Evaluation of Siamese Networks for Semantic Code Search

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Abstract

With the increase in the number of open repositories and discussion forums, the use of natural language for semantic code search has become increasingly common. The accuracy of the results returned by such systems, however, can be low due to 1) limited shared vocabulary between code and user query and 2) inadequate semantic understanding of user query and its relation to code syntax. Siamese networks are well suited to learning such joint relations between data, but have not been explored in the context of code search. In this work, we evaluate Siamese networks for this task by exploring multiple extraction network architectures. These networks independently process code and text descriptions before passing them to a Siamese network to learn embeddings in a common space. We experiment on two different datasets and discover that Siamese networks can act as strong regularizers on networks that extract rich information from code and text, which in turn helps achieve impressive performance on code search beating previous baselines on 2 programming languages. We also analyze the embedding space of these networks and provide directions to fully leverage the power of Siamese networks for semantic code search.

1 Introduction

Searching for code fragments is a very common activity in software development. The advent of large code repositories like GitHub[1] and Stack-Overflow[2] has only increased the number of developers to rely on these repositories to search and reuse existing code (Reiss, 2009). Traditional Information Retrieval techniques (Lu et al., 2015; Lv et al., 2015) do not work well for code search and retrieval tasks due to limited shared vocabulary between the source code and the natural language

search text (Sachdev et al., 2018). Often, developers who are new to a programming language, search for code snippets in a context-free natural language. The choice of words used to search may not overlap with the code snippets leading to failure of traditional information retrieval systems. Therefore, there is a need to gain a deeper understanding of code and text in order to find semantically relevant code snippet.

Consider an example where a developer has a functional requirement to validate if *age* is always lesser than 99 and alert otherwise. The developer is tasked to enforce this check in Java. A naive Java developer who is not familiar with the language might make a query based on the requirement as: *java check condition correctness*. The top 10 results[3] in StackOverflow do not discuss the *assert* keyword. A more programming friendly query such as *java boolean check* or the *assert* keyword itself results in code snippets demonstrating the steps as the top result in StackOverflow.

Use of deep neural network models have shown tremendous improvements in many tasks across domains including language tasks (Luong and Manning, 2015; Mishra et al., 2018; Gururangan et al., 2019). This success can be largely attributed, in part, to their ability to learn meaningful relationships among words in documents efficiently and represent them in a way such that semantically equivalent words tend to have similar representations (Mikolov et al., 2013a,b). One such family of models that are popular for determining text similarity are Siamese networks. First introduced by (Bromley et al., 1994), a typical Siamese network consists of two identical sub networks that share weights. They work in tandem on different inputs and the output of both the networks are evaluated by a distance measure that also acts as a scoring function. This has been successfully applied in many similarity tasks in im-

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*Work performed as part of IBM Research
[1] https://github.com/
[2] https://stackoverflow.com/

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[3] As of December 9, 2019

age domain (Taigman et al., 2014; Koch et al., 2015; Schroff et al., 2015a) and recently in text domain as well (Mueller and Thyagarajan, 2016; Neculoiu et al., 2016; Das et al., 2016). Another useful property of these models is their capability to learn from fewer data examples (Koch et al., 2015). Since code can be treated as a special kind of text data, one possible way to approach the problem of Semantic Code Search (commonly also referred to as *Code Retrieval*) is to treat it as a similarity task where the objective is to bring semantically equivalent code snippets and their natural language descriptions closer. Therefore, we study the application of Siamese networks to code and corresponding text descriptions for semantic code search.

We apply multiple variations of the base Siamese network model on two different datasets for semantic code search and study its efficacy. We further take the state of the art baselines - (Gu et al., 2018) and (Yao et al., 2019) on these datasets and observe that Siamese networks can improve over the baseline results invariably (upto 16% improvement in MRR on one of the datasets). Finally, we present our analysis on the performance of different Siamese network architectures explored and identify the conditions for improved performance.

The rest of the paper is organized as follows. We introduce some relevant prior art in section 2. Next, in section 3, we provide some background on Siamese networks and semantic code search and introduce terminology. In section 4, we describe our approach and the different architectures investigated. In section 5, we describe our experiments and present the results. Finally in section 6, we perform a detailed analysis of our observations, followed by conclusions in section 7.

