GraphSearchNet: Enhancing GNNs via Capturing Global Dependency for Semantic Code Search

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Abstract

Code search aims to retrieve the relevant code fragments based on a natural language query to improve the software productivity and quality. However, automatic code search is challenging due to the semantic gap between the source code and the query. Most existing approaches mainly consider the sequential information for embedding, where the structure information behind the text is not fully considered. In this paper, we design a novel neural network framework, named GraphSearchNet, to enable an effective and accurate source code search by jointly learning rich semantics of both source code and queries. Specifically, we propose to encode both source code and queries into two graphs with Bidirectional GGNN to capture the local structure information of the graphs. Furthermore, we enhance BiGGNN by utilizing the effective multi-head attention to supplement the global dependency that BiGGNN missed. The extensive experiments on both Java and Python datasets illustrate that GraphSearchNet outperforms current state-of-the-art works by a significant margin.

Introduction

With the fast development of software industry over the past few years, the global source code over public and private repositories (e.g., GitHub, Bitbucket) is reaching an unprecedented amount. It is already commonly recognized that the software industry is entering the "Big Code" era. Code Search, which aims to search the relevant code fragments based on the natural language query from a large code corpus (e.g., Github, Stack Overflow, or private ones), has become a vital problem in the "Big Code" era. An accurate code searching system can greatly improve software productivity and quality, while reducing the development cost.

Automated Code Search is far from settled. Some early attempts were made to capture the relationship of code and query by keyword matching(McMillan et al. 2011; Lu et al. 2015). However, such techniques are ad-hoc and do not take the advantage of the semantics relationship, making it limited especially when no common keywords or synonyms exist in the source code and queries. More recent attempts shifted to deep learning (DL)-based approaches (Gu, Zhang, and Kim 2018; Husain et al. 2019; Yao, Peddamail, and Sun 2019), which encode the source code and the query into the vectors

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(i.e., learning the embeddings). Then, the similarity between two vectors, such as cosine similarity, is used to measure the semantic relationship between the code fragment and the query. Code fragments with a high similarity score of the query are returned as the searching results. However, these works only rely on sequential models i.e., LSTMs to learn the embedding vectors, which fails to utilize the structure information hidden in the code and queries. Based on the simple sequential models are struggling to learn the semantic relationship. To sum up, although some recent progress has been made for automated code search, the key challenges are still existed: 1) source code and the natural language queries are heterogeneous (Gu, Zhang, and Kim 2018), they have completely different grammatical rules and language structure, which leads to the semantic mapping is hard. 2) the rich structure information hidden in the code and the guery fails to explore. Failing to utilize the rich structure information beyond the simple text may limit the effectiveness of these approaches for code search.

In addition, many existing graph-based works (Zhou et al. 2019; Liu et al. 2020a; Fernandes, Allamanis, and Brockschmidt 2018) in program learning have proved the effectiveness of GNNs (Kipf and Welling 2016; Allamanis, Brockschmidt, and Khademi 2017) on capturing program semantics. Furthermore, due to the powerful relation learning capacity of GNNs, they have also been widely used in many NLP reasoning applications, e.g., natural question generation (QG) (Chen, Wu, and Zaki 2019b; Su et al. 2020), conversational machine comprehension (MC) (Chen, Wu, and Zaki 2019a; Song et al. 2018; De Cao, Aziz, and Titov 2018). Annervaz et al. (Annervaz, Chowdhury, and Dukkipati 2018) further proved that augmenting graph information with LSTM can improve the performance of many NLP applications. Hence, a direct idea is how to utilize GNNs to learn the semantic relation of source code and the query for semantic code search? However, in code scenario, the size of the transformed program graph is bigger, i.e., they tend to have hundreds of nodes, which yield a problem (Hellendoorn et al. 2019; Liu et al. 2020a). The message passing of GNNs can only capture local neighborhood information while the global dependency of any pair of nodes is missed. For example, in Figure 1, when k = 1, node 1 can only know the information of its neighborhood node 2. When k = 2, node 1 can only know its neighborhood node 2 and the neighborhood (node 3)

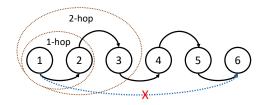


Figure 1: Message passing of GNNs within k-th neighborhood information where the dash area is the context that node 1 knows.

of neighborhood (node 2) of node 1. k is the hyper-parameter where usually is a small number such as 3. Hence, the remote node information such as node 6 from node 1 is missed.

