Mining Experienced Developers in Open-source Projects

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Abstract: Experienced developers are key for the success of software development projects. In open-source software development, due to openness and distance, one cannot always rely on interpersonal interactions to know who these key people are. Automating the mining of experienced developers is not an easy task either, because of the subjectivity and relativity of what experience is and also because the material to search from (code and development-related metadata) does not obviously relate developers to their capabilities. Some research works propose developer profiling or clustering solutions though, from which we take inspiration. This paper advocates that it is possible to learn from tangible metrics extracted from code and development-related artifacts who are the experienced developers. It uses a supervised learning-based approach trained with a manually labeled dataset of 703 developers from 17 open-source projects from GitHub for which 23 metrics are automatically extracted. Experienced developers classification results show a high F1 measure. A companion explainability study analyzes which metrics are the most influential.

1 Introduction

Thanks to their knowledge and skills, experienced developers are key to software projects. Indeed, Booch advocates that *"every project should have exactly one identifiable architect, although for larger projects, the principal architect should be backed up by an architecture team of modest size"* (Booch, 1996). Experienced developers are often those who possess both the historical and technical knowledge of the project. This technical knowledge often overlaps with the knowledge of the project's software architecture. Kruchten (Kruchten, 1999) argues that software project architects are often experienced developers who master various concepts and technologies. The loss of this knowledge, that could be induced by people leaving a project, is detrimental and imply human and technical management issues (Izquierdo-Cortazar et al., 2009). Therefore, the identification of experienced developers is a step towards better practices for the management of development teams. In open-source projects, where interpersonal relations are not followed as easily as they are in company teams, identifying experienced developers through human interactions is not always possible.

To overcome this issue, this paper investigates the possibility of **mining experienced developers automatically**, based on tangible metrics extracted from code and development-related artifacts from open-source software projects. It proposes a complete approach for mining experienced developers based on software metrics, as descriptive features of the problem, and supervised learning, as a binary classification method. As a first step, we create a dataset of 703 developers (contributors to projects) extracted from 17 Java open-source projects hosted on GitHub. Then, developers are manually labeled as being experienced or not, using manual searches in professional social networks and project documentation. To deal with an imbalanced dataset (lack of data in the experienced developer class) synthetic data generation (over-sampling using K-Means SMOTE) is used. Then, various classification methods are benchmarked from which Random Forest (RF) happens to be the most efficient. The classification reaches a good F1 measure, with well balanced recall and precision. Results prove that supervised classification is a valid approach to automatically mine experienced developers from project contributors using software metrics. Moreover, the classifier explanation (using the SHAP technique) provides valuable insight about the prominent characteristics in experienced developer profiles and, more specifically, architectural activities.

The remainder of this paper is organized as follows. Section 2 presents state-of-the art approaches to profile or cluster developers based on their experience. Section 3 details our proposed experienced developer mining approach. Section 4 presents and analyzes our

results. Section 5 discusses threats to validity. Section 6 concludes and provides perspectives about this work.

2 Related works on developer profiling and clustering

Several works exist that identify experienced developers or domains of expertise in software projects (Greene and Fischer, 2016; dos Santos et al., 2018; Hauff and Gousios, 2015; Teyton et al., 2013, 2014; Di Bella et al., 2013; Kagdi et al., 2008; Schuler and Zimmermann, 2008; Sindhgatta, 2008; Mockus and Herbsleb, 2002). Approaches fall into two categories: **profiling** and **clustering**.

2.1 Profiling

Profiling approaches discover experts for a single or several technologies in a given project.

