When Deep Learning Met Code Search

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ABSTRACT

There have been multiple recent proposals on using deep neural networks for code search using natural language. Common across these proposals is the idea of embedding code and natural language queries, into real vectors and then using vector distance to approximate semantic correlation between code and the query. Multiple approaches exist for learning these embeddings [15, 19, 24, 26], including unsupervised techniques, which rely only on a corpus of code examples, and supervised techniques, which use an aligned corpus of paired code and natural language descriptions. The goal of this supervision is to produce embeddings that are more similar for a query and the corresponding desired code snippet. Clearly, there are choices in whether to use supervised techniques at all, and if one does, what sort of network and training to use for supervision. This paper is the first to evaluate these choices systematically. To this end, we assembled implementations of state-of-the-art techniques to run on a common platform, training and evaluation corpora. To explore the design space in network complexity, we also introduced a new design point that is a minimal supervision extension to an existing unsupervised technique.

Our evaluation shows that: 1. adding supervision to an existing unsupervised technique can improve performance, though not necessarily by much; 2. simple networks for supervision can be more effective that more sophisticated sequence-based networks for code search; 3. while it is common to use docstrings to carry supervision, there is a sizeable gap between the effectiveness of docstrings and a more query-appropriate supervision corpus.

ACM Reference Format:
Jose Cambronero, Hongyu Li, Seohyun Kim, Koushik Sen, and Satish Chandra. 2019. When Deep Learning Met Code Search. In Proceedings of ACM Conference (Conference’17). ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/nmnnmnn.nmnnnn

1 INTRODUCTION

We have recently seen a significant uptick in interest in code search. The goal of code search is to retrieve code fragments from a large code corpus that most closely match a developer’s intent, which is expressed in natural language. Being able to examine existing code that is relevant to a developer’s intent is a fundamental productivity tool. Sites such as Stack Overflow are popular because they are easy to search for code relevant to a user’s question expressed in natural language.

It has typically been harder to search directly over public code repositories, such as GitHub, as well as private repositories internal to companies. Proprietary code repositories in particular pose a challenge, as developers can no longer rely on public sources such as Google or Stack Overflow for assistance, as these may not capture the required organization-specific API and library usage. However, recent works from both academia and industry [15, 19, 21, 26] have taken steps towards enabling more advanced code search using deep learning. We call such methods neural code search. See Table 1 for some examples of code snippets retrieved based on natural language queries: it is evident that the state of the technology has become promising indeed. The type of queries presented in Table 1, and the accompanying results, also highlight the difficulties associated with tackling this task purely based on simple approaches such as regular-expression matching.

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Figure 1 provides a general overview of neural code search and outlines different techniques, which we address in detail through this paper. The core abstraction in neural code search systems is the notion of embeddings, which are vector representations of inputs in a shared vector space. By computing a vector similarity measure, such as cosine similarity [31], over these embeddings, search can retrieve code fragments that are semantically related to a user query. For example, in Figure 1, the query “How do I iterate through a hashmap?” is mapped to the vector \([1.2, -0.1, 1.5] \) by one possible technique (NCS). Candidate code snippets are also mapped to vectors using the same technique. In Figure 1, one such code snippet, `public void forValuesAtSameKey(Map<K,V> map, ...) { ... }`, is mapped to the vector \([0.94, -0.2, 1.2] \). The candidate code snippets can then be ranked using vector similarity. A key challenge in neural code search is to learn these embeddings in a way that vector similarity coincides with semantic relatedness.

As shown in Figure 1, the models used to learn these representations can be broadly grouped into unsupervised and supervised. In our journey to explore the advantages of neural techniques, we started with NCS, an effective, unsupervised, neural code search technique we previously built in [26]. Because NCS showed promising results, we wanted to experiment with the possibility of improving upon this baseline through additional design enhancements. In particular, recent work [15, 19] presented promising supervised neural code search techniques, labeled CODEnn and SCS respectively, that successfully learned code and natural language embeddings using corpora of source code and docstrings.

The goal of this supervision is to learn a mapping that produces more similar vectors for user queries and the corresponding desired code. In Figure 1, this goal is depicted by the red and blue arrows, which move the embeddings for the query and correct code fragment, respectively, closer together when mapped using a supervised model.

With so many techniques to choose from, how does anyone trying to design and deploy a code search solution make an informed choice? What are the trade-offs involved? For instance, supervision sounds like a good idea, but how much benefit does it provide, relative to the overhead of obtaining the supervision data? How much value, if any, do the more sophisticated networks – which have many more parameters – bring compared to a simpler network, one of which we introduce in this work (UNIF in Figure 1, described further below)? Does model supervision carried out using docstrings (as is common practice in work on bimodal embeddings, including CODEnn and [21]), potentially limit performance when models are applied to real user queries?