To address these challenges, in this paper, we design a novel neural network framework, named GraphSearchNet, towards learning embeddings that fully utilize the structure information to capture the semantic relation of source code and queries for code search. In particular, GraphSearchNet encodes both the source code and the query into graphs with Bidirectional Gated Graph Neural Network (BiGGNN) to capture the structural information behind the programs and queries. Furthermore, to enhance BiGGNN, we further utilize the multi-head attention module to capture the global dependency of the nodes to supplement GNNs. We conduct a large-scale evaluation on the open-source dataset Code-SearchNet (Husain et al. 2019) with over **2 million** Java and Python functions, to demonstrate the effectiveness of our method. Overall, our main contributions are summarized as follows:

- We propose a novel graph-based framework for accurately learning unified semantic relation representation of the source code and queries.
- We further enhance BiGGNN by a multi-head attention module to capture both the local structure information by BiGGNN and the global dependency by multi-head attention.
- We conduct an extensive evaluation to demonstrate the effectiveness of GraphSearchNet on the large code corpora and we will make our code, dataset, and constructed graphs public to benefit academia and the industry.

Related Work

Code Search. Early works (Lu et al. 2015; Lv et al. 2015) in code search focus on extracting both query and code characteristics to match the relevant code. For example, Lu et al. (Lu et al. 2015) proposed to extend a query with synonyms generated from WordNet to improve the hit ratio. McMillan et al. (McMillan et al. 2011) proposed Protfolio, a code search engine that combines keyword matching to return functions. Lv et al. (Lv et al. 2015) proposed CodeHow, which combines Boolean model and API matching. Some recent works (Gu, Zhang, and Kim 2018; Husain et al. 2019; Cambronero et al. 2019; Shuai et al. 2020; Haldar et al. 2020) attempt to use the deep learning-based models *e.g.*, LSTM, CNNs to learn high-dimensional representations of programs and descriptions and return the best programs based on the cosine similarity of the queried vectors. However, the existing

works in code search ignore rich structural information behind programs and queries. In GraphSearchNet, we attempt to extract structural information hidden in the programs and queries, and build graphs to learn effective representations.

Graph Neural Networks. Recently, GNNs (Hamilton, Ying, and Leskovec 2017; Li et al. 2015; Kipf and Welling 2016; Xu et al. 2018) have become a hot research topic since their strengths in learning structure data. Various applications in different domains such as chemistry biology (Duvenaud et al. 2015), computer vision (Norcliffe-Brown, Vafeias, and Parisot 2018), natural language processing (Xu et al. 2018; Chen, Wu, and Zaki 2019b) have demonstrated the effectiveness of GNNs. In program scenario, compared with the early works to represent programs with abstract syntax tree (Alon et al. 2018, 2019; Liu et al. 2020b), more works have already attempted to use graphs (Allamanis, Brockschmidt, and Khademi 2017) to learn the semantics for various applications, e.g., source code summarization (Liu et al. 2020a; Fernandes, Allamanis, and Brockschmidt 2018), vulnerability detection (Zhou et al. 2019), type inference (Allamanis et al. 2020). Inspired by these state-of-the-art works that represent programs with graphs to capture the program semantics, in GraphSearchNet, we propose to convert both programs and descriptions into graphs with BiGGNN to learn the structure information for semantic search.

GraphSearchNet Framework

In this section, we introduce the proposed framework Graph-SearchNet, as shown in Figure 2, which includes three phases:

1) Graph Construction, which constructs directed graphs for programs and descriptions with comprehensive semantics.

2) Training Phase, which learns two different encoders i.e., program encoder and description encoder on the constructed program and description graph respectively by BiGGNN to capture local graph structure information and multi-head attention to capture the global dependency. 3) Query Phase, which returns the code fragments from the search codebase that have the nearest vector distance with the given query by the embedded vectors for both program and description encoder, where the query is independent with the description used for model training and the search codebase is different from the training set.