Mockus *et al.* (Mockus and Herbsleb, 2002) propose Expertise Browser to find expertise domains in project artifacts (documentation, code, product, etc.) using various data sources (repository data, documentation, etc.). Expertise Browser is based on their proposed concept of Experience Atom that models a developer's expertise on the basis of the modifications made on a project artifact. The collection of these Experience Atoms on each program unit composes the expertise of the developer.
Singhgatta (Sindhgatta, 2008) uses repository data and source code combined with clustering (K-Means) to extract key concepts of expertise such as security, database or multi-threading. Expertise concepts are then linked to developers using repository logs. It thus measures an expertise level on each expertise concept for each developer.
Schuler *et al.* (Schuler and Zimmermann, 2008) profile developers using CVS data and source code. They have implemented a system to measure the software expertise at the method level. They argue that a developer that changes a method must understand its functionality and therefore has an expertise. To do so, they count the number of methods used and changed by developers. Each method in the project is attach to all developers that have worked on it. Developers that changed or used the highest number of methods are considered to be experts.
LIBTIC (Teyton et al., 2013) is an approach created by Teyton *et al.* to find library experts. As proposed by Kagdi *et al.* (Kagdi et al., 2008), LIBTIC computes vectors to characterize expertise levels of developers. However, LIBTIC is focused on library usage. Data encoded in vectors come both from the source code of libraries (jar archive) and developers' Git repositories. It evaluates how developers master libraries and identifies the required expertise in project.
XTic (Teyton et al., 2014) is the most versatile approach. It uses source code and repository data. Teyton *et al.* (Teyton et al., 2014) analyze syntactical modifications made in a project. Skills of a given developer are represented as a collection of syntactical patterns. The level of expertise is a positive number representing how many times syntactical patterns appear for a given developer. Xtic provides a domain specific language to describe specific developer profiles to be searched for according to technologies that have to be mastered.
Hauff *et al.* (Hauff and Gousios, 2015) extract ontological concepts from job advertisements on programming, methodology or technologies. The same extraction is performed on README files in GitHub repositories for a given developer. All extracted concepts, methodology and technologies to master for jobs and mastered by the developers, are weighted. Developer skills are then associated to job advertisements by linking concepts with same weights in job advertisements and GitHub README files. This approach does not use data directly related to the source code.
CVExplorer (Greene and Fischer, 2016) uses metadata and README files from GitHub to generate a lattice of technologies mentioned by developers in README files of GitHub projects. The visualisation of lattice nodes uses a tag cloud. Users can select tag clouds to navigate through the lattice and refine a developer's profile according to their needs.
Santos *et al.* (dos Santos et al., 2018) define five skill scores to rank developers. Each skill is based on metrics (number of imports, lines of codes, number of projects, etc.) and thresholds are defined for each. According to values and thresholds, a rank is assigned to each developer.

2.2 Clustering

Clustering approaches group developers according to their skills or their experience in a given project.

Kagdi *et al.* (Kagdi et al., 2008) identify three groups of expert developers. These groups corresponds to three granularity levels in object-oriented projects: file, package and system. Kagdi *et al.* measure and vectorize contributions for each developer on project files and the number of days in the project. These

vectors are then used to compute an expertise factor called *XFactor* for each developer. By this means, experts are found at different granularity levels of the application.
Di Bella *et al.* (Di Bella et al., 2013) classify developers in four groups (*Core*, *Active*, *Occasional* and *Rare*) using clustering methods. Their classification is said to be "onion-like" and has been firstly described by Nakakoji *et al.* (Nakakoji et al., 2002). They extract metrics for each developer (such as number of commits, inter-commit days, lines of codes) from source code and Git data. They use data-mining methods (Principal Component Analysis and Factor Analysis) combined to unsupervised learning (K-Means) to classify developers in those predefined four groups.

Despite these works, to our knowledge, this paper is the first to mine experienced developers using supervised learning combined to software metrics. Besides, only three approaches profile architectural skills (Teyton et al., 2014; Greene and Fischer, 2016; dos Santos et al., 2018). Moreover, only two approaches use machine learning, more precisely unsupervised learning (Sindhgatta, 2008; Di Bella et al., 2013). Among of these works, Di Bella *et al.*'s proposal (Di Bella et al., 2013) is the only that uses software metrics to perform an unsupervised classification of developers in open-source projects.

3 Proposed approach for mining experienced developers

In this section, we detail our proposed approach to mine experienced developers from dataset creation to classifier selection and evaluation. In order to guarantee the reproducibility of this study, both our source code and data are available online[1]. The proposed approach is sketched in Figure 1.

3.1 Dataset creation

To our knowledge, there is no dataset of contributors related to open-source projects based on Spring.Therefore, we have chosen to create our own. Our goal here is to build a dataset of developers associated to metrics (described in Section 3.1.2) and developer experience (Experienced Software Engineer, Software Engineer or Unknown).

[1]https://github.com/qperez/MEDOS

3.1.1 Contributors extraction

First, we select 17 popular projects that use the architectural Java Spring Framework[2]. Using the GitHub REST API[3], we extract 951 developers that contribute to these projects. The data retrieved contain username, name and email from developers' GitHub accounts. Each extracted developer is linked to its project. A developer working on several projects appears several times in the extracted collection.