In this work, we attempt to understand these trade-offs quantitatively. To do so, we formulate experiments in the context of the code search techniques mentioned above, and use open-source evaluation corpora, described later. Three of these techniques are exactly as in previous work, and are state-of-the-art at this time:

- **NCS** An unsupervised technique for neural code search developed at Facebook [26], which uses only word embeddings derived from a code corpus.
- **CODEnn** A supervised technique from a recent paper on code search using deep neural networks [15], which uses multiple sequence-to-sequence-based networks, and was shown to outperform other state-of-the-art code search techniques. We use the implementation provided by the authors [16].
- **SCS** A supervised neural code search system using multiple sequence-to-sequence networks. We use the implementation provided by the authors in a blog post [19, 20].

Because we wanted to understand the extent to which the complex sequence-of-words based networks help, we also developed a minimal extension to the NCS technique, just adding supervision and nothing else:

- **UNIF** A supervised extension of the base NCS technique of our own creation. UNIF uses a bag-of-words-based network, which has significantly lower complexity compared to sequence-of-words-based networks. This simple model is a new contribution of this paper.

Our evaluation is structured using the following three research questions; we also give the summary of our findings along with the question.
**Research Question 1.** Does extending an effective unsupervised code search technique with supervision based on a corpus of paired code and natural language descriptions improve performance?

Our results show that UNIF performed better than NCS on our benchmark queries, though the improvement was not seen uniformly across all data sets.

**Research Question 2.** Do more sophisticated networks improve performance in supervised neural code search?

Our results show that UNIF, a simple, bag-of-words-based network, outperformed the sequence-of-words-based CODEnn and SCS. The additional sophistication did not add value.

**Research Question 3.** How effective is supervision based on docstrings as the natural language component of the training corpus?

We found that supervision based on docstrings – which is commonly the natural language component of an aligned corpus – did not always improve performance, contrary to expectations. To understand the possible room for improvement, we constructed an ideal alternate training corpus, where the code snippets and natural language, while disjoint from our benchmark queries, were drawn from the same source.

When trained on this corpus, all supervised techniques improved significantly, showing that, as a proof of concept, if given a training corpus that matches expected user evaluation, these techniques can provide impressive search performance.

**Contributions.** 1. We believe this is the first paper to compare recent neural code search systems running on the same platform and evaluation using the same corpora.

2. We present a new design point in the spectrum of neural code search systems: UNIF, an extension to NCS that minimally adds supervision and nothing else.

3. Our findings are that UNIF outperforms some of the more sophisticated network designs (CODEnn and SCS) as well as the NCS, the unsupervised technique. Moreover, the choice of the aligned corpus used in supervision is extremely pertinent: an idealized training corpus shows that supervised techniques can deliver impressive performance, and highlight the differences in performance that may not be immediately evident from training on the typical code and docstring aligned corpora.

These findings have implications for anyone considering designing and deploying a neural code search system in their organization. The findings also have implications for researchers, who should consider simple baseline models in evaluating their designs.

**Outline.** The rest of the paper is organized as follows. Section 2 introduces the core idea of embeddings and their use in neural code search. Section 3 details each of the techniques explored in this paper. Section 4 presents our evaluation methodology. Section 5 provides results supporting our research questions’ answers. Section 6 and Section 7 discuss threats to validity and related work, respectively. Finally, Section 8 concludes with the main takeaways and implications for neural code search system designers.

## 2 EMBEDDINGS FOR CODE

An embedding refers to a real-valued vector representation for an input. An embedding function $E : X \rightarrow \mathbb{R}^d$ takes an input $x$ in the domain of $X$ and produces its corresponding vector representation in a $d$-dimensional vector space. This vector is said to be distributed [6], where each dimension of the vector is not attributed to a specific hand-coded feature of the input, but rather the “meaning” of the input is captured by the vector as a whole.

Embeddings present multiple appealing properties. They are more expressive than local representations, such as one hot encodings, as values along each dimension are continuous [6]. Embeddings can also be learned, which makes them applicable to different domains where we have example data. One possibility is to learn these embeddings using a neural network, such that the function $E$ uses a network’s learned weights.

### 2.1 Running Example

We present a running example to illustrate some of the key concepts for the use of embeddings in code search. Suppose we want to produce a vector that can successfully represent the code snippet below.

```java
for (entry : map.entrySet()) {
    System.out.println(entry);
}
```

One possible approach is to treat this source code as text, and tokenize this input into a collection of individual words. The extent of tokenization (and filtering certain words) may depend on the specific model design. For this example, we will tokenize based on standard English conventions (e.g., white-space, punctuation) and punctuation relevant to code (e.g., snake and camel case). The code snippet can now be treated as the collection of words.

```java
for entry map entry set system out println entry
```

Given a corpus of multiple code examples, such as the source code corpus in Figure 1, we can tokenize all code examples and learn an embedding for each token.

