Sosed: a tool for finding similar software projects

Egor Bogomolov
JetBrains Research
Saint Petersburg, Russia
egor.bogomolov@jetbrains.com

Yaroslav Golubev
JetBrains Research
Saint Petersburg, Russia
yaroslav.golubev@jetbrains.com

Artyom Lobanov
JetBrains Research
Saint Petersburg, Russia
artem.lobanov@jetbrains.com

Vladimir Kovalenko
JetBrains Research
Saint Petersburg State University
Saint Petersburg, Russia
vladimir.kovalenko@jetbrains.com

Timofey Bryksin
JetBrains Research
Amsterdam, The Netherlands
timofey.bryksin@jetbrains.com

ABSTRACT
In this paper, we present Sosed, a tool for discovering similar software projects. We use fastText to compute the embeddings of subtokens into a dense space for 120,000 GitHub projects in 200 languages. Then, we cluster embeddings to identify groups of semantically similar subtokens that reflect topics in source code. We use a dataset of 9 million GitHub projects as a reference search base. To identify similar projects, we compare the distributions of clusters among their subtokens. The tool receives an arbitrary project as input, extracts subtokens in 16 most popular programming languages, computes cluster distribution, and finds projects with the closest distribution in the search base. We labeled subtoken clusters with short descriptions to enable Sosed to produce interpretable output.

Sosed is available at https://github.com/JetBrains-Research/sosed/. The tool demo is available at https://www.youtube.com/watch?v=LYLkztCGRt8. The multi-language extractor of subtokens is available separately at https://github.com/JetBrains-Research/buckwheat/.

ACM Reference Format:
Egor Bogomolov, Yaroslav Golubev, Artyom Lobanov, Vladimir Kovalenko, and Timofey Bryksin. 2020. Sosed: a tool for finding similar software projects. In 35th IEEE/ACM International Conference on Automated Software Engineering (ASE ’20), September 21–25, 2020, Virtual Event, Australia. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3324884.3415291

1 INTRODUCTION
Identification of similar projects in a large set of open-source repositories can help in several software engineering tasks: rapid prototyping, program understanding, plagiarism detection [25]. Additionally, it requires the development of new approaches to understand the meaning behind code and represent software projects on a large scale. In turn, if the developed methods can detect similar projects, they might be also applied in other software engineering tasks.

While popular web search engines provide an option to search for web pages or images similar to the input, there is no common approach for finding similar software projects. For instance, prior work on search for similar projects leveraged several sources of data: Java API calls [24], contents of README files [32], user reactions in the form of GitHub stars [32], tags on SourceForge [29].

Recently, researchers used splitting of code tokens into subtokens to improve results in method name prediction [8], variable misuse identification [15], and source code topic modeling [23]. Following these advances, we suggest a novel approach to represent arbitrary fragments of code based on subtoken embeddings, i.e., numerical representations in a dense space. We train subtoken embeddings with fastText [10], an algorithm for training word embeddings that works with cosine distance. The clusters represent topics that occurred in a large corpus of source code. We represent code as a distribution of clusters among its subtokens, i.e., probabilities of each cluster appearing among code’s subtokens.

We implemented the suggested approach to represent code as a tool for detecting similar projects called Sosed. We define similarity of projects as the similarity of the corresponding cluster distributions. To measure it, we suggest using either KL-divergence [18], or cosine similarity of the distribution vectors.

Sosed identifies similar projects based solely on their code, and supports 16 most popular programming languages. It does not make use of collaboration data (e.g., GitHub stars) to avoid popularity bias. Currently, Sosed supports searching for similar repositories across 9 million repositories that comprise all unique public projects on GitHub as of the end of 2016. In the future, we plan to update the dataset to use an up-to-date snapshot of GitHub.

An important feature of Sosed is the explainability of its output. We manually labeled the subtoken clusters with short descriptions of their topics. For each query result, we can provide descriptions of topics that contributed the most to the similarity measure.

The main contribution of our work is Sosed—an open-source tool for finding similar repositories based on the novel, subtoken based, code representation. Sosed provides explainable output, supports 16
programming languages, and searches across millions of reference projects.

The tool is available on GitHub [4]. The part of Sosed used for subtoken extraction and language identification is also available as a standalone tool [3].