3.1.2 Contributor metrics extraction

Using the PyDriller tool (Spadini et al., 2018), we compute 23 metrics for each developer of each project as described in Table 1. Metrics are extracted from the first to the last known commit for each project which results in 63,891 commits. To choose these metrics, we rely on the work of Di Bella *et al.* (Di Bella et al., 2013) and Perez *et al.* (Perez et al., 2021). Di Bella *et al.* uses an unsupervised method to classify developers in 4 groups from rare to core developers. They show that several metrics are discriminant for this classification: `Number of Commits`, `Lines of Codes`, `Days in Project` and `Inter-commit Time`. Hence, we choose to reuse these metrics in our classification context. Perez *et al.* used Spring markers (specific Java annotations) to statistically distinguish categories of developers having an experience in *runtime* architecture. Therefore, we used three specific variables in relation with Spring *runtime* architecture. Others variables regard software design and architecture (metrics **`bolded`**) and Maven or Gradle structure (metrics *`italized`*).
Non-contributors bring some noise to the data which could reduce the quality of the classifier. To exclude non-contributors to the source code, we remove from our dataset the contributors that did not change at least one line as synthesized in the following variables: *`AddLGM`*, *`DelLGM`*, `AddLoC`, `DelLoC`, `AddSAM`, `DelSAM`. By this means, the dataset size reduces from 951 contributors to 703.

3.1.3 Mapping contributors to developers' experience in projects

Next goal consists in labeling our dataset with the aim of using it for supervised learning. This amounts to map GitHub contributor profiles to their level of experience in projects. To do so, we search each

[2]https://spring.io/projects/spring-framework
[3]https://docs.github.com/en/rest

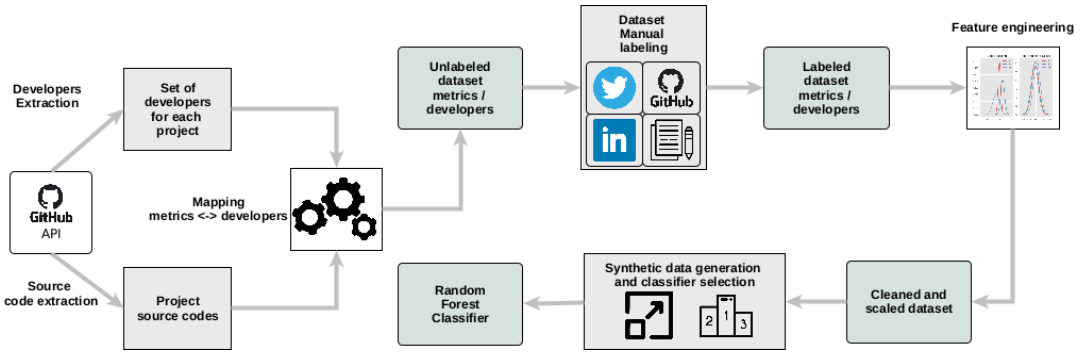


Figure 1: Experienced developers classification process.

Table 1: 23 Metrics extracted for each developer.

Variable code	Variable
NoAB	Number of Abstract Classes created by a given developer
NonAB	Number of non Abstract Classes created by a given developer
NoCII	Number of Classes Implementing an Interface created by a given developer
NoCnII	Number of Classes not Implementing an Interface created by a given developer
NoCE	Number of Classes Extending another class created by a given developer
NonCE	Number of Classes not Extending another class created by a given developer
NoInEI	Number of Interfaces not Extending another Interface created by a given developer
NoIEI	Number of Interfaces Extending another Interface created by a given developer
AddLGM	Lines added in Gradle or Maven files by a given developer
DelLGM	Lines deleted in Gradle or Maven files by a given developer in Gradle or Maven files
ChurnLGM	Difference between added and deleted lines in Gradle / Maven files for a given developer
NoMGM	Number of Modules Gradle or Maven created by a given developer
AddSAM	Spring Architectural Modifications (lines specific to Spring) added by a given developer
DelSAM	Spring Architectural Modifications (lines specific to Spring) by a given developer
ChurnSAM	Difference between added and deleted specific Spring lines for a given developer
AddLOC	Number of Lines Of Code added by a given developer in project files
DelLOC	Number of Lines Of Code deleted by a given developer in project files
ChurnLOC	Difference between added and deleted lines of code in project files for a given developer
DiP	Days in Project. Number of days the developer has been in the project (time between first and last commit)
IT	Inter-commit Time. Average time (days) between commits
NoC	Number of commit made by a developer
AddF	Number of files added for a given developer
DelF	Number of files deleted for a given developer

developer on internet using GitHub username and name. We use this method because many developers use social networks (Archambault and Grudin, 2012). As a perspective, another complementary solution might be to send questionnaires to developers but the weakness of this method is the usual low response rate (Tse, 1998; Cook et al., 2000). Therefore, we collect contributor's experience from LinkedIn, Twitter and GitHub profiles or project documentation websites. To do so, we manually search each developer GitHub name in search engines. If the search result is positive, to prevent homonyms in names, we check that the developer mentions that he is working on the given project. Finally, we inspect the developer's profile and **manually label** the developer.