One approach to learning token embeddings is with an unsupervised model. One popular technique is word2vec, which implements a skip-gram model [7, 24]. In the skip-gram model, the embedding for a target token is used to predict embeddings of context tokens within a fixed window size. In our example, given the embedding for the token set and a window size 2, the skip-gram model would learn to predict the embeddings for the tokens map, entry, system, and out. The objective of this process is to learn an embedding matrix $T$, where each row corresponds to the embedding for a token in the vocabulary, and where two embeddings are similar if the corresponding tokens often occur in similar contexts.

At this point, we can map each word in our tokenized code snippet to its corresponding embedding. For example, for may be represented by $(0.2, -1.0, 3.8)$, and entry may be represented by $(0.8, 0.9, -2.0)$.

### 2.2 Bags and sequences of embeddings

The next step in our procedure will be to combine the token-level embeddings for our code snippet into a single embedding that appropriately represents the snippet as a whole. We discuss two possible approaches to doing so using standard neural network architectures.
So far we have not discussed the impact of the token order in our snippet. We can treat words as a bag, occasionally called a multiset, and ignore order. In such a case, our example

```java
for entry map entry set system out println entry
```

would be equivalent to every other permutation, such as

```java
entry for map println entry set out system
```

A corresponding bag-based neural network would compute the representation for our code snippet without regard to token order. One simple example of such a bag-of-words-based architecture is one where we use \( T \), the matrix of learned token embeddings, to look up the embedding for each word in the tokenized example and then average (either simple or weighted) these vectors to obtain a single output vector.

In contrast, a neural network may instead consume the tokens in an input as a sequence, such that the ordering of elements is significant. We provide details on one common approach to handling sequence-based inputs: recurrent neural networks (RNN) [12].

An RNN starts with an initial hidden state, often initialized randomly, represented as \( h_0 \), and processes the words in the input sequentially one by one. In our example, the two permutations of the tokenized code snippet are no longer equivalent.

After processing each word, the RNN updates the hidden state. If the \( i \)th word in the sequence is \( w_i \) and the hidden state after processing the words before \( w_i \) is \( h_{i-1} \), then the next hidden state after processing \( w_i \) is obtained as follows:

\[
h_t = \tanh(W[h_{t-1}; w_t])
\]

where \( W \) is a matrix whose parameters are learned, \( [x; y] \) is the vector obtained by concatenating the vector \( x \) and \( y \), and \( \tanh(x) = \frac{e^x-e^{-x}}{e^x+e^{-x}} \) is a non-linear activation function which ensures that the value of \( \tanh(x) \) lies between 1 and -1.

There are multiple approaches to obtain a snippet-level embedding using this RNN. For example, one model might take the last hidden state \( h_T \) as the snippet embedding. Another could collect the hidden states \( h_t \) and apply a reduction operation such as dimension-wise max or mean to produce the snippet embedding.

The network described above is a simple RNN; in practice, an NCS adds a more complex function on \( h_{t-1} \) and \( w_t \). An example of such an RNN is long-short term memory (LSTM) [18].

2.3 Bi-Modal embeddings

So far, we have only discussed how to produce a representative vector given a code snippet. However, neural code search uses embeddings for both code snippets and the user’s natural language query. This means that our embedding approach must be able to represent both the code for (entry : map.entrySet) ... , and the query "how to iterate through a hashmap", which is expressed in natural language. Such embeddings that relate two different kinds of data are called bi-modal embeddings [2].

The computation of bi-modal embeddings of a code snippet and its natural language description can be abstractly formulated as two functions: \( E_c : C \rightarrow \mathbb{R}^d \) and \( E_q : Q \rightarrow \mathbb{R}^d \), where \( C \) is the domain of code snippets, \( Q \) is the domain of natural language descriptions, \( \mathbb{R}^d \) is a real-valued vector of length \( d \), \( E_c \) is an embedding function that maps a code snippet to a \( d \)-dimensional vector, and \( E_q \) is an embedding function that maps a natural language description to a vector in the same vector space. The goal is to learn the functions \( E_c \) and \( E_q \) such that for some similarity measure \( \text{sim} \), such as cosine similarity [31], \( \text{sim}(E_c(c), E_q(q)) \) is maximized for a code snippet \( c \) and its corresponding natural language description \( q \). Alternatively, for unsupervised models, such as NCS, \( E_c \) and \( E_q \) may be instantiated with the same token-level embedding matrix \( T \), as shown in Figure 1.

2.4 Applying embeddings to code search

Given \( E_c \) and \( E_q \), code search can be performed given the user query and a code corpus.

Figure 1 illustrates how embeddings are used in code search. The code embedding function \( E_c \) is used to convert each candidate code snippet in our search corpus into a vector.

For example, given the code snippet

```java
public void forValuesAtSameKey(Map<K, V> map, ...) {
    ...
}
```

in our search index, an unsupervised \( E_c \) (labeled NCS in the figure) returns the vector representation \((0.94, -0.2, 1.2)\). All the snippets in a corpus can be embedded in a similar fashion and used to construct an index that allows for fast lookups based on a similarity metric.