2 BACKGROUND

Previous work on detecting similar repositories leveraged several sources of data. McMillan et al. [24] suggested CLAN, a Java-specific approach that detects similar Java applications by analyzing their API calls. The authors applied Latent Semantic Indexing [12] to an occurrence matrix, where columns represent projects, and rows represent API calls. The authors obtained vector representations of Java applications and defined the similarity of two projects as the cosine similarity of the corresponding vectors.

Aside from analyzing the code, several approaches to similarity search used data specific to code hosting platforms (e.g., SourceForge [29] or GitHub [32]). Thung et al. [29] used the SourceForge’s tags system to define similarity of the projects. Tags are short descriptions of project characteristics: category, language, user interface, and so on. Since some tags are more descriptive than others, the authors proposed to assign a weight to each tag. Then, they computed similarity of two projects based on intersection of tag sets. Zhang et al. [32] measured similarity of projects hosted on GitHub based on the stars given by the same user in a short period of time and contents of the projects’ README files.

The problem of detecting similar applications is also actively researched in the domain of mobile apps [11, 14, 19, 20]. The main difference from open source software projects is the data associated with each app. For apps in app stores source code is often not openly accessible but other data is available: description, images, permissions, user reviews, download size.

Another method related to measuring similarity of projects is topic modeling on code. The goal of topic modeling is to automatically detect topics in a corpus of unlabeled data, e.g., software projects. The output of a topic modeling algorithm is a set of topics, and a distribution of topics in each item from the corpus. A topic is usually represented by a group of reference words or labels that are most frequent across data comprising the topic. According to the survey by Sun et al. [28], the most popular approach to topic modeling in software engineering is LDA [9]. It treats source code as a bag of tokens, such as variable names, function names, and other identifiers. Markovtsev et al. [23] used ARTM [31], an algorithm similar to LDA, to identify topics across 9 million GitHub projects, which makes it, to the best of our knowledge, the largest deduplicated dataset of software projects, which is suitable for our task straight away.

As a preprocessing step, we transform projects into numerical vectors. Firstly, we train embeddings of subtokens on a large corpus of code [22] with fastText [10]. Secondly, we find K clusters of subtokens with spherical K-means algorithm [16], where K is a manually selected parameter. Finally, for each repository, we compute the distribution of clusters among its subtokens. The distribution for a project is a K-dimensional vector, where each component C is a probability of cluster C appearing among the project’s subtokens.

We implement two methods for measuring similarity of projects: explicitly computing KL-divergence [18] (i.e., a measure of distribution similarity) of their cluster distributions, or computing cosine similarity of the distribution vectors. In both cases, we use Faiss [17] library to find the closest distributions.

In the rest of this section we describe parts of Sosed in more details.

Figure 1: Overview of the algorithm to compute projects’ similarity

Reference projects. For each repository, the dataset introduced by Markovtsev et al. [23] contains a set of all subtokens found in the project. We describe the process of extracting subtokens latter in this section.

The dataset is already cleared of both explicit and implicit forks (i.e., copies of other projects that are not marked as forks on GitHub by its authors). It contains all the GitHub projects as of the end of 2016. Even though the projects in the dataset are not up-to-date, it allows us to implement the search in a vast amount of projects. In the future, we plan to create an up-to-date version of the dataset.

Training subtoken embeddings. For training subtoken embeddings, we use a dataset of identifiers extracted from 120,000 GitHub repositories [22]. It contains sequences of subtokens from files in approximately 200 programming languages.

We use fastText [10] to compute embeddings of subtokens into a 100-dimensional space. Alongside with embeddings of input words, fastText also computes embeddings of encountered n-grams. It is helpful in the source code domain, because even at subtoken level there are some highly repetitive n-grams. Another important
Extracting subtokens from repositories. A part of this work used for subtoken extraction and language identification might be useful for other tasks as well. To share it with the community and facilitate its reuse, we make it available as a separate project [3]. The input of subtoken extractor is a list of either links to GitHub repositories or paths to local directories. The output is a list of all extracted subtokens and their quantities for each project.

On the first step of tokenization, we use enry [2] to recognize languages in files in each project. enry is a Go-based language tool that employs several strategies to determine the language of a given file, including its name, extension, and content. enry supports 382 programming languages, is fast, and does not require a git repository to work, meaning that the input project can be any collection of files.

When run on a directory, enry outputs a JSON file with the recognized languages as keys and lists of files as values. Using these keys, we filter languages that we are interested in. Based on the statistics on programming languages popularity [6], we currently support 16 languages, namely: C, C#, C++, Go, Haskell, Java, JavaScript, Kotlin, PHP, Python, Ruby, Rust, Scala, Shell, Swift, and TypeScript.

