Representation of Developer Expertise in Open Source Software

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ABSTRACT

With tens of millions of projects and developers, the OSS ecosystem is both vibrant and intimidating. On one hand, it hosts the source code for the most critical infrastructures and has the most brilliant developers as contributors, while on the other hand, poor quality or even malicious software, and novice developers abound. External contributions are critical to OSS projects, but the chances their contributions are accepted or even considered depend on the trust between maintainers and contributors. Such trust is built over repeated interactions and coding platforms provide “signals” of project or developer quality via measures of activity (commits), and social relationships (followers/stars) to facilitate trust. These signals, however, do not represent the specific expertise of a developer. We, therefore, aim to address this gap by defining the skill space for APIs, developers, and projects that reflects what developers know (and projects need) more precisely than could be obtained via aggregate activity counts, and more generally than pointing to individual files developers have changed in the past. Specifically, we use the World of Code infrastructure to extract the complete set of APIs in the files changed by all open source developers. We use that data to represent APIs, developers, and projects in the skill space, and evaluate if the alignment measures in the skill space can predict whether or not the developers use new APIs, join new projects, or get their pull requests accepted. We also check if the developers’ representation in the skill space aligns with their self-reported expertise. Our results suggest that the proposed embedding in the skill space achieves our aims and may serve not only as a signal to increase trust (and efficiency) of open source ecosystems, but may also allow more detailed investigations of other phenomena related to developer proficiency and learning.

KEYWORDS
Developer Expertise, Vector Embedding, Doc2Vec

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1 INTRODUCTION

The number of projects and developers involved with open source software has reached staggering heights. For example, open source and VCS platform GitHub reported over 10 million new developers joined and over 44 million new projects were created in 2019 alone. While many of these developers or projects are based on individual effort, further statistics, such as over 87 million pull requests being merged and 20 million issues being closed in the past year on GitHub alone, goes to show that open source development is a highly collaborative effort in general. In fact, the key premise of open source software is not only to share the code, but, even more importantly, to enable contributions from the community.

Despite improved tools and practices enabled by social coding platforms such as GitHub, it is not easy to get contributions accepted. Previous work [24, 34] has shown that both technical and social factors can play an important role in building the trust between contributors and maintainers. Social factors, such as repeated interactions [17] between maintainers and contributors, are often the best way to establish trust and increase the chances of pull request acceptance [11, 13, 38] or issue resolution [16]. However, the rapidly increasing pool of millions of developers and projects tests the scalability of the existing approaches to establish trust, due to the time cost associated with maintainers needing repeated interactions with every potential contributor. As a result, other, more efficient means of establishing trust are needed, such as trustworthy measures of a potential contributor’s technical experience.

The previous attempts at measuring developer expertise focus on either very specific details, such as counting “experience atoms” associated with changes made by a developer on a specific source code file [28], or, at the least granular level, counting the volume, frequency, and breadth [20, 30] of a developer’s overall activities. The former approach can not be applied for developers who have never participated in a specific project, while the latter does not take account of the specific experience that a developer has beyond aggregated activity traces and projects they’ve worked on. Aggregates of developer’s contributions by programming language was previously proposed by [20]; however, the experience in a specific language does not immediately confer experience in the variety of libraries or frameworks that define the rich functionality...
that many contemporary applications rely on. This specific expertise, the fluency of using specific APIs, is something that may be of greater concern to projects [30] than a potential contributor’s the overall skill in languages.

In this work, we try to measure and evaluate such API experiences by defining what we refer to as skill spaces, that can be applied to developers, projects, and to individual modules as well. Our aim is to derive a feasible representation of a developer’s expertise, that they may provide or a project may need, which would serve as a way to increase the trust between potential contributors and maintainers of a project, and, more generally, within open source software as a whole. To define and quantify this skill space we use World of Code (WoC) [22] data that contains APIs extracted from changes to source code files (discussed further in 3.5) in 13 programming languages. The naive definition of the skill space can be represented by the vector of length 110 million, that represents each of the distinct APIs extracted from over 4 billion changes to the source code of the languages under consideration. Such representation is not very effective and techniques from text analysis [10, 26] may be used to reduce the dimensionality of the developers’ and the projects’ skill space. In this paper, we customize several text embedding approaches to produce the skill space representation not just for individual APIs, but also for individual developers, projects, and even languages. As a result, the skill space representation can be used to calculate a direct measure of alignment between any pair of developers, projects, APIs, developers and APIs, developers and projects, and projects and APIs.

To evaluate the suitability of the our proposed skill space representation, we consider four practical scenarios where developer experience and trust should come into play: developers using a new API, developers joining a new project, a project accepting contributions from a new developer, and maintainers accepting pull requests. In all of these cases, we expect that closer alignment of developer and APIs or projects in the skill space will increase the likelihood of a positive outcome in these four types of events. Specifically, we pose the following hypotheses:

- **H1:** A developer is more likely to use APIs more closely aligned with them in the skill space.
- **H2:** A developer is more likely to join a new project that is more closely aligned to their skill space.
- **H3:** A project is more likely to accept contributions from developers who are aligned to the project in the skill space.
- **H4:** A developer whose skill space is aligned more closely to the project’s skill space will be more likely to have their pull requests accepted.
- **H5:** A developer’s self-reported API skills are closely aligned to their personal skill space.