2 Related Work

Traditionally solutions to code search were based on information retrieval techniques and natural language processing comprising of query expansion and reformulation (Lu et al., 2015; Lv et al., 2015). (Lu et al., 2015) expanded the query with synonyms from wordnet to search for code snippets. API documentation was leveraged for query expansion for code snippets retrieval by the Code-How tool proposed by (Lv et al., 2015). The fundamental drawback of the above techniques is that there is a disparity in word overlap, including their synonyms, between the intent expressed in natural language and the low-level implementation details in the source code. There is a need to semantically relate the words between the two domains.

Lately deep learning techniques have been administered for understanding code semantics and structure (Iyer et al., 2016; Gu et al., 2018; Sachdev et al., 2018; Alon et al., 2018; Yao et al., 2019; Cambronero et al., 2019; Alon et al., 2019). approaches the task of code summarization through an attention-based recurrent framework. The model generates a summary for the given code snippet which is then used to rank the relevance of the code to queries.

Deep Code Search (DCS) (Gu et al., 2018) follows a slightly different approach. DCS takes three aspects of code namely the a) method name, b) API invocation sequence, and c) the tokens and in parallel also takes the code descriptions as inputs to a different network and learns corresponding embeddings. Similarity between the embeddings are measured using cosine similarity. However, learning between embeddings is not explicitly shared. In one of our experiments we apply a Siamese network on top of DCS to combine the embedding learning framework with a Siamese style of sharing parameters between the two sub networks.

Neural Code Search (NCS) (Sachdev et al., 2018) is an unsupervised model that proposed a way to aggregate vector representation of the source code using TF-IDF weighting to form document embeddings. It uses FastText (Bojanowski et al., 2017) for learning the embeddings for these bags of words. Further, the similarity between these embeddings are used for retrieval. Embedding Unification (UNIF) (Cambronero et al., 2019) is an extension over NCS, applying attention on the code tokens. Again, both these works treat code and text as independent learning modules and project them in a common high dimension space.

CoaCor (Yao et al., 2019) proposed an Reinforcement Learning framework to generate code annotations and show the improvements on code retrieval (CR) when combined with existing CR models like DCS (Gu et al., 2018). Though the objective is similar, we study Siamese for joint learning on top of DCS without generation.

Siamese Networks are popular for tasks that involve finding similarity or a relationship between
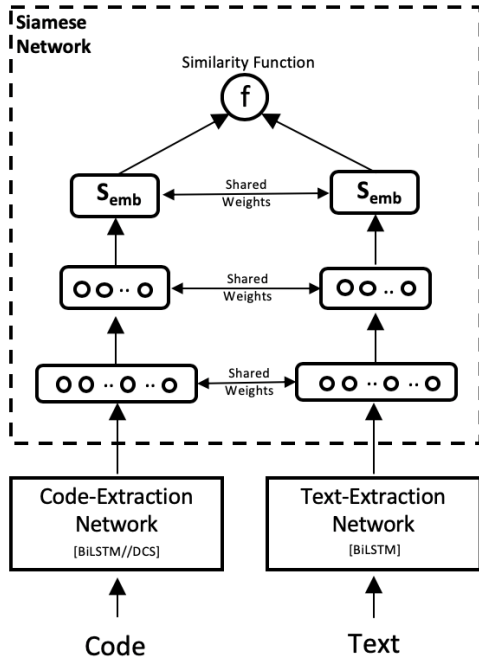
Figure 1: Architecture for Code Retrieval.

two comparable artifacts. Introduced first in images (Bromley et al., 1994), it has been applied in text domain to score relevance between a question and an answer candidate (Yin et al., 2016; Das et al., 2016) and for learning text similarity (Mueller and Thyagarajan, 2016; Neculoiu et al., 2016). But to the best of our knowledge, we are not aware of any work on applying Siamese networks for semantic code search.

3 Background

We now introduce some background relevant to our work in this paper.

3.1 Siamese Networks

As mentioned abovSiamese networks have been successfully applied to a variety of tasks that require jointly learning embeddings (Mueller and Thyagarajan, 2016; Neculoiu et al., 2016; Yin et al., 2016; Das et al., 2016). The primary idea behind Siamese networks is of two twin or identical networks that share weights and are connected at the top via an objective function. A pair of inputs is one to each twin network is expected to learn a similar representation for inputs. Several variations of this setup have been developed for various input modalities (Koch et al., 2015; Mueller and Thyagarajan, 2016; Abdelpakey and Shehata, 2019) and similarity functions (Koch et al., 2015;

Hoffer and Ailon, 2015; Das et al., 2016).