The user query can be similarly embedded using \( E_q \). For example, “How do I iterate through a hashmap?” is mapped to the vector \((0.2, 0.4, 0.5)\). To retrieve relevant code snippets, the code embeddings index can be searched based on similarity to the query embedding. The top \( N \) results based on this similarity are returned.

There are a number of possible neural architectures used to learn \( E_q \) and \( E_c \), and we will explore several of them in this paper.

3 NEURAL CODE SEARCH MODELS

We now introduce each of the neural techniques explored in this paper.

3.1 NCS

In NCS [26], a specific technique named after the general concept of Neural Code Search, the embedding functions \( E_c \) and \( E_q \) are implemented using a combination of token-level embeddings using fastText [7], which is similar to word2vec [24], and conventional information retrieval techniques, such as TF-IDF [11, 27]. As such this technique does not use conventional deep neural networks nor supervised training. NCS computes an embedding matrix \( T \in \mathbb{R}^{|V_c| \times d} \), where \( |V_c| \) is the size of the code token vocabulary, \( d \) is the chosen dimensionality of token embeddings, and the \( k \)th row in \( T \) is the embedding for the \( k \)th word in \( V_c \). Once the matrix \( T \) has been computed using fastText, it is not further modified using supervised training.

NCS applies the same embedding matrix \( T \) to both the code snippets and the query as follows. Let \( c = \{c_1, \ldots, c_n\} \) and \( q = \{q_1, \ldots, q_m\} \) represent the code snippet and query, respectively, as
We will introduce with a learned attention-based weighing scheme. We refer to this TF (term-frequency) for that token, but its weight will be scaled vector \( \mathbf{e} \) in the matrix \( \mathbf{T} \) for the token \( w \).

To combine the bag of code token embeddings into a single code vector \( \mathbf{e_c} \), NCS sums the embeddings for the set of unique tokens weighted by their corresponding TF-IDF weight. The TF-IDF weight is designed to increase the weight of tokens that appear frequently in a code snippet, and decrease the weight of tokens that appear too frequently globally across all of the code corpus. For example, in a NLP (natural language processing) corpus, a document with many repetitions of a common word such as “the” will have a high TF (term-frequency) for that token, but its weight will be scaled down by the IDF value (inverse document-frequency) as that token likely also appears in many other documents. We elide the classical TF-IDF weighing formula here for brevity.

For the query, NCS averages the bag of query token embeddings into a single query vector \( \mathbf{e_q} \).

The high level architecture of the NCS model is illustrated in Figure 2.

3.2 UNIF: a supervised extension of NCS

We will introduce UNIF next, as it is a supervised minimal extension of the NCS technique. In this model, we use supervised learning to modify the initial token embedding matrix \( \mathbf{T} \) and produce two embedding matrices, \( \mathbf{T_c} \) and \( \mathbf{T_q} \), for code and query tokens, respectively. We also replace the TF-IDF weighing of code token embeddings with a learned attention-based weighing scheme. We refer to this extended approach as Embedding Unification (UNIF).

We assume that an aligned corpus of code snippets and their natural language descriptions is available for training. We denote this corpus as a collection of \((c, q)\), where \( c \) is a bag of tokens \( e_1, \ldots, e_n \) from a code snippet and \( q \) is a bag of tokens from its corresponding natural language description.

The functions \( E_c \) and \( E_q \) are constructed as follows. Let \( T_q \in \mathbb{R}^{|V_q| \times d} \) and \( T_c \in \mathbb{R}^{|V_c| \times d} \) be two embedding matrices mapping each word from the natural language description (specifically the docstrings and the query) and code tokens, respectively, to a vector of length \( d \). The two matrices are initialized using the same initial weights, \( \mathbf{T} \), and modified separately during training.

We apply the respective embedding matrices to each element in the paired corpus, such that for a code snippet \( c \) we obtain a bag of embedding vectors \( \{T_c[e_1], \ldots, T_c[e_n]\} \), and similarly for each description \( q \). We compute a simple average to combine the query token embeddings into a single vector. The simple averaging is also present in NCS and we found it to outperform attention-based weighing during experiments.

To combine each bag of code token vectors into a single code vector that captures the semantic meaning of the corresponding entity, we use an attention mechanism [3] to compute a weighted average. The attention weights, \( a_c \in \mathbb{R}^d \), is a \( d \)-dimensional vector, which is learned during training. \( a_c \) acts as a learned counterpart to the TF-IDF weights in NCS.

