

# Identifying Guarantors of War Veterans Using Robust-SEAL: A Case of the Korean War

Jong In Choi<sup>1,2†</sup>, Won Kyung Lee<sup>1,3†</sup>, Jae Hwan Lee<sup>1</sup>, So Young Sohn<sup>1\*</sup>

<sup>1</sup>Yonsei University

<sup>2</sup>Finance AI Data Center, Korea Credit Information Services

<sup>3</sup>The Hartree Centre, STFC Daresbury Laboratory

jicho915@yonsei.ac.kr, wky.lee14@gmail.com, leejhi0415@yonsei.ac.kr, sohns@yonsei.ac.kr

## Abstract

Most countries provide veterans with various benefits to reward their sacrifice. Unfortunately, many veterans have failed to prove their status due to loss of military records. Thus, some governments allow the verification of those veterans through "buddy statements" obtained from the people who can vouch for the buddy's participation in the war. However, it is still challenging for veterans to find guarantors directly. With this background, we suggest to utilizing historical war records of combined operations to increase the pool of potential guarantors for the buddy statements. However, a combined operation network among troops can have missing edges and perturbations on attributes of the troop due to inaccurate information. In this study, we learn from some recorded interactions which might be incomplete and noisy, and predict missing linkages among the troops that might have interacted together in the war, by proposing Robust-SEAL (learning from Subgraphs, Embeddings, and Attributes for Link prediction). It combines two Graph Neural Network (GNN) architectures: robust Graph Convolutional Network which considers the uncertainty of node attributes with a probabilistic approach, and SEAL which improves the expressive power of the GNN with a labeling trick. Our proposed approach was applied to Korean War data with perturbations. For experimentations, we hid some actual interactions and found that Robust-SEAL restores missing interactions better than other GNN-based baselines.

## Introduction

In the 20th century, numerous wars broke out, including the Korean War, and the South African Border War. Currently, there are wars taking place in many areas. Many citizens are compulsorily conscripted into the military and must participate in the war. Even after the war ends, veterans suffer from aftereffects of the war such as post-traumatic stress disorder (PTSD) and chronic fatigue syndrome (CFS). Although there exist welfare benefits for the veterans honoring their commitments in some countries (Casler, Fosmire, and

Klein, 2019), it is a big hurdle for veterans to get the proof that they are veterans. One of the reasons is that there are many missing military records. In the past, many records were written manually and stored physically so they could easily have been lost. For example, some records of the U.S. Army were lost due to fire (Stender and Walker 1974). This kind of loss makes it difficult to prove the applicant's participation of the war.

Although some countries allow alternative documents from applicants such as medical reports, prescriptions due to the veteran's injury or illness, photographs or letters from the veteran's time in the service, there are still many veterans who do not have such documents. For those who could not submit the alternative documents can have chances to be registered if they get buddy statements from comrades in the war. However, it is also challenging for applicants to find comrades on their own after the war, although the applicants remember some of them. Some comrades might have died during the war, or after the war. While the finding can be accelerated by government organizations who have the military records, military records at an individual level are often not available.

Unfortunately, however, little has been addressed to solve such war veteran's difficulty in proving their identification. Most of the previous studies have dealt with aftereffects of the war on veterans such as problems in their social life and mental health (Ra 2017). Few studies have only mentioned the challenges of veterans to prove their participations in the war especially, non-regular soldiers who have insufficient military records (Nam 2013).

We propose a framework to recommend suitable guarantors for veterans who are not able to find the records or documents for proving their identification. Beyond recommendations of guarantors who were affiliated in the same unit, our framework can recommend guarantors from different

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<sup>†</sup> Equal contributions

\* Corresponding author

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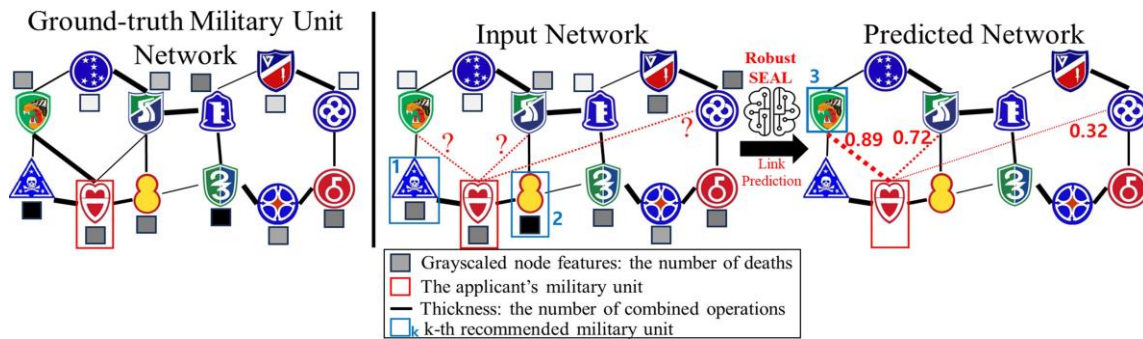


