

# Friend Ranking in Online Games via Pre-training Edge Transformers

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## ABSTRACT

Friend recall is an important way to improve Daily Active Users (DAU) in online games. The problem is to generate a proper lost friend ranking list essentially. Traditional friend recall methods focus on rules like friend intimacy or training a classifier for predicting lost players' return probability, but ignore feature information of (active) players and historical friend recall events. In this work, we treat friend recall as a link prediction problem and explore several link prediction methods which can use features of both active and lost players, as well as historical events. Furthermore, we propose a novel Edge Transformer model and pre-train the model via masked auto-encoders. Our method achieves state-of-the-art results in the offline experiments and online A/B Tests of three Tencent games.

## CCS CONCEPTS

• **Computing methodologies** → **Neural networks**; • **Information systems** → **Social networks**.

## KEYWORDS

Friend Ranking, Link Prediction, Transformer, Pre-training

### ACM Reference Format:

Liang Yao, Jiazhen Peng, Shenggong Ji, Qiang Liu, Hongyun Cai, Feng He, Xu Cheng. 2023. Friend Ranking in Online Games via Pre-training Edge Transformers. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '23)*, July 23–27, 2023, Taipei, Taiwan, China. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/XXXXXX.XXXXXX>

## 1 INTRODUCTION

Online gaming is one of the largest industries on the Internet, generating tens of billions of dollars in revenues annually. Tencent is China's largest Internet company and the largest game service provider. It has more than 800 million gaming users<sup>1</sup>. The payment revenue from games accounts for 31% of Tencent's overall revenue<sup>2</sup>.

<sup>1</sup><https://www.tencent.com/en-us/articles/2200928.html>

<sup>2</sup><https://www.statista.com/statistics/527280/tencent-annual-online-games-revenue/>

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*SIGIR'23, July 23–27, 2023, Taipei, Taiwan, China.*

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ACM ISBN 978-1-4503-9408-6/23/07...\$15.00  
<https://doi.org/10.1145/XXXXXX.XXXXXX>

In online games, one critical problem is how to design strategies to keep players playing. Friend recall is an essential way for the purpose. It means letting active players in the game invite their lost friends back. An illustration of friend recall is in Figure 1. An active player X in the game can see a number of events. In some events, the player can earn awards (e.g., coins, hero skins) by inviting his/her lost friend. X can click a photo of his friend Y in the recommendation list, then X will send an instant message to the clicked friend. The friend Y may return to the game after seeing the message. If Y is back, X will earn more rewards.

The friend recall problem is to generate a proper lost friend list essentially. There are two main traditional methods in our practice. One is to sort the lost friends by intimacy scores. A lost friend Y with a higher intimacy score will be listed before another friend Z with a lower intimacy score. The intimacy score between player X and Y is calculated by summing the interaction activities in the game (e.g., giving a gift, or playing in the same room). The basic idea is that intimate friends are more likely to be invited, and an invited friend is more likely to be back. The second is training a classifier for predicting lost players' return probability. The method collects features of lost players and uses natural return activities as labels. If a lost player logs in the game without invitation, the label is positive, otherwise, negative. A lost player with a higher natural return probability will be given a higher rank. The idea is to give players who are more likely to be back more chances to be invited.

The above two methods have some major limitations: 1). The intimacy scores neglect both features of active and lost players, an active player may not be willing to invite, and a lost friend may not be willing to return. 2). The natural return classifier only uses features of lost players, but the features of active players are ignored. 3). Both methods could not utilize information from historical friend recall events. Historical events indicate which active players (with features before the event) invited their friends, and which lost players are invited and then returned.

In this work, we overcome the above limitations by treating friend recall as a link prediction problem. The problem is to predict the edge existing probability in a bipartite graph. The bipartite graph contains two kinds of nodes: active players and lost players. The edge is labeled as positive if an active player successfully invites a lost player back in a game event. We explore several popular link prediction and friend ranking models for the task. Furthermore, we propose a novel Edge Transformer model and pre-train the model via Masked Auto-Encoders (MAE). The proposed method outperforms existing models and the two traditional methods in both offline and online evaluation. The implementation of our proposed method is available at: [https://github.com/yao8839836/edge\\_mae](https://github.com/yao8839836/edge_mae). To summarize, our contributions are as follows:

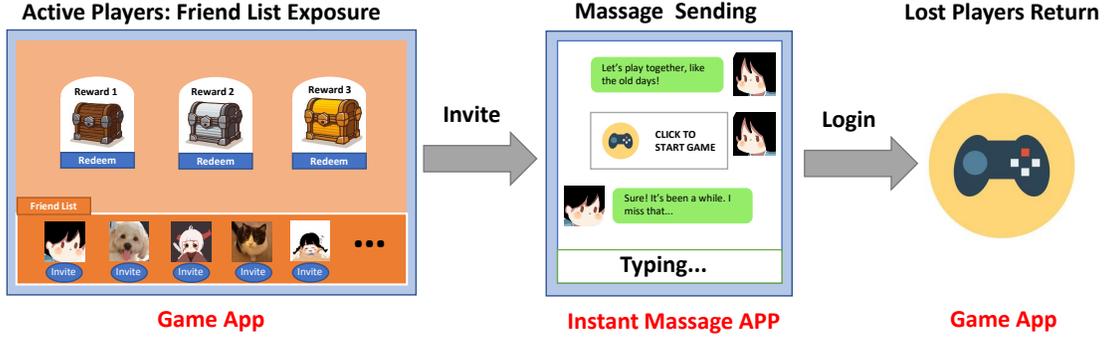


Figure 1: Illustrations of friend recall in online games. On the left, when an active player (say X) logs in the Game A, X can see a list of friends (in the bottom rectangle) who have been inactive in the game recently. X can click and invite them to return to the game and play with X together. In the middle, X invited a friend (say Y) in the friend list and sent Y a link to the game. On the right, Y saw the invitation and clicked the link, Y then returned to the game. The above process is a successful story, X may not invite any friend, and Y may not accept the invitation.

Table 1: Data Statistics.

Dataset	Game A	Game B
# labeled edges	6,396,834	11,982,659
# train edges	5,117,125	9,591,653
# val edges	1,279,709	2,391,006
# unlabeled edges	24,946,624	3,422,556,670
# active players features dim	80	25
# lost players features dim	80	26
# edge features dim	4	1

- To the best of our knowledge, this is the first study to systematically investigate the real-world friend recall problem.
- We propose a new Edge Transformer model and improve it by pre-training with masked auto-encoders and massive unlabeled edges. The model outperforms state-of-the-art link prediction models in our task.

## 2 DATA

We built our datasets from past events of Game A and Game B. The real game names are hidden for privacy reasons. In past events, an active player X who clicked at least one of his/her lost friends and X’s lost friends are collected as labeled edges and added to the training and validation dataset. If X clicked a lost friend Y, and Y was back, the edge is labeled as positive. If Y is not back, the edge is labeled as negative. All edges in the training and validation dataset without an invitation are also labeled as negative. For pre-training, we use massive unlabeled edges. All active players who did not invite any friends together with their lost friends are collected as unlabeled edges for pre-training. We construct node features, i.e., gaming activities and payment information, for two kinds of players and take intimacy scores as edge features. The statistics of the two datasets are listed in Table 1.

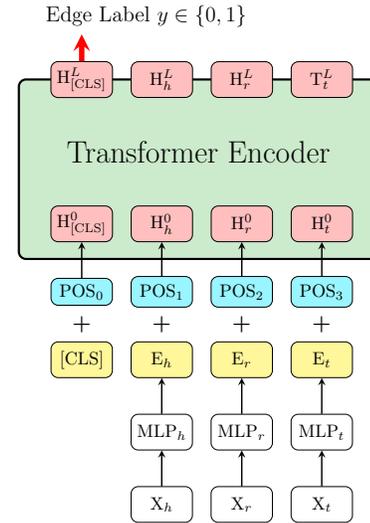
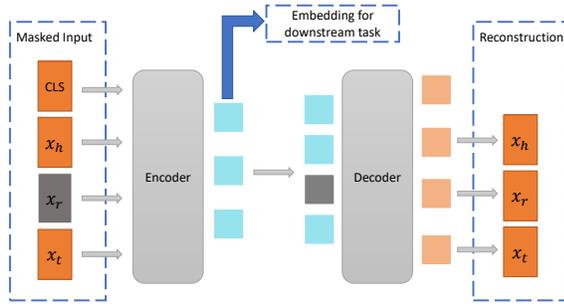


Figure 2: The proposed Edge Transformer model. For an edge, we linearly embed the head node feature  $X_h$ , edge feature  $X_r$ , and tail node feature  $X_t$  to the same dimension via three MLPs, then add position embeddings and feed the resulting vectors to a standard Transformer encoder. An extra learnable “classification token” is added to the first of the sequence to perform classification.

