

Improved Dota2 Lineup Recommendation Model Based on a Bidirectional LSTM

Lei Zhang, Chenbo Xu, Yihua Gao, Yi Han*, Xiaojiang Du, and Zhihong Tian*

Abstract: In recent years, e-sports has rapidly developed, and the industry has produced large amounts of data with specifications, and these data are easily to be obtained. Due to the above characteristics, data mining and deep learning methods can be used to guide players and develop appropriate strategies to win games. As one of the world's most famous e-sports events, Dota2 has a large audience base and a good game system. A victory in a game is often associated with a hero's match, and players are often unable to pick the best lineup to compete. To solve this problem, in this paper, we present an improved bidirectional Long Short-Term Memory (LSTM) neural network model for Dota2 lineup recommendations. The model uses the Continuous Bag Of Words (CBOW) model in the Word2vec model to generate hero vectors. The CBOW model can predict the context of a word in a sentence. Accordingly, a word is transformed into a hero, a sentence into a lineup, and a word vector into a hero vector, the model applied in this article recommends the last hero according to the first four heroes selected first, thereby solving a series of recommendation problems.

Key words: Word2vec; multiplayer online battle arena games; Continuous Bag Of Words (CBOW) model; Long Short-Term Memory (LSTM)

1 Introduction

In recent years, with the development of computer technology, the operation mode and protocol of

- Lei Zhang and Yihua Gao are with the Henan Key Laboratory of Big Data Analysis and Processing, Kaifeng 457004, China and also with Institute of Data and Knowledge Engineering, Henan University, Kaifeng 475004, China. E-mail: zhanglei@henu.edu.cn; gaoyihua.ding@foxmail.com.
- Chenbo Xu is with Institute of Data and Knowledge Engineering, Henan University, Kaifeng 475004, China and also with National Internet Emergency Center, Zhengzhou 450000, China. E-mail: xcb756622595@outlook.com.
- Xiaojiang Du is with Department of Computer and Information Sciences, Temple University, Philadelphia, PA 19122-6008, USA. E-mail: dxj@ieee.org.
- Yi Han and Zhihong Tian are with Cyberspace Institute of Advanced Technology, Guangzhou University, Guangzhou 510006, China. E-mail: hanyi@gzhu.edu.cn; tianzhihong@gzhu.edu.cn.

* To whom correspondence should be addressed.

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computer are constantly changing^[1-3]. The e-sports industry is moving toward the direction of professional sports, where data analysis plays an extremely important role^[4,5]. In traditional competitive sports, the construction of a lineup is essential. The world's top competitive sports of today have professional data analysis teams that perform data collection, processing, and analysis tasks to help their teams win competitions^[6-9]. In a computer operating environment, real time is very important and a multiplayer competitive control has a strong real time^[10,11]. The e-sports industry is different from the traditional sports industry, and the data it produces are accessible, objective, and real-time. Considering the above characteristics, data mining and deep learning methods can be used to assist players in developing the best strategies to help them win games.

Dota2, one of the most famous e-sports programs in the world, has a large audience base and a good game system. The main goal of the game is to destroy the ancient relics of the enemies' high ground^[12,13]. Over

time, gold coins will be earned for killing creeps and enemy heroes and destroying buildings^[14–16]. Dota2 has complex game mechanics and a wide variety of heroes. The heroes in Dota2 are defined by the roles that they are suited to play as a combination of their attributes, abilities, and items, and the ways that these shape the game. Hence, the competition in the game is highly entertaining and the winner cannot be easily predicted. In the Dota2 competition, the selection of heroes has a large restraint relationship, and it is difficult to choose the best winning team by traditional methods^[17]. Therefore, a new method is urgently needed to solve this problem. The authors in Ref. [18] proposed to use data mining and machine learning methods to improve players’ skills and help them make strategies. The authors in Ref. [19] proposed the use of data mining and machine learning methods to improve players’ skills and help them make strategies. But due to the complex relationship between heroes’ mutual collocation and restraints, neither method has achieved the expected good prediction effect.