Figure 1: Guarantor recommendation process: Guarantors are recommended within the direct neighbored units in the order of the number of combined operations with the applicant’s unit. Guarantors are further recommended from the units that have the highest probability of being linked, if there are insufficient guarantors in the direct neighbored units.

units that had participated in the same combined operation or those indirectly connected units by solving a link prediction problem as shown in Figure 1. In particular, we design the Graph Neural Networks (GNN) based link prediction model which has been leading this area (Zhang and Chen 2018; Cai et al. 2021). While many existing link prediction models are vulnerable to noisy data which are common especially in the war records such as the number of deaths in battles for each military unit, we address the issue by employing a probabilistic approach with assuming that node attributes have stochastic components. Furthermore, this approach is applied to the representative link prediction model, SEAL (learning from Subgraphs, Embeddings, and Attributes for Link prediction). This avoids suffering from limited expressive power in most of GNN-based link predictions, caused by non-awareness of global contexts in a graph such as a distance between target nodes, as they could not be captured within the  $k$ -hop neighbored information where  $k$  is the number of graph neural layers (Zhang and Chen 2018; Zhang et al. 2021). Our framework, Robust-SEAL, is applied to the Korean War and evaluated by comparing the recommendation performances with those of other GNN-based baseline models.

## Related Work

### Veterans Affairs

There have been several efforts to solve war veterans’ difficulties. Most studies have focused on what kinds of aftereffects the veterans in their physical, mental and social health have experienced, along with the corresponding compensations or benefits. For example, Kang et al. (2013) emphasized needs for testing and treating PTSD and CFS for veterans based on their finding that many of the U.S. veterans of the Gulf War suffer from those problems. Williamson et al. (2018) also stressed the need for further investigations on mental health and treatment of veterans especially aged 65 and older. Furthermore, Casler, Fosmire, and Klein (2019)

addressed the difficulties with respect to their communities, families, in addition to mental health. Nelson et al. (2015) focused on difficulties that veterans experience in employment due to physical and mental problems, and emphasized the necessity of research taking into account the employment-related demands of veterans to resolve the problem.

However, despite health and wellbeing benefits or programs for veterans, registration as a veteran is a huge challenge for some of them. For example, Nam (2013) focused on difficulties of non-regular soldiers who participated in the Korean War in getting their registration as veteran. The author found that most of the non-regular soldiers do not have sufficient evidence for their participation in the war and they suffer from various kinds of disorders. In particular, they had to sacrifice a lot, such as being deprived of educational opportunities in their young lives (Jeong and Kim 2018). However, little is known about a systematic framework to support the registration process.

### Graph Neural Network-based Link prediction

A prediction of missing links or potential links to be connected was proposed in 2007 and it has been actively applied to various real-world problems (Kumar et al. 2020). While hand-crafted feature engineering from domain knowledge was required to obtain useful features for a link prediction in earlier research, recent studies have shown that data-driven features could be learned from neural networks (NN). To be specific, GNN utilizes the structural information as well as the node or edge attributes.

Scarselli, Gori, and Tsoi (2009) first proposed a GNN that exploits structural information among nodes in NN. After a few years, some researchers introduced various Graph Convolutional Networks which generalize the concept of a convolution filter for graph-structured data (Bruna et al. 2014; Defferrard, Bresson, and Vandergheynst 2016; Kipf and Welling 2017). Since then, many GNN architectures have been developed (Hamilton, Ying, and Leskovec 2017; Veličković et al. 2018; Vaswani et al. 2017; Wu et al. 2020a). Those GNN models have been actively applied to

problems in various domains such as recommender systems, natural language processing, and computer vision to name a few (Wu et al., 2020b; Yuan et al. 2021).

Despite such innovations, some limitations have been reported. For example, most of the GNNs are vulnerable to nodal or structural perturbations as such perturbations affect not only the perturbed node or link, but also direct and indirect neighbors through connected links. It is still an open question, but main approaches include to identify suspicious nodes (Zhu et al. 2019) or links (Zhang and Zitnik 2020) and take less weights to them, or to modify a loss function with the worst-case loss or robust loss (Geisler et al. 2021).