Our evaluation results show that by creating skill space representation using the traditional technique of Latent Semantic Indexing (LSI) trained on past data, we find that (H1) a developer’s new APIs are more aligned to the APIs they used in the past than to a randomly selected set of APIs.

By creating a skill space using a Doc2Vec embedding we can create not only the API embeddings within the skill space, but also representations for developers, projects, and languages. Here we directly measure the alignment between developers and APIs and find that new APIs to be more closely aligned to the developers. Furthermore, a developer is more likely to (H2) join projects that are more closely aligned to them in the skill space than randomly selected projects and, likewise, (H3) projects add new developers that are more closely aligned to them in the skill space. We then fit a model explaining the fraction of accepted pull requests and find that (H4) the closer alignment of a developer with the project is associated with increased chances of acceptance. Finally, (H5) the developers’ self-reported API expertise aligns with their personal skill space.

In summary, we propose the concept of skill space, that allows the measurement of skill alignment among developers, projects, and APIs. We show that, under five scenarios, the skill space representation satisfies the expectations from such an embedding, that is more granular than the overall activity counts and more general than measures pertaining to individual files, with the expectation that it may provide a basis for ways to increased trust and efficiency in open source development.

In the rest of the paper, we start by describing the related works in Section 2. We describe our methodology in Section 3, and the evaluation results for our proposed embedding for skill spaces is described in Section 4. We describe the limitations to our study in Section 5, the planned extension of the proposed technique in Section 6, and conclude the paper in Section 7.

## 2 RELATED WORK

Here we first overview historic efforts to measure developer expertise and outline the role of word embeddings in the software engineering literature to clarify the existing gaps we try to address with our work.

### 2.1 Developer expertise

The fascination with developer expertise and its variation has roots in the early beginnings of software development [1, 5, 8, 9]. Early work was primarily motivated by the need for software project cost estimation and focused on various ways to measure the size of software by adjusting lines of code for different languages or attempting to design ways to have a language-independent measure of software size [6]. The later work embraced the idea that beyond language, each software project requires long and arduous work by a developer to comprehend its internal complexities [37]. This suggested that developer expertise is project and file specific with approaches such as Expertise Browser assuming that each change to a source code file represents an experience atom [28], whereby a developer changing code is forced to understand files’ internal design and, perhaps, impart of their own design through implementing that change. However, these early measures of lines of code written and file-specific experience atoms pertain to expertise within a specific project. They do not provide a general enough profile of developer expertise that can be transferred among software projects.

Presently, social coding platforms such as GitHub provide a variety of charts and indicators of developer activity (the timeline of commits) and their social status (followers). This has sparked a variety of research into how developer traces and developer profiles
can provide insight about a developer’s expertise. These studies include qualitative approaches, such as the one by Marlow et. al. [25], who showed that your developer profile on GitHub can help other developers gauge your general coding ability and project-relevant skills, but only at a more general level. Similarly, Singer et. al. [32] interviewed developers and employers to observe how they utilize developer profiles to gauge the quality of a potential new hire. The results showed that profile sites with a “skills” word-cloud representing the technologies (languages, frameworks, etc.) a developer claimed to be familiar with proved to be the most helpful assessment of a developer’s expertise. We use these works to motivate that more specific measures, such as language-specific technologies and frameworks, are desired to help others gauge the expertise of developers in open source.

There have also been several attempts to automate the process of identifying developer expertise through social coding platforms. For example, CVExplorer [14] is a tool created to expose developer expertise using a word-cloud of all relevant technologies, frameworks, and general skills by parsing developer commit messages and README files. SCSSMiner [35] is another tool created to help identify experts on GitHub based on an arbitrary input query. The authors also obtain expertise attributes by parsing README files of projects a developer has contributed to, but they extend this by creating a generative probabilistic expert ranking model to rank developers based on certain skills or expertise one might be looking for. Lastly, Hauff et. al. [19] attempt to match developers with job advertisements based on a developer’s expertise. Their approach involves extracting relevant terms from README files and mapping them to the same vector space as job advertisements. From there, they are able to rank all developer profiles based on the cosine similarity they share with the job advertisements. While all of these approaches are a similar step in the direction we are pursuing, they provide a weaker link between developers and their technologies than desired by utilizing README files as the main source of developer expertise. Rather than looking at README files in projects a developer has contributed to, we extract language-specific APIs from files a developer has directly modified. Furthermore, along with measuring a developer’s similarity to the technologies they use as attempted in previous work, we also aim to use the APIs to measure the similarity between developers, projects, developers and projects, and APIs as well.

We also motivate our work through some more recent research contributions. Montandon et. al. [30] present an approach to determine experts for three JavaScript libraries. The authors identify developers who have made changes to projects that depend on these libraries and conduct a survey of 575 developers to obtain their self-reported expertise. Using these survey results as validation, the authors argue that their clustering approach is feasible and can be used to identify relevant experts. However, they also present the shortcomings of using basic GitHub profile features for machine learning classifiers to predict expertise in software libraries. We utilize the survey dataset provided by the authors for our own evaluation and also attempt to better predict developer expertise in software libraries, an area in which the authors achieved poor performance.