In recent years, artificial intelligence has made tremendous development, and at the same time, deep learning technology^[20,21], as an important technology in artificial intelligence, is increasingly sought after^[22–24]. Word2vec is essentially a shallow neural network model. This model can be used in large datasets and high-dimensional dictionaries^[25–27]. We use an improved Bidirectional Long Short-Term Memory (Bi-LSTM) model to solve the problem of the best lineup recommendation in Dota2 games.

2 Definition of the Relationship Between Heroes

Dota2’s best lineup can be understood as the relationship between heroes in Dota2, which can be divided into the relationship between hero matching and restraint. In this section, the hero vector method is adopted to solve the matching problem between heroes, and the restraint relationship index calculated by log5 formula is adopted to solve the restraint relationship problem between heroes.

2.1 Definition of collocation relationships in Dota2

In this study, we use the Continuous Bag Of Words (CBOW) model to solve the matching relationship problem between heroes. The CBOW model in Word2vec can predict a word based on the context of the word in the sentence. This model can get the correlation between different words in a sentence. Therefore, we

build a model to treat different heroes as different words, a hero lineup as a sentence composed of words, and a hero vector generated by the model. Seen as word vector, the correlation between words is expressed as the correlation between heroes. The structure of CBOW model is shown in Fig. 1.

In the hero vector model, we define model parameters in this way:

$C_1–C_4$: The input hero vector, and the vector is represented as one-hot vector. Data dimension is $d \times N$, where d is the hero vector dimension, and N is the hidden unit dimension.

W_1 : Input hero weight matrix, and data dimension is $d \times N$.

W_2 : Output hero weight matrix, and data dimension is $N \times d$.

H : Output hero vector x , and data dimension is $2d$.

During the training of the word vector, the distance between the word vectors converted from words with similar meaning should also be close. For example, for “emperor” and “king”, the distance between the word vectors is very small. For the hero vector, “Rubick” (a Dota2 support hero) and “Crystal Maiden” (another Dota2 support hero) are positioned as “Support”, so the distance between them will be small when the hero vector is used.

2.2 Definition of restraint relationship in Dota2

Restraint relationships generally refer to unequal results under fair conditions when things encounter each other due to their different attributes.

The heroic restraint relationship in Dota2 is especially important when matching a lineup. The restraint relationship in Dota2 can be defined as the ability to affect the enemy hero alignment, development, out loading, late output environment, and group combat

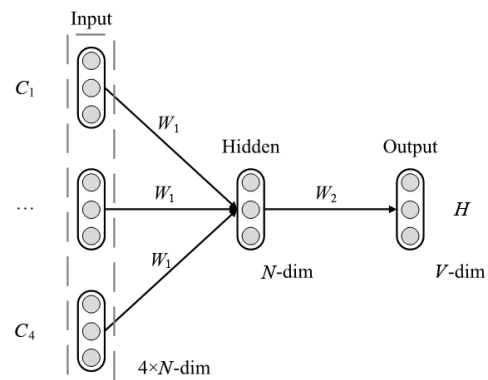


Fig. 1 CBOW model structure.

location at a minimal cost (such as a small skill). It is divided into two aspects:

(1) The support hero restrains the enemy’s core hero. This situation often occurs in the first half of the Dota2 game.

(2) The core hero restrains the enemy’s core hero. This situation mainly occurs in the late stage of the Dota2 game.

These restraint relationships are often derived from the experience of Dota2 players after playing many games and are difficult to objectively quantify and evaluate, so we introduce the log5 formula to quantify this relationship.

log5 formula uses the concept of two teams to estimate the expected winning probability of the two teams (Teams A and B) against each other according to their overall winning probability. In this study, we locate this expected winning probability into the restraint relationship index between heroes:

$$p_{A,B} = \frac{p_A - p_A p_B}{p_A + p_B - 2p_A p_B},$$

where $p_{A,B}$ refers to the probability of winning for Team A against Team B, p_A is the global win rate defined as the probability that Team A appears and wins in all games, and p_B is the global win rate defined as the probability

that Team B appears and wins in all games.