Considering a given project, if the profile of a given developer mentions:

- "Architect" or "Senior Software Engineer" then we label this developer as "Experienced Software Engineer" (ESE) (Kruchten, 1999),
- "Junior Software Engineer" or "Software Engineer" then we label this developer as "Software Engineer" (SE),
- "Developer" then we search if the developer has a Master of Sciences in Software Engineering. If so, the developer is labelled as "SE"; else the developer is labelled as "OTHER".
- Other descriptions than "SE" or "ESE" then we label the developer as "OTHER".

If the GitHub username of the developer contains the word "bot" then he is labelled as "BOT". Finally, if no information is available about the experience of the developer in the project then it is labelled as "UNKNOWN". Labeling results in one of the five values listed in Table 2.

After having used this raw labeling technique, deeper analysis shows that "SE" or "UNKNOWN" develop-

Table 2: Labels used to annotate developers.

Label acronym	Label	Description
ESE	Experienced Software Engineer	Contributor declaring himself as being an experienced or senior software engineer.
SE	Software Engineer	Contributor declaring himself as being a software engineer.
OTHER	Other	Contributor declaring himself as not belonging to one of the above categories.
UNKNOWN	Unknown	No information available about the contributor.
BOT	Bot	Machine of continuous integration having a GitHub profile to: test, commit, release, etc.

ers can have metrics comparable to "ESE". To avoid these misclassifications, we have sought outliners using an Isolation-Forest method. Isolation-Forest calculates a score for each observation in the dataset. This score provides a measure of normality for each observation. We assume that some "SE" or "UNKWNON" may be declared "ESE". After an inspection of outliners spotted by Isolation-Forest, we have **manually relabeled** 21 of them: 4 "UNKNOWN" to "ESE" and 17 "SE" to "ESE". Table 3 details the number of contributors for each category before and after manual relabeling. This labeling will allow a wider use of the dataset in other contexts than the binary classification that we perform here.

Our goal is now to perform a binary classification of developers separating "ESE" from "Non-ESE". All contributors associated to labels other than "ESE" are considered "Non-ESE". As a result of this process, we obtain 98 contributors labelled as being "ESE" and 605 contributors considered to be "Non-ESE".

3.2 Feature engineering

To be efficient, classification requires a preprocessing phase called feature engineering (Zheng and Casari, 2018). In this phase, various transformations are applied on data: scaling, mathematical transformation, normalization, outliner detection etc.

The first step of feature engineering we apply is a log transformation to reduce the high data skewness of 6 variables: `DiP`, `NoC`, `AddLOC`, `DelLOC`, `AddSAM`, `DelSAM`. High skewness leads to a large variance in estimates that finally decreases classifier performance.
Having variables (features) with different scales and units, we perform a data standardization step. We use the Min-Max method to reduce the effect of outliners and scale data in the range $[-1,1]$. Min-Max scaling is defined as follows:

$$X_{scaled} = \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \times (max - min) + min$$

with :

- X the feature value to scale,
- X_{scaled} the feature value scaled,
- X_{min} and X_{max} the minimum and maximum observed value for feature X,
- max the upper bound for the range,
- min the lower bound for the range.

3.3 Data over-sampling

A point of attention is our highly imbalanced dataset. Our dataset contains 98 experienced developers (minority class) and 605 non-experienced developers (majority class). Keeping these categories imbalanced would lead to a biased classification model. To overcome the lack of data on the minority class, we use the SMOTE (Synthetic Minority Over-sampling Technique) over-sampling method (Chawla et al., 2002). SMOTE is designed to create synthetic data based on existing data. It selects existing points in space, creates vectors between them and randomly generates a synthetic point on this vector. SMOTE has proven its performance as compared to other data generation methods such as random over-sampling (Chawla et al., 2002; Dudjak and Martinović, 2020). More precisely, a variant of SMOTE called K-Means SMOTE (Douzas et al., 2018) is used here. Compared to SMOTE, K-Means SMOTE reduces noise in the generated data (Douzas et al., 2018). By this means, we generate synthetic experienced contributor profiles. Synthetic data generation is performed during the classifier training phase to increase the number of learning data. Figure 2 shows the combination of over-sampling and 4-fold. The over-sampling is performed on the minority class on each test fold.

