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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.

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 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 identify “interesting” locations where attention should be focused.

We apply this network to an “extreme” summarization prob-
A Convolutional Attention Network for Extreme Summarization of Source Code

Our convolutional attentional model receives as input a sequence of code subtokens\(^1\) \(c = [c_{e<>}, c_1, \ldots, c_N, c_{<>S}]\) and outputs an extreme summary in the form of a concise method name. The summary is a sequence of subtokens \(m = [m_{e<>}, m_1 \ldots m_M, m_{<>S}]\), where \(<<>\) and \(<S>\) are the special start and end symbols of every subtoken.

\(^1\)Subtokens refer to the parts of a source code token e.g. `getInputStream` has the `get`, `Input` and `Stream` subtokens.
sequence. For example, in the shouldRender method (top left of Table 3) the input code subtokens are \( \mathbf{c} = \langle \text{<S}, \text{try}, \text{, return}, \text{render}, \text{requested} \rangle \) while the target output is \( \mathbf{m} = \langle \text{<S}, \text{should, render, <S> \rangle} \). The neural network predicts each summary subtoken sequentially and models \( P(m_0 | m_1, \ldots, m_{t-1}, \mathbf{c}) \). Information about the previously produced subtokens \( m_1, \ldots, m_{t-1} \) is passed into a recurrent neural network that represents the input state with a vector \( \mathbf{h}_{t-1} \). Our convolutional attentional neural network (Figure 1) uses the input state \( \mathbf{h}_{t-1} \) and a series of convolutions over the embeddings of the tokens \( \mathbf{c} \) to compute a matrix of attention features \( L_{feat} \), (Figure 1) that contains one vector of attention features for each sequence position. 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 the weights, a context representation is computed and is used to predict the probability distribution over the targets \( m_t \). This model is a generative bimodal model of summary text given a code snippet.

2.1. Learning Attention Features

We describe our model from the bottom-up (Figure 1). First we discuss how to compute the attention features \( L_{feat} \) from the input \( \mathbf{c} \) and the previous hidden state \( \mathbf{h}_{t-1} \). 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 \textit{attention_features} is a sequence of code subtokens \( \mathbf{c} \) of length \( \text{LEN}(\mathbf{c}) \) and each location is mapped to a matrix of attention features \( L_{feat} \), with size \( (\text{LEN}(\mathbf{c}) + \text{const}) \times k_2 \) where the \text{const} is a fixed amount of padding. The intuition behind \textit{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 \( L_2 \).

\textit{attention_features} is described with the following pseudocode:

\[
\text{attention_features}(\text{code tokens } \mathbf{c}, \text{ context } \mathbf{h}_{t-1})
\]

\[
C \leftarrow \text{LOOKUPANDPAD}(\mathbf{c}, E)
\]

\[
L_1 \leftarrow \text{RELU}((\text{CONV} \mathbf{D}(C, K_{1}))
\]

\[
L_2 \leftarrow \text{CONV} \mathbf{D}(L_1, K_{2}) \circ \mathbf{h}_{t-1}
\]

\[
L_{\text{feat}} \leftarrow L_2 / \| L_2 \|_2
\]

\[
\text{return } L_{\text{feat}}
\]

Here \( E \in \mathbb{R}^{V \times D} \) contains the \( D \) dimensional embedding of each subtoken in names and code (i.e. all possible \( c_j \)s and \( m_i \)s). The two convolution kernels are \( K_{1} \in \mathbb{R}^{D \times w_1 \times k_1} \) and \( K_{2} \in \mathbb{R}^{k_1 \times w_2 \times k_2} \), where \( w_1, w_2 \) are the window sizes of the convolutions and RELU refers to a rectified linear unit (Nair & Hinton, 2010). The vector \( \mathbf{h}_{t-1} \in \mathbb{R}^{k_2} \) represents information from the previous subtokens \( m_0 \ldots m_{t-1} \). \text{CONV} \mathbf{D} \ performs a one-dimensional (throughout the length of sentence \( c \)) narrow convolution. Note that the input sequence \( c \) is padded by \text{LOOKUPANDPAD}. The size of the padding is such that with the narrow convolutions, the attention vector (returned by \textit{attention_weights}) has exactly \( \text{LEN}(\mathbf{c}) \) components. The \( \odot \) operator is the elementwise multiplication of a vector and a matrix, \( i.e. B = A \odot v \) for \( v \in \mathbb{R}^M \) and \( A \in M 