The next step of tokenization is extraction of identifiers. Since we are only interested in identifiers and names, we need to iterate over all the tokens in the file and gather only those that belong to specific types (excluding literals, comments, etc.). To do that, we employ two different tools. 12 out of 16 languages (including 10 most popular ones) are passed on to Tree-sitter [7], a fast parsing tool that uses language-specific grammars to parse a given file into an abstract syntax tree (AST). We then filter the AST leaves to obtain various kinds of identifiers, names, constants, etc.

The four remaining languages (Scala, Swift, Kotlin, and Haskell) either do not have a Tree-sitter grammar at the time of writing or the grammar is in development. The files in these languages are passed on to Pygments [5] lexers. A Pygments lexer splits the code into tokens, each of which also has a certain type. From the list of tokens, we extract those that are of interest to us.

The last step of tokenization is splitting each token into subtokens. Following Markovtsev et al. [23], we split the tokens by camel case and snake case, append short subtokens (less than three characters) to the adjacent longer ones, and stem subtokens longer than 6 characters using the Snowball stemmer [26].

For a given project, we carry out identifier extraction and subtokenization for all files written in the supported languages and accumulate the results. In the end, the repository is represented as a dictionary with subtokens as keys and their counts as values.

Clustering subtoken embeddings. We use the spherical K-means algorithm [16] to find clusters of similar subtokens. The algorithm is similar to the regular K-means [21], but it works with cosine distance instead of the Euclidean distance. Since we work with millions of high-dimensional vectors and cosine distance, other approaches like DBSCAN [13] turn out to be too computationally expensive.

Spherical K-means requires choosing the number of clusters $K$ beforehand. We estimate an optimal number of clusters with gap statistic [30], a technique based on comparing the distribution of the inner-cluster distances with a uniform distribution. It has not shown any significant difference for the number of clusters above 256, so we decided to set $K$ to 256 to reduce the dimensionality of project representations at the next step.

Clusters represent groups of semantically similar subtokens. They can be seen as topics at the subtoken level. As in topic modeling, the topic can be guessed from a set of representatives. In our case, the representatives are the most frequent subtokens in the cluster and subtokens closest to the cluster center. To further elevate this information and make Sosed’s output explainable, we manually labeled clusters with short descriptions by looking both at the representatives and projects where they are frequently used.

Table 1 shows an example of 12 labeled clusters, picked uniformly at random.

| 2D Geometry | Interative DOM, ns1DOM, HTML | File operations |
|---|---|---|
| vertex | html | file |
| mesh | ile | exists |
| vertices | aname | files |
| indices | atype | filename |
| vert | ody | directory |

| ML, Statistics | Mathematics, Greek letters | Network, packets |
|---|---|---|
| sum | prod | stats |
| weight | eps | cnt |
| dataset | fac | dropped |
| mean | rho | rts |
| weights | omega | collisions |

| Windows API | WiFi, wireless drivers | Audio effects |
|---|---|---|
| param | scan | play |
| iswindow | assoc | volume |
| idfrom | sta | sound |
| dlg | stype | pan |
| wnd | sdata | feedback |
we get a $K$-dimensional vector where a coordinate along the dimension $C$ is equal to the probability of the cluster $C$ appearing among project’s subtokens.

We applied the described technique to compute representations of 9 million repositories from the dataset of Markovtsev et al. [23], which includes all unique projects (excluding both the explicit and implicit forks) on GitHub as of the end of 2016. This large set of projects forms the Sosed’s search space.

**Searching for similar repositories.** To find similar repositories to a given one, we should compute a cluster distribution for it. Firstly, we tokenize the project as previously described. Then, we collect pre-computed cluster indices for the subtokens encountered in reference projects. We do not compute embeddings for OOV subtokens in the new projects for two reasons. Firstly, their number is small, because the reference projects contain 40 million different subtokens. Secondly, OOV subtokens may refer to libraries and technologies that emerged after the reference dataset had been collected, i.e., the end of 2016. In this case, the embeddings will not reflect the underlying semantics of subtokens.

