

# A Convolutional Attention Network for Extreme Summarization of Source Code

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## Abstract

Attention mechanisms in neural networks have proved useful for problems in which the input and output do not have fixed dimension. Often there exist features that are locally translation invariant and would be valuable for directing the model’s attention, but previous attentional architectures are not constructed to learn such features specifically. We introduce an attentional neural network that employs convolution on the input tokens to detect local time-invariant and long-range topical attention features in a context-dependent way. We apply this architecture to the problem of extreme summarization of source code snippets into short, descriptive function name-like summaries. Using those features, the model sequentially generates a summary by marginalizing over two attention mechanisms: one that predicts the next summary token based on the attention weights of the input tokens and another that is able to copy a code token as-is directly into the summary. We demonstrate our convolutional attention neural network’s performance on 10 popular Java projects showing that it achieves better performance compared to previous attentional mechanisms.

difficulties, because not only are the input and output high-dimensional, but the dimensionality is not fixed in advance. Recent research has tackled these problems using neural models of attention (Mnih et al., 2014), which have had great recent successes in machine translation (Bahdanau et al., 2015) and image captioning (Xu et al., 2015). Attentional models have been successful because they separate two different concerns: predicting which input locations are most relevant to each location of the output; and actually predicting an output location given the most relevant inputs.

In this paper, we suggest that many domains contain translation-invariant features that can help to determine the most useful locations for attention. For example, in a research paper, the sequence of words “in this paper, we suggest” often indicates that the next few words will be important to the topic of the paper. As another example, suppose a neural network is trying to predict the name of a method in the Java programming language from its body. If we know that this method name begins with `get` and the method body contains a statement `return ____ ;`, then whatever token fills in the blank is likely to be useful for predicting the rest of the method name. Previous architectures for neural attention are not constructed to learn translation-invariant features specifically.

We introduce a neural convolutional attentional model, that includes a convolutional network within the attention mechanism itself. Convolutional models are a natural choice for learning translation-invariant features while using only a small number of parameters and for this reason have been highly successful in non-attentional models for images (LeCun et al., 1998; Krizhevsky et al., 2012) and text classification (Blunsom et al., 2014). But to our knowledge they have not been applied within an attentional mechanism. Our model uses a set of convolutional layers — without any pooling — to detect patterns in the input and

## 1. Introduction

Deep learning for structured prediction problems, in which a sequence (or more complex structure) of predictions need to be made given an input sequence, presents special dif-

<sup>†</sup>Work partially done while author was an intern at the University of Edinburgh.

identify “interesting” locations where attention should be focused.

We apply this network to an “extreme” summarization problem: We ask the network to predict a short and descriptive name of a source code snippet (*e.g.* a method body) given solely its tokens. Source code has two distinct roles: it is a means of instructing a CPU to perform a computation but also acts as an essential means of communication among developers who need to understand, maintain and evolve software systems. For these reasons, software engineering research has found that good names are important to developers (Liblit et al., 2006; Takang et al., 1996; Binkley et al., 2013). Additionally, learning to summarize source code has important applications in software engineering, such as in code understanding and in code search. The highly structured form of source code makes convolution naturally suited for the purpose of extreme summarization. Our choice of problem is inspired by previous work (Allamanis et al., 2015a) that tries to name existing methods (functions) using a large set of hard-coded features, such as features from the containing class and the method signature. But these hard-coded features that may not be available for arbitrary code snippets and in dynamically typed languages. In contrast, in this paper we consider a more general problem: given an arbitrary snippet of code — without any hard-coded features — provide a summary, in the form of a descriptive method name.

This problem resembles a summarization task, where the name is viewed as a natural language summary to be extracted from source code. However, extreme source code summarization is drastically different from natural language summarization, because unlike natural language, source code is unambiguous and highly structured. Furthermore, a good summary needs to explain how the code instructions compose into a higher-level meaning and not naïvely explain what the code does. This necessitates learning higher-level patterns in the source code that use both the structure of the code and the identifiers to detect and explain complex code constructs. Our extreme summarization problem may also be viewed as a translation task, in the same way that any summarization problem can be viewed as translation. But a significant difference from translation is that the input source code sequence tends to be very large (72 on average in our datasets) and the output summary very small (3 on average in our dataset). The length of the input sequence necessitates the extraction of both temporally invariant attention features and topical sentence-wide features and — as we show in this paper — existing techniques from neural machine translation yield sub-optimal results.

Furthermore, source code presents the additional challenge of out-of-vocabulary words, that is, each new software

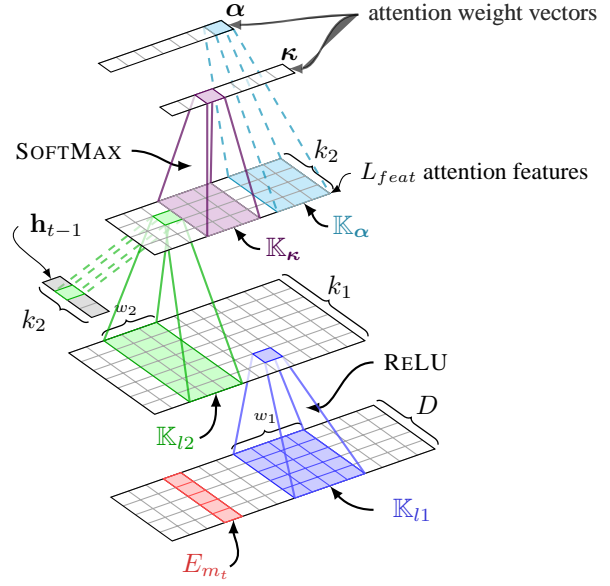


Figure 1. The architecture of the convolutional attentional network. **attention\_features** learns location-specific attention features given an input sequence  $\{m_i\}$  and a context vector  $\mathbf{h}_{t-1}$ . Given these features **attention\_weights** —using a convolutional layer and a SOFTMAX— computes the final attention weight vectors such as  $\alpha$  and  $\kappa$  in this figure.