The more recent Import2Vec [33] paper produces embeddings for each imported package. The authors do such embeddings for JavaScript, Python, and Java, and provide some qualitative evidence suggesting that these embeddings of APIs accurately reflect different functionality profiles by providing a number of examples where the similar APIs also appear to implement similar functionality.

Unfortunately, none of the proposed approaches are not suitable for directly comparing developers and projects, as neither developers nor projects are accurately represented in the same vector space of the API embeddings. It is, therefore, not clear how Import2Vec embeddings can be used to characterize developer skill spaces nor if such profiles would accurately reflect developer proficiency. Furthermore, the Import2Vec approach can not be applied in a cross-language context. Our proposed approach tries to address this gap by constructing a skill space representation that, on one hand, may transcend the specific programming languages, while, on the other hand, it may identify a meaningful representation that can be matched with skill sets of other developers or projects.

2.2 Vector Embeddings

Vector embeddings have been used in software engineering for various tasks. For example, a number of works explore natural language associated with coding to determine sentiment [7], use writing style in commit messages to determine developer identity [4], or improve requirements traceability [15]. In these cases the natural language techniques do not need to be modified substantially as the underlying data represents natural language.

Even more techniques have been applied to model programming language source using text analysis techniques. For example, these approaches can improve Interactive Development Environments (IDEs) by performing next token prediction [3], suggesting better class names [2], or even automatic patching [23]. The attempt to provide a common embedding space for natural language and code is proposed in [36] by training the natural language models on the documentation of the APIs and the applications that use these APIs.

Unlike these approaches, we focus on training the models on the APIs used in files that undergo a code change. While we do not go to the level of a specific function used in the API, we treat each import/use statement as an indication of the specific functionality provided by the corresponding package.

As noted above, the best natural language analysis techniques typically exploit the order of the words in a text document (such as commit messages, requirements, or documentation). The programming language modelling techniques also rely heavily on the specific sequence that is necessary to do accurate prediction of the next token, for example.

In contrast, our work looks at embedding package imports within source code files, where the order of import statements is not important. Thus, the existing techniques that attempt to model the order of the tokens need to be modified, or techniques that do not rely on the ordering of words (APIs) need to be employed.

3 METHODOLOGY

In this section, we describe the data and the methodology used in this paper for the purpose of answering our research questions.
3.1 Vector Embedding

Since the total number of possible APIs that can be used by a developer or a project across different languages is extremely large and the naive embedding representing use of an API as a component of over 100M-dimensional vector is not practical, we reduce the dimensionality of the skill space via more advanced techniques borrowed from the field of natural language processing. Specifically, we considered two types of embeddings: Latent Semantic Indexing (LSI) and Doc2Vec because the first is conceptually very simple and scalable, and the second because it is capable of embedding not only the APIs themselves but also developers and projects.

3.1.1 LSI: Latent Semantic Indexing (LSI) \[10\] or Latent Semantic Analysis (LSA) is used for analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms. In the context of our problem, a document refers to a developer or a project, and the terms correspond to the APIs used by that developer/ in that project. The primary assumption behind LSI is the distributional hypothesis \[18\], which states that words (APIs) that are close in meaning (functionality) will occur in similar pieces of document (file), which is valid in our context as well. In LSI, a term-document matrix is created using all the available documents, and the dimension of the matrix (specifically, the no. of terms in that matrix) is reduced using singular value decomposition (SVD) while preserving the similarity structure among the documents. The similarity between the documents in the reduced space is then typically measured using cosine similarity. LSI is conceptually very similar to what we’re trying to achieve by vector embedding, so we decided to use it as the base embedding techniques for creating the skill space representation. For evaluation, we used the Python implementation of LSI in Gensim framework.

3.1.2 Doc2Vec: Doc2Vec \[21\] is a well-known extension of Word2Vec \[26\] used to create a numerical representation for a document using a continuous bag of words or skip gram (two distinct algorithms). The primary assumption of Word2Vec is that only words that are close together in a document are semantically related, but in our context, that assumption doesn’t hold, because there is no semantic order for the APIs used by a developer or a project. To circumvent this problem we use the continuous bag of words algorithm and employ a very wide window of 50 terms, so that, practically, in all cases (see below) the algorithm predicts one API using all remaining APIs. Doc2Vec is an extension of Word2Vec, where in addition to word (API) embeddings, the model also produces the embeddings for an arbitrary set of tags associated with a group of APIs, as is the case when an author, a project, and a language is associated with the set of APIs extracted from each change of every file. The continuous bag of words analog in Doc2Vec corresponds to obtaining doc-vectors by training a neural network on the synthetic task of predicting a center word based on an average of both context word-vectors and the full document’s doc-vector. Once again, we used the Gensim framework for evaluation due to its high performance.

3.2 World of Code

The data required for embedding the expertise of developers was obtained from the World of Code (WoC) infrastructure. WoC is a prototype of an updatable and expandable infrastructure, aimed at supporting research and tools that rely on version control data from the entirety of open source projects that use Git. It stores the huge and rapidly growing amounts of data in the entire FLOSS ecosystem, and provides basic capabilities to efficiently extract and analyze the data at that scale. In a nutshell, WoC is a software analysis pipeline starting from data discovery and retrieval, data storage and regular updates, and enablement of the transformations and data augmentations necessary for analytic tasks downstream. In addition to storing objects from all git repositories, WoC also provides relationships among them. The primary focus of WoC is on the types of analyses that require global reach across FLOSS projects, so it is the most appropriate choice for answering the research questions we presented in this paper.

