Is a Single Model Enough? MuCoS: A Multi-Model Ensemble Learning for Semantic Code Search

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ABSTRACT
Recently, deep learning methods have become mainstream in code search since they do better at capturing semantic correlations between code snippets and search queries and have promising performance. However, code snippets have diverse information from different dimensions, such as business logic, specific algorithm, and hardware communication, so it is hard for a single code representation module to cover all the perspectives. On the other hand, as a specific query may focus on one or several perspectives, it is difficult for a single query representation module to represent different user intents. In this paper, we propose MuCoS, a multi-model ensemble learning architecture for semantic code search. It combines several individual learners, each of which emphasizes a specific perspective of code snippets. We train the individual learners on different datasets which contain different perspectives of code information, and we use a data augmentation strategy to get these different datasets. Then we ensemble the learners to capture comprehensive features of code snippets. The experiments show that MuCoS has better results than the existing state-of-the-art methods.

CCS CONCEPTS
• Software and its engineering → Reusability: Search-based software engineering; • Information systems → Novelty in information retrieval.

KEYWORDS
code search, ensemble learning, data augmentation, deep learning

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1 INTRODUCTION
Code search is the most frequent developer activity in software development process [16]. Reusable code examples help improve the efficiency of developers in their developing process [1, 17]. Given a natural language query that describes the developer’s intent, the goal of code search is to find the most relevant code snippet from a large source code corpus.

Many code search engines have been developed for code search. They mainly rely on traditional information retrieval (IR) techniques such as keyword matching [13] or a combination of text similarity and Application Program Interface (API) matching [14]. Recently, many works have taken steps to apply deep learning methods [3, 8, 18, 20, 22] to code search [2, 4, 5, 7, 10–12, 17, 19, 21, 23, 24], using neural networks to capture deep and semantic correlations between natural language queries and code snippets, and have achieved promising performance improvements. These methods employ various types of model structures, including sequential models [2, 4, 5, 7, 10, 17, 19, 21, 23, 24], graph models [6, 12], and transformers [4].

Existing deep learning code search methods mainly use a single model to represent queries and code snippets. However, code may have diverse information from different dimensions, such as business logic, specific algorithm, and hardware communication, making it hard for a single code representation module to cover all the perspectives. On the other hand, as a specific query may focus on several perspectives, it is difficult for a single query representation module to represent different user intents.

To address the problems above, we propose MuCoS: Multi-Model for Code Search. First, we use data augmentation strategy to train multiple models that focus on different perspectives of code. Then, we combine these models using an ensemble learning strategy. For one natural language query in the training corpus, there are multiple corresponding code snippets with the same functionality but different structures or variable names after data augmentation. We believe our model can be induced to be less focused on the
To summarize, this paper makes the following contributions:

- We propose a novel multi-model architecture MuCoS for code search. We use an ensemble learning strategy to capture different perspectives of code information and query intents.
- We do data augmentation based on semantic invariance of programs to get multiple individual learners which focus on different features of code. To the best of our knowledge, we are the first to employ data augmentation to solve the semantic code search problem.
- We conduct extensive experiments to evaluate the effectiveness of our approach. The results show that our approach significantly outperforms the state-of-the-art methods by 12% on the standard dataset and 14% on the sampled dataset.

2 PROPOSED MODEL: MUCOS

Fig. 3 illustrates the overall structure of the proposed model framework MuCoS. This framework consists of three phases: data augmentation/separation, individual encoder fine-tuning, and ensemble learning.

The basic idea of our method is to learn several individual encoders, each of which focuses on a specific aspect of code snippets based on different datasets. These datasets are generated from the original dataset through domain knowledge of programming language, such as API information from JVM library and semantic equivalent transformations of code snippets [15]. Finally, we leverage ensemble learning to integrate the individual modules.