3.4 Classifier selection

In this study, we now compare 6 different classifiers to choose from. We test 3 classifiers that are known to have good performances on small datasets (SVM, LR, kNN) and, for the comparison, 3 more complex classifiers (SGD, RF, MLP). Using our labeled dataset, we test these classifiers using their implementations in the Scikit-learn API (Lars Buitinck, 2013)

- **Logistic Regression (LR)** is a binomial regression model used to describe data and the relationship between a dependent variable and one or more independent variables. LR estimates the

Table 3: Dataset details before and after manual relabeling.

	#ESE	#SE	#UNKNOWN	#BOT	#OTHER
Before manual relabeling	81	86	509	10	17
After manual relabeling	98	73	505	10	17

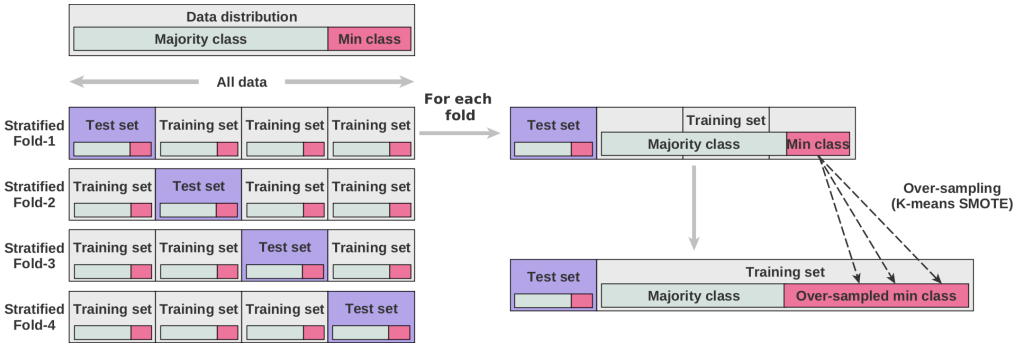


Figure 2: Synthetic data generation during 4-fold evaluation.

probability of an event occurence using a sigmoid function.

- **k-Nearest Neighbors (kNN)** is a non-parametric method in which the model stores the data of the training dataset to perform the classification. To assess the class of a new input, kNN looks for its k closest neighbors using a distance formula (*e.g.*, Euclidean distance) and chooses the class of the majority of neighbors.
- **Support Vector Machines (SVMs)** are non probabilistic classifiers based on linear algebra. Training SVMs creates hyperplanes that separate multi-dimensional data into different classes. SVMs optimize hyperplanes' positions by maximizing their distance with the nearest data. These classifiers generally reach a good accuracy.
- **Multi-Layer Perceptron (MLP)** is a type of formal neural network that is organized in several layers. Information flows from the neurons of the input layer to the neurons of the output layer through weighted connections. Supervised training incrementally adjusts the weights of connections (error back-propagation) so that the expected outputs can be learned by the MLP. Through the use of multi-layers, a MLP is able to classify data that is not linearly separable (using multiple learned hyperplanes).
- **Random-Forest (RF)** is a parallel learning method based on multiple, randomly constructed, decision trees. Each tree of the random forest is trained on a random subset of data according to the bagging principle, with a random subset of features according to the principle of random projections.
- **Stochastic Gradient Descent (SGD)** uses the iterative gradient descent method to minimize an objective function defined as a sum of functions:

$$Q(w) = \frac{1}{n}\sum_{i=1}^{n} Q_i(w),$$

where w is the parameter to be estimated in order to minimize function $Q(w)$. Q_i corresponds to the i-th observation in the training dataset.

Classifiers have hyper-parameters values influencing the model. Thus, setting correct hyper-parameter values provides better classifications. To do so, hyper-parameters values are tuned using a Grid-Search algorithm. Grid-Search, also called parameter sweep, is a brute-force method that searches for an optimal combination of parameters' values using their n-fold Cartesian product. Classifier performances are evaluated using a stratified k-fold cross-validation protocol ($k = 4$). We selected a small k and stratified version because dataset size is modest. As shown by Figure 2, we oversample only the train folds. Test folds keep the distribution of original data so as to be representative of real data from projects Indeed, performing validation on a over-sampled test fold would have biased the evaluation.

4 Results

4.1 Classifier selection

As explained in Section 3.4, we test and compare six classifiers using the F1 measure: Multi-layer Perceptron (MLP), k-Nearest Neighbors (kNN), Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM) and Stochastic Gradient De-

scent (SGD). Classifier hyper-parameters are previously coarsely optimized using a Grid-Search algorithm. Classifiers are then evaluated with a stratified 4-fold protocol (see Section 3.3). Table 4 compiles optimized hyper-parameter values and experimental results for each classifier. RF happens to be the classifier that performs best (bold figures). Hence, RF will be the chosen classifier for the remaining.