WoC data is versioned, with the latest version labeled as Q, containing 7.2 billion blobs, 1.8 billion commits, 7.6 billion trees, 16 million tags, 116 million projects (distinct repositories), and 38 million distinct author IDs. This version of WoC data was collected during November and December of 2019.

3.3 Project Clones: Fork Resolution

As is often the case with datasets of this size, certain data cleaning steps are important in order to accurately perform any analysis. Since our skill space considers the relationship between projects, developers, and their API usage, it is important to carefully measure all three of these entities in the context of the WoC infrastructure.

The inherent ease of cloning or forking Git projects creates a unique data cleaning problem for WoC, which has over 100 million projects, many of which are clones or forks of each other, with many forks of parent projects and making little to no changes to the cloned project. This poses several problems for our expertise analysis. One such problem is that a developer who contributes to a highly-cloned project will have their commits appear in the remaining cloned projects as well. Specifically, if a developer contributes to one project using the Flask module in Python and 10 other people clone this project and make little to no changes, the developer would be attributed with having worked with Flask on 11 different projects, rather than just one.

To address this, we use the dataset published in \[29\]. The authors apply the Louvain community detection algorithm to a massive graph consisting of links between commits and projects in WoC (because two projects are highly unlikely to share the same exact commit unless they are clones). We leverage that work to combine commits from the forked projects. The shared dataset allowed us to ensure that we do not count the same project-related information multiple times due to these forks/clones.

3.4 Identifying a Developer: Identity Resolution

A single developer may use multiple author IDs in their commits and on social coding platforms, such as GitHub. At its core, WoC
extracts the author ID tag attributed with each git commit. In a perfect world, this author ID would correspond to a single developer, and we could then use that author ID to aggregate all commits associated with the author ID and perform our expertise analysis. However, this is seldom the case because developers may free-fill this author ID tag with each commit as they choose. Furthermore, this author ID tag may differ from machine to machine that a developer uses. As a result, a developer might have several additional author IDs (that they might not even be aware of) inside WoC that collectively correspond to a single developer.

To address this, we have used a dataset shared by by Fry et al. [12] that resolves the 38 million author identities in WoC version Q by creating blocks of potentially related author IDs (e.g., IDs that share the same email, unique first/last name) and then predicting which IDs actually belong to the same developer using a machine learning model. The approach identified over 14 million author IDs belonging to at least one other author ID. From this set, around 5.5 million developers were identified, with a median of two author IDs per developer. When performing the expertise analysis described in this paper, we identify each developer using the new associations created by the identity resolution approach. This allows us to create a much more accurate representation of each developer’s API usage and expertise and helps us avoid comparing two author IDs that are in fact the same developer.

### 3.5 API Extraction

To obtain developer API usage, we utilize the language mappings inside WoC. These mappings contain APIs extracted from changes to source code files in C, C#, FORTRAN, Go, JavaScript, Python, R, Rust, Scala, Java, Perl, Ruby, and Julia languages, as well as source code present in Jupyter Notebooks. The mappings are created by first obtaining all files in WoC with extensions in each of the languages listed previously. For each language, the WoC file-to-commit map is used to obtain all commits associated with language-specific files. From there, the commit-to-blob map is used to view the file’s source code and extract the API import statements depending on the syntax of each language (#include in C, import in Java/Python, use statement in Perl, the dependencies in the package.json file for Node.js, and so forth).

However, instead of stopping here and having files mapped to their import statements, we tie in the project and author as well using WoC’s commit-to-project and commit-to-author mappings. We use the modified version of commit-to-author which includes the identity-resolved authors as discussed in the previous section and also includes the time of the commit, allowing us to perform time-based evaluation of some of our models as discussed in 3.7.

Through all this, the final mapping and data used by some of the models is a compressed file of entries containing: project;timestamp;author;API1;API2;..., where each entry represent all modules/APIs included in the file that the developer added to the project at the instance in time. There is a unique set of entries for each language listed earlier, and each is stored in its own compressed file. While this mapping serves as the base data for most of our analysis, there are several intermediate steps that require transformation of the provided mapping as well. For example, when performing time-insensitive analysis, it can be more helpful to have data in the form project;author;API1;API2;... to represent all APIs of a certain language used by an author in a project. We perform these transformations as needed throughout our analysis.

### 3.6 The Dataset

As noted above, we use WoC (version Q) data representing the association of each commit with the project, blob created by that commit, and the import statements extracted by parsing that blob. We treat each blob created by the same commit as a distinct entity (delta). Each commit contains commit’s author and timestamp when the commit was created.

We use repository aliasing data published in [29] and author aliasing data published in [12] to combine commits from all forks to the parent project and to use a single ID for each developer even though they may have had their credentials spelled differently in different commits they made.

Table 1 shows the number of delta (blobs) associated with each language as well as the number of distinct authors and projects involved. Please not that many authors make changes to several languages (and many projects involve multiple languages), so the right tow columns do not add up to the number of distinct authors or projects. The largest number of delta by far involve C and C++ (we do not distinguish between the two), followed by Java and Python. The reason for the relatively low number of JavaScript delta is caused by the way dependencies are specified in JavaScript projects where a single file PACKAGES.json is used to specify the dependencies while in C, Java, or Python, every source code file has to have dependencies explicitly included.