The calculated probability refers to the expected probability of the victory of one team against another. If a team with a high average wins against a team with a low average, then there is a strong restraint relationship between the two teams because a team with a high winning average has a high expectation of winning against a team with a low winning average. The larger difference of the actual win rate between the two teams indicates a more obvious restraint relationship between them. Therefore, in this study, the expected probability of winning among heroes calculated by log5 formula is defined as the hero restraint relationship index.

For example, the global win rate of the “Legion Commander” hero is less than 50%, which proves that the probability of winning this hero in the competition is low. Figure 2 shows the global win rate for “Legion Commander” hero and all heroes. Figure 3 shows the global win rate for “Anti-Mage” hero and all heroes. The global win rate of “Anti-Mage” hero is higher than 50%, which proves that the probability of winning this hero in the competition is higher. Then from the global win data, when the two opponents have two heroes, “Legion Commander” and “Anti-Mage”, “Anti-Mage” has a higher probability of winning. However, the real

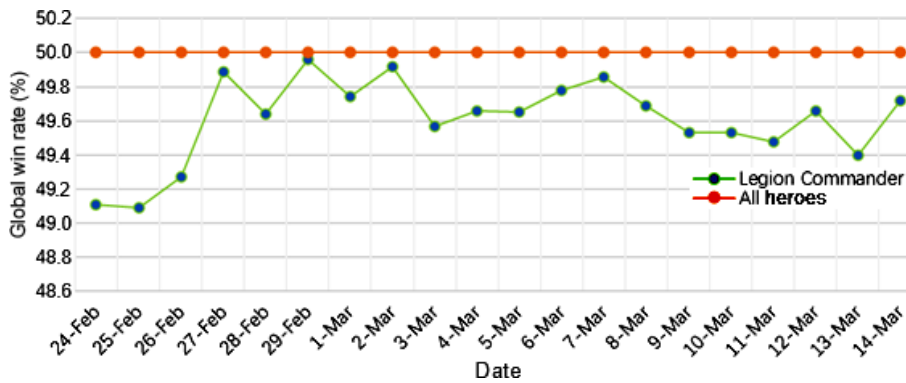


Fig. 2 Global win rate for “Legion Commander” hero and all heroes.

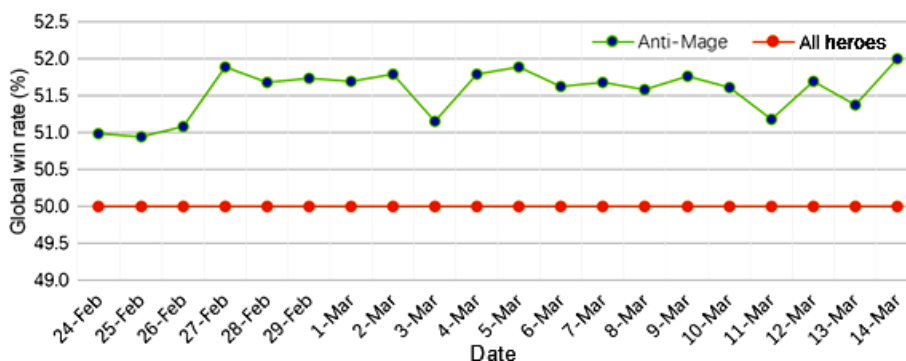


Fig. 3 Global win rate for “Anti-Mage” hero and all heroes.

match data show that “Legion Commander” and “Anti-Mage” have a greater win rate in the duel^[28,29]. The data sources refer to the Dotabuff website, as shown in Fig. 4.