Table 4: Results obtained with SciKit classifiers using a stratified 4-fold cross-validation 23 features.

CLF	Specific Classifier Parameters Grid-Search Optimized	F1 Measure
RF	criterion='gini', n_estimators=300, random_state=0, max_depth=2, max_features='log2'	**0.789 IC 95%: 0.053**
SGD	loss='modified_huber', max_iter=2000, random_state=0, tol=0.1, alpha=0.1, learning_rate='invscaling'	0.775 IC 95%: 0.057
kNN	weights='distance', n_neighbors=6, algorithm='ball_tree', p=2	0.767 IC 95%: 0.073
MLP	activation='relu', learning_rate='constant', max_iter=100, random_state=0, hidden_layer_sizes=(50, 50), solver='adam'	0.766 IC 95%: 0.046
SVM	C=0.2, gamma='scale', kernel='poly',random_state=0, tol=0.0001	0.763 IC 95%: 0.021
LR	C=0.52, random_state=9090, solver='sag', tol=0.1	0.757 IC 95%: 0.142

4.2 Detailed results

In order to determine the respective influence of each step in our process, we evaluate our RF classifier with different settings. For each setting we compute F1 measure, recall, precision and balanced accuracy. Results are given by Figure 3 and Table 5.

Setting 1. In this configuration, feature scaling, data transformation and synthetic data generation are not used. Moreover, RF classifier hyper-parameter values are set to default (*i.e.*, as set by the Scikit-Learn API). Evaluation results in a good precision (0.8608) but a poor recall (0.6829). Confidence intervals are large on all measures.

Setting 2. This configuration replicates Setting 1 except for classifier hyper-parameters, which are optimized as calculated by Gird-Search. In this configuration, the F1-Measure is almost unaffected (0.7591) as compared to the previous configuration (0.7601). However, as compared to Setting 1, confidence intervals are reduced or stable for all measures.

Setting 3. In this configuration, Setting 2 is improved using log transformation and data scaling. As compared to Setting 2, Setting 3 shows a positive influence on F1 measure (+0.0063), recall (+0.010) and accuracy (+0.005). All confidence intervals are substantially increased. These transformations increase the performance of the classifier but induce more variability.

Setting 4. Setting 3 is in turn altered with the addition of synthetic data generation as described in Section 3.4. Training the classifier on a balanced dataset has a positive impact on measures. As compared to Setting 3, F1 (+0.0233), recall (+0.413) and accuracy (+0.0198) are increased. Confidence intervals are reduced on all measures as compared to Setting 3 but close to those of Setting 2. As in Setting 3, precision is decreased (-0.002) but there is a good trade-off between recall (0.7446) and precision (0.8390).

4.3 Feature contribution

One of the challenges of Machine Learning algorithms is their explainability. Explainability techniques show which features are most significant for classification. Several technology-agnostic explanation methods could be considered: feature permutation (Breiman, 2001), Local Interpretable Model-agnostic Explanation (LIME) (Ribeiro et al., 2016), SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017) and Anchors (Ribeiro et al., 2018). These methods are post-hoc, meaning they analyze classifiers after they have been trained on data. Only feature permutation, LIME and SHAP explain the classifier globally, *i.e.*, explain feature contribution. Anchors explains only classification results for a given instance. Feature permutation is the most simple method but not the most reliable (Hooker and Mentch, 2019). Studies comparing LIME and SHAP conclude that SHAP gives more consistent explanations (Lundberg and Lee, 2017; Moscato et al., 2021). Therefore, we choose SHAP (Lundberg and Lee, 2017) to explain our RF classifier. SHAP uses game theory, more precisely the Shapley value (Shapley, 1953) to measure feature contribution to classification. We combine SHAP explanation with our stratified 4-fold protocol to explain results on each fold. Feature contribution values returned by SHAP are thus saved for each fold and their means computed for each feature afterwards.

Figure 4 shows results about the explanation of the RF classifier. We observe that four features have a preponderant impact on classification: number of lines of code added (`AddLOC`), churn of lines of code (`ChurnLOC`), number of deleted files (`DelF`) and number of non-abstract classes created (`NoNAB`). Di Bella *et al.* (Di Bella et al., 2013) have shown that lines of codes are discriminant features to categorize developers using an unsupervised method. Here, in a supervised context, we make the same observation.