Problem Formulation

The goal of code search is to find the most relevant program fragment c based on the query q in natural language. Formally, given a set of training data $D = \{(c_i, q_i) | c_i \in \mathcal{C}, q_i \in \mathcal{Q}\}, i \in \{1, 2, ..., n\}$, where \mathcal{C} and \mathcal{Q} denote the set of functions and the corresponding queries. We define the learning problem as

$$\min_{f_c, f_q} \sum_{i=1}^{n} \mathcal{L}(f_c(c_i), f_q(q_i)))$$
 (1)

where f_c and f_q are the encoders for programs and queries, which are learnt from the training data D. However, in the real scenario, since D is hard to collect, it is a common practise (Gu, Zhang, and Kim 2018; Husain et al. 2019) to replace q_i with the description s_i regarding the function c_i i.e., $D = \{(c_i, s_i) | c_i \in C, s_i \in S\}$ where $i \in \{1, 2, ..., n\}$ and

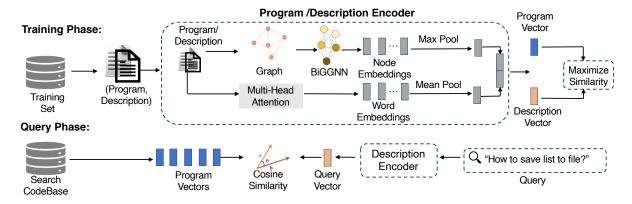


Figure 2: The overall framework of GraphSearchNet.

 \mathcal{S} is the corresponding description set. Once the embedding functions are trained, given a query q and the search code database \mathcal{C}_{base} where $\mathcal{C}_{base} \neq D$, we can obtain the most relevant program:

$$c = \max_{c_i \in \mathcal{C}_{base}} sim(f_c(c_i), f_q(q))$$
 (2)

where sim is the function that measures the cosine similarity between the program vector and query vector.

Graph Construction

Next, we introduce the construction of the graphs for both programs and descriptions.

Program Graph Given a program c, we extract its multiedged directed graph $g(V, A) \in \mathcal{G}$, where V is a set of nodes that are built on the Abstract Syntax Tree (AST) and $A \in \{0,1\}^{k \times m \times m}$ is the adjacency matrix that represents the relationships between the nodes (*i.e.*, the edges), where k and m are the total number of edge types and nodes in g, respectively. In particular, AST consists of leaf nodes and nonleaf nodes where leaf nodes correspond to the identifier in the program and non-leaf node represent different compilation unit such as "Assign", "BinOp", "Expr" and the node set V is the entire AST nodes. In addition, we also construct the syntactic edges (*i.e.*, NextToken, Subtoken) and data-flow edges (*i.e.*, ComputedFrom, LastUse, LastWrite) based on AST nodes, which can represent the program:

- *NextToken*, connects each leaf node in AST to its successor. As shown in Figure 3 a), for the statement "fn_a(x)", there is a *NextToken* edge points from "fn_a" to "x".
- *Subtoken*, defines the connection of subtokens split from identifiers (*i.e.*, variable names, function names) based on *camelCase* and *pascal_case* conventions. For example, "fn_a" will be divided into "fn" and "a".
- *LastUse*, represents the immediate last read of each occurrence of variables. As shown in Figure 3 b), x^3 points to x^1 since x^1 is used as the conditional judgement.
- LastWrite, represents the immediate last write of each occurrence of variables. Since there is an assignment statement to update x², hence there is a LastWrite edge points from x⁴ to x².

• *ComputedFrom*, connects the left variable to all right variables appeared in the assignment statements. Based on the definition, x² connects x³ and y.

Figure 3 a) and b) give a simplified example of our constructed program graph.

Description/Query Graph To capture structure information behind the natural language, we construct a directed graph based on dependency parsing (De Marneffe et al. 2006). Given a description s or a query q, we extract its dependency parsing graph as $g'(V', A') \in \mathcal{G}'$, where V' is the node set and each node is the token in the original sequence s or q. A' is the adjacency matrix, denoting the relations between the nodes i.e., tokens. Different edges in g' represent tokens with different grammatical relations, e.g., "aux", "prep". In addition, we also construct NextToken and Subtoken edge for the graph, which is similar to the program graph. As shown in Figure 3 c), one query q can be parsed into tokens with different dependency relations, for example, "How", "to" and "for" are used to describe the verb "check" but have different relations, i.e., "advmod", "aux", "prep" accordingly.