We implement two methods to compare cluster distributions between projects from a query and reference projects: direct computation of KL-divergence [18] between two distributions and cosine similarity of the distribution vectors. Cosine similarity equals to the inner product of the normalized distribution vectors. KL-divergence can be expressed by the following formula:

$$D_{KL}(P_Q||P_R) = \sum_{c \in \text{Clusters}} P_Q(c) \log \frac{P_Q(c)}{P_R(c)},$$

where $P_Q$ and $P_R$ are cluster distributions for a query and a reference project, respectively. Finding a reference project $R$ that minimizes KL-divergence for the given query project is equivalent to maximizing the following function:

$$\sum_{c \in \text{Clusters}} P_Q(c) \log P_R(c).$$

The function is an inner product of the normalized distribution $P_Q$ and a point-wise logarithm of the distribution $P_R$. Thus, both for KL-divergence and cosine similarity, the search of similar projects reduces to maximizing an inner product between two vectors.

We utilized the Faiss [17] library to find vectors giving the maximal inner product. Faiss transforms reference vectors into an indexing structure that can be further used for querying. The indexing structure used in our work does not introduce a significant memory overhead, which allows us to use it with a large search space.

To enable the tool to provide explanations for project similarity, we find subtoken clusters corresponding to the terms that contribute the most to the vectors’ inner product. Within the tool’s output, we display their contributions alongside with manually given labels and subtokens from these clusters. An example of Sosed’s output can be found on GitHub [4].

### 4 EVALUATION

To the best of our knowledge, the only approach to evaluate the output of algorithms for finding similar projects used in previous work [24, 29, 32] is conducting a survey of developers.

Since Sosed works with programming projects in 16 languages, thorough evaluation of its performance without diving deep into specific ecosystems becomes challenging. We plan to conduct a survey of a large group of programmers with different expertise in order for its results to be reliable.

For now, we evaluated Sosed’s output on a set of 94 GitHub projects that comprises top-starred repositories in different languages. The results are available on our GitHub page [4]. For example, top-5 most similar projects to TensorFlow¹ are deep learning and machine learning frameworks. For Bitcoin² Sosed detected other open-sourced cryptocurrencies. Among projects similar to Python³ we found Brython⁴, a Python implementation running in a browser.

### 5 CONCLUSION

Finding similar software projects among a large set of repositories might be beneficial for practical software engineering tasks like quick prototyping and program understanding. Aside from that, it requires development of new methods for representing source code, which can find application in other software-related tasks.

We created a novel approach to represent code based on the topic distribution among its subtokens. We implemented it as a tool for finding similar software repositories called Sosed. The main features of Sosed are explainability of its output, support of 16 programming languages, and independence of project popularity. Sosed is available on GitHub [3, 4].

For now, Sosed searches among a set of 9 million GitHub projects. While it is a large set of data, open-source community grew rapidly over the recent years [1]. In order to catch up with the growth of the open-source ecosystem, we plan to collect a new dataset, which will contain an up-to-date set of GitHub projects.

Implementation of open-source tools for the novel ideas has several benefits. This way, we can quickly evaluate the method’s performance, check its practical applicability, and gather feedback from the tool’s users. We encourage others to create open-source software based on the developed methods in order to speed up communication and evolution in the research community.

### REFERENCES

1. 2019. The State of the Octoverse. https://octoverse.github.com/
2. 2020. go-enry GitHub: enry. https://github.com/go-enry/enry
3. 2020. JetBrains Research GitHub: Buckwheat. https://github.com/JetBrains-Research/buckwheat
4. 2020. JetBrains Research GitHub: Sosed. https://github.com/JetBrains-Research/sosed
5. 2020. Symplel: Python syntax highlighter. https://pygments.org/
6. 2020. The most popular languages of GitHub’s pull requests, 1 quarter, 2020. https://madmouh.github.io/github-w-pull_requests/2020/1
7. 2020. tree-sitter GitHub: tree-sitter. https://github.com/tree-sitter/tree-sitter
8. Uri Alon, Omer Levy, and Eran Yahav. 2018. code2seq: Generating Sequences from Structured Representations of Code. CoRR abs/1808.01400 (2018). arXiv:1808.01400 http://arxiv.org/abs/1808.01400
9. David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. Latent Dirichlet Allocation. J. Mach. Learn. Res. 3, null (March 2003), 993–1022.
10. Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching Word Vectors with Subword Information. Transactions of the Association for Computational Linguistics 5 (2017), 135–146.
11. Ning Chen, Steven Hoi, Shaohua Li, and Xiaokui Xiao. 2015. SimApp: A Framework for Detecting Similar Mobile Applications by Online Kernel Learning.