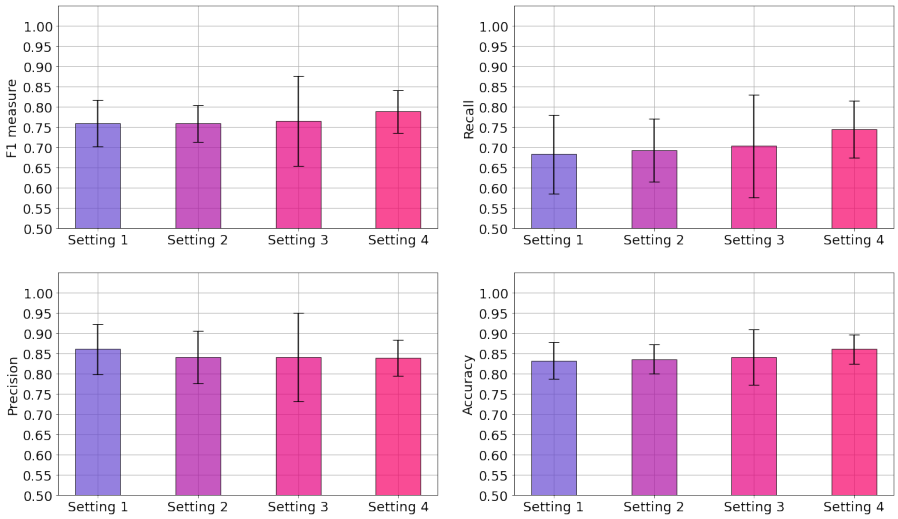


Figure 3: Values and confidence intervals for F1, recall, precision and accuracy on 4 settings.

Table 5: Values and confidence intervals for F1, recall, precision and accuracy on 4 settings.

	Setting 1		Setting 2		Setting 3		Setting 4		Evaluation
	Value	IC 95%	Value	IC 95%	Value	IC 95%	Value	IC 95%	protocol
F1	0.7601	0.0571	0.7591	0.0458	0.7654	0.1111	0.7887	0.0529	Stratified 4-fold
Recall	0.6829	0.0978	0.6933	0.0777	0.7033	0.1267	0.7446	0.0708	Stratified 4-fold
Precision	0.8608	0.0625	0.8412	0.0654	0.8411	0.1098	0.8390	0.0438	Stratified 4-fold
Accuracy	0.8324	0.0459	0.8359	0.0363	0.8409	0.0678	0.8607	0.0364	Stratified 4-fold

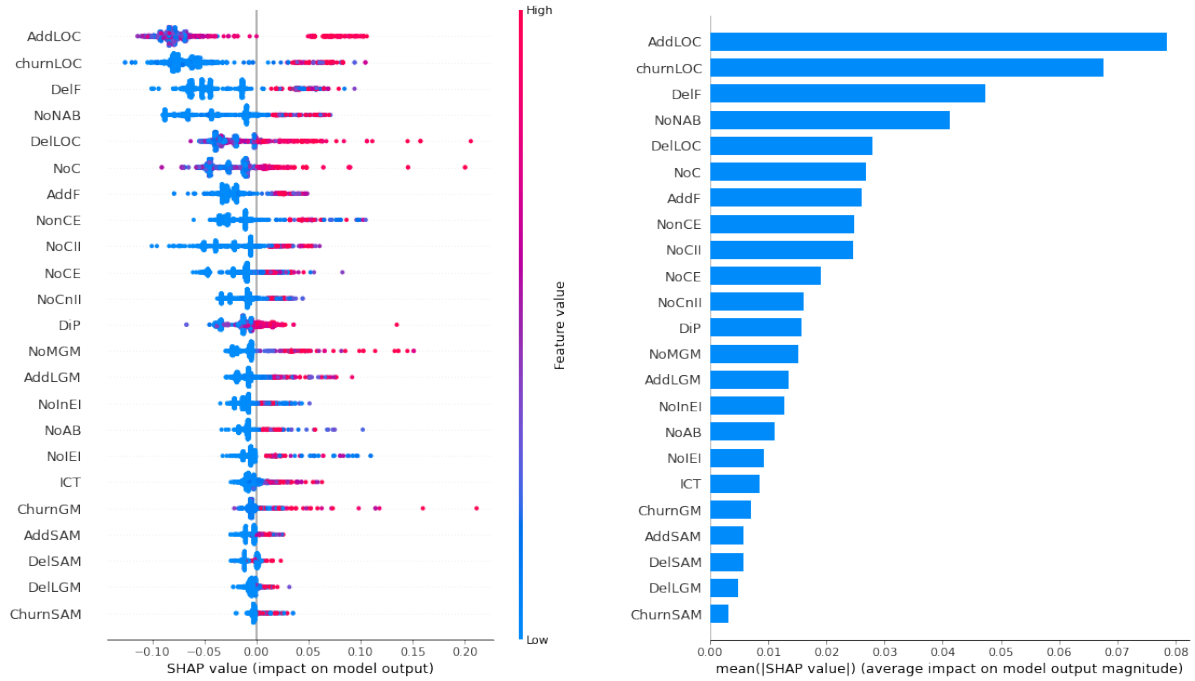
Number of deleted files and number of non-abstract classes created could be a sign of refactoring performed by experimented developers. Among features with lower importance, number of commits (NoC) is in sixth place and days in project (DiP) in twelfth place. These two features are also considered discriminant by Di Bella *et al.* (Di Bella et al., 2013). We observe the same here. From the eighth to the eleventh position in Figure 4, we find different features related to the Java object structure: number of classes not extending another class (NonCE), number of classes implementing an interface (NoCII), number of classes not implementing an interface (NoCnII) and number of classes extending another class (NoCE). These four features tend to show that taking into account the activities on the structure of the Java code of projects has only a moderate impact to discriminate experimented developers from others. Number of Gradle/Maven modules created (*NoMGM*) and number of Gradle/Maven lines added (*AddLGM*) (ranked thirteenth and fourteenth) are less important than the Java structure but should not be neglected. The most surprising observation concerns features about Spring architecture (AddSAM, DelSAM, ChurnSAM), which are the least important for classification. Spring architectural contributions seems to be not discriminant to classify developers contrary to our intuition. Although these tasks are taken over by experienced and often long time contributors in projects (Perez et al., 2021), they correspond to the very specific role of architect are thus assumed by a smaller proportion of the experienced developers.