Another challenge is that most of the GNNs have limited expressive power, which means that they fail to capture high-order features in graphs such as distance-based ones which could be critical to a link prediction task (Xu et al. 2019; Zhang et al. 2021). For this reason, many researchers have struggled to improve the expressive power of GNNs (Morris et al. 2021), and higher-order GNNs which utilize subgraphs for each node or labeling tricks for incorporating global contexts in the graph are some of the representative GNN methods towards the improved expressivity.

### Data and Methodology

In our framework, we recommend guarantors from war records which include information regarding military units and their interactions via combined operations along with the number of deaths. However, as those records are not complete, we try to restore missing interaction among units via a link prediction model. We recommend guarantors for an applicant not only from veterans who had participated in the same operation together following the war records, but also from those who might have had participated in together or even those who might have had an indirect or higher-order interaction via direct neighbored unit beyond the war records. We expect Government such as Ministry of Patriots and Veterans Affairs to apply the link prediction results to alleviate difficulty required for veterans to find guarantors themselves. Details of data and methods in our framework are presented in the following sections.

### Data

In this paper, we introduce a case of the Korean War as an example. We collect the war records to construct a combined operation network among military units. The Korean War was fought for about three years, from June 25, 1950 to July 27, 1953. During this entire period, a total of 376 major combined operations between forces were officially executed (Cho et al. 2017), where combined operations mean joint operations among units, such as small-scale combat and alert operations. As most of the combined operations were carried out in the certain period between September 16

and October 31 in 1950 (Cho et al. 2017), the war records in this period were investigated in this study.

The details of the combined operation data were collected through Min (2009) to construct the network for guarantor recommendations. By analyzing operational orders and movement paths between Army units included in the data, we identified cases in which combined operations between units such as shift changes and battles were executed. In particular, the movement route, base occupation, and advancement of each unit were converted into daily data. Hierarchical unit structure and the combined operation data of the Eastern front (capital and 3rd divisions) and the Western front (1st, 6th, 7th, and 8th divisions) were extracted as shown in Figure 2.

Some combined operations were conducted between different regiments. For example, the recapture operation of Yongbyon was conducted in the Western Front between the 3rd unit of the 19th regiment in the 6th division, and all units of the 15th regiment in the 1st division, on October 24, 1950.

Next, the time period in this study was classified into four smaller periods based on the dates when the number of soldiers killed per division per day changed significantly. For instance, the full period over which the Capital division operated was split at September 21, October 1, and October 11, as displayed in Figure 2. The 7th division was organized as a reserve division during this period, and due to infrequent combined operations, the period was not split for this division.

As soldiers did not necessarily participate in the war for all the periods, there exists various clusters of soldiers even within the same unit. For instance, some of them participated only in the first two periods while others did in the last two periods. Thus, we introduce different nodes depending on the periods that the soldiers participated in, and their affiliated unit information composed of the division, regiment, and unit. In detail, 15 groups are defined for each unit as the number of cases to participate in the war for four periods is 15, except for the units in the 7th division. In addition, each division includes three regiments, and each regiment also includes three units. Therefore, 675 (5 divisions × 3 regiments × 3 units × 15 groups) nodes are created for all divisions except for the 7th, for which 9 (3 regiments × 3 units)

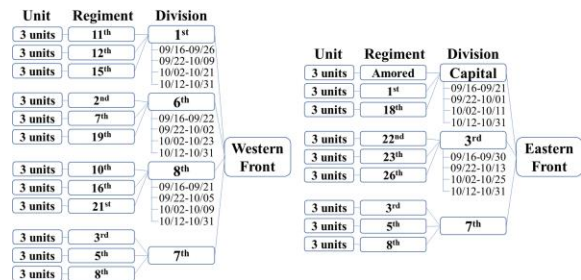


Figure 2: Western and Eastern Front of ROKA (Republic of Korea Army), 1950

nodes are created. In total, 684 unit nodes are introduced, where each node represents a group of soldiers who co-participated within a unit at a specific time period.

In addition, an edge indicates whether the two groups had interactions or not where those interactions are approximated via whether the groups had the combined operation, while its weight denotes the number of combined operations between the groups. The number of edges in our network is 32,967, and the average weight is 2.3526. The average weighted node degree is 98.2. However, there might be some missing interactions which have not been recorded considering the characteristics of war data.