Given a bag of code token embedding vectors \( \{e_1, \ldots, e_n\} \), the attention weight \( a_{ci} \) for each \( e_i \) is computed as follows:

\[
 a_{ci} = \frac{\exp(a_c e_i^T)}{\sum_{i=1}^{n} \exp(a_c e_i^T)}
\]  

Here we compute the attention weight for each embedding vector as the softmax over the inner product of the embedding and attention vectors. We normalize each attention weight to make sure that weights add up to 1, and apply exponentiation to make each weight positive and sharp.

The summary code vector of a bag of embedding vectors is then computed as the sum of the embedding vectors weighted by the attention weights \( a_{ci} \):

\[
 e = \sum_{i=1}^{n} a_{ci} e_i
\]  

\( e \) corresponds to the output of \( E_c \).

Our training process learns parameters \( T_q, T_c, \) and \( a_c \) using classic backpropagation.

Figure 3 shows a high level diagram of the embedding unification network.

3.3 CODEnn

Similar to UNIF, CODEnn [15] also models both \( E_c \) and \( E_q \) using neural networks and employs supervised learning; however, the networks used are more sophisticated and deep. We refer to this model as CODEnn, short for CodeDescriptionEmbeddingNeuralNetwork.
Instead of treating a code snippet as a bag of tokens, CODEnn extracts a sequence of words from the name of the method containing the code snippet, the sequence of API calls in the snippet, and a bag of tokens from the code snippet. The word sequence from a method name is extracted by splitting the method name on camel-case and snake-case.

The method name sequence and API sequence are given as input to two separate bi-directional long-short term memory (bi-LSTM) networks [18].

After applying two separate LSTMs to the method name and API sequences, CODEnn obtains two sequences of hidden states. CODEnn summarizes each such sequence of hidden states to obtain a single vector. For summarization, CODEnn uses the max-pooling function.

Each token in the bag of code tokens is given individually as input to a feed forward dense neural network and the output vectors are max-pooled. A final code embedding is then obtained by concatenating these three vectors (two from the LSTMs and one from the feed-forward network) and feeding them to a dense neural network which produces a single summary vector $e_c$. All the above networks together implement the function $E_c$.

CODEnn implements the function $E_q$ using a bi-directional LSTM, which takes as input sequence the description of the code snippet found in the doc string to produce $e_q$. Figure 4 provides an overview of the architecture.

### 3.4 SCS

We introduce another supervised sequence-based deep neural network for code search, described and implemented by the data science team at GitHub [19]. We will refer to this model as SCS, short for Semantic Code Search.

SCS is divided into three separate training modules. A sequence-to-sequence gated recurrent unit (GRU) network [8] learns to generate a docstring token sequence given a code token sequence. We refer to this as the code-to-docstring model.

An LSTM network [23] learns a language model for docstrings in the training corpus [29]. This model can be used to embed natural language and compute the probability of a given natural language input.

A final module learns a transformation (in the form of a feed forward layer) to predict a query embedding given a sequence of code tokens. To learn this transformation, the module takes the encoder portion of the code-to-docstring model, freezes its layers, and trains the network on code sequence inputs and the corresponding query embedding produced using the language model. A final training phase fine-tunes the network as a whole by unfreezing the encoder layer for a few epochs. SCS uses this fine-tuned encoder portion of the code-to-docstring model as $E_c$ and the language model as $E_q$. Figure 5 provides an overview of the architecture.

Table 2 provides an overview of the network details for models that employ supervision when learning their $E_c$ and $E_q$: UNIF, CODEnn, and SCS.

## 4 EVALUATION METHODOLOGY

Our evaluation uses different datasets and benchmarks. We use the following terminology throughout for clarity:

- **training corpus** refers to a dataset of paired code and natural language. An example for natural language could be the code fragment’s corresponding docstring. A training corpus is used to train the models and may contain duplicate code / natural language pairs. An unsupervised model, such as NCS, uses only the code fragments from a dataset.

- **search corpus** refers to a dataset of unique code entries. Entries are unique in order to avoid repetition in search results. We apply a trained model to a search corpus to search for the top results for a given user query. This dataset is used during the evaluation of the models.

- **benchmark queries** refers to a set of evaluation queries used to gauge the performance of trained models. Each query in a benchmark is accompanied by a gold-standard code fragment result, which we use to score results retrieved from a search corpus by a trained model.

Our evaluation uses three different training corpora, two search corpora, and two sets of benchmark queries.

### 4.1 Training Corpora

We use three training corpora for our experiments.