Table 2 shows the number of APIs by language as well as the number of distinct authors and projects involved. Notably, Java language dominates in terms of the number of unique APIs, presumably because the APIs in Java can be specified using global namespace, while for other languages they are defined by package managers or within the source code files (like .h files in C/C++ that may share the same name but be otherwise unrelated (see Section 5).

As we note above, the total number of distinct APIs we observe is far higher than the number of words in a natural language putting computational strains on the text analysis methods designed to deal with many orders of magnitude smaller dictionaries. As we noted above, the order of the APIs as they are specified in source code files is not important, hence we need to apply methods that do not attempt to model the sequences. Some early text analysis methods, such as LSI, work strictly on the bag of words (BOW) and are immune from this problem. Others, such as continuous bag of words (CBOW), try to predict words within a certain window size. The wider the window, the more complicated and time consuming it is to fit these models. To investigate what window sizes might be appropriate, we investigate the distribution of the number of distinct APIs within a single delta (a modification by a single commit to one source code file). Table 2 shows the fraction of delta for each language where the number of distinct APIs is less than 10, 25, and 50 and also shows the maximum number of APIs. Again, JavaScript is an outlier since a single file (package.json) defines APIs for the entire project. If we reach 25 or 50 APIs, the vast majority of delta
are covered. We, therefore chose to consider the window size of 50 or less for the CBOW models. The project/authors with huge numbers of APIs used may indicate unusual cases or outliers that may not bring much information to which APIs are used together and it is not unreasonable to exclude those from consideration.

In addition to the CBOW model, we also considered the technique used in [33] where the authors employed the window size of just one, but replaced any combination of more than two APIs by all possible pairs of such APIs. For example, the change with three APIs (A, B, C), is represented as three pairs: (A, B), (B, C), and (A, C). Such replacement is of concern because the author with 10K APIs in a single delta would produce an equivalent of 100M delta, thus overwhelming the information from the remaining authors. We avoid that problem by excluding instances with over 50 APIs from model training.

The total number of delta and the number of distinct APIs pose serious computational challenges if we want to fit the complete dataset obtained from WoC with 4.3B delta and over 100M distinct APIs not counting the number of distinct projects and authors.

We, therefore, fit several smaller datasets by filtering the data to a more manageable size. First, for the multi-language model, we focus on developers that made between 100 and 25K commits partially to exclude the bot activities and partly to consider ordinary but productive developers. This filter reduces the total number of delta down to 1.2B.

For language specific models we are dealing with much smaller datasets, but we can decrease that size even further by randomly sampling projects or developers. We used these smaller samples to debug the techniques and to find the parameters for the skill space embeddings that produce feasible results before running the computation on the entire model.

3.7 Evaluation strategies

The evaluations we have used depend both on the model used and on the specific question we’re trying to answer. Since not all models are suitable for all evaluations, we describe the strategy for each evaluation below.

First, we evaluate if the new APIs a developer uses are more aligned to what they used in the past than to a random set of APIs. We train the model on past activities and measure the alignment of these activities (using LSI models) or the alignment of developer embeddings to the embeddings of the APIs new to the developers over the testing period. Since developers tend to continue using the same APIs over time, we only consider alignment to APIs they have not been using during the testing period.

The evaluation strategy for LSI model involves first creating a vector in the LSI “feature” space of the APIs a developer has used in the past and comparing that to the vector representing new APIs developer has used in the training period. The training is conducted by fitting LSI model on the corpus where each developer/language pair is represented by the set of APIs the developer has used in the past. We then gauge if the APIs developers actually use are more aligned than a randomly selected set of APIs of the same cardinality as the one used by the developer.

The evaluation using Doc2Vec model involves fitting a Doc2Vec model on past data where each document represents a set of APIs encountered in a single delta and the tags for each document represent the language, the project, and the developer. The resulting model thus creates vectors for each API, for each developer, each project, and each language. We then obtain new APIs a developer uses during the testing period, the new projects the developer joins, and the new developers who join a project during the testing period. The alignment to these factual APIs/projects/developers are then compared with randomly chosen sets of APIs/projects/developers of the same size.

To conduct the study of pull request acceptance, we, as in the other cases, obtain embeddings for using past data and then model the acceptance rate during the future PR activity using the binomial regression with the independent variable representing the alignment of the developer and project vectors where the PRs have been submitted to.

Finally, we use previously reported survey [30] of the JavaScript developers to compare how aligned each surveyed developer is to the the API in which developers were reported to be proficient. Since the survey did not include APIs where developers reported
being not proficient, we randomly chose ten other APIs under the assumption that they might not be equally proficient in these 10 randomly chosen APIs. As in other comparisons, we report the difference in alignment between the self-reported expert APIs and the randomly chosen APIs.

3.8 Tailoring of Text Embeddings for Programming APIs
As noted above, we have a situation that’s quite unlike the typical context of text analysis. While the number of documents (4.3B) may be encountered in text analysis contexts, the number of tokens appears to exceed that of a typical text analysis tasks by three orders of magnitude. We, therefore, first investigate the applicability of the approach on much smaller datasets before fitting a model for the entire set of languages.