project and each new source file introduces new vocabulary about aspects of the software’s domain, data structures, and so on, vocabulary which often does not appear in the training set. To address this problem, we introduce a *copy mechanism*, which uses the convolutional attentional mechanism to identify important tokens in the input even if they are out-of-vocabulary tokens that do not appear in the training set. The decoder can then choose to copy tokens directly from the input sequence to the output sequence, resembling the functionality of Vinyals et al. (2015).

The key contributions of our paper are: (a) a novel convolutional attentional network that can successfully perform extreme summarization of source code; (b) a comprehensive approach to the extreme code summarization problem, with interest both in the machine learning and software engineering community; and (c) a comprehensive evaluation of four competing algorithms on real-world data that demonstrates the advantage of our method compared to standard attentional mechanisms.

## 2. Convolutional Attention Model

Our convolutional attentional model receives as an input a sequence of code subtokens<sup>1</sup>  $\mathbf{c} = [c_{<S>}, c_1, \dots, c_N, c_{</S>}]$  and outputs an extreme summary in the form of a concise method name. The summary is a sequence of subtokens  $\mathbf{m} = [m_{<S>}, m_1 \dots m_M, m_{</S>}]$ . For example, in the `shouldRender` method (shown in the top left of Table 3) the input code subtokens are  $\mathbf{c} = [<S>, \text{try}, \{, \text{return}, \text{render}, \text{requested}, \dots]$  while the target output is  $\mathbf{m} = [<S>, \text{should}, \text{render}, </S>]$ . The neural network predicts each summary subtoken sequentially and models  $P(m_t | m_{<S>}, \dots, m_{t-1}, \mathbf{c})$ . Information about the previously produced tokens  $m_{<S>}, \dots, m_{t-1}$  is passed into a recurrent neural network that represents the current state with a vector  $\mathbf{h}_{t-1}$  vector. Our convolutional attentional neural network (Figure 1) uses the current state  $\mathbf{h}_{t-1}$  and a series of convolutions over the embeddings of the tokens  $\mathbf{c}$  to compute a set of attention features. The resulting features are used to compute one or more normalized attention vectors (e.g.  $\alpha$  in Figure 1) which are distributions over input token locations containing a weight (in  $\mathbb{R}^{(0,1)}$ ) for each subtoken in  $\mathbf{c}$ . Finally, given these weights, a representation of the context is computed and is used to predict the probability distribution over the targets  $m_i$ . This model may also be thought as a generative bimodal model of summary text given a code snippet.

### 2.1. Learning Attention Features

The basic building block of our model is a convolutional network (LeCun et al., 1990; Collobert & Weston, 2008) for extracting position and context dependent features. The input to **attention\_features** is a sequence of code tokens  $\mathbf{c}$  of length  $\text{LEN}(\mathbf{c})$  and each location is mapped to a set of attention features into  $L_{feat}$ , a matrix of size  $(\text{LEN}(\mathbf{c}) + \text{const}) \times k_2$  where the constant is a fixed amount of padding. The intuition behind **attention\_features** is that given the input  $\mathbf{c}$ , it uses convolution to compute  $k_2$  features for each location. By then using  $\mathbf{h}_{t-1}$  as a multiplicative gating-like mechanism, only the currently relevant features are kept in  $L_2$ . In the final stage, we normalize  $L_2$ . **attention\_features** is described with the following pseudocode:

```
attention_features (code tokens  $\mathbf{c}$ , context  $\mathbf{h}_{t-1}$ )
   $C \leftarrow \text{LOOKUPANDPAD}(\mathbf{c}, E)$ 
   $L_1 \leftarrow \text{RELU}(\text{CONV1D}(C, \mathbb{K}_{l1}))$ 
   $L_2 \leftarrow \text{CONV1D}(L_1, \mathbb{K}_{l2}) \odot \mathbf{h}_{t-1}$ 
   $L_{feat} \leftarrow L_2 / \|L_2\|_2$ 
  return  $L_{feat}$ 
```

<sup>1</sup>By subtokens we refer to the parts of a complex source code token e.g. `getInputStream` contains the `get`, `Input` and `Stream` subtokens.