Program/Description Encoder

GNN-based models have been widely used in modelling programs (Allamanis, Brockschmidt, and Khademi 2017; Liu et al. 2020a; Fernandes, Allamanis, and Brockschmidt 2018; Zhou et al. 2019; Allamanis et al. 2020) due to the effectiveness of learning structure information hidden in the programs as compared with sequential models. However, most GNN-based models in program modelling ignore the direction of message passing among nodes in the graph. So essentially, these approaches simply treat the program graph as the undirected graph. Furthermore, the global dependency within the program will be missed by GNNs (Hellendoorn et al. 2019). In order to better capture the structure information on the graphs as well as to learn the global dependency, we introduce our well-designed encoder.

Bidirectional GGNN Inspired by the existing works (Chen, Wu, and Zaki 2019b), we introduce the Bidirectional Gated Graph Neural Network (BiGGNN), which learns node embeddings from both incoming and

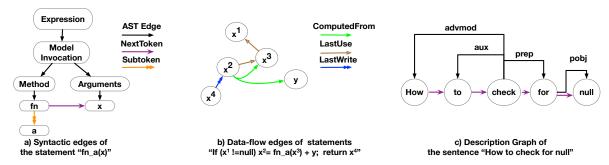


Figure 3: The example of our built graph with some simple program fragments, where a) and b) are the syntactic edges and data-flow edges of the program graph. Please note that we distinguish the variable x into x^1 , x^2 , x^3 , x^4 for ease of the expression.

outgoing directions for the program graph i.e., g(V, A) and description graph i.e., g'(V', A'). In particular, each node v is initialized by a learnable embedding matrix E and gets its initial representation $h_v^0 \in \mathbb{R}^{1 \times d}$ where d is the dimensional length. We apply the message passing function for a fixed number of hops i.e., k. During each hop n, for node v, we apply an aggregation function to take as input a set of incoming (or outgoing) neighboring node vectors and outputs a backward (or forward) aggregation vector. The summation function is selected as the aggregation function, where $N_{(v)}$ denotes the neighbors of node v and v0 is the backward or forward direction.

$$\mathbf{h}_{\mathcal{N}_{\dashv(v)}}^{n} = \text{SUM}(\{\mathbf{h}_{u}^{n-1}, \forall u \in \mathcal{N}_{\dashv(v)}\})$$

$$\mathbf{h}_{\mathcal{N}_{\vdash(v)}}^{n} = \text{SUM}(\{\mathbf{h}_{u}^{n-1}, \forall u \in \mathcal{N}_{\vdash(v)}\})$$
(3)

Then, we fuse the node embedding for both directions.

$$\boldsymbol{h}_{\mathcal{N}_{(v)}}^{n} = \operatorname{Fuse}(\boldsymbol{h}_{\mathcal{N}_{\dashv(v)}}^{n}, \boldsymbol{h}_{\mathcal{N}_{\vdash(v)}}^{n})$$
 (4)

Here the fusion function is designed as a gated sum of two inputs.

Fuse
$$(\boldsymbol{a}, \boldsymbol{b}) = \boldsymbol{z} \odot \boldsymbol{a} + (1 - \boldsymbol{z}) \odot \boldsymbol{b}$$

 $\boldsymbol{z} = \sigma(\boldsymbol{W}_z[\boldsymbol{a}; \boldsymbol{b}; \boldsymbol{a} \odot \boldsymbol{b}; \boldsymbol{a} - \boldsymbol{b}] + \boldsymbol{b}_z)$ (5)

where \odot is the component-wise multiplication, σ is a sigmoid function and z is a gating vector. Finally, we feed the resulting vector to a Gated Recurrent Unit (GRU) (Cho et al. 2014) to update node representations.

$$\boldsymbol{h}_{v}^{n} = GRU(\boldsymbol{h}_{v}^{n-1}, \boldsymbol{h}_{\mathcal{N}(v)}^{n})$$
 (6)

After k hops of computation, we obtain the final node representation \boldsymbol{h}_v^k and then apply max-pooling over all nodes $\{\boldsymbol{h}_v^k, \forall v \in V\}$ to get a d-dim graph representation \boldsymbol{h}^g .

$$\boldsymbol{h}^g = \operatorname{maxpool}(\operatorname{FC}(\{\boldsymbol{h}_v^k, \forall v \in V\})) \tag{7}$$

where FC is the fully-connected layer.

