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Bidirectional Transformer Language Models for Smart Autocompletion of Source Code

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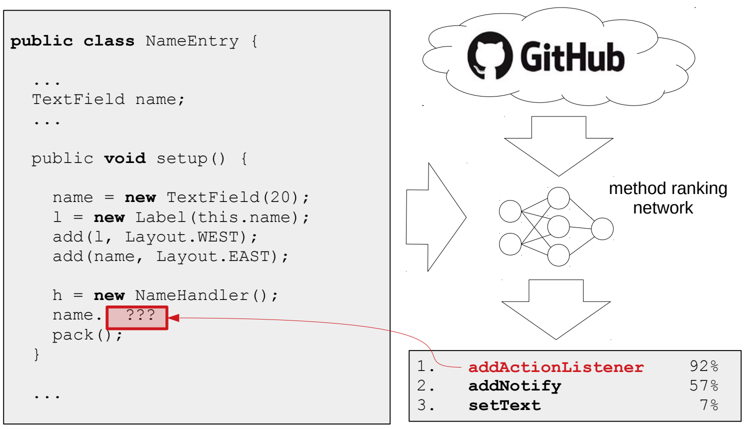
AI-based support in software engineering has recently emerged as a research field: Recommenders for software commits [Da16], predicting code changes [Zh19], semantic code search [Hu19] or code captioning [ALY18] have been developed. These are usually based on machine learning components, trained on vast amounts of source code and documentation from open-source platforms such as GitHub. Another challenge – and the subject of this paper – is *smart autocompletion*: As the developer types source code, an AI-based system suggests names for methods/interfaces to use next. To do so, the system infers the plausibility of method calls from the local code context. Take a look at the following example: The AI system (more specifically, a neural *method ranking network*) analyzes a position in the current code (red, left), and infers that – out of the class `TextField`'s methods – `addActionListener` seems most plausible. The network has learned this suggestion from a vast training set of Java projects on GitHub, which contain similar usages of GUI components as the target code:



We refer to this challenge of ranking an object's method names by their plausibility in a given code context as *method ranking*. While previous work has used n-grams [Hi12],

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recurrent networks [Wh15] and left-to-right language modeling [In20], we evaluate the transformer network BERT [De18] based on *masked* language modeling. While masked language modeling has been very successful in *natural* language processing, it has not been used for method ranking / smart autocompletion in source code yet. Our approach first pre-trains a BERT model (more precisely, RoBERTa [Li19]) on a dataset of 10.414 open-source projects (250 million lines of code) from the GitHub Java Corpus [AS13]. Training is done by masking out tokens (more precisely, BPE tokens [SHB16]) in pieces of source code and forcing the model to predict those missing tokens. We call the resulting model *JavaBERT*.

To utilize JavaBERT for method ranking, we address the fact that method names may consist of *multiple* tokens (e.g., `add-Action-Listen-er`). We suggest two alternatives:

1. *JavaBERT-unsup*: The pre-trained (unsupervised) JavaBERT is applied by masking out variable numbers of tokens. JavaBERT's predictions on token-level are then combined in a probabilistic reasoning to predictions on method level.
2. *JavaBERT-sup*: JavaBERT is fine-tuned in an additional supervised training as a binary classifier, estimating whether a certain method call is plausible or not in context.

We evaluate both approaches in quantitative experiments on a set of random samples from the test split of the GitHub Java Corpus. Our results indicate that masked language modeling is surprisingly accurate, with a top-3 accuracy of up to 98%. We also study the impact of different contexts, e.g. only the code up to the target method call, or shorter vs. larger pieces of code.

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