Here  $E \in \mathbb{R}^{|V| \times D}$  contains the  $D$  dimensional embedding of each code token and name subtoken (i.e. all possible  $c_i$ s and  $m_i$ s). The two convolution kernels are  $\mathbb{K}_{l1} \in \mathbb{R}^{D \times w_1 \times k_1}$  and  $\mathbb{K}_{l2} \in \mathbb{R}^{k_1 \times w_2 \times k_2}$ , where  $w_1, w_2$  are the window sizes of the convolutions. The vector  $\mathbf{h}_{t-1} \in \mathbb{R}^{k_2}$  represents information from the previous subtokens  $m_0 \dots m_{t-1}$ . CONV1D performs a one-dimensional (throughout the length of sentence  $\mathbf{c}$ ) narrow convolution. Note that the input sequence  $\mathbf{c}$  is padded by LOOKUPANDPAD. The size of the padding is such that with the narrow convolutions, the attention vector (returned by **attention\_weights**) has exactly  $\text{LEN}(\mathbf{c})$  components. The  $\odot$  operator is the elementwise multiplication of a vector and a matrix, i.e.  $B = A \odot \mathbf{v}$  for  $\mathbf{v} \in \mathbb{R}^M$  and  $A$  a  $M \times N$  matrix,  $B_{ij} = A_{ij}v_i$ . We found the normalization of  $L_2$  into  $L_{feat}$  to be useful during training. We believe it helps because of the widely varying lengths of inputs  $\mathbf{c}$ . Note that no pooling happens in this model; the input sequence  $\mathbf{c}$  is of the same length as the output sequence (modulo the padding).

To compute the final attention weight vector — a vector with non-negative elements and unit norm — we define **attention\_weights** as a function that accepts  $L_{feat}$  from **attention\_features** and a convolution kernel  $\mathbb{K}$  of size  $k_2 \times w_3 \times 1$ . **attention\_weights** returns the normalized attention weights vector with length  $\text{LEN}(\mathbf{c})$  and is described by the following pseudocode:

```
attention_weights (attention features  $L_{feat}$ , kernel  $\mathbb{K}$ )
  return  $\text{SOFTMAX}(\text{CONV1D}(L_{feat}, \mathbb{K}))$ 
```

**Computing the State  $\mathbf{h}_t$ .** Predicting the full summary  $\mathbf{m}$  is a sequential prediction problem, where each subtoken  $m_t$  is sequentially predicted given the previous state containing information about the previous subtokens  $m_0 \dots m_{t-1}$ . The state is passed through the vector  $\mathbf{h}_t \in \mathbb{R}^{k_2}$  which is computed using a Gated Recurrent Unit (Cho et al., 2014) i.e.

```
GRU(current input  $\mathbf{x}_t$ , previous state  $\mathbf{h}_{t-1}$ )
   $\mathbf{r}_t \leftarrow \sigma(\mathbf{x}_t W_{xr} + \mathbf{h}_{t-1} W_{hr} + \mathbf{b}_r)$ 
   $\mathbf{u}_t \leftarrow \sigma(\mathbf{x}_t W_{xu} + \mathbf{h}_{t-1} W_{hu} + \mathbf{b}_u)$ 
   $\mathbf{c}_t \leftarrow \tanh(\mathbf{x}_t W_{xc} + \mathbf{r}_t \odot (\mathbf{h}_{t-1} W_{hc}) + \mathbf{b}_c)$ 
   $\mathbf{h}_t \leftarrow (1 - \mathbf{u}_t) \odot \mathbf{h}_{t-1} + \mathbf{u}_t \odot \mathbf{c}_t$ 
  return  $\mathbf{h}_t$ 
```

where  $\odot$  denotes the Hadamard product. During testing the next state is computed by  $\mathbf{h}_t = \text{GRU}(E_{m_t}, \mathbf{h}_{t-1})$  i.e. using the embedding of the current output subtoken  $m_t$ . For regularization during training, we use a trick similar to Bengio et al. (2015) and with probability equal to the dropout rate we compute the next state as  $\mathbf{h}_t = \text{GRU}(\hat{\mathbf{n}}, \mathbf{h}_{t-1})$ , where  $\hat{\mathbf{n}}$  is the predicted embedding.

## 2.2. Simple Convolutional Attentional Model

We now use the components described above as our building block for our extreme summarization model. We first build **conv\_attention**, a convolutional attentional model that uses an attention vector  $\alpha$  computed from **attention\_weights** to weight the embeddings of the tokens in  $\mathbf{c}$  and compute the predicted target embedding  $\hat{\mathbf{n}} \in \mathbb{R}^D$ . The model returns a probability distribution  $\mathbf{n} \in \mathbb{R}^{|V|}$  over all possible target tokens  $m_t$ .

```

conv_attention(code  $\mathbf{c}$ , previous state  $\mathbf{h}_{t-1}$ )
   $\alpha \leftarrow \text{attention\_weights}(L_{feat}, \mathbb{K}_{att})$ 
   $\hat{\mathbf{n}} \leftarrow \sum_i \alpha_i E_{c_i}$ 
   $\mathbf{n} \leftarrow \text{SOFTMAX}(E \hat{\mathbf{n}}^\top + \mathbf{b})$ 
  return  $\mathbf{n}$ 

```

where  $\mathbf{b} \in \mathbb{R}^{|V|}$  is a bias vector. We train this model by using maximum likelihood. This model works as follows, we start with the special  $m_0 = \langle s \rangle$  subtoken and  $\mathbf{h}_0$ . Then at each timestep  $t$ , we sequentially generate each subtoken  $m_t$  using the probability distribution  $\mathbf{n}$  returned by calling **conv\_attention** ( $\mathbf{c}, \mathbf{h}_{t-1}$ ). Given the newly generated token  $m_t$  the new state  $\mathbf{h}_t = \text{GRU}(E_{m_t}, \mathbf{h}_{t-1})$  is then computed. The process stops when the special  $\langle /s \rangle$  subtoken is generated.

