. Better correlation corresponds to more sensible results from the players’ perspective. As shown in Table 3 for similarity queries, GAE’s results better correlate with human ratings than those by the baseline, suggesting that similarity search based on the learned embeddings by GAE are more sensible. For synergy and opposition queries, both GAE and the baseline correlate with human ratings with high Pearson’s \( r \) (\( \geq 0.7 \)) with \( p \)-value < 0.001, which indicates both methods are sensible to human players. This can be explained by the similarity of FM and GAE’s approach in using the factorization/embedding technique to model pairwise interactions.

Case Study

In this section, we would like to qualitatively demonstrate the quality and utility of GAE within the context of practical applications. All analyses are done with the help of three seasoned DOTA2 players, conducted on GAE’s results (\( K = 75 \)) as learned from DOTA2 data. Game avatars are called heroes in DOTA2.

Application - Similarity Search

One direct downstream application utilizing GAE’s game avatar vectors is similarity search. It can help players, both starters or pros, to expand their hero pools by recommending heroes similar to what they are already familiar with or good at. For example, given input hero Clinkz, the top three heroes GAE returns are Weaver, Riki and Mirana. After examining the results, the three seasoned DOTA2 players all agreed that the top three heroes are very similar to Clinkz, as they are all Agility Carry heroes with low hit points, great escape capability, and sharing a stealthy play style.

Application - Personalized Recommendation

Kim et al. (Kim et al. 2016) suggested that the ideal game avatar to maximize the winning chance fit players’ personal expertise and team congruency in parallel, guided by which GAE could be used for a personalized avatar pick recommendation system. We select a real match played by one of our DOTA2 players for illustration although the real implementation and verification of this idea requires more work in the future.

In a ranked match, the player is the last to pick a hero, when his team have picked Puck, Ember Spirit, Lion, Necrophos, and the opposite team picked Silencer, Pudge, Sand King, Juggernaut, Anti-Mage. Given 30 seconds to make the pick, he wants to prioritize the hero selection that synergizes with his team and opposes the other team. Using Eqn. 3 to search the hero that maximizes the winning probability, GAE returns the top recommendation, Ursa. However, the player has not played Ursa before, thus are less confident about playing it. Based on the similarity search on the learned game avatar embeddings, GAE returns a list of heroes similar to Ursa, top 3 being Troll Warlord, Sven and Juggernaut. Finally, the player decides to go for Sven since that is the hero he is experienced with and Sven is also one of the top 5 heroes identified with best overall synergy and opposition besides Ursa.

Analyzing the above example, all the three DOTA2 players strongly agreed that Ursa is a very suitable choice given that this player’s team lacks burst physical damage. In addition, they had different extra interpretations on the Ursa pick. For example, one player identified that Ursa could help the player finish the game early, disallowing the opposing team to elongate the game when Anti-mage will show his max advantage as a late game Carry. Another player recognized that Ursa could increase team fights capability since Ursa is a Tank Carry hero who is durable in fights. All the three players agreed that Sven is similar to Ursa, as both heroes output high burst physical damage. They also proposed that GAE recommendation can be used differently according to personal prioritization. For example, some players who strongly prefer skill familiarity can first use GAE to list their familiar heroes then run synergy and opposition search.

As a summary, GAE provides an interface to perform queries of similar, synergy and opposition simultaneously. These capabilities can then be incorporated into downstream applications, giving users a white-box tool to help them better understand the game and make better in-game choices that maximize the winning chance.

Conclusions, Limitations and Future Works

Modeling synergy and opposition relationships between game avatars is an important task that helps players understand the game and make better decisions in forming effective teams. To tackle this task, our proposed embedding-based method models synergy and opposition relationships with game avatars encoded as vector representation. Our quantitative and qualitative analyses show that GAE is able to capture pairwise synergy and opposition relationships between game avatars that are sensible to human players. Moreover, the learned game avatar embeddings effectively capture important characteristics of game avatars because similarity search based on the game avatar embeddings also highly correlate with human ratings. Our model opens new doors to many downstream tasks, such as similarity search on game avatars and personalized avatar recommendation.

There are some future directions that we will pursue next. First, we want to study the extension of GAE in capturing higher-order relationships that involve more than two avatars, as well as study the trade-offs between its performance improvement and computation overhead incurred. Second, we are currently limited to access to sensitive human player information. In the future, we hope to collect
match data with richer player information and model player and game avatar embeddings within the same model.

References

[Agarwala and Pearce 2014] Agarwala, A., and Pearce, M. 2014. Learning dota 2 team compositions. Technical report, tech. rep., Stanford University.

[Anagnostopoulos et al. 2012] Anagnostopoulos, A.; Becchetti, L.; Castillo, C.; Gionis, A.; and Leonardi, S. 2012. Online team formation in social networks. In Proceedings of the 21st international conference on World Wide Web, 839–848. ACM.

[Bhattacharya and Sabik] Bhattacharya, R., and Sabik, A. Data-driven recommendation systems for multiplayer online battle arenas.

[Chen et al. 2016] Chen, Z.; Sun, Y.; Seif El-Nasr, M.; and Nguyen, T.-H. D. 2016. Player skill decomposition in multiplayer online battle arenas. In Meaningful Play.

[Duchi, Hazan, and Singer 2011] Duchi, J.; Hazan, E.; and Singer, Y. 2011. Adaptive subgradient methods for online learning and stochastic optimization. Journal of Machine Learning Research 12(Jul):2121–2159.