This property of jointly learning an embedding for a pair of inputs is particularly relevant for semantic code search which we explore in this work.

3.2 Code Retrieval and treating Code as Text

The objective of Semantic Code Search (henceforth referred to as simply, Code Retrieval) systems is to retrieve the most relevant code snippet(s) from a code repository in response to a natural language query or question by a user. A common way to approach the problem is to map all snippets in the repository to an embedding space. When a user query arrives, it is mapped to the same embedding space and the code snippet(s) closest to the query's embedding in this space are returned as the result. Learning an appropriate embedding is critical for this task. As introduced in the previous section, a variety of methods have been explored for Code retrieval. Although Abstract Syntax Tree (AST) representations have also been used, a majority of these approaches process code as text for input to a deep neural network.

Preprocessing is an imperative step for this task and several methods have been studied for representing code for input to deep neural networks. The most obvious way is to remove all code punctuation and tokenize code on whitespace. Language specific keywords are considered stop-words and are removed. We tokenize variable names and method names on camel-case and snake-case as these names may contain useful information about what the identifier is responsible for. Preprocessing done by (Gu et al., 2018) looks at multiple representations of code for input to a deep network, such representations have been leveraged in multiple prior works and in our approach.

We now introduce some terminology. We refer to the code snippets from any code repository that are used during training as well as a response to the users' queries as simply *code* or *code snippet*. The code snippets can be a few lines of coherent code or entire function definitions. This distinction is irrelevant unless the function name is required by the model. We use the same term regardless. The natural language text that describes a code snippet (available in the documentation) or is the query to which the code snippet is an answer (mined from online forums) is referred to in this work as just *text* or *text description*. Thus, a [*code,text*] pair can

refer to any snippet of code and a natural language text that is closely related to that code snippet.

4 Approach

In this work, we explore Siamese architectures for code retrieval where a code snippet is input to one branch of a Siamese network and the text description is input to the other. This distinction is important, in spite of the shared weights between the networks because even though we treat code as text, the code tokens can convey different meanings than text tokens. Therefore, all architectures we explore follow a common blueprint as shown in Figure 1.

The code and text inputs are subjected to separate networks that process their respective input modalities in distinct ways (called extraction networks in the figure) and do not share weights. The outputs of these individual networks are passed to the Siamese network and a loss function computes the similarity between the representations learned by the two branches of the Siamese network. As highlighted in (Das et al., 2016), this helps to capture the different expressions of the same concept in code and text. For example, the code snippet corresponding to the query *"sort an array"* may not contain these terms or their synonyms. Thus, any candidate solution for code retrieval should have the capability to relate language semantics and code syntax.

With this motivation, we evaluate Siamese networks for code retrieval using 4 pairs of architectures for the extraction networks as listed below. Each architecture pair is followed by a Siamese network that outputs an embedding of size S_{emb}. The code and text embeddings are compared using a loss function that encourages learning of similar embeddings for matching code and text pairs and diverse embeddings for unrelated code and text pairs. The candidates for such loss functions are discussed in section 4.2.

4.1 Model Architectures

The base model for all our extraction networks for both code and text inputs is a BiLSTM (*BiL*) network. The text extraction network takes the text as a sequence of tokens. However, the code extraction network can be provided with method names (*M*), API calls (*A*), or entire code snippet (*CS*) as token sequences.

In the first architecture **BiLSTMs-MethodName (BiL-M)**, we extract only the method name and tokenize it on camel-case and snake-case. The final hidden state vectors from code and text networks are provided as input to a Siamese network. This architecture cannot be applied if the code snippet is missing a method name. Instead of method name sequence, we provide the sequence of API calls in the code snippet as input to the code extraction networking after tokenization on camel-case and snake-case instantiating our second architecture **BiLSTMs-APIs (BiL-A)**. The third architecture **BiLSTMs-CodeSnippet (BiL-CS)** applies the same camel-case and snake-case tokenization on the entire code snippet.