Moreover, we utilize some nodal features in our analysis such as division, regiment, and the number of deaths in the unit during the periods, collected from the information retrieval system in the War Memorial of South Korea. The division and regiment information are considered as nominal variables, while the number of deaths is reflected as a continuous variable. In particular, the number of deaths can reflect complexity or type (local or total war, etc.) of battles, which provides useful information for the analysis. However, the casualty information was not available at the unit level so we use the daily casualties at a regiment-level which indicates that the nodal information might include some noises. For this reason, consideration of uncertainties in the nodal feature is important in this research. Our dataset covers 191,451 deaths in this period among 588,000 casualties of the Republic of Korea Armed Forces and 538,000 casualties of the United Nation Forces in the War.

## Robust-SEAL

A goal of this study is to restore the interaction network by predicting missing or potential interactions between unit nodes in order to recommend guarantors for applicants of veteran's registration. While GNN-based models have made a great success in link prediction tasks in various domains, challenges remain in terms of the vulnerability of the models against perturbations on the nodal attributes and limited expressive power of the GNN. With this background, we propose a robust-SEAL, a hybrid approach of the robust GCN (Zhu et al. 2019) and the SEAL (Zhang and Chen 2018; Zhang et al. 2021). We address uncertainty by employing a probabilistic approach for node representations motivated by the robust GCN, while a labeling trick from the SEAL is applied to improve the expressive power of the GNN through incorporations of global contexts in a graph. An overall framework of the robust-SEAL is shown in Figure 3.

We consider a troop interaction network presented in Data section as  $G = (V, X, E, A)$ , where  $V$  is a set of the unit nodes, and each node represents the unit during a certain period.  $X$  is a node feature matrix including the number of cas-

ualties, categorical variables that describe affiliated regiment and division of the unit.  $E$  indicates a set of edges where each edge means whether a pair of nodes has interactions.  $A$  is the weight matrix representing the number of combined operations in an edge describing the strength of interaction.

While this background, our model aims to predict binary labels of a set of unlinked node pairs  $(v_i, v_j)$ , where  $1 \leq i, j \leq N$  and  $i \neq j$ . We define each node in a node pair as a target node, and the model obtains embedding of the target node pair. A typical GNN-based link prediction model embeds each node representation of the affiliated pair, considering its neighbors within up to  $k$  hops via extracting its subgraph. Then, the pair of node representations is combined followed by a non-linear function such as a multi-layer perceptron, dot-product-based operation, and so on, to produce the representation of the node pair.

Our method also follows a similar approach, but we utilize the labeling trick (Zhang et al. 2021), which labels the distance to the target node pair as an additional node features before processing the graph neural layers. In detail, we define the subgraph  $G_{ij}$  for target node pairs  $(v_i, v_j)$  as the network by the union of  $i$  and  $j$ 's neighbors within up to  $k$  hops. Then, we apply Double Radius Node Labeling to the nodes in the subgraph following (Zhang and Chen 2018). For target nodes  $v_i$  and  $v_j$ , we assign 1, while for other nodes of the subgraph  $G_{ij}$ , denoted as  $c$ , we assign the value  $f_{ij}(c)$  bigger than 1, where details are presented in the following equation. For node  $c$  in subgraph  $G_{ij}$ ,

$$f_{ij}(c) = 1 + \min(d_i, d_j) + (d'/2)[(d'/2) + (d'\%2) - 1] \quad (1)$$

, where  $d_i = d(c, i)$  is distance of node  $i$  to  $c$ ,  $d' = d_i + d_j$ . The  $(d'/2)$  and  $(d'\%2)$  indicate the integer quotient and remainder of  $d'$  divided by 2, respectively. This label injects global contexts in the graph such as distance between target nodes to the input node features.

Then we use RGCN (Robust Graph Convolutional Networks) (Zhu et al. 2019) as the GNN architecture addressing issues caused by perturbations of data such as node attributes which can lead to inaccurate prediction. The RGCN allows uncertainty of the node attributes by assuming that the node representation is not deterministic and introducing a down-weighting module that takes less weights to the node representations which have high variance.