The restraint relationship matrix is defined as follows:

$$R = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n,1} & r_{n,2} & \cdots & r_{n,n} \end{bmatrix}.$$

Each element in matrix R is defined as the restraint index between different heroes. $r_{1,2}$ is the forbearance index of Hero 1 against Hero 2. In this matrix, $r_{1,1}$, $r_{2,2}$, and $r_{n,n}$ are recorded as 0.

3 Lineup Recommendation Model Design

Bi-LSTM is one of the variants of LSTM. The main structure of the Bi-LSTM constructed in this study is as follows: an input layer, a hidden layer, a splicing layer, a full-connection layer, and an output layer. Dota2’s lineup recommendation questions can be translated into classic classification questions, so this model uses the softmax function as the output function of the output layer. The hidden layers in the model are all used in LSTM units. The model structure is shown in Fig. 5.

The basic steps for building this model are shown below:

(1) Input layer: Dota2 has 116 different heroes so far, and the hero vector definition for each hero has been given in the previous article. As this model is used to

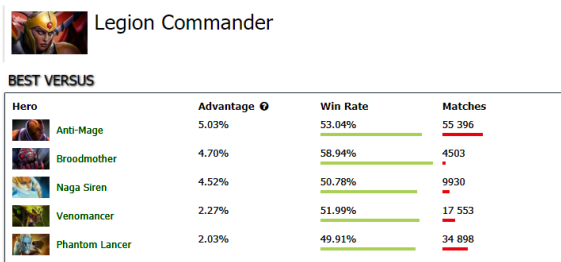


Fig. 4 Win rate of “Legion Commander” against “Anti-Mage”.

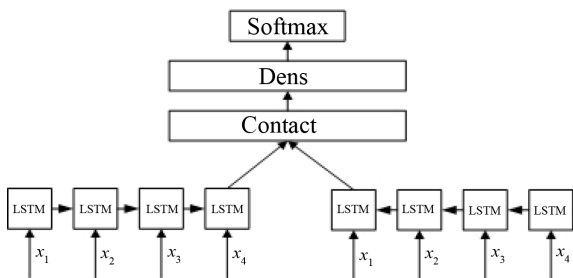


Fig. 5 Flow chart for improved LSTM neural network Dota2 of success rate prediction.

recommend a Dota2 lineup, this experiment uses the hero vector as one of the model input data. In the model, x_i represents the input data of the first four heroes selected by the opposing team in a Dota2 match, c_i represents the hero vector of each hero, and r_i represents the hero’s restraint relationship data. The hero vector dimension is set to 20, and each hero restraint relationship data dimension is set to 1. The other team has a total of five heroes, so the total hero restraint relationship dimension is 5. The input layer’s data format is derived as follows:

$$x_i = c_i + r_i,$$

$$r_i = r_{i,1} + r_{i,2} + r_{i,3} + r_{i,4} + r_{i,5}.$$

(2) Output layer: The main function of this model is to recommend a lineup in a Dota2 match. The output layer is the 5th hero recommended by the model and it uses the sigmoid function to classify the final results. The output dimension is set to 116.

(3) Bi-LSTM layer: This layer uses two LSTM units to obtain information from two different directions. The activation function of LSTM memory cells is set to the sigmoid and tanh functions. Finally, the activation function from the hidden layer to the output layer is classified using the softmax function.

(4) Concat layer: This model uses a splicing layer to stitch the output of two LSTMs into one output. The LSTM cell dimension is 16, and the stitching layer consists of two LSTM unit stitchings, so the splicing layer’s total data dimension is 32.

(5) Full-connection layer: This model uses a full-connection layer to process the output of the stitching layer. The output-layer dimension is 116 and the splicing-layer dimension is 32, so the full-connection layer data dimension is set to 96 to perform transition between the two layers.

(6) Training parameters: This model uses the cross-entropy loss function to obtain the output error of the model. The whole model is converged using the random gradient descent method (stochastic gradient descent).