5 Threats to validity

This section discusses the main threats to the validity of our proposal.

Internal Threats. The main internal threat is linked to the quality of our dataset. Our approach strongly relies on labels that are set by contributors who self-report their level of experience in projects on social networks (LinkedIn, Twitter) or in project documentation. This labeling may be thus subject to bias if some developers consider themselves to be experienced when they are not, or vice versa. To mitigate this risk, our proposal includes a manual relabeling phase using a mathematical method. Despite this, errors may still exist in our dataset.

External Threats. External threats might have an impact on the generalizability of our proposal. The selected projects are open-source projects, written in the Java language that use the Spring framework. Contributors might be mainly Java developers. Moreover, three metrics used in our dataset (DelSAM, AddSAM,



(a) SHAP values for each classified instance.

(b) Mean SHAP values.

Figure 4: SHAP values for the 23 features.

CHURNSAM) are specific to the Spring framework and this paper focuses exclusively on two levels of experience (experienced or not). These characteristics might impede the generalization of our proposal to projects written in different programming languages, using other technologies or employing contributors with different profiles. Such alternate studies still are perspective works.

6 Conclusion

This paper proposes an approach to mine experienced developers in open-source projects using metrics and supervised learning. Firstly, it builds a dataset of project contributors and define a binary classification process to discriminate between experienced developers and non-experienced developers. Contributors are extracted from 17 open-source projects and 23 metrics evaluated for each of them. The dataset is then manually labeled with the experience of contributors in each project, as needed by supervised learning. Data is then processed (log transformation and scaling) to ease its interpretation by classification algorithms. As the dataset is strongly imbalanced, synthetic data generation is also performed (with the SMOTE method) to create synthetic profiles of experienced contributors as a compensation. Six supervised classification algorithm are then benchmarked. The RF classifier provides the best results showing both a good F1 measure (0.7887) and a good accuracy (0.8607). The balance between recall (0.7446) and precision (0.8390) is fairly equitable. The explainability of our classifier shows that the metrics that have the most influence on the classification are the number of lines of code and the churn of lines of code. Contrary to our intuition, the metrics related to the Spring architecture have very little influence on the classifier's decision. The number of files added, the number of commits and the variables related to the Java structure are among those with a medium influence. This could indirectly mean that experienced developers make a lot of of changes to the project structure but that contributing to the runtime architecture is a very specific task only devoted to architects. This work opens many perspectives. A first idea is to improve the genericity of our approach by training a technology-agnostic classifiers. To do so means both collecting technology-independant metrics and extracting contributors from projects that use other programming languages. A second perspective is to study the correlation between the number of experienced developers in a given project and project quality using project-level software metrics.

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