In detail, we assume that a node representation follows Gaussian distribution. Let  $h_i^{(l)} = N(\mu_i^{(l)}, \text{diag}(\sigma_i^{(l)}))$  is the latent representation of node  $v_i$  at the layer  $l$ , where  $\mu_i^{(l)}$  is the mean vector,  $\text{diag}(\sigma_i^{(l)})$  is the diagonal variance matrix. Moreover, we adopt  $M^{(l)} = [\mu_1^{(l)}, \dots, \mu_N^{(l)}]$ ,  $\Sigma^{(l)} = [\sigma_1^{(l)}, \dots, \sigma_N^{(l)}]$  to the matrix of means and variances of all nodes. Then, a Gaussian graph convolution layer is defined. In this first layer, the matrix of means and variances can be obtained by the following equations:

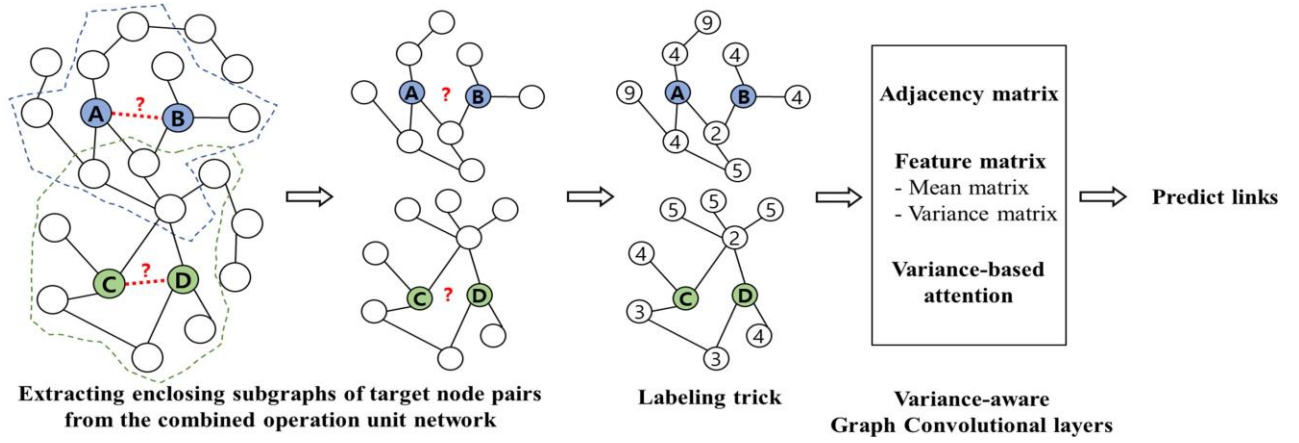


Figure 3: Framework of Robust-SEAL

$$M^{(1)} = \rho(H^{(0)}W_{\mu}^{(0)}), \Sigma^{(1)} = \rho(H^{(0)}W_{\sigma}^{(0)}), \quad (2)$$

where  $\rho(\cdot)$  is a non-linear activation function and  $H^{(0)}$  corresponds to the input node features  $x_v$  ( $\forall v \in V$ ). Moreover,  $W_{\mu}^{(0)}$  and  $W_{\sigma}^{(0)}$  indicate learnable parameter matrices. In subsequent layers, the matrix of means and variances of the nodes at the  $(l+1)$ -th layer are defined as:

$$M^{(l+1)} = \rho\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}(M^{(l)} \odot \mathcal{A}^{(l)})W_{\mu}^l\right), \quad (3)$$

$$\Sigma^{(l+1)} = \rho\left(\tilde{D}^{-1}\tilde{A}\tilde{D}^{-1}(\Sigma^{(l)} \odot \mathcal{A}^{(l)} \odot \mathcal{A}^{(l)})W_{\sigma}^l\right), \quad (4)$$

where  $\tilde{D} = D + I_N$ ,  $\tilde{A} = A + I_N$ ,  $D$  is the diagonal weight matrix,  $I_N$  is the identity matrix, and  $\odot$  means the element-wise product. To be specific,  $\mathcal{A}^{(l)} = \exp(-\gamma\Sigma^{(l)})$ , with hyperparameter  $\gamma$ , and this part helps the GNN model takes less weights to the high-variance nodes, which makes the model be robust against node perturbations.  $W_{\mu}^l$  and  $W_{\sigma}^l$  are parameters to determine the means and variances in the hidden layer. These parameters are learned to detect highly variated nodes in a data-driven way to minimize the training loss. At the last hidden layer  $L$ , we sample a node representation for each node, and then compute the score of the target link.