(7) Adjust neural network-related parameters: To obtain the best prediction, the learning rate of the neural network model, including the number of hidden layer neurons, epoch, batch, and size, is constantly adjusted.

4 Data Preprocessing and Parameter Settings

This section introduces the dataset acquisition of the experiment, preprocessing method of the data, experiment of the lineup recommendation model, and evaluation method.

4.1 Experimental environment settings and datasets

(1) Experimental environment settings

This model uses the Python-based Keras deep learning library, which uses TensorFlow as the model's backend. The experimental hardware of this model is shown in Table 1.

(2) Dataset

The data in this section are from a foreign website that specializes in providing Dota2 data services OpenDota^[30]. This experiment collected data from 54 218 matches from May to September 2019. During this period, Dota2 has not been updated in a large version, so the positioning of the hero and the probability of winning will not change significantly. The website returns game data through Json format data and parses the original data to get a lineup data table. The specific content of the data is shown in Table 2.

4.2 Data preprocessing

The hero lineup data need to be preprocessed before the model can be trained. The preprocessing process performs integrity, repetitive, and internal missing checks of the collected game data. Preprocessed data include five heroes of radiant team, five heroes of dire team, and the results of the match.

4.3 Hero vector and dimension display

In Dota2, heroes have distinct role positioning characteristics, which can be classified into Carry, Solo, Offline, and Support according to their own attributes. The hero vector trained in this experiment can be used to show the relationship between heroes and as the input data of the model. An example of a trained hero vector is shown below:

Table 1 Hardware parameter configuration of dota2 success rate prediction model.

Operating system	Memory	CPU
Win10	16 GB	I7-7700
Graphic processing unit	Vedio memory	
Nvidia Gtx1070	8 GB	

Table 2 Match lineup data sheet.

Field name	Parameter format	Entrysaved
match_id	int	Game ID
match_seq_num	int	Game number
radiant_win	int	Tianhui side victory
start_time	int	Start time
duration	int	Time of duration
radiant_team	string	Tianhui side lineup
dire_team	string	Nightmare side lineup

Juggernaut

[−0.235 375 651, 0.394 725 472, 0.859 726 156,
−0.173 908 635],

Shadow Fiend

[−0.827 485 729, 0.846 279 259, −0.637 480 141,
0.846 265 175].

In this experiment, word vectors are trained with Word2vec tools. The trial scores seven training sessions, and three test sets are randomly divided into the obtained match records. By building the hero vector model, the preprocessed data are trained on the model to derive the corresponding hero vector weight. The hero vector is visualized by the Principal Component Analysis (PCA) dimension reduction method, followed by the calculation of the hero correlation of four differently positioned heroes in Dota2 and finally, an evaluation of the recommended effect based on the winning probability of the model's recommended lineup on the test set.

The specific parameters of the hero vector model are shown in Table 3.

The model-related parameters are explained below:

(1) The model output hero vector is the dataset assigned to the heroes.

(2) The CBOW model's sg parameter is set to 0.

(3) The model sets the hero vector dimension to 20.

(4) The window is the maximum distance between the current hero and the target hero in a match, considering that one team in the Dota2 match is made up of five heroes. Therefore, this parameter is set to 5 in this experiment.

(5) In this experiment, the min count is set to 5.

(6) A negative sample signifies whether the negative sampling optimization mechanism is adopted to adjust parameters. The default setting of this parameter is adopted in this experiment.

(7) In this experiment, hs parameters are set by default.

(8) The number of workers is set to 10 to accelerate the model training.

Table 3 Parameters of the hero vector model.

Parameter	Parameter explanation	Value
Heroes	Hero data	
sg	Mode selection	0
Size	Dimension	20
Window	Window distance	5
min count	Low-frequency word filtering	5
Negative sample	Negative sampling mechanism	Default
hs	Level softmax	Default
Workers	Parallelization	10

4.4 Hyperparameter settings of the model

The specific hyperparameters of the improved Dota2's win rate prediction model are shown in Table 4.