\times N \) matrix, \( B_{ij} = A_{ij}v_i \). We found the normalization of \( L_2 \) into \( L_{\text{feat}} \) to be useful during training. We believe it helps because of the widely varying lengths of inputs \( c \). Note that no pooling happens in this model; the input sequence \( c \) 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 \textit{attention_weights} as a function that accepts \( L_{\text{feat}} \) from \textit{attention_features} and a convolution kernel \( K \) of size \( k_2 \times w_3 \times 1 \). \textit{attention_weights} returns the normalized attention weights vector with length \( \text{LEN}(\mathbf{c}) \) and is described by the following pseudocode:

\[
\text{attention_weights}(\text{attention features } L_{\text{feat}}, \text{ kernel } K) \rightarrow \text{SOFTMAX}(\text{CONV} \mathbf{D}(L_{\text{feat}}, K))
\]

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 \( m_0 \ldots m_{t-1} \). The state is passed through \( \mathbf{h}_t \in \mathbb{R}^{k_2} \) computed by a Gated Recurrent Unit (Cho et al., 2014) \textit{i.e.}

\[
\text{GRU}(\text{current input } x_t, \text{ previous state } \mathbf{h}_{t-1})
\]

\[
r_t \leftarrow \sigma(x_t W_xr + h_{t-1} W_hr + \mathbf{b}_r)
\]

\[
u_t \leftarrow \sigma(x_t W_xu + h_{t-1} W_hu + \mathbf{b}_u)
\]

\[
c_t \leftarrow \tanh(x_t W_xc + r_t \odot (h_{t-1} W_hc) + \mathbf{b}_c)
\]

\[
\mathbf{h}_t \leftarrow (1 - u_t) \odot \mathbf{h}_{t-1} + u_t \odot c_t
\]

\[
\text{return } \mathbf{h}_t
\]

During testing the next state is computed by \( \mathbf{h}_t = \text{GRU}(E_{m_t}, \mathbf{h}_{t-1}) \text{ i.e. using the embedding of the current output subtoken } m_t \). 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 \( \mathbf{h}_t = \text{GRU}(\tilde{n}, \mathbf{h}_{t-1}) \), where \( \tilde{n} \) is the predicted embedding.

2.2. Simple Convolutional Attentional Model

We now use the components described above as building blocks for our extreme summarization model. We first build \textit{conv_attention}, a convolutional attention model that uses an attention vector \( \alpha \) computed from \textit{attention_weights} to weight the embeddings of the tokens in \( \mathbf{c} \) and compute the predicted target embedding \( \tilde{n} \in \mathbb{R}^D \). It returns a distribution over all subtokens in
A Convolutional Attention Network for Extreme Summarization of Source Code

We obtained the

\[ \sigma \]

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 predicts an UNK but the subtoken can be predicted exactly by the copy mechanism, otherwise \( \mu = 1 \). We arbitrarily used \( \mu = e^{-10} \), although variations did not affect performance.

### 2.4. Predicting Names

To predict a full method name, we use a hybrid breath-first search and beam search. We start from the special \( m_0 = \langle \rangle \) subtoken and 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 subtoken, pushing them back to the heap. When the \( \langle \rangle \) subtoken is generated the suggestion is moved onto the list of suggestions. Since we are interested in 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 the process tractable, we limit the partial suggestion heap size 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 dataset of good quality, we cloned 11 open source Java projects from 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 libgd to 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 and code can be found at groups.inf.ed.ac.uk/cup/codeattention.

**Experimental Setup.** To measure the quality of our suggestions we compute two scores. Exact match is the percentage 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. 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 BLEU (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 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 but this yielded significantly worse results for all algorithms. For each project, we split the files (top-level Java classes) uniformly at random into training (65%), validation (5%) and test (30%) sets. We optimize hyperparameters using Bayesian optimization with Spearmint (Snoek et al., 2012) maximizing F1 at rank 5.