For the loss function, binary cross entropy  $\mathcal{L}_{bce}$  is used and regularization to the first hidden layer is also considered like Zhu et al. (2019). The regularization terms help to ensure node representations follow Gaussian distributions. Finally, our loss function is defined as:

$$\mathcal{L} = \mathcal{L}_{bce} + \beta_1\mathcal{L}_{reg1} + \beta_2\mathcal{L}_{reg2}, \quad (5)$$

$$\mathcal{L}_{reg1} = \sum_{i=1}^N KL\left(N\left(\mu_i^{(1)}, \text{diag}(\sigma_i^{(1)})\right) \parallel N(0,1)\right), \quad (6)$$

$$\mathcal{L}_{reg2} = \left\|W_{\mu}^{(0)}\right\|_2^2 + \left\|W_{\sigma}^{(0)}\right\|_2^2 \quad (7)$$

, where  $KL(\mathcal{D}_1 \parallel \mathcal{D}_2)$  is the KL-divergence between the distributions  $\mathcal{D}_1$  and  $\mathcal{D}_2$ , while  $\beta_1$  and  $\beta_2$  are hyperparameters.

## A Real-World Application

The trained Robust-SEAL model is applied to the real-world combined operation network to do link prediction. Then,

guarantors can be identified in the following manner from the link prediction results of the Robust-SEAL.

- Find guarantors from the applicant's affiliated unit; otherwise find them from the units that had co-participated with the applicant's unit in the order of the number of combined operations;
- If no guarantors are found, recommend guarantors from the units that had been likely to have interactions with the applicant's affiliated unit with the highest probabilities from the Robust-SEAL.

## Experiments

For evaluation of the proposed Robust-SEAL to the Korean war data, we put aside some links in the dataset for various testing scenarios, and the other links are used for training. Therefore, we train the model with the incomplete dataset as we set some links aside and recommend top  $k$  pairs of military units with the highest probabilities from the trained model. Then, we investigate how well the model recommends the actual links between military units, especially those with highly weighted links representing units that co-participated many times in the testing data. Furthermore, we also observe how the model performs in various perturbation strategies on nodal attributes or network structure. The recommendation performance of the Robust-SEAL is compared with other representative GNN-based link prediction models such as GCN (Kipf and Welling 2017), GraphSAGE (Hamilton, Ying, and Leskovec 2017), Graph Attention Networks (GAT) (Veličković et al. 2018), SEAL (Zhang and Chen 2018), GraphSAINT (Zeng et al. 2019), robust GCN (Zhu et al. 2019), and Line Graph Link Prediction (LGLP) (Cai et al. 2021). All data and implementation codes can be found in <https://github.com/jongin915/Robust-SEAL>.

## Experimental Setup

Although our dataset is restricted to the Korean War, our aim is to make a generalized model which can be applied for unseen military units, for example, unofficial military units composed of volunteer soldiers such as students, or even other wars beyond the Korean War. Therefore, we evaluate the model not only in a transductive setting but also in a semi-inductive setting. In the transductive link prediction, all nodes can be seen in all phases, training, validation and testing. In contrast, only a certain set of nodes can be seen in training and the model is trained by only links among the visible nodes, and then the model is evaluated for the links that are associated with the unseen nodes in the semi-inductive setting.

In detail, we randomly divide the entire edges into the training, validation, and testing sets by 85:5:10, which is a popular setting for a typical transductive link prediction (Zhang and Chen 2018). For each set, corresponding number of negative samples are also randomly selected from the unlinked node pairs. The training set is used for model training while the validation set is utilized for selecting a best-performing model, then the selected model is applied to the test set.

On the other hand, the dataset is split in terms of nodes for the semi-inductive setting following the prior literature (Hao et al. 2020). We randomly select 10% of nodes for testing and validation, respectively. The rest of nodes are used for training. Edges between training nodes and the same amounts of negative samples from unlinked node pairs are used for training while edges among validation nodes, and those between training nodes and validation nodes are utilized for validation in the same way to optimize hyperparameters.

Also, we perform additional experiments, where more perturbed situations are considered for evaluation of robustness. Random perturbations on nodal attributes or network structure are employed in training data. In detail, Gaussian noises are added on one of nodal attributes, the number of casualties in a unit. Otherwise, 5% or 20% of edges in the training data are randomly selected and removed. We test how models perform in validation dataset with either of such noises. All experiments are conducted using NVIDIA Tesla T4 computing nodes in the Google Colab environment.

## Evaluation Metric

Our link prediction model is used to recommend units that have the highest probabilities of linkage; thus we evaluate the model based on the nDCG (normalized Discounted Cumulative Gain) score, one of representative measures of ranking quality (He et al. 2015). The DCG (Discounted Cumulative Gain) is the evaluation measure to compare the ranked list according to the actual relevance with that over the top- $K$  recommended nodes from a link prediction model.