The next architecture - **Deep Code Search (DCS)** is based on the model presented in (Gu et al., 2018). The code extraction network comprises of individual networks that process method names, API sequences and Bag-of-Words tokens and their representations are then combined using max pooling. The text extraction network is a simple BiLSTM. This setup has shown impressive results for the code retrieval task and their performance has been further surpassed by (Yao et al., 2019) which also leverages the same setup.

For evaluating any model given a correct [code,text] pair, we compute the text embedding by passing it through the network. We then compare the text embedding with all of the code embeddings and rank them based on cosine similarity. Note that the embeddings at any layer can be considered for similarity computation. For the first three extraction networks (BiL-M, BiL-A, BiL-CS), the final layer of the Siamese network is used for evaluation. However, for the DCS extraction network, we perform evaluation on both the output of the final Siamese layer and the output of the DCS extraction network. This gives the final two model architectures, **DCS-Eval** and **Siamese-Eval**, differing in what layer is used for evaluation/retrieval purposes. When this distinction is irrelevant, we refer to the model leveraging the DCS extraction network with a Siamese network as **DCS-Siamese**.

For the above 5 models, we experimented with multiple sizes of S_{emb} and the results are presented in the next section.

Dataset	Baseline	BiL-M	BiL-A	BiL-CS	DCS-Eval	Siamese-Eval
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Java 16M	0.6 (DCS-Gu Model)	0.294	0.180	0.318	**0.703**	0.638*
StaQC SQL	0.576 (CoaCor Model)	–	0.02	0.02	**0.593**	0.208

Table 1: Baselines considered in this work for each of the datasets and the MRR on the test sets for the extraction networks followed by a Siamese network. Method names are not available for SQL and hence BiL-M model is not applicable. For the DCS-Siamese network, we perform evaluation on both the output of the DCS extraction network and the top Siamese layer. We report only the best performance over the different values of S_{emb}. The * indicates the reported number was obtained with $S_{emb} = 200$ as opposed to $S_{emb} = 2$ everywhere else.

4.2 Loss functions

We explore three optimization functions for jointly learning the embeddings.

- **Contrastive Loss**: This distance based loss performs pair-wise optimization of code snippets and text descriptions (Hadsell et al., 2006).

- **Triplet Loss**: Distance is calculated between an anchor (code-snippet), a positive candidate (related description) and a negative candidate (unrelated description). The distance between positive candidate and anchor is minimised, whereas, the distance between negative candidate and anchor is maximised (Hoffer and Ailon, 2015; Schroff et al., 2015b).

- **Cosine-Contrastive loss**: This is a trade-off between cosine and contrastive loss functions. Since the responses to a query are retrieved using cosine distance during inference, we use the cosine distance during training as well. Additionally, the contrastive component ensures pair-wise optimisation between code and descriptions.

5 Experiments

We now describe the datasets used in our experiments, the training and evaluation processes in our setup, followed by our results.

5.1 Datasets and Baselines

One of the primary concerns while evaluating a code retrieval approach is the lack of standard datasets. Most approaches prefer collecting their own dataset and compare against some baseline that can be applied on the newly collected data, which again might not be openly available.

This makes it extremely difficult to compare approaches on uniform grounds. Limited by this issue, we selected two datasets that have been evaluated on atleast two separate approaches. These datasets represent two different kinds of languages (strongly typed and declarative) and have enough variation to test the general applicability of our approach.

The first dataset consists of $16M$ Java method definitions and corresponding descriptions crawled from Github [3]. (Gu et al., 2018) reported impressive results on this dataset. We refer to their model as the *DCS-Gu* model. We selected this dataset due to the large training set size. We also use a reduced version of this dataset comprising of 1% of the data to explore and filter multiple architectures in our experiments. The limitation of this dataset is that it is only available in processed form and the original code-description pairs are not publicly available.

The next dataset is the StaQC SQL dataset comprising of $119K$ SQL queries and question title pairs extracted from StackOverflow [4]. The *CoaCor* model (Yao et al., 2019) achieves superior performance on this dataset surpassing the methods of (Gu et al., 2018) and (Iyer et al., 2016). Their approach also uses the DCS network of (Gu et al., 2018) as a component. The baselines we use for each dataset are summarized in Table 1. Mean Retrieval Rank (MRR) is the commonly used metric for Code retrieval and is used for all our evaluations.