For comparison, we use two 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 copy_attention and conv_attention we optimize the objective using stochastic gradient descent with RMSGProp 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 copy_attention and conv_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 out-of-vocabulary (OoV) word accuracy as the percentage 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 OoV. 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 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 test our hypothesis, we shuffle the subtokens in libgdx, essentially removing all features that depend on the sequential information. Without any lo-
A Convolutional Attention Network for Extreme Summarization of Source Code

<table>
<thead>
<tr>
<th>Project Name</th>
<th>Git SHA</th>
<th>Description</th>
<th>tf-idf</th>
<th>Standard Attention</th>
<th>copy_attention</th>
</tr>
</thead>
<tbody>
<tr>
<td>cassandra</td>
<td>53e370f</td>
<td>Distributed Database</td>
<td>40.9</td>
<td>35.1</td>
<td>46.5</td>
</tr>
<tr>
<td>elasticsearch</td>
<td>485915b</td>
<td>REST Search Engine</td>
<td>27.8</td>
<td>20.3</td>
<td>30.8</td>
</tr>
<tr>
<td>grade</td>
<td>8263663</td>
<td>Build System</td>
<td>30.7</td>
<td>23.1</td>
<td>35.3</td>
</tr>
<tr>
<td>hadoop-common</td>
<td>426f1a4</td>
<td>Map-Reduce Framework</td>
<td>34.7</td>
<td>27.0</td>
<td>38.0</td>
</tr>
<tr>
<td>hibernate-orm</td>
<td>e65a883</td>
<td>Object/Relational Mapping</td>
<td>53.9</td>
<td>49.3</td>
<td>57.5</td>
</tr>
<tr>
<td>intellij-community</td>
<td>d36c8c1</td>
<td>IDE</td>
<td>28.5</td>
<td>23.8</td>
<td>33.1</td>
</tr>
<tr>
<td>liferay-portal</td>
<td>39037ca</td>
<td>Portal Framework</td>
<td>59.6</td>
<td>55.4</td>
<td>63.4</td>
</tr>
<tr>
<td>presto</td>
<td>4311986</td>
<td>Distributed SQL query engine</td>
<td>41.8</td>
<td>33.3</td>
<td>46.3</td>
</tr>
<tr>
<td>spring-framework</td>
<td>826d0f8</td>
<td>Application Framework</td>
<td>35.7</td>
<td>29.7</td>
<td>35.9</td>
</tr>
<tr>
<td>wildfly</td>
<td>c324eaa</td>
<td>Application Server</td>
<td>45.2</td>
<td>32.6</td>
<td>45.5</td>
</tr>
</tbody>
</table>

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

### 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 decides 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 meta-attention mechanism is highly confident about the copying mechanism ($\lambda = 0.97$ 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 (preended 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 structure of the code, even though no code tokens contain the summary subtokens.

### 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
### 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.

<table>
<thead>
<tr>
<th>Method</th>
<th>Code</th>
<th>Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>boolean shouldRender()</code></td>
<td>try { return renderRequested</td>
<td></td>
</tr>
<tr>
<td><code>void reverseRange(Object[] a, int lo, int hi)</code></td>
<td>hi--; while (lo &lt; hi) { Object t = a[lo]; a[lo++] = a[hi]; a[hi--] = t; }</td>
<td>reverse, range (22.2%) reverse (13.0%) reverse, lo (4.1%) reverse, hi (3.2%) merge, range (2.0%)</td>
</tr>
<tr>
<td><code>int createProgram()</code></td>
<td>GL20 gl = Gdx.gl20; int program = gl.glCreateProgram(); return program != 0 ? program : -1;</td>
<td>create (18.36%) init (7.9%) render (5.0%) initiate (5.0%) load (3.4%)</td>
</tr>
<tr>
<td><code>boolean isBullet()</code></td>
<td>return (m_flags &amp; e_bulletFlag) == e_bulletFlag;</td>
<td>is (13.5%) is, bullet (5.5%) is, enable (5.1%) enable (2.8%) mouse (2.7%)</td>
</tr>
<tr>
<td><code>float getAspectRatio()</code></td>
<td>return (height == 0) ? Float.NaN : width / height;</td>
<td>get, UNK (9.0%) get, height (8.7%) get, width (6.5%) get, size (4.2%)</td>
</tr>
<tr>
<td><code>int minRunLength(int n)</code></td>
<td>if (DEBUG) assert n &gt;= 0; int r = 0; while (n &gt;= MIN_MERGE) { r</td>
<td>= (n &amp; 1); n &gt;&gt;= 1; } return n + r;</td>
</tr>
<tr>
<td><code>JsonWriter pop()</code></td>
<td>if (named) throw new IllegalStateException(UNKSTRING); stack.pop().close(); current = stack.size == 0 ? null : stack.peek(); return this;</td>
<td>close (21.4%) pop (10.2%) first (6.5%) state (3.8%) remove (2.2%)</td>
</tr>
<tr>
<td><code>Rectangle setPosition(float x, float y)</code></td>
<td>this.x = x; this.y = y; return this;</td>
<td>set (54.0%) set, y (12.8%) set, x (9.0%) set, position (8.6%) set, bounds (1.68%)</td>
</tr>
<tr>
<td><code>float surfaceArea()</code></td>
<td>return 4 * MathUtils.PI * this.radius * this.radius;</td>
<td>dot, radius (26.5%) dot (13.1%) crs, radius (9.0%) dot, circle (6.5%) crs (4.1%)</td>
</tr>
</tbody>
</table>