[Friedman 2001] Friedman, J. H. 2001. Greedy function approximation: a gradient boosting machine. Annals of statistics 1189–1232.

[Jolliffe 2002] Jolliffe, I. 2002. Principal component analysis. Wiley Online Library.

[Kim et al. 2016] Kim, J.; Keegan, B. C.; Park, S.; and Oh, A. 2016. The proficiency-congruency dilemma: Virtual team design and performance in multiplayer online games. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, 4351–4365. ACM.

[Kittur 2010] Kittur, A. 2010. Crowdsourcing, collaboration and creativity. ACM Crossroads 17(2):22–26.

[Kolda and Bader 2009] Kolda, T. G., and Bader, B. W. 2009. Tensor decompositions and applications. SIAM review 51(3):455–500.

[Koren, Bell, and Volinsky 2009] Koren, Y.; Bell, R.; and Volinsky, C. 2009. Matrix factorization techniques for recommender systems. Computer (8):30–37.

[Lappas, Liu, and Terzi 2009] Lappas, T.; Liu, K.; and Terzi, E. 2009. Finding a team of experts in social networks. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining, 467–476. ACM.

[Liemhetcharat and Veloso 2012] Liemhetcharat, S., and Veloso, M. 2012. Modeling and learning synergy for team formation with heterogeneous agents. In Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems-Volume 1, 365–374. International Foundation for Autonomous Agents and Multiagent Systems.

[Maas et al. 2011] Maas, A. L.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning word vectors for sentiment analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, 142–150. Association for Computational Linguistics.

[Maaten and Hinton 2008] Maaten, L. v. d., and Hinton, G. 2008. Visualizing data using t-sne. Journal of Machine Learning Research 9(Nov):2579–2605.

[Mikolov et al. 2013] Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, 3111–3119.

[Minotti 2016] Minotti, M. 2016. Comparing MOBAs: League of Legends vs. Dota 2 vs. Smite vs. Heroes of the Storm. http://venturebeat.com/2015/07/15/comparing-mobas-league-of-legends-vs-dota-2-vs-smite-vs-heroes-of-the-storm/. Online; accessed May, 2016.

[Neidhardt, Huang, and Contractor 2015] Neidhardt, J.; Huang, Y.; and Contractor, N. 2015. Team vs. team: Success factors in a multiplayer online battle arena game. In Academy of Management Proceedings, volume 2015, 18725. Academy of Management.

[Nguyen, Chen, and El-Nasr 2015] Nguyen, T.-H. D.; Chen, Z.; and El-Nasr, M. S. 2015. Analytics-based AI Techniques for Better Gaming Experience, volume 2 of Game AI Pro. Boca Raton, Florida: CRC Press.

[Pobiedina et al. 2013a] Pobiedina, N.; Neidhardt, J.; Calatrava Moreno, M. d. C.; Grad-Gyenge, L.; and Werthner, H. 2013a. On Successful Team Formation: Statistical Analysis of a Multiplayer Online Game. In 2013 IEEE 15th Conference on Business Informatics, 55–62. IEEE.

[Pobiedina et al. 2013b] Pobiedina, N.; Neidhardt, J.; Calatrava Moreno, M. d. C.; and Werthner, H. 2013b. Ranking factors of team success. In Proceedings of the 22nd international conference on World Wide Web companion, 1185–1194. International World Wide Web Conferences Steering Committee.

[Rahman et al. 2015] Rahman, H.; Thirumuruganathan, S.; Roy, S. B.; Amer-Yahia, S.; and Das, G. 2015. Worker skill estimation in team-based tasks. Proceedings of the VLDB Endowment 8(11):1142–1153.

[Rendle 2010] Rendle, S. 2010. Factorization machines. In 2010 IEEE International Conference on Data Mining, 995–1000. IEEE.

[Roy et al. 2015] Roy, S. B.; Lykourentzou, I.; Thirumuruganathan, S.; Amer-Yahia, S.; and Das, G. 2015. Task assignment optimization in knowledge-intensive crowdsourcing. The VLDB Journal 24(4):467–491.

[Semenov et al. 2016] Semenov, A.; Romov, P.; Korolev, S.; Yashkov, D.; and Neklyudov, K. 2016. Performance of Machine Learning Algorithms in Predicting Game Outcome from Drafts in Dota 2. In Analysis of Images, Social Networks and Texts. Springer. 26–37.

[Suznjevic, Matijasevic, and Konfic 2015] Suznjevic, M.; Matijasevic, M.; and Konfic, J. 2015. Application context based algorithm for player skill evaluation in MOBA games.
In *Network and Systems Support for Games (NetGames)*, 2015 International Workshop on, 1–6. IEEE.

[Tassi 2016] Tassi, P. 2016. Riot’s ‘League of Legends’ Reveals Astonishing 27 Million Daily Players, 67 Million Monthly. [http://www.forbes.com/sites/insertcoin/2014/01/27/riots-league-of-legends-reveals-astonishing-27-million-daily-players-67-million-monthly/#26ff8e543511](http://www.forbes.com/sites/insertcoin/2014/01/27/riots-league-of-legends-reveals-astonishing-27-million-daily-players-67-million-monthly/#26ff8e543511) Online; accessed May, 2016.

[Yang, Qin, and Lei 2016] Yang, Y.; Qin, T.; and Lei, Y.-H. 2016. Real-time esports match result prediction. *arXiv preprint arXiv:1701.03162*. 