Considering the number of heroes in Dota2 and the experimental effect, this model sets the dimension of hero vector to 20 and the dimension of restraint relation between heroes to 1. The splicing layer is divided into two LSTM hidden units, so the dimension is 32. The output dimension of this model is 116, so setting the data dimension of the full-connection layer to 96 can play a good role in the transition.

5 Experiment and Result Analysis

This section introduces the experiment and result analysis of the improved LSTM lineup recommendation model, mainly including the experimental evaluation standard, simulation experiment, result of real data, and experiment result of the actual combat comparison.

5.1 Assessment criteria

In this study, offline experiments and user surveys are selected to verify the recommendation effect of the model from the objective and subjective aspects.

(1) Objective evaluation criteria: In this experiment, the trained two-way LSTM lineup recommendation model is used for the hero lineup recommendation. The test set selects the preprocessed data of actual wins. By selecting the first four heroes of the winner as input and putting them into the lineup recommendation model to output five recommended heroes, finally, the heroes recommended by the model and the top four heroes are composed into five different recommended lineups; then each of the original lineups based on the recommended lineup is analyzed. Win rates in the dataset are averaged, and the accuracy of the recommended lineup is used as the evaluation index result.

(2) Subjective evaluation criteria: At the current stage of the Chinese online environment, the best

Table 4 Hyperparameter setting values of the win rate prediction model.

Hyperparameter	Set value
Hero vector dimension	20
LSTM hidden unit dimension	16
Learning rate	0.01
Batch_size	100
Hero suppression relational data dimension	1
Mosaic layer data dimension	32
Full-connection layer data dimension	96
Output dimension	116

recommendation for the Dota2 match lineup is the Dota2 assistant officially launched by Dota2. This assistant can provide players with lineup recommendation support before Dota2 matches. In this experiment, five players with a ladder score of 2600–4900 are actually selected for the ladder ranking competition as a subjective evaluation. The players in this score segment account for about 60% of Dota2 players, which is in line with the level of public players. The five players will compete in 10 personal ladder rankings. After all four players have selected their heroes, they will select the last supplementary hero according to the Dota2Plus assistant and the hero recommended by this model. Finally, we observe whether the recommended line-up wins the ladder game.

5.2 Simulation experiment and results of real data

The objective recommendation results of the model are shown in Table 5. Table 5 shows that the accuracy rate of prediction roughly decreases with the order of recommended heroes. The hero with the recommended order of 1 is brought into the original game dataset to achieve a prediction accuracy rate of 78.32%. The accuracy rate of recommended Hero 3 in Table 5 is higher than that of recommended Hero 2. The main reason for this situation is that not every Dota2 match has a regular hero role collocation (one carry, one solo, one offline, and two supports), so it is difficult for this model to predict these ambiguous role collocation matches. The average accuracy rate of the selected five recommended heroes is 67.74%.

5.3 Actual game of the experimental results

The subjective recommendation result of the model selects five players' real ladder competition data. Players select the Dota2Plus assistant or the heroes recommended by this model to form a lineup for the ladder competition, and finally, observe whether they win and calculate the model recommendation accuracy rate.

The data of model subjective recommendation results are shown in Table 6. We can know that the average

Table 5 Hero recommendation evaluation index.

Recommend order of hero	Accuracy rate (%)
Hero 1	78.32
Hero 2	70.15
Hero 3	72.11
Hero 4	67.48
Hero 5	50.63

Table 6 Hero recommendation evaluation index table.