Where `UNKSTRING` represents a string that is not known at compile time.
A Convolutional Attention Network for Extreme Summarization of Source Code

<table>
<thead>
<tr>
<th>Target</th>
<th>Attention Vectors</th>
<th>$\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_1$ set</td>
<td>$\alpha = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td></td>
</tr>
<tr>
<td>$m_2$ use</td>
<td>$\alpha = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td>0.974</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td></td>
</tr>
<tr>
<td>$m_3$ browser</td>
<td>$\alpha = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td>0.969</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td></td>
</tr>
<tr>
<td>$m_4$ cache</td>
<td>$\alpha = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td>0.583</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td></td>
</tr>
<tr>
<td>$m_5$ END</td>
<td>$\alpha = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{this} \rangle { \text{use Browser Cache = use Browser Cache; } } \langle \text{this} \rangle$</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2. Visualization of copy_attention used to compute $P(m_c|m_0 \ldots m_{t-1}, e)$ for setUseBrowserCache in libgdx. The darker the color of a subtoken, the higher its attention weight. This relationship is linear. Yellow indicates the convolutional attention weight 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 meta-attention probability of using the copy attention $\kappa$ vs. the convolutional attention $\alpha$. More visualizations of libgdx methods can be found at \url{http://groups.inf.ed.ac.uk/cup/codeattention/}.

<table>
<thead>
<tr>
<th>Target</th>
<th>Attention Vectors</th>
<th>$\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_1$ is</td>
<td>$\alpha = \langle \text{return (m Flags &amp; e Bullet Flag) == e Bullet Flag } \rangle$</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{return (m Flags &amp; e Bullet Flag) == e Bullet Flag } \rangle$</td>
<td></td>
</tr>
<tr>
<td>$m_2$ bullet</td>
<td>$\alpha = \langle \text{return (m Flags &amp; e Bullet Flag) == e Bullet Flag } \rangle$</td>
<td>0.436</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{return (m Flags &amp; e Bullet Flag) == e Bullet Flag } \rangle$</td>
<td></td>
</tr>
<tr>
<td>$m_3$ END</td>
<td>$\alpha = \langle \text{return (m Flags &amp; e Bullet Flag) == e Bullet Flag } \rangle$</td>
<td>0.174</td>
</tr>
<tr>
<td></td>
<td>$\kappa = \langle \text{return (m Flags &amp; e Bullet Flag) == e Bullet Flag } \rangle$</td>
<td></td>
</tr>
</tbody>
</table>

Figure 3. Visualization of copy_attention modeling $P(m_c|m_0 \ldots m_{t-1}, e)$ for isBullet in libgdx. The copy_attention captures location-invariant features and the topicality of the input code sequence. For information about the visualization see Figure 2.

networks for text classification (Blunsom et al., 2014) and networks 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 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 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 to learn vector representations for code and classify
student submissions into 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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References


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