## 2.3. Copy Convolutional Attentional Model

We extend **conv\_attention** by using an additional attention vector  $\kappa$  in a novel copying mechanism that can suggest out-of-vocabulary subtokens. In our data a significant proportion of the output subtokens (about 35%) also appear in  $\mathbf{c}$ . Motivated by this, we extend **conv\_attention** and allow a direct copy from the input sequence  $\mathbf{c}$  into the summary. Now the neural network when predicting  $m_t$  with probability  $\lambda$  copies a token from  $\mathbf{c}$  into  $m_t$  and with probability  $1 - \lambda$  predicts the target subtoken as in **conv\_attention**. When copying a subtoken  $c_i$  is copied into  $m_t$  with probability equal to the attention weight  $\kappa_i$ . This process is described by the following pseudocode:

```

copy_attention(code  $\mathbf{c}$ , previous state  $\mathbf{h}_{t-1}$ )
   $L_{feat} \leftarrow \text{attention\_features}(\mathbf{c}, \mathbf{h}_{t-1})$ 
   $\alpha \leftarrow \text{attention\_weights}(L_{feat}, \mathbb{K}_{att})$ 
   $\kappa \leftarrow \text{attention\_weights}(L_{feat}, \mathbb{K}_{copy})$ 
   $\lambda \leftarrow \max(\sigma(\text{CONV1D}(L_{feat}, \mathbb{K}_\lambda)))$ 
   $\hat{\mathbf{n}} \leftarrow \sum_i \alpha_i E_{c_i}$ 
   $\mathbf{n} \leftarrow \text{SOFTMAX}(E \hat{\mathbf{n}}^\top + \mathbf{b})$ 
  return  $\lambda \text{Pos2Voc}(\kappa, \mathbf{c}) + (1 - \lambda) \text{ToMap}(\mathbf{n}, V)$ 

```

where  $\sigma$  is the sigmoid function,  $\mathbb{K}_{att}$ ,  $\mathbb{K}_{copy}$  and  $\mathbb{K}_\lambda$  are different convolutional kernels,  $\mathbf{n} \in \mathbb{R}^{|V|}$ ,  $\alpha, \kappa \in \mathbb{R}^{\text{LEN}(\mathbf{c})}$ , Pos2Voc is a method that maps each subtoken  $c_i$  to the probability  $\kappa_i$  assigned by the copy mechanism. ToMap maps each subtoken in  $V$  to its probabil-

ity  $n_i$ . Finally, the two maps are merged, returning a map that contains all potential target subtokens in  $V \cup \mathbf{c}$  and marginalizing over the copy probability  $\lambda$ . Note that  $\alpha$  and  $\kappa$  are analogous attention weights but are computed from different kernels. Note that  $\mathbf{n}$  is computed exactly as in **conv\_attention**.

**Objective.** To obtain signal from the copying mechanism and  $\lambda$  for each prediction step, we input to **copy\_attention** a binary vector  $\mathbb{I}_{\mathbf{c}=m_t}$  of size  $\text{LEN}(\mathbf{c})$  where each component is one if the code token is identical to the current target subtoken  $m_t$ . We can then compute the probability of a correct copy and train using maximum likelihood over the marginalization of the two mechanisms, *i.e.*

$$P(m_t | \mathbf{h}_{t-1}, \mathbf{c}) = \lambda \frac{\sum_i \kappa_i \mathbb{I}_{c_i=m_t}}{\sum_i \kappa_i} + (1 - \lambda) \mu r_{m_t}$$

where the first term is the probability of a correct copy (weighted by  $\lambda$ ) and the second term is the probability of the target token  $m_t$  (weighted by  $1 - \lambda$ ). We use  $\mu \in (0, 1]$  to penalize the model when the simple attention part of the model needs to predict the special UNK subtoken that could have been predicted exactly by the copy mechanism, otherwise  $\mu = 1$ . In this work, we arbitrarily used  $\mu = e^{-10}$ , although variations do not affect the performance.

## 2.4. Predicting Names

To predict a full method name, we use a hybrid BFS and beam search method. We start all predictions from the special  $m_0 = \langle s \rangle$  subtoken, while we maintain a (max-)heap of the highest probability partial predictions so far. At each step, we pick the highest probability prediction and predict its next possible subtokens, pushing them back to the heap. If the special  $\langle /s \rangle$  subtoken is produced the suggestion is moved onto the list of suggestions. Since we are interested in producing the list of the top  $k$  suggestions, at each point, we prune partial suggestions that have a probability less than the current best  $k$ th full suggestion. To make this process tractable, we limit the size of the partial suggestion heap and stop iterating after 100 steps.

## 3. Evaluation

**Dataset Collection.** We are interested in the extreme summarization problem where we summarize a source code snippet into a short and concise method-like name. Although such a dataset does not exist for arbitrary snippets of source code, it is natural to consider existing method (function) bodies as our snippets and the method names picked by the developers as our target extreme summaries.