The second difference concerns the lack of order of the APIs (more precisely, the lack of semantic significance of the order in which the import statements occur. Fortunately, the early text analysis techniques did not take into account the order of the words in a document. These so called bag-of-words techniques were later supplanted by more accurate embeddings that take the word order into account. We, therefore, rely either on the older techniques or employ continuous-bag-of-words techniques where the order of words does not matter within a sliding window. For the latter case we pick a very wide sliding window of 50 words to ensure that we can capture interdependencies even in cases where a large number of APIs are used together in the same file.

4 RESULTS
We start by investigating if the measures produced by Doc2Vec embeddings appear sensible to a language expert and then conduct quantitative evaluations based on the hypothesised relationships and finish by validating if they correspond with the self-reported measures of expertise.

### Table 2: The distribution of the number of distinct APIs within a single delta

| Language | Fraction10 | Fraction25 | Fraction50 | Number of APIs | Max APIs |
|----------|------------|------------|------------|----------------|----------|
| F        | 0.864287   | 0.978319   | 0.996817   | 1714314        | 106      |
| jl       | 0.918882   | 0.982022   | 0.994654   | 1173066        | 108      |
| R        | 0.953017   | 0.996757   | 0.999581   | 6591806        | 117      |
| ipy      | 0.76009    | 0.981094   | 0.999316   | 10480954       | 117      |
| pl       | 0.958241   | 0.999547   | 0.999989   | 21561320       | 109      |
| Rust     | 0.949491   | 0.997445   | 0.999999   | 12400022       | 105      |
| Cs       | 0.844412   | 0.993558   | 0.99971    | 219984011      | 150      |
| Go       | 0.841157   | 0.988415   | 0.999108   | 106791380      | 1362     |
| Scala    | 0.765806   | 0.978922   | 0.998829   | 37173969       | 124      |
| PY       | 0.814464   | 0.977265   | 0.997004   | 560726046      | 1001     |
| JS       | 0.791007   | 0.889159   | 0.920681   | 140972726      | 1014     |
| rb       | 0.978319   | 0.996     | 0.999357   | 85990225       | 1002     |
| java     | 0.574622   | 0.87325    | 0.973206   | 1119433526     | 1004     |
| C        | 0.731285   | 0.965926   | 0.998161   | 2019398881     | 1007     |

4.1 Qualitative Evaluation of Skill Space Embeddings
For a qualitative evaluation of our proposed embedding, we decided to observe which APIs are reported as similar to others in different languages, which APIs are reported as the most similar to a language (i.e. which are the most common APIs for a language), and also which APIs provide similar functionality across different languages.

We start our evaluation by picking a package that extends the data frame functionality for tidyverse suite of packages in R language (the role of readr is to read in the data as, for example, provided by pandas package in Python).

```python
>>> mod.most_similar('readr')
>>> [('tidyr', 0.984), ('tidyverse', 0.983), ('stringr', 0.980), ('stringi', 0.978)]
```

The most similar package is tidyr (which is exactly the same but renamed version of readr), and the second is the meta-package that imports all tidyverse packages. The remaining most similar packages are all closely related to data frame and data manipulation.

Similarly, for the Python package "pandas", we observed that the APIs reported to be most similar are indeed the ones that are most frequently used with it, primarily for data manipulation/ machine learning applications.

```python
>>> mod.most_similar('pandas')
>>> [('matplotlib', 0.894), ('seaborn', 0.876), ('numpy', 0.847), ('scipy.stats', 0.847)]
```

Looking at the “R” language, we observe that the APIs returned by the following query does indeed return the most widely used packages in R, which can also be verified using the WoC package counts.

```python
>>> mod.wv.similar_by_vector(mod.docvecs['R'])
>>> [('ggplot2', 0.942), ('dplyr', 0.927), ('testthat', 0.92), ('reshape2', 0.917)]
```

For JavaScript as well, we see a very similar scenario:

```python
>>> mod.wv.similar_by_vector(mod.docvecs['JS'])
>>> [('lodash', 0.815), ('moment', 0.806),

```
Finally, we can do some arithmetic with the resulting vectors by asking what are packages the most similar to Python “pandas” package in R language:

```r
>>> mod.wv.similar_by_vector(-mod.docvecs['PY']
+mod.docvecs['R']mod.wv.get_vector('pandas'))
```

Not surprisingly, the result shows the most popular R packages, but it also has data frame related packages high on the similarity list. It is pretty amazing that only R packages appear in the most similar list even though we start from the python package and move in the direction of R language.

### 4.2 H1: A developer is more likely to use APIs more closely aligned with them in the skill space

To address this question, we first create a skill space using LSI model based on the past data where a document represents the set of all APIs used up to that time for each developer, language, project tuple. Due to the large size of the model we only consider developers who made 100 to 25K commits over their entire career. We then represent the set of APIs in each of these tuples in the skill space by obtaining a vector of length 200. Similarly, we obtain the set of APIs for each tuple that were not used in the past and transform each into another 200-dimensional vector using LSI skill space. Finally, for each such tuple with a new APIs, we also generate randomly a set of APIs of the same size for comparison and obtain the third 200-dimensional vector. To compare the alignment between old and new APIs and between old and randomly chosen APIs we use cosine distance as is common. The results show that new APIs are more closely aligned to past APIs than to randomly selected APIs, suggesting that in the LSI-generated skill space past and future APIs used by a developer are aligned and also suggests that the LSI-generated skill space may be a viable representation of the developers’ expertise.