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2 Dataset is deduplicated after tokenization.
**CODEnn-Java-Train** is the dataset publicly released by the authors of CODEnn. This corpus consists of approximately 16 million pre-processed Java methods and their corresponding docstrings, intended for training. The dataset includes four types of inputs: method name sequences, API sequences, a bag of method body tokens, and docstring sequences. We additionally derive another input by concatenating the method name sequences to the API sequences and treating this concatenated sequence as a bag of tokens. This derived input is used to train UNIF and SCS.\(^3\)

**GitHub-Android-Train** is an Android-specific corpus that we built by collecting methods from approximately 26,109 GitHub repositories with the Android tag. We took all methods with an accompanying docstring, approximately 787,000 in total, and used these as training data. Similar to CODEnn-Java-Train, we derive the four types of input collections (method name sequences, API sequences, bag of method body tokens, and docstring sequences) necessary to train CODEnn. We train UNIF and SCS on the input sequence generated for NCS, which uses a parser to qualify method names with their corresponding class, extracts method invocations, enums, string literals and source code comments, while ignoring variable names, and applies a camel and snake case tokenization [26].\(^5\)

**StackOverflow-Android-Train** is an Android-specific training corpus that we built by collecting Stack Overflow question titles and code snippets answers. We prepared this dataset by extracting all Stack Overflow posts with an Android tag from a data dump publicly released by Stack Exchange [28]. The dataset is filtered on the following heuristics: (1) The code snippet must not contain XML tags; (2) The code snippet must contain a left parenthesis ‘(’ to indicate presence of a method call; and (3) The post title must not contain keywords like “gradle”, “studio” and “emulator”. After filtering, we end up with 451k Stack Overflow title and code snippet pairs. This dataset is disjoint from the Android Stackoverflow benchmark queries described later on in Section 4.3.

The goal of StackOverflow-Android-Train is to serve as an alternate training corpus that is ideal relative to our evaluation, which leverages Stack Overflow titles and code snippets as benchmark queries and answers, respectively. By training on this corpus, we can measure the possible room for improvement compared to training on a typical aligned corpus, which uses docstrings as natural language. \(^6\)

### 4.2 Search Corpora

We use two search corpora during our evaluation. **CODEnn-Java-Search**: 4 million unique Java methods released by the authors of CODEnn.

**GitHub-Android-Search**: 5.5 million unique Android methods collected from GitHub. This corpus is derived from the same 26,109 repositories used to construct GitHub-Android-Train, but also includes methods that do not have a docstring available.

### 4.3 Benchmark Queries

We use two sets of queries as evaluation benchmarks for our models. In both benchmark sets, the queries correspond to Stack Overflow titles and the ground truth answers for each query are the accepted answer or highly voted answer for the corresponding post, which we independently collected. This approach to collecting ground truth answers was borrowed from the original NCS paper [26].

**Java-50** is a set of 50 queries used to evaluate CODEnn in the original paper. These queries correspond to Stack Overflow titles for the top 50 voted Java programming questions. The authors included questions that had a “concrete answer” in Java, included an accepted answer in the thread with code, and were not duplicate questions. When evaluating on this benchmark, models are trained on CODEnn-Java-Train.

**Android-287** is a set of 287 Android-specific queries used to evaluate NCS in the original paper. These questions were chosen by a script with the following criteria: (1) the question title includes “Android” and “Java” tags; (2) there exists an upvoted code answer; and (3) the ground truth code snippet has at least one match in a corpus of GitHub Android repos. When evaluating on this benchmark, models are trained on GitHub-Android-Train, unless otherwise specified.

Table 3 provides a summary of the training corpora, search corpora, and benchmark queries used in our evaluation, and what combinations we use for our results.

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\(^3\) Supervised models trained on CODEnn-Java-Train train for 50 hours on an Nvidia Tesla M40 GPU.

\(^4\) This data has been generously made available the CODEnn authors at: [drive.google.com/drive/folders/1GZYLT_lNhVceXiBqdywVUViDpHMB6L7](https://drive.google.com/drive/folders/1GZYLT_lNhVceXiBqdywVUViDpHMB6L7)

\(^5\) Supervised models trained on GitHub-Android-Train train for 3 hours on an Nvidia Tesla M40 GPU.

\(^6\) Supervised models trained on StackOverflow-Android-Train train for 3 hours on an Nvidia Tesla M40 GPU.

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| Model          | Summary                                                                 | Parameters                                                                 |
|----------------|-------------------------------------------------------------------------|---------------------------------------------------------------------------|
| UNIF           | Embeds code/query tokens.                                               | Embedding matrices $T_e, T_q$ (Figure 3 $T_1, T_3$).                        |
|                | Combines code embeddings with attention.                                | Attention vector $a_e$ (Figure 3 $a_k$).                                   |
| CODEnn         | Embeds method name, API sequence and query as sequences.                | Embedding matrices $T_1, T_2, T_3, T_4$ (Figure 4 $T_1, T_2, T_3, T_4$)  |
|                | Embeds a bag of tokens from body.                                       | Bi-directional LSTM parameters for RNNs (Figure 4 $r_1, r_2$)              |
|                | Combines method name, API, and token embeddings using another layer.    | MLP parameters (Figure 4 $m_2$).                                           |
| SCS            | Embeds sequence of code tokens.                                         | GRU parameters for RNNs (Figure 5 $r_1, r_2$)                              |
|                | Transforms code embedding into query token space.                       | LSTM parameters for RNN (Figure 5 $r_3$).                                  |
|                |                                                                          | MLP parameters (Figure 5 $m_1$).                                           |