To collect a good quality dataset, we cloned 11 open source Java projects found on [GitHub](#). We obtained the most popular projects by taking the sum of the  $z$ -scores of



the number of watchers and forks of each project, using GHTorrent (Gousios & Spinellis, 2012). We selected the top 11 projects that contained more than 10MB of source code files each and use libgdx as a development set. These projects have thousands of forks and stars, being widely known among software developers. The projects along with short descriptions are shown in Table 1. We used this procedure to select a mature, large, and diverse corpus of real source code. For each file, we extract the Java methods, removing methods that are overridden, are abstract or are the constructors of a class. We find the overridden methods by an approximate static analysis that checks for inheritance relationships and the `@Override` annotation. Overridden methods are removed, since they are highly repetitive and their names are easy to predict. Any full tokens that are identical to the method name (e.g. in recursion) are replaced with a special SELF token. We split and lowercase each method name and code token into subtokens  $\{m_i\}$  and  $\{c_i\}$  on camelCase and snake\_case. The dataset can be found at <http://groups.inf.ed.ac.uk/cup/codeattention/>.

**Experimental Setup.** To measure the quality of our suggestions we compute two scores. *Exact match* shows the percent of the method names predicted exactly, while the F1 score is computed in a per-subtoken basis. When suggesting summaries, each model returns a ranked list of suggestions. We compute exact match and F1 at rank 1 and 5, as the best score achieved by any one of the top suggestions (i.e. if the fifth suggestion achieves the best F1 score, we use this one for computing F1 at rank 5). Using the BLEU score (Papineni et al., 2002) would have been possible, but it would not be different from F1 given the short lengths of our output sequences (3 on average). We use each project separately, training one neural network for each project and testing on the respective test set. This is because each project’s domain varies widely and little information can be transferred among them, due to the principle of code reusability of software engineering. We note that we attempted to train a single model using all project training sets and tested on each project separately but this yielded significantly worse results for all algorithms.

For each project, we split the *files* uniformly at random into a training (65%), a validation (5%) and a test (30%) set. Each file is a top-level Java class. We perform hyperparameter optimizations using Bayesian optimization with spearmint (Snoek et al., 2012) maximizing the F1 at rank 5.

For comparison, we use two different algorithms: a tf-idf algorithm that computes a tf-idf vector from the code snippet subtokens and suggests the names of the nearest neighbors using cosine similarity. We also use the standard attention model of Bahdanau et al. (2015) that uses a biRNN

and fully connected components, that has been successfully used in machine translation. We perform hyperparameter optimizations following the same protocol on libgdx.

**Training.** To train **conv\_attention** and **copy\_attention** we optimize the objective using stochastic gradient descent with RMSProp and Nesterov momentum (Sutskever et al., 2013; Hinton et al., 2012). We use dropout (Srivastava et al., 2014) on all parameters, parametric leaky RELUs (Maas et al., 2013; He et al., 2015) and gradient clipping. Each of the parameters of the model is initialized with normal random noise around zero, except for **b** that is initialized to the log of the empirical frequency of each target token in the training set. For **conv\_attention** the optimized hyperparameters are  $k_1 = k_2 = 8$ ,  $w_1 = 24$ ,  $w_2 = 29$ ,  $w_3 = 10$ , dropout rate 50% and  $D = 128$ . For **copy\_attention** the optimized hyperparameters are  $k_1 = 32$ ,  $k_2 = 16$ ,  $w_1 = 18$ ,  $w_2 = 19$ ,  $w_3 = 2$ , dropout rate 40% and  $D = 128$ .

### 3.1. Quantitative Evaluation

Table 1 shows the F1 scores achieved by the different methods for each project while Table 2 shows a quantitative evaluation, averaged across all projects. “Standard Attention” refers to the machine translation model of Bahdanau et al. (2015). The tf-idf algorithm seems to be performing very well, showing that the bag-of-words representation of the input code is a strong indicator of its name. Interestingly, the standard attention model performs worse than tf-idf in this domain, while **conv\_attention** and **copy\_attention** perform the best. The copy mechanism gives a good F1 improvement at rank 1 and a larger improvement at rank 5. Although our convolutional attentional models have an exact match similar to tf-idf, they achieve a much higher precision compared to all other algorithms.

These differences in the data characteristics could be the cause of the low performance achieved by the model of Bahdanau et al. (2015). Although source code snippets resemble natural language sentences, they are more structured, much longer and vary greatly in length. In our training sets, each method has on average 72 tokens (median 25 tokens, standard deviation 156) and the output method names are made up from 3 subtokens on average ( $\sigma = 1.7$ ).

**OOV Accuracy.** We measure the OOV word accuracy as the percent of the out-of-vocabulary subtokens that are correctly predicted by **copy\_attention**. On average, across our dataset, 4.4% of the test method name subtokens are out-of-vocabulary. Naturally, the standard attention model and tf-idf have an OOV accuracy of zero, since they are unable to predict those tokens. On average we get a 10.5% OOV accuracy at rank 1 and 19.4% at rank 5. This shows that the copying mechanism is useful in this domain and especially in smaller projects that tend to have more OOV tokens. We