All the differences are statistically significant with p-value indistinguishable from zero and the differences in alignment are shown in Table 3.

As noted above, LSI embeddings work for APIs only, and developers (or projects) can only be represented by a linear combination of APIs. We therefore, also fit a Doc2Vec model on the same data but prepared data for it in a slightly different manner to handle the scale of the problem. As noted above, we reduce the size of the dataset by only considering authors with 100 to 25K commits. This, however, was still computationally challenging problem and we followed the approach in [33] to consider as documents only pairs of APIs produced by first creating the complete set of APIs for each tuple representing developer, language and project and then, for sets of the APIs that are smaller than 50, creating a document for each pair of the APIs. The computational advantage was that we could use the window size of 1, instead of the much wider window size of 50. The resulting set of documents was also much smaller at 275,185,908. This also massively reduced the number of parameters that we need to fit in the Doc2Vec model, thus allowing to do the computation in under 300GB of RAM and the model converging much faster than the model fit on documents representing individual delta. We compared the performance of the two approaches on smaller datasets and found the cutoff of 50 APIs to be reasonable and equivalent to CBOW window size of 50. As shown in Table 3, the differences in the LSI-generated skill space appear to be for the most part larger than ones generated based on Doc2Vec, but in both cases the statistical significance of the difference is extremely high.

### 4.3 H2: A developer is more likely to join a new project that is more closely aligned to their skill space

The Doc2Vec has the advantage of embedding not only APIs but also authors, languages, and projects and that provides for the ability to directly measure how skill spaces of developers relate to project skill space. A reasonable expectation would be that the new projects a developer will join (make an accepted contribution) would be more likely to be closely aligned with the developer’s skill vector than a randomly selected project would be. Because of the reasons mentioned earlier, this hypothesis was tested only using the Doc2Vec embedding.

Using a similar approach used to investigate API adoption of developers, we calculated the alignment between embeddings of each developer and the projects they contributed to and a set of random other projects in the same language that they did not contribute to, and measured if there is any significant difference between them using t-test. We found there is indeed a significant difference (p-value < 2.2e-16) with a 95% confidence interval of [0.112, 0.115]. This supports our previous hypothesis that there is a similarity between the skill spaces of developers and the projects they contribute to in future.

### 4.4 H3: A project is more likely to accept contributions from developers who are aligned to the project in the skill space

We wanted to further test the validity of our embedding of developer expertise and project skill space, so we decided to observe whether the new contributors to a project has skill spaces aligned to that of a project. Once again, we constructed skill spaces for the developers who contributed to a project, measured the alignment between them and the skill spaces of the corresponding projects, and compared them with the alignment between skill spaces of a project and the skill spaces of randomly chosen developers who did not contribute to that project. The differences between the alignments was found to be significant using t-test, with p-value < 2.2e-16 and 95% confidence interval of [0.111, 0.114].
The final question we pose is whether or not the measures of expertise we model relate to developer’s opinions about their own expertise related to a specific technology. To do that we use data reported in [30] that surveys a sample of GitHub users to create a ground truth for self-reported developers expertise related to a specific technology.

4.5 H4: A developer whose skill space is aligned more closely to the project’s skill space will be more likely to have their pull requests accepted.

In addition to the previous three evaluations, we hypothesize that developers who have a better skill space alignment with the APIs used in a software project should have higher pull request acceptance rates. To test that, we used GHTorrent to obtain 2334 pull requests created by 766 developers. We obtained all changes made by these developers and fitted a Doc2Vec model on their activities prior to date Feb 16, 2018. We then used logistic regression to model the acceptance rate of the pull requests they submitted after that date. As predictors, in addition to the similarity between the developer and the project, we used other metrics that have been shown to affect the PR acceptance rates [11, 13]. Specifically, we included the most powerful predictor: whether or not the developer had any PRs accepted in the past. As shown in Table 4, for both the models that regress the acceptance rate on similarity and the model where the most important covariate of past acceptance is included, the skill space alignment is highly statistically significant with higher alignment associated with a higher acceptance rate.

4.6 H5: A developer’s self-reported API skills are closely aligned to their personal skill space.

The final question we pose is whether or not the measures of expertise we model relate to developer’s opinions about their own expertise related to a specific technology.

Table 3: The differences in alignment for each language

| Language | rb | Scala | Rust | Java | C | JS | Cs | ipy | jl | F | PY | R | Go | pl |
|----------|----|-------|------|------|---|----|----|-----|----|---|----|---|----|----|
| Difference: LSI | 0.248 | 0.29 | 0.17 | 0.27 | 0.046 | 0.06 | 0.29 | 0.18 | 0.33 | 0.11 | 0.28 | 0.13 | 0.28 | 0.16 |
| Difference: D2V | 0.069 | 0.107 | 0.069 | 0.072 | 0.099 | 0.106 | 0.148 | 0.071 | 0.205 | 0.163 | 0.03 | 0.164 | 0.11 | 0.081 |