## 3 METHOD

Inspired by the Transformer [13] scaling successes in natural language processing (NLP) [3, 5] and computer vision (CV) [6], we experiment with applying a standard Transformer directly to edges, with the fewest possible modifications, as the scalable NLP and CV Transformer architectures and their implementations can be reused. We treat node and edge features as word tokens in NLP, and image patches in CV. We take the sequence of linear embeddings of these features as an input to a Transformer.



**Figure 3: The proposed Edge MAE model. During pre-training, a random subset of edge tokens (e.g., 1/3) is masked out. The encoder is performed on the subset of visible tokens. Masked tokens are introduced after the encoder, and the full set of encoded tokens and masked tokens are processed by a small decoder that reconstructs the original features of nodes or edges. After pre-training, the decoder is discarded and the encoder is applied to uncorrupted edges (full sets of tokens) for edge classification.**

An overview of the Edge Transformer model is depicted in Figure 2. The standard Transformer receives a 1D sequence of token embeddings as input. To handle edges, we linearly embed the head node feature  $X_h$  (for active players), edge feature  $X_r$  (intimacy scores), and tail node feature  $X_t$  (for lost players) to the same dimension via three multilayer perceptions (MLP). The Transformer uses latent vector size  $D$  through all of its layers, so we map the features to  $D$  dimensions. We refer to the output of these projections as the token embeddings.

Similar to BERT [5] and ViT [6]’s [CLS] token, we add a learnable embedding to the sequence of embedded tokens. Its state at the output of the Transformer encoder  $H_{[CLS]}^L$  serves as the edge representation for classification. Position embeddings  $POS_0$ ,  $POS_1$ ,  $POS_2$  and  $POS_3$  are added to the tokens embeddings to keep positional information. The resulting sequence of embedding vectors  $H_{[CLS]}^0$ ,  $H_h^0$ ,  $H_r^0$  and  $H_t^0$  is as input to the encoder. The details of the Transformer encoder are the same as in [13].

The Transformer encoder can be only trained on labeled edges, while massive unlabeled edges are not used. Inspired by MAE [7] in CV which pre-trains masked auto-encoders on unlabeled images, we propose to improve Edge Transformer with an Edge MAE model. The model is depicted in Figure 3. Following MAE, Edge MAE randomly masks a proportion of input tokens. The encoder of an Edge MAE is an Edge Transformer but only applied on unmasked tokens. All four edge tokens are the input to the Edge MAE decoder. The decoder is another series of Transformer blocks and is only used in pre-training to perform node/edge feature reconstruction tasks. The reconstruction target is to predict each feature value of mask tokens. The last layer of the decoder is a linear projection that maps the hidden vector (size  $D$ ) to the original feature dimension. Our loss function computes the mean squared error (MSE) between the reconstructed and original features. After pre-training, the parameters of the encoder are used as the initialization of the Edge Transformer model for edge classification fine-tuning.

## 4 EVALUATION

In this section, we evaluate our Edge Transformer and Edge MAE in two settings. Specifically, we want to determine:

- Can our model achieve satisfactory ranking performance on validation data?
- Can our model outperform traditional methods in online A/B tests?

### 4.1 Baselines

We compare our proposed method with the two traditional methods Intimacy scores and XGBoost [4] for lost players, as well as several popular link prediction models: TranS [17], ConvKB [9], TransE [2], DistMult [16] and Bilinear<sup>3</sup>. We also perform MLP and XGB on the concatenation of three features  $X_h$ ,  $X_r$  and  $X_t$  and we call them Edge MLP and Edge XGB. Additionally, we compare our method with the pairwise ranking in a recent friend ranking method GraFRank [12].