Project Name	Git SHA	Description	F1							
			tf-idf		Standard Attention		conv_attention		copy_attention	
			Rank 1	Rank 5	Rank 1	Rank 5	Rank 1	Rank 5	Rank 1	Rank 5
cassandra	53e370f	Distributed Database	40.9	52.0	35.1	45.0	46.5	60.0	<b>48.1</b>	<b>63.1</b>
elasticsearch	485915b	REST Search Engine	27.8	39.5	20.3	29.0	30.8	45.0	<b>31.7</b>	<b>47.2</b>
gradle	8263603	Build System	30.7	45.4	23.1	37.0	35.3	52.5	<b>36.3</b>	<b>54.0</b>
hadoop-common	42a61a4	Map-Reduce Framework	34.7	48.4	27.0	45.7	38.0	54.0	<b>38.4</b>	<b>55.8</b>
hibernate-orm	e65a883	Object/Relational Mapping	53.9	63.6	49.3	55.8	57.5	67.3	<b>58.7</b>	<b>69.3</b>
intellij-community	d36c0c1	IDE	28.5	42.1	23.8	41.1	33.1	49.6	<b>33.8</b>	<b>51.5</b>
liferay-portal	39037ca	Portal Framework	59.6	70.8	55.4	70.6	63.4	75.5	<b>65.9</b>	<b>78.0</b>
presto	4311896	Distributed SQL query engine	41.8	53.2	33.4	41.4	46.3	59.0	<b>46.7</b>	<b>60.2</b>
spring-framework	826a00a	Application Framework	35.7	47.6	29.7	41.3	35.9	49.7	<b>36.8</b>	<b>51.9</b>
wildfly	c324eaa	Application Server	45.2	57.7	32.6	44.4	<b>45.5</b>	61.0	44.7	<b>61.7</b>

Table 1. Open source Java project used and F1 scores achieved. Standard attention refers to the model of Bahdanau et al. (2015).

	F1 (%)		Exact Match (%)		Precision (%)		Recall (%)	
	Rank 1	Rank 5	Rank 1	Rank 5	Rank 1	Rank 5	Rank 1	Rank 5
tf-idf	40.0	52.1	<b>24.3</b>	29.3	41.6	55.2	<b>41.8</b>	51.9
Standard Attention	33.6	45.2	17.4	24.9	35.2	47.1	35.1	42.1
conv_attention	43.6	57.7	20.6	29.8	57.4	73.7	39.4	51.9
copy_attention	<b>44.7</b>	<b>59.6</b>	23.5	<b>33.7</b>	<b>58.9</b>	<b>74.9</b>	40.1	<b>54.2</b>

Table 2. Evaluation metrics averaged across projects. Standard Attention refers to the work of Bahdanau et al. (2015).

also note that OOV accuracy varies across projects, presumably due to different coding styles.

**Topical vs. Time-Invariant Feature Detection.** The difference of the performance between the **copy\_attention** and the standard attention model of Bahdanau et al. (2015) raises an interesting question. What does **copy\_attention** learn that cannot be learned by the standard attention model? One hypothesis is that the biRNN of the standard attention model fails to capture long-range features, especially in very long inputs. To confirm our hypothesis, we shuffle the subtokens in libgdx, essentially removing all features that depend on the sequential information. Without any local features all models should reduce to achieving performance similar to tf-idf. Indeed, **copy\_attention** now has an F1 at rank 1 that is +1% compared to tf-idf (presumably thanks to the language model-like structure of the output), while the standard attention model worsens its performance getting an F1 score (rank 1) of 26.2%, compared to the original 41.8%. This suggests that the biRNN fails to capture long-range topical attention features.

**A simpler  $h_{t-1}$ .** Since the target summaries are quite short, we tested a simpler alternative to the GRU, assigning  $h_{t-1} = W \times [G_{m_{t-1}}, G_{m_{t-2}}]$ , where  $G \in \mathbb{R}^{D \times |V|}$  is a new embedding matrix (different from the embeddings in  $E$ ) and  $W$  is a  $k_2 \times D \times 2$  tensor. This model is simpler and slightly faster to train and achieves similar performance to **copy\_attention**, reducing F1 by less than 1%.

### 3.2. Qualitative Evaluation

Figure 2 shows a visualization of a small method that illustrates how **copy\_attention** typically works. At the first step, it focuses its attention at the whole method and de-

cides upon the first subtoken. In a large number of cases this includes subtokens such as `get`, `set`, `is`, `create` etc. In the next steps the copying mechanism is highly confident ( $\lambda = 0.97$  in Figure 2) and sequentially copies the correct subtokens from the code snippet into the name. We note that across many examples the copying mechanism tends to have a significantly more focused attention vector  $\kappa$ , compared to the attention vector  $\alpha$ . Presumably, this happens because of the different training signals of the attention mechanisms.

A second example of **copy\_attention** is seen in Figure 3. Although due to space limitations this is a relatively short method, it illustrates how the model has learned both time-invariant features and topical features. It correctly detects the `==` operator and predicts that the method has a high probability of starting with `is`. Furthermore, in the next step (prediction of the  $m_2$  bullets subtoken) it successfully learns to ignore the `e` prefix (prepended on all enumeration variables in that project) and the `flag` subtoken that does not provide useful information for the summary.