2.1 Data Augmentation or Separation

The first step is to generate proper datasets for feeding individual learners. We design three data augmentation or separation strategies for separately building a structure-focused dataset, a variable-focused dataset, and an API-focused dataset:

- **Structure-focused data generation:** To reduce the impact of local variable names and make the model focus more on the program structure, we use the variable renaming program transformation method in [15] to generate semantic equivalent code snippets with local variable names replaced by varN, as shown in Fig. 2. Then we mix them with origin data.

- **Variable-focused data generation:** To reduce the impact of structure and make the model focus more on lexical information, we use the statement permutation program transformation method in [15] to change the program structure, swapping two independent statements (i.e., with no data or control dependency) in a basic block of a method while maintaining semantic equivalence, as shown in Fig. 1. Then we mix them with origin data.

- **API-focused data generation:** We select the samples that the code snippets have API invocation from JVM library as the training data for API-focused model.

The general idea behind the first generation method is that the model will not highly rely on variable names to determine the similarity between query-code pairs, because the code snippets with different variable names will correspond to the same query, and hence the model will pay more attention to structural characteristics. Similarly, the model fine-tuned by the second dataset will pay significant attention to local variable names and the third dataset will pay more attention to lexical characteristics.
more attention to variable names of code snippets. The generation method of the third one is easy to understand via directly selecting the code snippets with API invocation.

2.2 Individual Model Fine-Tuning and Model Combination

We follow CodeBERT [4] to use a multi-layer bidirectional Transformer as the model architecture. We feed positive and negative samples in the model, and the ratio of them is 1:1. To build negative examples, for each positive sample we change the query into a randomly mismatched one while the code snippet remains unchanged.

We use an ensemble learning strategy to combine the structure-focused model, variable-focused model, and API-focused model. We first concatenate the embedding of the hidden state’s last layers of these models, then append an MLP classifier with two linear layers to the last layer of the concatenated neural network, training and updating its weights using the origin data. The loss functions of individual model fine-tuning and ensemble learning are both cross entropy to discriminate the positive pair and the negative pair.

3 EXPERIMENTAL SETUP

3.1 Dataset

To evaluate the effectiveness of our method, we use a widely used dataset for the code search task: CodeSearchNet [9], containing 500,754 pairs of function-level Java code snippets and their descriptions. There are 454,443 pairs as the training set, 30,655 pairs as the validation set and 26,909 pairs as the test set.

We extend the training dataset by collecting the same number of negative samples as the positive samples. For each positive pair sample, we randomly select a mismatched query replacing the original query while maintaining the code snippet unchanged to construct a negative pair sample.

3.2 Evaluation Metrics

We use three widely used metrics for the evaluation of code search methods: FRank, SuccessRate@k, and MRR. The FRank, or best hit rank, is the rank of the first hit result in this result list. A smaller FRank implies lower inspection effort for finding the desired result [5]. FRank can represent the effectiveness of a single code search query. The SuccessRate@k measures the percentage of queries for which more than one correct result exists in the top k ranked results. In our evaluation, is calculated as follows:

\[
\text{SuccessRate}@k = \frac{1}{|Q|} \sum_{q=1}^{Q} \delta(\text{FRank}_q \leq k)
\]

where \( Q \) is a set of queries, \( \delta(\cdot) \) is a characteristic function, i.e., \( \delta(\cdot) = 1 \) if \( \cdot \) satisfied, otherwise \( \delta(\cdot) = 0 \). A higher SuccessRate@k means better code search performance. The MRR is the average of the reciprocal ranks of results of a set of queries \( Q \). The reciprocal rank of a query is the inverse of the rank of the FRank. In our evaluation, is calculated as follows:

\[
\text{MRR} = \frac{1}{|Q|} \sum_{q=1}^{Q} \frac{1}{\text{FRank}_q}
\]
Table 1: Evaluation of different baselines on full Code Search Net corpus.