Multi-Head Attention Since GNNs usually consider the k-hop neighborhood information of the nodes in the graph, the global relation may be ignored. In GraphSearchNet, the leaf nodes of the constructed graph are the tokens/subtokens from the program c or the description s, to capture the remote dependency relation, we directly employ Multi-Head

attention (Vaswani et al. 2017) among the tokens in the sequence to capture the global dependency. Specifically, given the query, key and value matrix defined as Q, K and V, where Q, K, $V = (E_{t_1}, ..., E_{t_l})$ are the embeddings of the sequence for the program and description and t_i is the i-th token in the sequence $T = \{t_1, ..., t_l\}$, the output by multihead attention can be expressed as follows.

$$h_{t_1}, ..., h_{t_l} = \text{MultiHead}(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V})$$
 (8)

To get the final representation vector \mathbf{h}^s over the sequence, we use the mean pool operation on $\mathbf{h}_{t_1}, ..., \mathbf{h}_{t_l}$ as follows.

$$\boldsymbol{h}^{s} = \operatorname{meanpool}((\{\boldsymbol{h}_{t_{i}}, \forall t_{i} \in T\})) \tag{9}$$

Finally, we concatenate the vector from both Bidirectional GGNN i.e., h^g and the multi-head attention i.e., h^s to get the final representation $[h^g; h^s]$.

We utilize the above algorithm to obtain the vector representations by feeding the program and description (c_i, s_i) to the program encoder i.e., f_c and description encoder i.e., f_q separately and define the obtained vectors as $(\mathbf{r}, \mathbf{r}')$.

Training

Given n pairs of code and description (c_i, s_i) , we train f_c and f_q simultaneously by minimizing the loss as follows:

$$-\frac{1}{n}\sum_{i}^{n}\log\left(\frac{\boldsymbol{r}_{i}^{\prime}\boldsymbol{r}_{i}^{T}}{\sum_{j}\boldsymbol{r}_{i}^{\prime}\boldsymbol{r}_{j}^{T}}\right)$$
(10)

The loss function minimizes the inner product of (r_i, r'_i) between the description s_i and its corresponding program c_i , while maximizing the inner product between the description s_i and other distractor programs, i.e., c_j where $j \neq i$.

Code Searching

Once the model is trained, given a query q, GraphSearchNet aims to return the most relevant program c. To achieve this, we first embed all programs from the search code database \mathcal{C}_{base} , which is independent with the data set used for model training, into program vectors by the learned program encoder f_c in an off-line manner. During the online search, for a new query q, GraphSearchNet embeds it via the description encoder f_q and computes the cosine similarity between the query vector and all program vectors in the search codebase. The top k programs whose vectors are the most similar to the query are returned as the search results.

Table 1: Statistics of the used data.

Code Search		Train	Validation	Test	Search CodeBase
Java	Original	454,451	15,328	26,909	1,569,889
Java	Processed	198,056	6,431	11,297	756,012
Python	Original	412,278	23,107	22,176	1,156,085
Python	Processed	283,234	15,482	15,306	756,146

Evaluation

In this section, we introduce the experimental setup including the dataset, evaluation metrics, compared baselines and configuration of GraphSearchNet. Then we compare GraphSearchNet with the baselines and perform an ablation study to investigate each component. We further conduct the analysis on the hyper-parameter and show some queried results by GraphSearchNet.

Experimental Setup

Dataset In code search, sufficient amount of (program, query) pairs is challenging to collect and existing works (Husain et al. 2019; Gu, Zhang, and Kim 2018; Haldar et al. 2020) utilized the function description to replace query for model training *i.e.*, the pair of (program, description) where the description describes the functionality of the program. We also follow this settings and select Java and Python data set from the open-source dataset CodeSearchNet (Husain et al. 2019). The statistics about the data set are shown in Table 1. We utilize spaCy (Honnibal and Montani 2017) for description graph construction and the released tool (Rice 2018; Fernandes, Allamanis, and Brockschmidt 2018) for Java and Python program graph construction. We only keep the graphs with node size within 200 for the efficiency. The remaining number of data is also shown in Table 1. Furthermore, to simulate the real code search scenario, CodeSearchNet provides a number of 99 natural language queries, e.g., "convert decimal to hex", to search the related programs from the search codebase and this is independent with train/validation/test data set. We also follow this setting to evaluate these queries by GraphSearchNet. On the search codebase, we employ the open-source tool ElasticSearch (Gormley and Tong 2015) to store program vectors obtained by the program encoder for acceleration. Converting all programs from the search codebase into vectors costs nearly 70 minutes for Java or Python over **756k** samples in an offline manner. The query process is fast and it only takes about 0.15 second to produce 10 candidates for each query. To sum up, in the evaluation section, we first investigate the performance of GraphSearchNet on the test set with the selected metrics. Then we shown some cases over the real 99 natural queries on the search codebase.