Table 4: Logistic Regression Models showing the Effect of Skill Space similarity between PR creator and Project in Predicting PR acceptance with and without the variable representing if their PR was accepted earlier as a predictor

| Predictor                  | Model 1     | Model 2     |
|----------------------------|-------------|-------------|
| (Intercept)                | -1.02 ± 0.13| -1.01 ± 0.13|
| p-Value: 1.40e-14          | p-Value: 3.44e-15|
| Skill Space Similarity     | 1.28 ± 0.29 | 0.95 ± 0.31 |
| p-Value: 1.29e-5           | p-Value: 1.83e-3|
| Previous PR Acceptance     | 0.37 ± 0.09 | 0.37 ± 0.09 |
| p-Value: 1.08e-4           | p-Value: 3.27e-4|

Table 5: Linear Regression model explaining Developer-API:socketio -0.82 ± 0.45 < 2e-16
API:socketio 0.17 ± 0.01 < 2e-16
log(No. of Commits) 0.003 ± 0.001 0.06
Self-Reported Score 0.01 ± 0.004 0.0002

Finally, we try to model the self-reported score using the amount of activity (commits) as reported in [30] and adding the skill space similarity. Again, we find that the increase in skill alignment has a statistically significant positive relationship with the self-reported score even after adjusting for the direct measure of experience based on the number of commits. The result of the model is shown in Table 6.

Table 6: Linear Regression model explaining Self Reported Skill Score (R² value: 0.24)

| Predictors                  | Estimate ± Std. Err. | p-Value |
|-----------------------------|----------------------|---------|
| (Intercept)                 | 2.49 ± 0.16          | < 2e-16 |
| API:react                   | 0.67 ± 0.13          | 2.6e-7  |
| API:socketio                | -0.82 ± 0.17         | 2.5e-6  |
| log(No. of Commits)         | 0.072 ± 0.018        | 9.2e-5  |
| Developer-API Alignment     | 1.96 ± 0.45          | 0.0002  |

In summary, we find that the proposed skill space embedding based on Doc2Vec models of the APIs in files changed by a developer has a strong and statistically significant relationship with the self-reported developer expertise.
5 LIMITATIONS

It is important to note the primary objective of the skill space: the ability to compare developers, projects and APIs in a single space with the longer term goals of arriving at ways to make open source software development more effective by creating signals that provide skill information that is more general than the modification of specific files, but more specific than the volume of overall activity. The definition of the skill space we chose is based on API usage, but the skill embeddings can be conducted for other types of skills as well. We validate the proposed skill space by checking if it would satisfy the intuitive properties the skill space should exhibit, but there may be additional properties we do not consider (and the proposed skill space does not satisfy). For example, our primary concern in this work is to capture the aspects of developer expertise related to the APIs they use and we are not concerned with other types of expertise, such as their proficiency to do good design, architecture, testing, and so forth, or with their ability to communicate with other developers.

The particular mechanism of what it means to use an API may be refined. We only consider if the file has certain import statements but do not verify that the API is actually exercised in the file, and we do not check if the developer made a change to the part of the code that exercises a specific subset of the API used in the file.

Since our aim is to capture the profile of expertise as a trust-building support and we attempt to create such measures that equally apply to individual APIs, projects, and developers, there no general datasets that could be created to evaluate the objectivity of all such measures. Specifically, there is no convincing test everyone would agree upon that a developer is a good fit for a project. As such, we can evaluate the goodness of the measures we propose through several indirect means (i.e., can a specific developer be trusted when they make a contribution if there has been no prior interaction between the developer and maintainer?)

As we noted above, different languages have different conventions in which APIs are declared and these differences may play a role or need to be taken into account in order to improve upon the proposed implementation of the skill space.

6 FUTURE WORK

A recent paper [20] utilized WoC as a way to estimate the reputation of a developer. The authors created a tool (DRE) that displays a developer’s aggregated contributions to open source as derived from their commits. The measures include both expertise (e.g., total commits, files, programming language usage, and how widely a developer’s code has been re-used) and social aspects (e.g., projects they worked on, collaborators, and the Torvalds Index), with some of the measures overlapping both aspects. Overall, DRE serves up developer profiles that provides a broad overview of many facets of a developer’s activity. However, we propose that the skill spaces presented in this paper can be used to enhance developer profile tools such as DRE. For example, we can first filter the need for specific developer expertise by providing a developer’s skill space that consists of their API usage. Furthermore, rather than just serving as a developer profile, we believe our embedding approaches can provide recommendation features for both the developer and those who are browsing the profile. For example, as a developer, our approach allows us to recommend: similar projects that you might consider joining, similar developers that you might want to work with in the future, and similar technologies/APIs you might consider working with, all based on the skill space generated for you by our embedding approach.

7 CONCLUSION

At the beginning of this paper, we set out to define a unified skill space for developers, projects, and APIs. We implemented the skill space embeddings by using LSI and Doc2Vec models, and tested the usefulness of our embedding by testing several hypotheses with the proposed embeddings. We found that our embeddings produce expected results when we tested our proposed hypotheses H1-H3, the similarity score obtained by our embedding was found to be an important predictor for predicting PR acceptance (H4), and the skill space representation of developers was found to very similar to their self-reported expertise (H5). Overall, the proposed skill space representation was found to be useful in determining the specific expertise of individual developers, projects, and APIs used in the project.

We extensively used open data from WoC and other researchers and we will, upon publication, share the data, scripts, and models we used and will ask the maintainers of WoC to integrate the skill spaces with WoC infrastructure due to the extensive size of the data representing skill spaces.

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