5.2 Experimental Setup

For all our experiments on the extraction networks, we experimented with multiple architectures for the Siamese network using the different loss functions. We observed that the *contrastive-*

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[3]https://github.com/guxd/deep-code-search
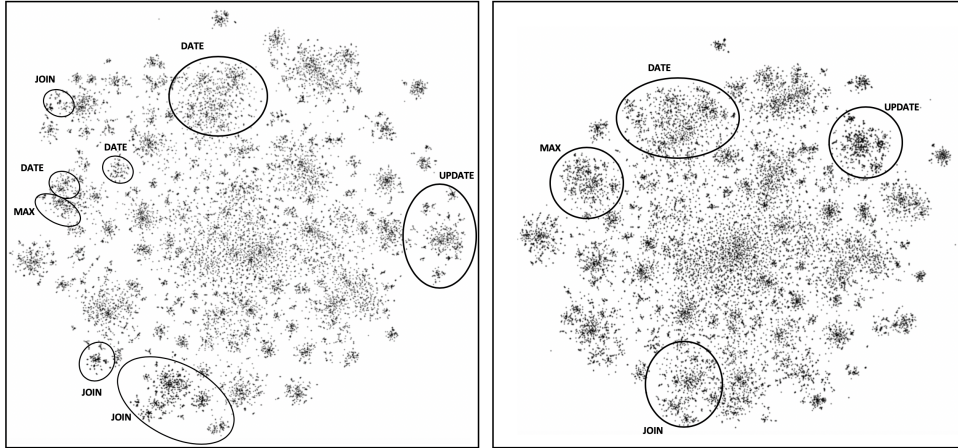[4]https://github.com/LittleYUYU/StackOverflow-Question-Code-Dataset

Figure 2: t-SNE visualizations of the embeddings learnt by the DCS network (left) as described in (Gu et al., 2018) compared to the embeddings produced by the DCS extraction network after using a Siamese network on top (right). The points in the figure represent texts in StaQC SQL dataset. Some clusters are highlighted.

cosine loss performed better than the other loss functions. We also experimented with $S_{emb} = \{2, 100, 200\}$ for each of these architectures. For Siamese networks that have $S_{emb} = 200$, we use layers of sizes $\{400, 300\}$ after the extraction network. For $S_{emb} = 100$, an additional layer of size 200 was used and for $S_{emb} = 2$, another layer of size 50 is used. When evaluating the DCS extraction network, the first layer of the Siamese network is of size 800, to account for the output dimensionality of DCS. All layers are followed by ReLU and BatchNorm layers.

The extraction network pair and its corresponding Siamese network are trained in an end-to-end fashion with Adam optimizer, initial learning rate 0.001 and patience 40. After 40 epochs of stagnant performance, the learning rate is halved and the training resumed. This is repeated up to 4 times.

5.3 Results

Table 1 (columns 3, 4 and 5) lists the MRR values of the best performing models for retrieval on the test sets for the first 3 extraction network architectures. None of the architectures were able to surpass the baseline performance on the two datasets. With this experiment, for the given datasets, we find that Siamese networks by themselves were not able to achieve a comparable performance with any of the baselines.

Further, we observed that the performance of these architecture was influenced mostly by the choice of S_{emb} while the number and sizes of the intermediate layers did not have any notable effect. These models consistently achieved their best per-

Cluster Name	Sample Questions
MAX	Get value based on max of a different column grouped by another column How to query row with max value in a column in a referencing table ?
DATE	How to use if and else to check the hour and run a specific query? Counting the number of days excluding Sunday between two dates
JOIN	How to prevent join from matching same row over and over again? How do i pull multiple items out of a table with one join?
UPDATE	How to update a row from another row of same table? Mysql update attribute only when value is not null

Table 2: Some example questions from the clusters shown in t-SNE comparison in Figure 2.

formance for $S_{emb} = 2$.

Table 1 (columns 6 and 7) summarizes the performance of the Siamese network with DCS extraction network on the two datasets. Not only is the retrieval MRR on the test sets observed to be better than any of the other architectures, the DCS-Eval model consistently outperforms the baseline models on each of the datasets. However, in this case, we observed that the best performing models were not always with $S_{emb} = 2$. The Siamese-Eval model when trained on the Java $16M$ dataset and evaluated at the output of the Siamese layer performed better for $S_{emb} = 200$. We denoted this with an *.