Evaluation Metrics Similar to the previous works (Gu, Zhang, and Kim 2018), we use SuccessRate@k, Mean Reciprocal Rank (MRR) as our automatic evaluation metrics. We further add Normalized Discounted Cumulative Gain (NDCG) as another evaluation metric.

 SuccessRate@k. The SuccessRate@k measures the percentage of the correct result existed in the top k ranked results and it can be calculated as follows:

SuccessRate@k =
$$\frac{1}{|Q|} \sum_{q=1}^{|Q|} \delta(\text{FRank}_q \le k)$$
 (11)

where Q is a set of queries, $\delta(\cdot)$ is a function which returns 1 if the input is true and 0 otherwise and FRank is the rank position of the first hit result in the result list. We set k to 1, 5, 10.

• MRR. MRR is the average of the reciprocal ranks of results for a set of queries Q. The reciprocal rank of a query is the inverse of the rank of the first hit result, defined as follows:

$$MRR = \frac{1}{|Q|} \sum_{q=1}^{|Q|} \frac{1}{FRank_q}$$
 (12)

NDCG. NDCG measures the gain of the result based on its
position in the result list and it is the division of discounted
cumulative gain (DCG) and ideal discounted cumulative
gain (IDCG) where DCG and IDCG are calculated as follows:

$$DCG_{p} = \sum_{i=1}^{p} \frac{2^{rel_{i}} - 1}{\log_{2}(i+1)} \quad IDCG_{p} = \sum_{i=1}^{|REL|_{p}} \frac{2^{rel_{i}} - 1}{\log_{2}(i+1)}$$
(13)

where p is the rank position, rel_i is the graded relevance of the result at position i and $|\mathrm{REL}|_p$ is the list of relevant results up to position p. We set p equals to 10 for all experiments.

To sum up, the higher these metric values, the better code search performance.

Compared Baselines To demonstrate the effectiveness of GraphSearchNet, we select the following approaches as baselines, which are summarized as follows.

- CodeSearchNet (Husain et al. 2019). CodeSearchNet provides a framework to encode programs and their descriptions for the query. It contains several different encoders, *i.e.*, Natural Bag of Words (NBoW), 1D Convolutional Neural Network (1D-CNN), Bidirectional RNN (biRNN) and Self-Attention (SelfAtt) to learn the representations. For SelfAtt encoder, it has 3 identical multi-head attention layers with 128 dimensional size and each layer has 8 heads to learn different subspace features.
- **DeepCS** (Gu, Zhang, and Kim 2018). DeepCS jointly embeds code snippets and natural language descriptions into a high-dimensional vector space. For code encoding, it fuses method name, API sequence, and Tokens to learn a high-dimensional vector. For description, an RNN is utilized for learning the embedding.
- CAT (Haldar et al. 2020). CAT encodes programs based on the original sequences and the transformed AST sequences to capture both syntactic and semantic features for programs, we also reproduce it as the baseline model on our Java and Python dataset.
- CARLCS-CNN (Shuai et al. 2020). CARLCS-CNN learns the representations for the code and query with a coattention mechanism, which learns a correlation matrix

Table 2: Experimental results on Java and Python dataset as compared to baselines.