Player serial number	Match making rating score	Dota2Plus recommended accuracy rate (%)	Recommended accuracy rate of this model (%)
Player 1	3010	40	60
Player 2	4970	70	60
Player 3	2540	40	50
Player 4	3810	30	40
Player 5	3460	60	50

accuracy rate of the recommended lineup of the Dota2Plus assistant is 48%, and the accuracy rate of the recommended lineup has a large fluctuation. The average accuracy rate of the recommended lineup of this model is 52%, and the fluctuation range is small. By analyzing specific matches, we can find that Dota2Plus assistant often recommends heroes with high average win rate but more difficult operation, such as Meep, Brewmaster, and Arc Warden. If the player does not master the hero's gameplay, it will be difficult to win in the game.

6 Conclusion

This article proposes an improved Bi-LSTM model for recommendation of Dota2 lineup. The model uses the CBOW model in the Word2vec model to generate hero vectors. This model can predict and recommend the 5th hero based on the first four heroes in the lineup. The design verification experiments show that the model can distinguish the heroes with different roles. Finally, the heroes recommended by the model and the top four heroes in the original lineup form a new recommended lineup to verify the accuracy of the recommendation. Through training of 54 218 match datasets, experimental results show that the prediction accuracy rate of the new recommended lineup composed of recommended Hero 1 is 78.32%. Based on the results of above experiments, the average accuracy rate of five recommended heroes is 67.74%.

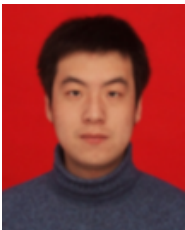
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Lei Zhang received the PhD degree from Harbin Institute of Technology in 2015. He is an associate professor at Henan University, Kaifeng, China. His research interests include deep learning, data mining, and information security.



Chenbo Xu received the bachelor's degree in computer science and technology from Henan University in 2017, and the master's degree in computer technology from Henan University in 2019. His research interest is machine learning.



Yihua Gao received the bachelor's degree in computer science and technology from Henan University in 2018. She is a postgraduate student at Computer and Information Engineering College, Henan University. Her research interests include machine learning, blockchain, and remote sensing.



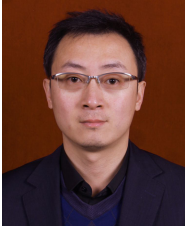
Xiaojiang Du is currently a tenured professor at the Department of Computer and Information Sciences, Temple University, Philadelphia, PA, USA. He has authored over 260 journal and conference papers, and a book (Springer). His research interests are wireless communications, wireless networks, security, and systems.

He has been awarded over 5 million US dollars research grants from the US National Science Foundation, Army Research Office, Air Force Research Laboratory, NASA, the State of Pennsylvania, and Amazon. He is a life member of ACM. He serves on the editorial boards of three international journals. He is a fellow of the IEEE.



Yi Han is a professor at Institute of Cybersecurity, Guangzhou University. He received the BEng, MEng, and PhD degrees from National University of Defense Technology in 2004, 2006, and 2011, respectively. His research interests can be summarized as developing effective and efficient data analysis techniques for novel data intensive applications. Particularly, he is currently interested in various techniques of data mining, web search, information retrieval, data warehousing, online analytical

processing, and database systems as well as their applications in social networks and business. His research has been supported in part by the National Natural Science Foundation of China, National High-Tech R&D Program of China (863 Program), National Basic Research Program of China (973 Program), and Postdoctoral Science Foundation of China.



Zhihong Tian received the BS, MS, and PhD degrees in computer science and technology from Harbin Institute of Technology in 2001, 2003, and 2006, respectively. He is a professor and dean at Cyber Institute of Advanced Technology, Guangzhou University, Guangzhou, China. He is honored as “Pearl River Scholar” in

Guangdong Province. His research interests include cyber range, intrusion detection and data fusion, proactive real-time protection, and computer forensics and recovery. He has authored over 180 journal and conference papers in such areas. As a project leader, he has managed a number of projects including the National Natural Science Foundation of China, National Key Research and Development Plan, the 863 Program, the 973 Program, and the Pre-Research Project from the General Armament Department.