| Model  | S@1  | S@5  | S@10 | MRR  |
|--------|------|------|------|------|
| NBoW  | 0.499| 0.698| 0.752| 0.589|
| 1D-CNN | 0.424| 0.631| 0.699| 0.518|
| biRNN | 0.485| 0.685| 0.743| 0.644|
| SelfAtt | 0.486| 0.682| 0.738| 0.575|
| ConvSelfAtt | 0.413| 0.619| 0.681| 0.507|
| CODEnn | 0.146| 0.146| 0.146| 0.146|
| CodeBert | 0.642| 0.792| 0.825| 0.708|
| MuCoS  | 0.750| 0.843| 0.860| 0.793|

Table 2: Evaluation of different baselines on sampled Code Search Net corpus.

| Model  | S@1  | S@5  | S@10 | MRR  |
|--------|------|------|------|------|
| NBoW  | 0.271| 0.441| 0.507| 0.354|
| 1D-CNN | 0.052| 0.151| 0.224| 0.110|
| biRNN | 0.178| 0.364| 0.454| 0.270|
| SelfAtt | 0.298| 0.487| 0.562| 0.388|
| ConvSelfAtt | 0.193| 0.375| 0.461| 0.282|
| CODEnn | 0.043| 0.043| 0.043| 0.043|
| CodeBert | 0.624| 0.773| 0.805| 0.661|
| MuCoS  | 0.702| 0.815| 0.831| 0.754|

4.2 RQ2. How does MuCoS perform compared to other baselines on a small dataset?

We try a small sampled dataset with 60k samples to test whether code search models can maintain good performance on a small dataset. The training set is sampled from CodeSearchNet’s training set, the number of training data is 60000, while the validation data and testing data keep the same amount. The baselines are trained with default parameters. Table 2 shows that the performance of most baselines drop largely on the small dataset. Our method and CodeBert have significantly less performance drop than other methods. We assume that pre-trained models can better adapt to scenarios with small data on the code search task. Moreover, our method still has a 14% advantage compared to CodeBert on the small dataset.

4.3 RQ3. How the individual models in MuCoS affect its overall effectiveness?

In this research question, we evaluate whether each individual model contribute to building our final model MuCoS. Fig. 4 shows the results. Surprisingly, the three models that capture individual features all perform better than the baselines. The reason may be that the baselines do not model information of different features separately, which causes the baseline model to be confused with information from different features. On the other hand, MuCoS is significantly better than the three individual learners, which is also in line with the basic assumptions of ensemble learning.

4.4 Case Study

We now provide an example to show our individual models can capture the specific feature and contribute to the performance of MuCoS. Fig. 5 shows the corresponding code snippet for the natural language query "get the field label". We evaluate them on our individual models and find that the correct result ranks first in the API-focused model, third in the structure-focused model, fifth in the var-focused model, and also first in our MuCoS model.

In this case, the API-focused model can better capture code features than the structure-focused model and the var-focused model. Since the query has many overlaps with the APIs in the code snippet, the API-focused model can capture more information and have better performance. It also contributes to the overall performance of MuCoS.

5 RELATED WORK

Code search is a cross-field of natural language processing and software engineering which aims to retrieve code snippets from a large code corpus that most match the developer’s thoughts using natural language. There are mainly two kinds of approaches of code search, information retrieval (IR) based [13, 14] and deep learning based [2, 4, 5, 7, 10–12, 17, 21, 23, 24].

Most of the existing code search engines rely on IR-based techniques, employing keyword matching or text similarity to retrieve code snippets. Recently, deep learning methods become mainstream since they do better at capturing deep and semantic correlations between code snippets and search queries and have promising performance. For example, [5] proposed CODEnn, which can jointly embed code snippets and natural language descriptions into a high-dimensional vector space and then compute similarity. [4] present
CodeBERT, a bimodal pre-trained model for natural language and programming language which can solve code search problem.

6 CONCLUSION

In this paper, we propose a novel multi-model architecture MuCoS for code search. Instead of training one single model for code snippets and queries, we train multiple models which have specific features and combine them, which can help us better capture the diverse meaning from code snippets and natural language queries. To train models with specific features, we use a data augmentation and separation strategy to force the models to capture features of specific perspectives. Then we use an ensemble learning strategy to combine our models. Our experimental study has shown that the proposed approach is effective and outperforms other state-of-the-art approaches.