¹https://github.com/tensorflow/tensorflow/
²https://github.com/bitcoin/bitcoin/
³https://github.com/python/cpython/
⁴https://github.com/brython-dev/brython/
[12] Scott C. Deerwester, Susan T. Dumais, Thomas K. Landauer, George W. Furnas, and Richard A. Harshman. 1990. Indexing by Latent Semantic Analysis. J. Am. Soc. Inf. Sci. 41 (1990), 391–407.

[13] Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. 1996. A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD’96). AAAI Press, 226–231.

[14] Hugo Gonzalez, Natalia Stakhanova, and Ali Ghorbani. 2014. DroidKin: Lightweight Detection of Android Apps Similarity, Vol. 152. https://doi.org/10.1007/978-3-319-23829-6_30

[15] Vincent J. Hellendoorn, Charles Sutton, Rishabh Singh, Petros Maniatis, and David Bieber. 2020. Global Relational Models of Source Code. In International Conference on Learning Representations. https://openreview.net/forum?id=R1nhbRNtwr

[16] Kurt Hornik, Ingo Feinerer, Martin Kober, and Christian Buchta. 2012. Spherical k-Means Clustering. Journal of Statistical Software 50 (09 2012), 1–22. https://doi.org/10.18637/jss.v050.i10

[17] Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2017. Billion-scale similarity search with GPUs. arXiv preprint arXiv:1706.08774 (2017).

[18] S. Kullback and R. A. Leibler. 1951. On Information and Sufficiency. Ann. Math. Statist. 22, 1 (03 1951), 79–86. https://doi.org/10.1214/aoms/1177729694

[19] L. Li, T. F. Bissyandé, and J. Klein. 2017. SimiDroid: Identifying and Explaining Similarities in Android Apps. In 2017 IEEE Trustcom/BigDataSE/ICESS. 136–143.

[20] Martin F. Porter. 2001. Snowball: A language for stemming algorithms. J. Am. Soc. Inf. Sci. 41 (1990), 391–407. https://doi.org/10.1111/1467-9868.00293

[21] Konstantin Vorontsov and Anna Potapenko. 2015. Additive regularization of topic models. Machine Learning 101, 1 (01 Oct 2015), 303–323. https://doi.org/10.1007/s10994-014-5476-6

[22] Vadim Markovtsev and Eiso Kant. 2017. Topic modeling of public repositories at scale using names in source code. arXiv preprint arXiv:1704.00135 (2017).

[23] Vadim Markovtsev and Eiso Kant. 2017. Topic modeling of public repositories at scale using names in source code. arXiv preprint arXiv:1704.00135 (2017).

[24] Collin McMillan, Mark Grechanik, and Denys Poshyvanyk. 2012. Detecting Similar Software Applications. In Proceedings of the 34th International Conference on Software Engineering (ICSE ’12). IEEE Press, 364–374.

[25] Tom Mens, Alexander Serberbrenik, and Anthony Cleve. 2014. Evolving Software Systems. Springer Publishing Company, Incorporated.

[26] Martin F. Porter. 2001. Snowball: A language for stemming algorithms.

[27] Tobias Schnabel, Igor Labutov, David Mimno, and Thoresten Joachims. 2015. Evaluation methods for unsupervised word embeddings. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Lisbon, Portugal, 298–307. https://doi.org/10.18653/v1/D15-1036

[28] Xiaobing Sun, Xiangyue Liu, Li Bin, Yuqong Duan, Hui Yang, and Jiajun Hu. 2016. Exploring topic models in software engineering data analysis: A survey. 357–362. https://doi.org/10.1109/SNPD.2016.7515925

[29] Collin McMillan, Mark Grechanik, and Denys Poshyvanyk. 2012. Detecting Similar Software Applications. In Proceedings of the 34th International Conference on Software Engineering (ICSE ’12). IEEE Press, 364–374.

[30] Robert Tibshirani, Guenther Walther, and Trevor Hastie. 2001. Estimating the number of clusters in a data set via the gap statistic. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 63, 2 (2001), 411–423. https://doi.org/10.1111/1467-9868.00293

[31] Konstantin Vorontsov and Anna Potapenko. 2015. Additive regularization of topic models. Machine Learning 101, 1 (01 Oct 2015), 303–323. https://doi.org/10.1007/s10994-014-5476-6

[32] Yu Zhang, David Lo, Pavneet Singh Kochhar, Xin Xia, Quanli Li, and Jianling Sun. 2017. Detecting similar repositories on GitHub. 13–23. https://doi.org/10.1109/SANER.2017.7884605