M- 4-1	Java			Python						
Model	R@1	R@5	R@10	NDCG	MRR	R@1	R@5	R@10	NDCG	MRR
NBoW	0.521	0.726	0.790	0.543	0.616	0.568	0.785	0.842	0.552	0.666
biRNN	0.456	0.677	0.753	0.621	0.559	0.542	0.770	0.833	0.708	0.645
SelfAtt Encoder	0.421	0.630	0.710	0.672	0.520	0.578	0.790	0.845	0.766	0.674
1D-CNN	0.379	0.588	0.671	0.549	0.478	0.412	0.646	0.726	0.636	0.521
DeepCS	0.334	0.565	0.673	0.488	0.446	0.647	0.820	0.860	0.753	0.726
CAT	0.075	0.182	0.251	0.151	0.136	0.340	0.629	0.734	0.528	0.473
CARLCS-CNN	0.383	0.609	0.696	0.528	0.491	0.651	0.820	0.858	0.756	0.731
QC-based CR	0.190	0.408	0.517	0.339	0.297	0.210	0.438	0.542	0.363	0.320
GCN	0.415	0.660	0.729	0.575	0.529	0.487	0.722	0.791	0.637	0.595
GraphSearchNet	0.570	0.760	0.812	0.695	0.658	0.653	0.842	0.891	0.773	0.739

Table 3: Ablation study of the performance when using different component on the program and description encoder, where the check mark denotes the used corresponding component.

Dataset		NDCG	MDD		
Dataset	Multi-Head	BiGGNN_forward	BiGGNN_backward	NDCG	WIKK
	✓			0.443	0.401
		✓		0.686	0.647
Java			✓	0.611	0.567
		✓	✓	0.691	0.652
	✓	✓	✓	0.695	0.658
	✓			0.509	0.467
		✓		0.746	0.710
Python			\checkmark	0.725	0.686
		✓	✓	0.771	0.734
	✓	✓	✓	0.773	0.739

and co-attends the semantic relationship of the embedded code and query via row/column-wise max-pooling.

- QC-based CR (Yao, Peddamail, and Sun 2019). The original paper utilizes a code annotations model to take the code as a input and output an annotation. Then it utilizes the generated annotation with the query for a QN-based code retrieval model and the code with the query for a QC-based code retrieval model to distinguish the relevant code snippets from others. The entire model cannot trained correctly by the official released code, for simplify we select QC-based Code Retrieval Model as one of our baselines.
- GCN (Kipf and Welling 2016). To investigate the performance of other GNNs compared with BiGGNN, we replace BiGGNN with GCN (graph convolutional network) for both program and description encoder for comparison.

For the above papers that released the source code, we directly reproduce their methods on our dataset.

Model Settings For the initial embedding layer, we embed the most frequent 150,000 words for the programs and descriptions in the training set with 128-dimensional size. We set the dropout as 0.3 after the word embedding layers for training. The optimizer is selected with Adam (Kingma and Ba 2014) with an initial learning rate 0.01. The batch size is set as 1,000, following the existing work (Husain et al. 2019). We set the number of maximum epoch as 100. The number of hops on Java and Python are set to 4 and 3, respectively.

Table 4: Ablation study of the performance on the separate encoder *i.e.*, program or description with different component on Java and Python data set.

Dataset	Program		Description		NDCG	MRR
	Multi-Head	BiGGNN	Multi-Head	BiGGNN	NDCG	MIKK
	✓		✓	✓	0.466	0.417
		✓	✓	\checkmark	0.598	0.557
Java	✓	\checkmark	✓		0.409	0.362
	✓	✓		\checkmark	0.628	0.585
	✓	\checkmark	✓	\checkmark	0.695	0.658
	✓		✓	✓	0.285	0.245
		✓	✓	\checkmark	0.693	0.654
Python	✓	\checkmark	✓		0.439	0.392
	✓	✓		\checkmark	0.733	0.696
	✓	✓	✓	\checkmark	0.773	0.739

The number of heads in multi-head attention is set to 2 on both Java and Python dataset for efficiency. All experiments were run on the DGX server with 80 cores and 180G RAM. Four 32 GB Nvidia Graphics Tesla V100 are used for the learning process.

Experimental Results

Table 2 summarizes the results of GraphSearchNet in line with the baseline methods. The column R@1, R@5 and R@10 show the results of SuccessRate@k, where k is 1, 5 and 10. As we can see, GraphSearchNet outperforms the baseline methods by a significant margin on both Java and Python benchmark for all metrics, indicating that Graph-SearchNet can return more relevant programs based on the query. Furthermore, we can see that the overall performance on Python is superior to Java, we conjecture that Python has a simpler grammatical structure and the semantic gap between the programs and descriptions is smaller than Java. The results indicate that, compared with these sequential baselines, which treats programs and descriptions as sequences and ignores the structure behind the text, by capturing both local structure information and global dependency, GraphSearch-Net could learn the semantic relations between programs and descriptions better, making it more effective and accurate in code search. In addition to the compared sequential models, we additionally compared with other GNN variants e.g., GCN and we can see that BiGGNN outperforms GCN by a significant margin on both dataset, which further confirms

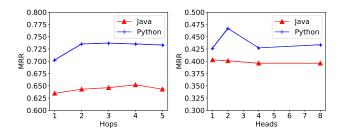


Figure 4: Effect of the number of BiGGNN hops and multihead attention heads.

the effectiveness of BiGGNN.