This work is ongoing. In the future, we plan to evaluate our methods on more datasets. And we will train more individual learners focusing on more features. Moreover, we want to build a selection module to help select individual learners which are most suitable for the search query.

REFERENCES

[1] Joel Brandt, Philip J. Guo, Joel Lewenstein, Mira Dontcheva, and Scott R. Klemmer. 2009. Two Studies of Opportunistic Programming: Interleaving Web Foraging, Learning, and Writing Code. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (Boston, MA, USA) (CHI ’09) Association for Computing Machinery, New York, NY, USA, 1589–1598. https://doi.org/10.1145/1518701.1518944

[2] Jose Cambronerro, Hongyu Li, Seohyun Kim, Koushik Sen, and Satish Chandra. 2019. When deep learning met code search. ESEC/FSE 2019 - Proceedings of the 2019 27th ACM Joint Meeting European Software Engineering Conference and Symposium on the Foundations of Software Engineering (2019), 964–974. https://doi.org/10.1145/3389065.3340458 arXiv:1905.03013

[3] Kyunghyun Cho, Bart van Merriënboer, Çaglar Gulec, Dmitriy Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. In Empirical Methods in Natural Language Processing. 1724–1734.

[4] Zhangyin Feng, Duya Guo, Dayi Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, and Ming Zhou. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. (2020), 1536–1547. https://doi.org/10.18653/v1/2020-findings-emnlp.139 arXiv:2002.08155

[5] Xiaofeng Gu, Hongyu Zhang, and Sunghun Kim. 2018. Deep code search. Proceedings - International Conference on Software Engineering (2018), 933–944. https://doi.org/10.1109/ICSE.2018.3180167

[6] Duya Guo, Shao Ren, Shuai Lu, Zhangyin Feng, Dayi Tang, Shujie Liu, Long Zhou, Nan Duan, Alexey Svyatkovskiy, Shengyu Fu, Michele Tufano, Shao Kun Deng, Colin Clement, Dawn Drain, Neel Sundaresan, Jian Yin, Daxin Jiang, and Ming Zhou. 2020. GraphCodeBERT: Pre-training Code Representations with Data Flow. (2020), 1–14. arXiv:2009.08366 http://arxiv.org/abs/2009.08366

[7] Rajarshi Haldar, Lingfei Wu, Linjun Xiong, and Julia Hockenmaier. 2020. A multi-perspective architecture for semantic code search. arXiv (2020). https://doi.org/10.18653/v1/2020.acl-main.758 arXiv:2005.06980

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. 770–778.

[9] Hamel Hussian, Ho Hsiang Wu, Tiferet Gazit, Miltiadis Allamanis, and Marc Brockschmidt. 2019. CodeSearchNet challenge evaluating the state of semantic code search. arXiv (2019). arXiv:1909.09436

[10] Wei Li, Haozhe Qin, Shuhan Yan, Beijun Shen, and Yuting Chen. 2020. Learning Code-Query Interaction for Enhancing Code Searches. Proceedings - 2020 IEEE International Conference on Software Maintenance and Evolution, ICSEM 2020 (2020), 115–126. https://doi.org/10.1109/ICSEM49900.2020.00021

[11] Chunyang Ling, Zeqi Lin, Yanzhen Zou, and Bing Xie. 2020. Adaptive deep code search. IEEE International Conference on Program Comprehension (2020), 48–59. https://doi.org/10.1145/3387904.3389278

[12] Xiang Ling, Lingfei Wu, Saihuo Wang, Gaoning Pan, Tengfei Ma, Fangli Xu, Alex X. Liu, Chunming Wu, and Shouling Ji. 2020. Deep Graph Matching and Searching for Semantic Code Retrieval. 0, 0 (2020), 1–21. arXiv:2010.12908