For example, the DCG of node  $i$  for top- $K$  recommendation is defined as follows:

$$DCG_{i,K} = \sum_{k=1}^K \frac{a_{ij_k}}{\log_2(k+1)}, \quad (8)$$

where  $j_k$  denotes the node with the  $k$ -th highest score from the link prediction results so the  $a_{ij_k}$  means the edge weight between the node  $i$  and the node which has the  $k$ -th highest score for  $i$ .

The  $DCG_{i,K}$  is normalized by its maximum  $DCG_{i,K}$ , also called as ideal  $DCG_{i,K}$ , resulting in  $nDCG_{i,K}$ . Then, across nodes in the testing set, average  $nDCG_K$  is calculated to compare the performances of various link prediction models. We consider a small  $K$  from 1 to 5 in order not to lose practicality of the recommendations.

## Hyperparameters

For all models in both transductive and semi-inductive learning, we set the number of hidden units as 32, hidden layers as 2, and batch size as 32. We train each model for 300 epochs with Adam optimizer (Kingma and Ba 2015) and early stopping strategy is used on the validation set with a patience of 20 epochs. Learning rate is optimized in  $\{0.05, 0.01, 0.001, 0.0005, 0.0001\}$ . These are common hyperparameters across our proposed model and the baselines.

In addition, the model-specific hyperparameters are optimized via a grid search. For GCN, parameters are used as the optimal value set in the original paper (Kipf and Welling 2017). For GAT, 8 attention heads with 4 features for each head are used. For GraphSAGE, we conduct exploration for 1-hop and 2-hop sample sizes, selected in  $\{5, 10, 15\}$ . As every node in our war dataset has at least 15 neighbors, we set the sample size as less than or equal to 15. The selected 1-hop and 2-hop sample sizes are both 15. Regarding GraphSAINT, we explore sampling methods for training graph in  $\{\text{Node, Edge, Random Walk}\}$ , the number of expected edges  $\{50, 100, 150, 200, 250, 300\}$ , and dropout rate  $\{0.1, 0.2, 0.3\}$ . For the random walk sampler, we use the length of each walker to 2 following Zeng et al. (2020).

We experiment on both the number of hop  $h=1,2$  for the SEAL, LGLP and Robust-SEAL. For loss function in the LGLP and Robust-SEAL, we set  $\beta_1 = \beta_2 = 0.0005$  following Zhu et al. (2019).

## Results

Table 1 shows the results of all models in transductive and semi-inductive learning, respectively. The experiments were conducted over 10 runs with different random seeds.

In particular, models employing the SEAL framework significantly outperformed the rest of the GNN-based models at 0.05 significance level, by Welch’s  $t$ -test. It implies that exploitation of high-order information to nodal feature could contribute to capturing global contexts in a graph resulting in more expressive features for link prediction via

Transductive	nDCG@1	nDCG@2	nDCG@3	nDCG@4	nDCG@5
GCN	0.6062(0.0218)	0.6059(0.0231)	0.6198(0.0227)	0.6307(0.0156)	0.6542(0.0220)
GraphSAGE	0.5652(0.0197)	0.5650(0.0157)	0.5854(0.0184)	0.5984(0.0193)	0.6122(0.0251)
GAT	0.5923(0.0236)	0.6017(0.0192)	0.6238(0.0189)	0.6319(0.0173)	0.6438(0.0233)
GraphSAINT	0.5287(0.0157)	0.5814(0.0124)	0.6527(0.0119)	0.6918(0.0152)	0.7432(0.0195)
Robust GCN	0.5814(0.0221)	0.6283(0.0223)	0.6617(0.0180)	0.6792(0.0177)	0.7144(0.0152)
SEAL	0.6256(0.0224)	0.6674(0.0237)	0.7031(0.0209)	0.7336(0.0196)	0.7568(0.0188)
LGLP	0.6132(0.0125)	0.6545(0.0145)	0.6827(0.0101)	0.6915(0.0123)	0.7235(0.0152)
<b>Robust-SEAL</b>	<b>0.6591(0.0174)</b>	<b>0.6926(0.0169)</b>	<b>0.7238(0.0182)</b>	<b>0.7578(0.0123)</b>	<b>0.7831(0.0117)</b>
Semi-Inductive	nDCG@1	nDCG@2	nDCG@3	nDCG@4	nDCG@5
GCN	0.4924(0.0169)	0.4940(0.0172)	0.5810(0.0207)	0.6224(0.0151)	0.5346(0.0133)
GraphSAGE	0.5212(0.0132)	0.5217(0.0112)	0.5341(0.0183)	0.5570(0.0132)	0.5203(0.0123)
GAT	0.5635(0.0209)	0.5641(0.0221)	0.5965(0.0254)	0.6190(0.0232)	0.6021(0.0258)
GraphSAINT	0.4928(0.0274)	0.5556(0.0323)	0.6203(0.0288)	0.6826(0.0225)	0.6731(0.0301)
Robust GCN	0.5523(0.0268)	0.5901(0.0191)	0.6332(0.0212)	0.6698(0.0209)	0.6576(0.0241)
SEAL	0.6006(0.0152)	0.6211(0.0135)	0.6945(0.0208)	0.7244(0.0232)	0.6751(0.0256)
LGLP	0.5723(0.0121)	0.5910(0.0176)	0.6232(0.0185)	0.6678(0.0144)	0.6469(0.0137)
<b>Robust-SEAL</b>	<b>0.6299(0.0255)</b>	<b>0.6613(0.0198)</b>	<b>0.7342(0.0251)</b>	<b>0.7641(0.0237)</b>	<b>0.7208(0.0205)</b>