Table 3 presents a set of hand-picked examples from libgdx that show interesting challenges of the domain and how our **copy\_attention** handles them. Understandably, the model does *not* distinguish between `should` and `is` — both implying a `boolean` return value — and instead of `shouldRender`, `isRender` is suggested. The `getAspectRatio`, `surfaceArea` and `minRunLength` examples show the challenges of describing a previously unseen abstraction. Interestingly, the model correctly recognizes that a novel (UNK) token should be predicted after `get` in `getAspectRatio`. Most surprisingly, `reverseRange` is predicted correctly, because of the struc-

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<b>boolean shouldRender()</b> <pre>try {     return renderRequested    isContinuous; } finally {     renderRequested = false; }</pre> <p><u>Suggestions:</u>      ▶ is, render (27.3%)                           ▶ is, continuous (10.6%)    ▶ is, requested (8.2%)                           ▶ render, continuous (6.9%)   ▶ get, render (5.7%)</p>	<b>void reverseRange(Object[] a, int lo, int hi)</b> <pre>hi--; while (lo &lt; hi) {     Object t = a[lo];     a[lo++] = a[hi];     a[hi--] = t; }</pre> <p><u>Suggestions:</u>   ▶ reverse, range (22.2%)   ▶ reverse (13.0%)                           ▶ reverse, lo (4.1%)                   ▶ reverse, hi (3.2%)                           ▶ merge, range (2.0%)</p>
<b>int createProgram()</b> <pre>GL20 gl = Gdx.gl20; int program = gl.glCreateProgram(); return program != 0 ? program : -1;</pre> <p><u>Suggestions:</u>      ▶ create (18.36%)    ▶ init (7.9%)                           ▶ render (5.0%)    ▶ initiate (5.0%)   ▶ load (3.4%)</p>	<b>VerticalGroup right()</b> <pre>align  = Align.right; align &amp;= ~Align.left; return this;</pre> <p><u>Suggestions:</u>   ▶ left (21.8%)   ▶ top (21.1%)   ▶ right (19.5%)                           ▶ bottom (18.5%)   ▶ align (3.7%)</p>
<b>boolean isBullet()</b> <pre>return (m_flags &amp; e_bulletFlag)     == e_bulletFlag;</pre> <p><u>Suggestions:</u>      ▶ is (13.5%)    ▶ is, bullet (5.5%)                           ▶ is, enable (5.1%)   ▶ enable (2.8%)   ▶ mouse (2.7%)</p>	<b>float getAspectRatio()</b> <pre>return (height == 0) ?     Float.NaN : width / height;</pre> <p><u>Suggestions:</u>      ▶ get, Unk (9.0%)    ▶ get, height (8.7%)                           ▶ get, width (6.5%)   ▶ get (5.7%)   ▶ get, size (4.2%)</p>
<b>int minRunLength(int n)</b> <pre>if (DEBUG) assert n &gt;= 0; int r = 0; while (n &gt;= MIN_MERGE) {     r  = (n &amp; 1);     n &gt;&gt;= 1; } return n + r;</pre> <p><u>Suggestions:</u>      ▶ min (43.7%)    ▶ merge (13.0%)                           ▶ pref (1.9%)   ▶ space (1.0%)   ▶ min, all (0.8%)</p>	<b>JsonWriter pop()</b> <pre>if (named) throw     new IllegalStateException(UNKSTRING); stack.pop().close(); current = stack.size == 0 ?     null : stack.peek(); return this;</pre> <p><u>Suggestions:</u>   ▶ close (21.4%)   ▶ pop (10.2%)   ▶ first (6.5%)                           ▶ state (3.8%)   ▶ remove (2.2%)</p>
<b>Rectangle setPosition(float x, float y)</b> <pre>this.x = x; this.y = y; return this;</pre> <p><u>Suggestions:</u>      ▶ set (54.0%)    ▶ set, y (12.8%)                           ▶ set, x (9.0%)    ▶ set, position (8.6%)                           ▶ set, bounds (1.68%)</p>	<b>float surfaceArea()</b> <pre>return 4 * MathUtils.PI *     this.radius * this.radius;</pre> <p><u>Suggestions:</u>      ▶ dot, radius (26.5%)    ▶ dot (13.1%)                           ▶ crs, radius (9.0%)   ▶ dot, circle (6.5%)   ▶ crs (4.1%)</p>

Table 3. A sample of handpicked snippets (the sample is necessarily limited to short methods because of space limitations) and the respective suggestions that illustrate some interesting challenges of the domain and how the **copy\_attention** model handles them or fails. Note that the algorithms do *not* have access to the signature of the method but only to the body. Examples taken from the libgdx Android/Java graphics library test set.

Target		Attention Vectors		$\lambda$
$m_1$	set	$\alpha =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	0.012
		$\kappa =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	
$m_2$	use	$\alpha =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	0.974
		$\kappa =$	<code>&lt;s&gt;{ this . <u>use</u> <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	
$m_3$	browser	$\alpha =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	0.969
		$\kappa =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	
$m_4$	cache	$\alpha =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	0.583
		$\kappa =$	<code>&lt;s&gt;{ this . use <u>Browser</u> <u>Cache</u> = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	
$m_5$	END	$\alpha =$	<code>&lt;s&gt;{ this . use <u>Browser</u> Cache = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	0.066
		$\kappa =$	<code>&lt;s&gt;{ this . use <u>Browser</u> <u>Cache</u> = use <u>Browser</u> Cache ; } &lt;/s&gt;</code>	

Figure 2. Visualization of **copy\_attention** used to compute  $P(m_t|m_0 \dots m_{t-1}, c)$  for `setUseBrowserCache` in `libgdx`. The darker the color of a subtoken, they higher its attention weight. This relationship is linear. Yellow indicates the convolutional attention of the **conv\_attention** component, while purple the attention of the copy mechanism. Since the values of  $\alpha$  are usually spread across the tokens the colors show a normalized  $\alpha$ , i.e.  $\alpha / \|\alpha\|_\infty$ . In contrast, the copy attention weights  $\kappa$  are usually very peaky and we plot them as-is. Underlined subtokens are out-of-vocabulary.  $\lambda$  shows the probability of using the copy attention  $\kappa$  vs. the convolutional attention  $\alpha$ . More visualizations of `libgdx` methods can be found at <http://groups.inf.ed.ac.uk/cup/codeattention/>.