Table 2: Summary of details for models trained with supervision. In terms of network complexity (in terms of parameters, and layers), from least to most complex, we have: UNIF, CODEnn, and SCS.
### 4.4 Evaluation Pipeline

We found that manually assessing the correctness of search results can be difficult to do in a reproducible fashion, as deciding the relevance or correctness of a code snippet relative to the input query can vary across authors and people trying to reproduce our results. As such, we decided to carry out our evaluation using an automated evaluation pipeline. Our pipeline employs a similarity metric [22] between search results and a ground truth code snippet to assess whether a query was correctly answered. With this pipeline, we can scale our experiments to a much larger set of questions, such as Android-287, and assess correctness of results in a reproducible fashion. We use code answers found on Stack Overflow to provide a consistent ground truth for evaluation. This approach was introduced by the authors of [26]. Figure 6 gives an overview of this evaluation pipeline.

The automated pipeline does require that we pick a similarity threshold to decide whether a query has been answered. To decide this value, two authors manually assessed the relevance of the top 10 search results for Java-50 produced by CODEnn and UNIF. This assessment was done individually and conflicting decisions were cross-checked and re-assessed. Once a final set of relevant results was determined, we computed the similarity metric for each result with respect to the appropriate ground truth answer. This yielded a distribution of scores that was approximately normal. We took the mean and use this as the similarity threshold in our evaluation. This threshold chosen produces evaluation metrics for CODEnn that generally correspond to those in its original paper [15].

In our evaluation, we present the number of questions answered in the top k results. We consider the top 1, 5 and 10 results, and display the corresponding number of questions answered as Answered@1,5,10, respectively.

### 5 RESULTS

We now present our study's results and the answer for each of the research questions posed.

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1 We tried to obtain code snippets marked as relevant from the original CODEnn authors for completeness, but they were unable to share them [14].
Table 4: Number of queries answered in Java-50 in the top 1, 5, and 10 results improves when we extend NC3 (unsupervised) to UNIF (supervised). For Android-287, supervision increased results in the top 5 and top 10.

| Benchmark queries | Model code (CPU) | code (GPU) | query (CPU) | query (GPU) |
|-------------------|------------------|------------|-------------|-------------|
| Java-50           | UNIF             | 15         | 29          | 37          |
|                   | UNIF             | 11.72      | 58.55       | 103.83      | 10.75       |
| Android-287       | UNIF             | 33         | 74          | 98          |
|                   | UNIF             | 11.92      | 35.01       | 105.10      | 15.94       |

Table 5: The evaluation results on both benchmarks show that UNIF outperforms more sophisticated sequence-based networks such as CODEnn and SCS.

| Benchmark queries | Model Answered@1 Answered@5 Answered@10 |
|-------------------|-----------------------------------------|
|                   | UCIF                                      |
| Java-50           | CODEnn                                   |
|                   | SCS                                       |
| Android-287       | CODEnn                                   |
|                   | SCS                                       |

5.3 RQ3

How effective is supervision based on docstrings as the natural language component of the training corpus?

The supervised techniques presented so far use the same kind of natural language during training: docstrings. Docstrings are used as a proxy for user queries and allow neural code search practitioners to collect sizeable aligned datasets for training. However, Table 8 shows that when training on GitHub-Android-Train, search performance did not always improve, contrary to expectations.

In this experiment, we use an alternate idealized training corpus, StackOverflow-Android-Train, which is drawn from the same source as our benchmarks Android-287, but is still disjoint from the queries.

Intuitively, the performance attained with this corpus provides a measure for how much supervised techniques could improve search, given a training corpus that matches eventual user queries.

Table 7 shows that when we train on StackOverflow-Android-Train, all supervised techniques improve significantly (with one exception, queries answered in the top 1 using the SCS). This highlights the impressive search performance that a supervised technique could deliver, if given access to an ideal training corpus with a natural language component that better matches user queries.

Table 7: The number of Android-287 answered in the top 1, 5, and 10 when the supervised techniques were trained on our idealized StackOverflow-Android-Train corpus. Search performance increases substantially, demonstrating the potential for supervised techniques, when given access to a training corpus that resembles eventual user queries.

| Model  | Answered@1 | Answered@5 | Answered@10 |
|--------|------------|------------|-------------|
| UNIF   | 25 → 104   | 74 → 164   | 110 → 188   |
| CODEnn | 22 → 36    | 60 → 91    | 82 → 117    |
| SCS    | 9 → 11     | 19 → 24    | 34 → 47     |

Table 8 provides a comprehensive performance summary detailed previously in each research question.