We summarize these results as follows:

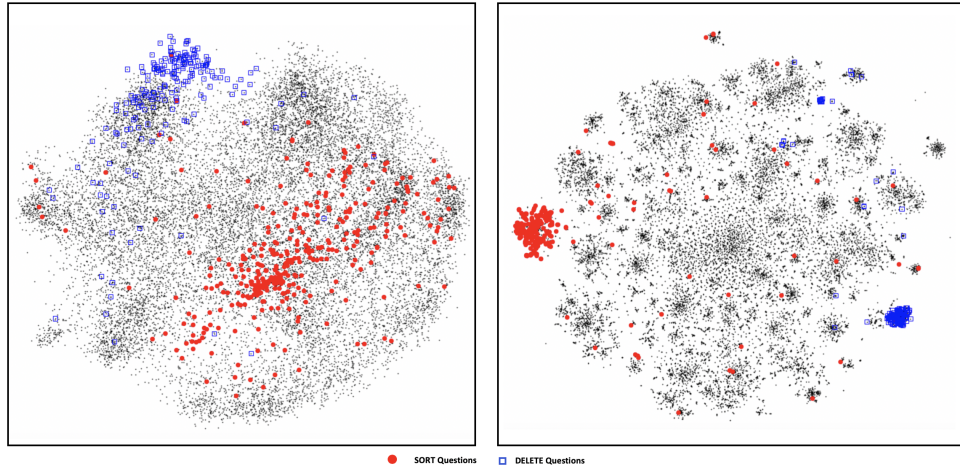1. The DCS extraction network with a Siamese

Figure 3: t-SNE visualizations of the Siamese (left) and DCS layer embeddings (right) of the DCS-Siamese network with $S_{emb} = 2$ for two sets of questions. The blue squares represent questions about deleting rows. The red circles are questions on sorting and ordering.
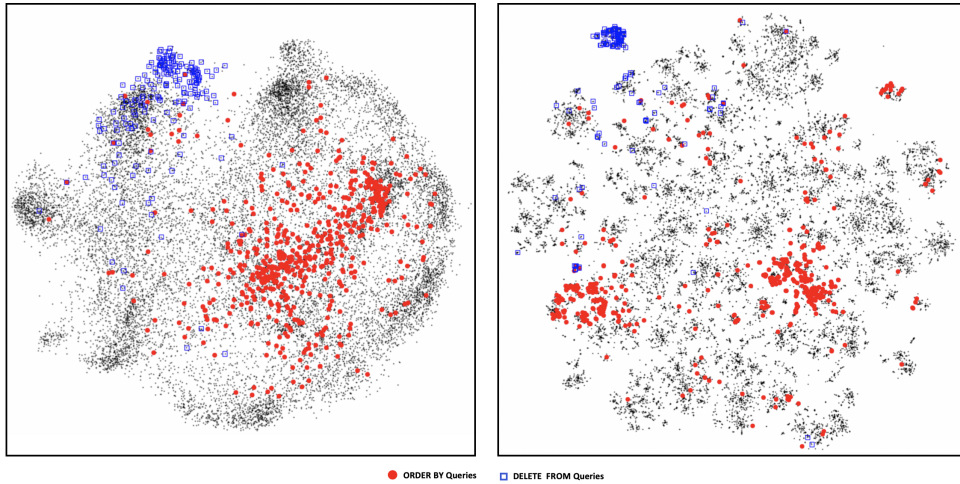

Figure 4: t-SNE visualizations of the Siamese (left) and DCS layer embeddings (right) of the DCS-Siamese network with $S_{emb} = 2$ for two sets of SQL queries. The blue squares represent 'DELETE FROM' queries. The red circles are queries containing 'ORDER BY'.

network performs better than the rest of the extraction networks considered and outperforms the baselines on the two datasets.

2. This superior performance is achieved when the retrieval is performed using embeddings at the output of the DCS extraction network, rather than at the output of the Siamese network.

3. Siamese network seem to have a regularizing effect that forces the extraction networks to learn good embeddings.

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