Ablation Study

We conduct an ablation study to evaluate the impact of different components, i.e., Multi-Head Attention and BiGGNN on both the program encoder and description encoder, the results of which are summarized in Table 3. Overall, GraphSearch-Net achieves the best performance when all components are used, indicating the usefulness of the designed neural network in GraphSearchNet. In addition, we also have the following findings. First, when turning off BiGGNN, only using multihead attention, the performance on Java and Python drops dramatically, which indicates the local structural information captured by BiGGNN contributes more to the final performance rather than global dependency. This also confirms the necessity of encoding programs and descriptions into graphs for code search. Second, the forward message passing (i.e. GGNN_forward) has a better performance than the backward (i.e. GGNN_backward), we conjecture that it is caused by the constructed program/description graphs are directed and forward information is more effective than backward. However, combing both directions, we can reach the best.

Furthermore, we also perform an ablation study of different components on the separate encoder, i.e., program encoder or description encoder and the results are shown in Table 4. We can observe that BiGGNN improves the performance significantly compared with multi-head attention on program or description encoder, which confirms the necessity of encoding program and description into graphs. An interesting finding is that when we turn off multi-head attention and use BiGGNN alone for program and description, MRR are 0.652 and 0.734 on Java and Python from Table 3, which are higher than turning on one of multi-head attention with BiGGNN on program or description encoder e.g., turning on multi-head attention in program encoder (0.585 and 0.696), but are still lower than turning on both attention i.e., 0.658 and 0.739 on Java and Python respectively. We conjecture that it is because the learnt space by BiGGNN and multi-head attention is different, combining both for program and description is beneficial, however turning off one for program or description while the other uses both will degrade the performance.

Hop&Head Analysis

In BiGGNN, the number of hops (see k in Eq. 7) affects the capacity to capture the local structure information and

the head number also affects global dependency from different representation subspaces (Vaswani et al. 2017). We conduct the experiment to investigate the performance and the experimental results are shown in Figure 4. We can see that for BiGGNN, when the number of hops equal to 4 and 3 on Java and Python data set is sufficient to capture graph structure information. For multi-head attention, we set the head number to 2 for both Java and Python to capture the global dependency.

Case Study

Due to the space limit, here we just show three examples of the queried results by GraphSearchNet for Java and Python respectively in Table 5. The most similar top-10 results of 99 queries produced by GraphSearchNet are provided in the supplementary materials. From Table 5, we can find that the returned programs are very relevant with the queries.

Conclusion

In this paper, we propose GraphSearchNet, a novel graph-based framework for code search to capture the semantic relations of source code and the query. We construct the program and description graphs with BiGGNN to learn the local structure information hidden in the text. Furthermore, we also employ multi-head attention to capture the global dependency that BiGGNN missed. The extensive experiments on both Java and Python dataset demonstrate the effectiveness of GraphSearchNet.

Table 5: Three examples of the queried top-1 results from the search codebase C_{base} .

Query	Java	Python def strings_to_integers(strings: Iterable[str]) -> Iterable[int]: return strings_to_(strings,		
convert string to number	<pre>public Number convertToNumber(String s, NumberType type) { return scanner.</pre>			
how to extract zip file recursively	<pre>public static void extractZip(final String path, final File dest) throws IOException { extractZip(path, dest, null); }</pre>	<pre>def extract_zipfile(self, zipfile_path, unpack_dir): with zipfile.ZipFile(zipfile_path,</pre>		
how to determine a string is a valid word	<pre>public static boolean isWord (@Nullable final String sStr) { if (StringHelper.hasNoText (sStr)) return false; return isWord (sStr.toCharArray ()); }</pre>	<pre>def isValid(self, text, word): return bool(re.search(word, text,</pre>		

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