### 4.2 Parameter Settings

For Edge Transformer and Edge MAE, we set the latent vector size  $D$  as 256, the dropout rate as 0.0, and the number of attention heads as 3. We tuned the encoder layer as 6 for Game A and 2 for Game B. The decoder layer of Edge MAE is tuned as 1. For pre-training Edge MAE, we tuned the learning rate as  $1.5e-4$ , weight decay as 0.05, the mask ratio as 1/3, and batch size as 2048. For fine-tuning, we tuned the learning rate as 0.001, and the batch size as 2048. The model was pre-trained with 20 epochs (about 15.5 hours for Game A and 153 hours for Game B) and fine-tuned for 50 epochs (about 3.2 hours for Game A and 4.5 hours for Game B) on an NVIDIA A100 GPU. For baseline methods, we use default parameter settings in their original papers or implementations. We found small changes of parameters for our method and baselines didn’t change the results much. For a fair comparison, we add three MLP modules to produce the token embeddings  $E_h$ ,  $E_r$ , and  $E_t$  as the initialization before the input of link prediction and pairwise ranking models.

### 4.3 Validation Results

The ranking performances of different methods on the validation set are listed in Table 2 and Table 3. We use the commonly used ranking metrics Hits@k, Mean Rank (MR, lower is better), Mean Reciprocal Rank (MRR), and the number of players who were back in a method’s top 5/10 recommendation. From the two tables, we can see that, Edge Transformer outperforms almost all baseline models, and the results can be further improved by pre-training Edge MAE on unlabeled edges. The encouraging results showcase the effectiveness of the Transformer model and masked pre-training with massive unlabeled data. For more in-depth performance analysis, we found link prediction models are much better than the two traditional methods: even a classical MLP or XGB can perform quite well, which indicates link prediction is a proper setting for the friend recall task. The main reasons why our proposed method outperforms others are 1). Self-attention allows Edge Transformer to integrate information across nodes and edges. 2). The reconstruction target in MAE allows the model to learn the prior distribution of node and edge features.

<sup>3</sup><https://pytorch.org/docs/stable/generated/torch.nn.Bilinear.html>

**Table 2: Ranking performances of different methods on validation data of Game A. The best result is in bold font. We run all models 10 times and found Edge MAE significantly outperforms baselines based on student  $t$ -test ( $p < 0.05$ ).**

Method	Hits@1	Hits@3	Hits@5	Hits@10	MR	MRR	# top 5 back	# top 10 back
Intimacy	0.2804	0.5857	0.8116	0.9368	4.0638	0.4824	44,957	51,897
XGB for lost players	0.5305	0.8498	0.9429	0.9856	2.2507	0.6993	52,235	54,598
Edge MLP	0.5482	0.8616	0.9491	0.9871	2.1490	0.7130	52,576	54,682
Edge XGB	0.5492	0.8622	0.9487	0.9872	2.1439	0.7129	52,554	54,703
Bilinear	0.5478	0.8625	0.9490	0.9874	2.1491	0.7128	52,569	54,697
DistMult	0.5424	0.8593	0.9475	0.9871	2.1751	0.7088	52,488	54,673
TransE	0.5276	0.8460	0.9419	0.9839	2.2715	0.6971	52,179	54,505
ConvKB	0.5478	0.8624	0.9494	0.9872	2.1462	0.7130	52,594	54,688
TranS	0.5450	0.8616	0.9477	0.9874	2.1628	0.7108	52,499	54,696
Pairwise Ranking	0.5353	0.8564	0.9467	0.9862	2.1982	0.7040	52,443	54,630
Edge Transformer	0.5475	0.8627	0.9488	<b>0.9875</b>	2.1470	0.7127	52,562	<b>54,704</b>
Edge MAE	<b>0.5497</b>	<b>0.8628</b>	<b>0.9495</b>	<b>0.9875</b>	<b>2.1437</b>	<b>0.7139</b>	<b>52,596</b>	<b>54,704</b>

**Table 3: Ranking performances of different methods on validation data of Game B. The best result is in bold font. We run all models 10 times and found Edge MAE significantly outperforms baselines based on student  $t$ -test ( $p < 0.05$ ).**