6 THREATS TO VALIDITY

Our evaluation shows that a supervised extension of NCS performed better. There may exist other unsupervised techniques which require more in-depth modification to successfully take advantage of supervision. Our goal, however, is not to show that our minimal extension is guaranteed to improve any unsupervised technique, but rather that it improves NCS specifically.

UNIF is presented a simple alternative to state-of-the-art architectures. We explored two techniques from current literature and show that UNIF outperforms them. More sophisticated architectures may successfully outperform UNIF but we believe that our result highlight the importance of exploring parsimonious configurations first.

Our experiments were carried out using three training corpora (CODEnn-Java-Train, GitHub-Android-Train, and StackOverflow-Android-Train) and two benchmark query sets (Java-50 and Android-287). Both benchmark query sets have been used in prior neural code search literature. We believe that this extensive evaluation provides generalizable insight into the performance of these techniques.
We relied on an automated evaluation pipeline to provide reproducible and scalable evaluation of code search results. With this we scaled evaluation to a much larger set of benchmark queries (Android-287). While performance may vary depending on the similarity threshold chosen, we derived our similarity threshold choice through manual evaluation of answers produced by two techniques (CODEnn and UNIF) and believe it correlates well with human judgment. This threshold produces in evaluation results for CODEnn that roughly correspond to those found in its original paper [15].

| Benchmark queries | Search corpus | Training corpus | Model | Answered@1 | Answered@5 | Answered@10 | MRR  |
|-------------------|---------------|----------------|-------|------------|------------|-------------|------|
| Java-50           | CODEnn-Java-Search |                | Unsupervised | NCS        | 15         | 29          | 37   | 0.437 |
|                   |               | CODEnn-Java-Train |               | UNIF       | 22         | 39          | 43   | 0.582 |
|                   |               |               | CODEnn      | 16         | 31         | 39          | 0.456|
|                   |               |               | SCS         | 9          | 17         | 21          | 0.166|
| Android-287       | GitHub-Android-Search |         | Unsupervised | NCS        | 33         | 74          | 98   | 0.189|
|                   |               | GitHub-Android-Train |               | UNIF       | 25         | 74          | 110  | 0.178|
|                   |               |               | CODEnn      | 22         | 60         | 82          | 0.150|
|                   |               |               | SCS         | 9          | 19         | 34          | 0.124|
|                   |               | StackOverflow-Android-Train |           | UNIF       | 104        | 164         | 188  | 0.465|
|                   |               |               | CODEnn      | 36         | 91         | 117         | 0.215|
|                   |               |               | SCS         | 11         | 24         | 47          | 0.138|

Table 8: Summary of evaluation results.

7 RELATED WORK

Recent works from both academia and industry have explored the realm of code search. NCS [26] presented a simple yet effective unsupervised model. CODEnn [15] and SCS [19] provided a deep learning approach by using sophisticated neural networks. The supervised code search techniques build on the idea of bimodal embeddings of source code and natural language.

Existing work in natural language processing [4, 9, 13] has explored constructing embeddings for two languages with little bilingual data. It is possible that some of these techniques might be applicable to the code search task, and address some of the issues we identified during our analysis. However, in the code search task the embedding alignment we care about is not just at the word (i.e. token) level, but rather should aggregate successfully to whole code snippets and queries.

Other than code search, a line of work has explored enhancing developing productivity by exploiting an aligned corpus of code and natural language. Allamanis et al. [2] proposes a probabilistic model to synthesize a program snippet from a natural language query. Bayou [25] is a system that uses deep neural networks to synthesize code programs from a few API calls and a natural language input. CODE-NN [21] uses LSTM networks to produce natural language descriptions given a code snippet.

Interest in applications of neural networks to software engineering has increased significantly. Existing work has introduced neural networks to identify software defects [10], guide program synthesis [5, 30], enable new representations for program analysis [1, 3], facilitate code reuse [17]. The models we present here make use of these technologies to varying degrees to explore the design space and impact of these choices on code search quality.

8 CONCLUSION

In this paper we questioned some of the assumptions made in previous works (e.g. sequence-based models, docstring supervision), and find that these assumptions are not always justifiable. We compared three state-of-the-art techniques for neural code search with a novel extension of our own, and provided quantitative evidence for key design considerations.

We showed that supervision, shown by extending NCS to UNIF, can improve performance over an unsupervised technique. We suggest baselining against an unsupervised neural code search system and comparing incremental improvements, which should be weighed against the time and resources required to collect supervision data.

We found that more sophisticated networks did not necessarily payoffs: UNIF outperformed both CODEnn and SCS. With this observation in mind, we suggest evaluating simple architectures before incorporating more sophisticated components such as RNNs into their systems.

Finally, we showed that an ideal training corpus that resembled eventual user queries provided impressive improvements for all supervised techniques. We suggest considering the extent to which a training corpus resembles eventual user queries for optimal results, and exploring the possibility of better training corpora, rather than assuming a code/docstring corpus will provide the best performance.

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