Table 1: The mean(standard deviation) of nDCG@K from transductive and semi-inductive link prediction results.

the SEAL. Also, the SEAL framework shows its robustness against noises on nodal attributes, or random edge removals according to Table 2.

In addition, variance-based attention used in the Robust GCN and Robust-SEAL shows significantly improved performances in most experiments. In particular, improvement is outstanding in robustness tests based on comparison between the GCN and Robust GCN in Table 2, showing 11-25% of improvements, which is much higher than 9% of improvement in Table 1.

## Conclusion

The aim of this study was to reduce the difficulties experienced by veterans in the process of obtaining a buddy statement by increasing a pool of guarantors to be recommended and investigated. Although combined operation unit network enables the recommendations of guarantors who participated in the same operations or belonged to the same units, the pool is very limited due to various reasons. More

Semi-Inductive	Noise on # of casualties		Edge deletion	
	N(0, 10 <sup>2</sup> )	N(0, 100 <sup>2</sup> )	5%	20%
GCN	0.515(0.024)	0.501(0.022)	0.523(0.022)	0.501(0.012)
GraphSAGE	0.526(0.015)	0.532(0.018)	0.524(0.014)	0.514(0.015)
GAT	0.553(0.027)	0.557(0.028)	0.565(0.021)	0.524(0.018)
GraphSAINT	0.564(0.028)	0.551(0.024)	0.578(0.021)	0.519(0.025)
Robust-GCN	0.623(0.018)	0.625(0.022)	0.615(0.019)	0.557(0.021)
SEAL	0.662(0.021)	0.649(0.023)	0.673(0.022)	0.607(0.028)
LGLP	0.594(0.019)	0.598(0.019)	0.587(0.020)	0.562(0.022)
<b>Robust-SEAL</b>	<b>0.718(0.022)</b>	<b>0.713(0.021)</b>	<b>0.723(0.016)</b>	<b>0.692(0.017)</b>

Table 2: The mean(standard deviation) of nDCG@3 for perturbation experiments with regard to nodal attributes with Gaussian noise and random edge deletion, respectively.

over, some combined operation records may have been lost. In that case, our link prediction model can restore the missing links and also recommend links that might have had indirect connections help to find guarantors.

The experimental results verified higher accuracy and effectiveness of the proposed framework than various state-of-the-art baselines in both transductive and semi-inductive settings. The superior performances in the semi-inductive settings imply that our model could be applied to new nodes such as those from the war records additionally found or veterans who were in irregular military units. We expect that veterans who have devoted themselves to the nation can be recognized for their services in a better manner using our proposed approach.

Our study developed robust AI-based recommender systems against noisy data for social good. However, significant challenges have been presented for deployment (Dwivedi et al. 2021), for instance, explainability of recommendations, although some of them can be alleviated by employing several modern approaches (Ying et al. 2019). Another example of the challenges is fairness because current methods could be biased depending on node degrees (Liu, Nguyen, and Fang, 2023), where the prediction on high-degree nodes is usually more accurate than that on low-degree nodes.

Although we could not apply to other war datasets due to data availability, it would be interesting to apply our model to various wars such as the South African Border war, the war between the Ukraine and Russia, to name a few, in a fully inductive setting. Another direction for further research could be generation of the war network from texts, images, and videos in an automatic way. They are left as areas for further research.

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