Method	Hits@1	Hits@3	Hits@5	Hits@10	MR	MRR	# top 5 back	# top 10 back
Intimacy	0.1324	0.2933	0.4661	0.6238	12.6622	0.2779	61,461	82,249
XGB for lost players	0.4055	0.6582	0.774	0.9011	4.1478	0.5659	102,052	118,811
Edge MLP	0.4428	0.699	0.8052	0.9148	3.7798	0.5998	106,161	120,616
Edge XGB	0.4399	0.6994	0.8054	0.9157	3.7906	0.5981	106,197	120,742
Bilinear	0.4435	0.6998	0.8047	0.9154	3.7788	0.6003	106,103	120,697
DistMult	0.4149	0.6709	0.7856	0.9067	4.0437	0.5755	103,583	119,555
TransE	0.1502	0.3582	0.5131	0.6814	10.7953	0.3120	67,651	89,848
ConvKB	0.4424	0.6982	0.8054	0.9155	3.7845	0.5993	106,190	120,704
TranS	0.4335	0.6906	0.7992	0.9134	3.8723	0.5919	105,382	120,439
Pairwise Ranking	0.3653	0.6158	0.7360	0.8771	4.7332	0.5291	97,039	115,651
Edge Transformer	0.4441	0.7004	0.8068	0.9159	3.7630	0.6011	106,379	120,761
Edge MAE	<b>0.4451</b>	<b>0.7023</b>	<b>0.8091</b>	<b>0.9173</b>	<b>3.7485</b>	<b>0.6021</b>	<b>106,675</b>	<b>120,953</b>

**Table 4: Online A/B test result of different methods in a recent event of Game A.**

Method	Click Rate	Return Rate	Conversion Rate	Improvements
XGB for lost	4.43 %	13.70 %	1.2556 %	–
Bilinear	4.46 %	14.37 %	1.3467 %	7.26%
ConvKB	4.43 %	14.61 %	1.3378 %	6.55%
Edge MAE	<b>4.65 %</b>	<b>15.24 %</b>	<b>1.4704 %</b>	<b>17.11 %</b>

**Table 5: Online A/B test result of different methods in a recent event of Game C.**

Method	Click Rate	Return Rate	Conversion Rate	Improvements
XGB for lost	8.41 %	26.55 %	7.2168 %	–
ConvKB	9.41 %	26.59 %	7.6109 %	5.46%
Edge MAE	<b>9.64 %</b>	<b>27.86 %</b>	<b>8.1204 %</b>	<b>12.52 %</b>

#### 4.4 Online A/B Tests

We conducted online A/B tests in recent events of two games. We randomly assigned different algorithm labels to each active player and his/her lost friends, the lost friends are ranked by corresponding models. The statistics are calculated after the online events given in Table 4 and Table 5. The click rate is the proportion of active players who invited at least one friend after seeing the friend list. The return rate is the proportion of players who went back after being invited. The conversion rate (the final metric) is the number of return players divided by the number of active players who saw

the friend list. We can see the proposed Edge MAE achieves the best results, and link prediction models perform better as they model the whole return process entirely.

## 5 RELATED WORK

Transformers [13] was first introduced for machine translation, then become the de-facto standard for NLP tasks [5]. Recently, Transformers became dominant in CV since the invention of ViT [6]. The ViT models are further improved by pre-training masked auto-encoders on unlabeled images [7]. Transformers have also been explored in the graph domain [8]. Our method is inspired by the line of works, the distinction is we train a Transformer directly on edges (features) while most existing graph Transformer architectures are trained on graph-level or node-level tasks. A recent work [1] applies Transformers to edges in complete graphs for NLP tasks, but the model is not pre-trained.

With a variety of real-world applications, link prediction has been recognized as of great importance and attracted the wide attention of the research community. Existing link prediction approaches can be categorized into three families: heuristic feature-based, embedding-based and neural network-based methods. The closest line of works to ours in link prediction is the knowledge graph embedding approach [15] which learns node and edge embeddings for triples. The major difference is that in knowledge graph embeddings, the node/edge embeddings are randomly initialized, while we explicitly use features of nodes and edges.

There are also a number of studies for friend ranking [12] or churn prediction in social platforms [10, 11, 14]. These works focus on building network features for a user, then feeding user features to a classifier (like XGB for lost players). In contrast, our method learns representation for an edge (a pair of users with interactions) in an end-to-end manner.

## 6 CONCLUSION

In this work, we study the real-world friend recall problem and solve the problem via a novel Edge Transformer model with masked auto-encoders. The method outperforms traditional strategies, link prediction, and ranking models. We plan to improve the model with more unlabeled edges and multi-modal information for future work.

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