[13] Merli Li, Xiaohong Sun, Shaowei Wang, David Lo, and Yucong Duan. 2015. Query expansion via WordNet for effective code search. In 2015 IEEE 22nd International Conference on Software Analysis, Evolution, and Reengineering (SANER). 545–549. https://doi.org/10.1109/SANER.2015.7081874

[14] Fei Lv, Hongyu Zhang, Jian-guang Lou, Shaowei Wang, Dongmei Zhang, and Jianjun Zhao. 2015. CodeFlow: Effective Code Search Based on API Understanding and Extended Boolean Model (E). In 2015 IEEE/ACM International Conference on Automated Software Engineering (ASE). 260–270. https://doi.org/10.1109/ASE.2015.42

[15] Md. Rafiqul Islam Rabin, Nghi D. Q. Bui, Yijun Yu, Lingxiao Jiang, and Mohammad Amin Alipour. 2020. On the Generalizability of Neural Program Models with respect to Semantic-Preserving Program Transformations. (2020). arXiv:2008.01566 http://arxiv.org/abs/2008.01566

[16] Caixian Sadowski, Kathryn T. Stoler, and Sebastian Elbaum. 2015. How Developers Search for Code: A Case Study. In Joint Meeting of the European Software Engineering Conference and the Symposium on the Foundations of Software Engineering (ESEC/FSE ). 1600 Amphitheatre Parkway.

[17] Jianhuang Shuai, Ling Xu, Chao Liu, Meng Yan, Xin Xia, and Yan Lei. 2020. Improving code search with co-attentive representation learning. IEEE International Conference on Program Comprehension (2020), 196–207. https://doi.org/10.1109/3387904.3389269

[18] Junshan Wang, Zhicong Lu, Guojia Song, Yue Fan, Lun DU, and Wei Lin. 2019. Tag2vec: Learning tag representations in tag networks. In The World Wide Web Conference. 3341–3350.

[19] Yanlin Wang, Lun Du, Enheng Shi, Xuyuan Hu, Shi Han, and Dongmei Zhang. 2020. Cocogum: Contextual code summarization with multi-relational gen on umls. Technical Report. Microsoft, MSR-TR-2020-16. [Online]. Available: https://www.microsoft.com/en-us/research/publication/cocogum-contextual-code-summarization-with-multi-relational-gen-on-umls

[20] Yun Wang, Lun Du, Guojie Song, Xiaojun Ma, Lichen Jin, Wei Lin, and Fei Sun. 2019. Tag2Gauss: Learning Tag Representations via Gaussian Distribution in Tagged Networks. In IJCAI. 3799–3805.

[21] Shuhan Yan, Hang Yu, Yuting Chen, Beijun Shen, and Lingxiao Jiang. 2020. Are the Code Snippets What We Are Searching for? A Benchmark and an Empirical Study on Code Search with Natural-Language Queries. SANER 2020 - Proceedings of the 2020 IEEE 27th International Conference on Software Analysis, Evolution, and Reengineering (2020), 344–354. https://doi.org/10.1145/3364827.2050484

[22] Shuwen Yang, Guojie Song, Yilun Jin, and Lun Du. 2020. Domain Adaptive Classification on Heterogeneous Information Networks. In International Joint Conferences on Artificial Intelligence.

[23] Wei Ye, Rui Xie, Jingli Zhang, Tianshuang Xu, Xiaoyin Wang, and Shikun Zhang. 2020. Leveraging Code Generation to Improve Code Retrieval and Summarization via Dual Learning. The Web Conference 2020 - Proceedings of the World Wide Web Conference, WWW 2020 (2020), 2309–2319. https://doi.org/10.1145/3366423.3380295 arXiv:2002.10198

[24] Qihao Zhu, Zeyu Sun, Xiran Liang, Yingfei Xiong, and Lu Zhang. 2020. OCoR: An Overlapping-Aware Code Retriever. Proceedings - 2020 35th IEEE/ACM International Conference on Automated Software Engineering, ASE 2020 (2020), 883–894. https://doi.org/10.1145/3387904.3389269