Target		Attention Vectors		$\lambda$
$m_1$	is	$\alpha =$	<code>&lt;s&gt;{ return ( mFlags &amp; eBulletFlag ) == eBulletFlag ; } &lt;/s&gt;</code>	0.012
		$\kappa =$	<code>&lt;s&gt;{ return ( mFlags &amp; eBulletFlag ) == eBulletFlag ; } &lt;/s&gt;</code>	
$m_2$	bullet	$\alpha =$	<code>&lt;s&gt;{ return ( mFlags &amp; eBulletFlag ) == eBulletFlag ; } &lt;/s&gt;</code>	0.436
		$\kappa =$	<code>&lt;s&gt;{ return ( mFlags &amp; eBulletFlag ) == eBulletFlag ; } &lt;/s&gt;</code>	
$m_3$	END	$\alpha =$	<code>&lt;s&gt;{ return ( mFlags &amp; eBulletFlag ) == eBulletFlag ; } &lt;/s&gt;</code>	0.174
		$\kappa =$	<code>&lt;s&gt;{ return ( mFlags &amp; eBulletFlag ) == eBulletFlag ; } &lt;/s&gt;</code>	

Figure 3. Visualization of **copy\_attention** modeling  $P(m_t|m_0 \dots m_{t-1}, c)$  for `isBullet` in `libgdx`. For information about how this visualization was made see Figure 2. This example shows an indication that **copy\_attention** captures location-invariant features and the topicality of the input code sequence. More visualizations of `libgdx` methods can be found at <http://groups.inf.ed.ac.uk/cup/codeattention/>.

ture of the code, even though no code tokens contain the summary tokens.

## 4. Related Work

Convolutional neural networks have been used for image classification with great success (Krizhevsky et al., 2012; Szegedy et al., 2015; LeCun et al., 1990; 1998). More related to this work is the use of convolutional neural networks for text classification (Blunsom et al., 2014). Closely related is the work of Denil et al. (2014) that learns representations of documents using convolution but uses the network activations to summarize a document rather than an attentional model. Rush et al. (2015) use an attention-based encoder to summarize sentences, but do not use convolution for their attention mechanism. Our work is also related to other work in attention mechanisms for text (Hermann et al., 2015) and images (Xu et al., 2015; Mnih et al., 2014) that does not use convolution to

provide the attention values. Finally, pointer networks (Vinyals et al., 2015) are similar to our copy mechanism but use an RNN for providing attention. Finally, distantly related to this work is research on creating neural network architectures that learn code-like behaviors (Graves et al., 2014; Zaremba & Sutskever, 2014; Joulin & Mikolov, 2015; Grefenstette et al., 2015; Dyer et al., 2015; Reed & de Freitas, 2015; Neelakantan et al., 2015).

In recent years, thanks to the insight of Hindle et al. (2012) the use of probabilistic models for software engineering applications has grown. Research has mostly focused on token-level (Nguyen et al., 2013; Tu et al., 2014) and syntax-level (Maddison & Tarlow, 2014) language models of code and translation between programming languages (Karaivanov et al., 2014; Nguyen et al., 2014). Movshovitz-Attias et al. (2013) learns to predict code comments using a source code topic model. Allamanis et al. (2015b) create a generative model of source code snip-



pets given a natural language query and Oda et al. (2015) use machine translation to convert source code into pseudocode. Closer to our work, Raychev et al. (2015) aim to predict names and types of variables, whereas Allamanis et al. (2014) and Allamanis et al. (2015a) suggest names for variables, methods and classes. Similar to Allamanis et al. (2015a), we aim to predict method names but using only the tokens within a method and no other features (e.g. method signature). Mou et al. (2016) use syntax-level convolutional neural networks, ignoring identifiers, to learn a vector representations of code and classify student submissions into their original tasks without considering naming. Piech et al. (2015) also learn program embeddings from student submissions using the program state, to assist MOOC students debug their submissions but do not consider naming. Additionally, compared to Piech et al. (2015) and Mou et al. (2016) our work looks into highly diverse, non-student submission code that performs a wide range of real-world tasks.

## 5. Discussion & Conclusions

Modeling and understanding source code artifacts through machine learning can have a direct impact in software engineering research. The problem of extreme code summarization is a first step towards the more general goal of developing machine learning representations of source code that will allow machine learning methods to reason probabilistically about code resulting in useful software engineering tools that will help code construction and maintenance.

Additionally, source code — and its derivative artifacts — represent a new modality for machine learning with very different characteristics compared to images and natural language. Therefore, models of source code necessitate research into new methods that could have interesting parallels to images and natural language. This work is a step towards this direction: our neural convolutional attentional model attempts to “understand” the highly-structured source code text by learning both long-range features and localized patterns, achieving the best performance among other competing methods on real-world source code.

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