Deep Learning for Agile Effort Estimation
Have We Solved the Problem Yet?

Vali Tawosi, Rebecca Moussa, Federica Sarro

Abstract—In the last decade, several studies have proposed the use of automated techniques to estimate the effort of agile software development. In this paper we perform a close replication and extension of a seminal work proposing the use of Deep Learning for agile effort estimation (namely Deep-SE), which has set the state-of-the-art since. Specifically, we replicate three of the original research questions aiming at investigating the effectiveness of Deep-SE for both within-project and cross-project effort estimation. We benchmark Deep-SE against three baseline techniques (i.e., Random, Mean and Median effort prediction) and a previously proposed method to estimate agile software project development effort (dubbed TF-IDF-SE), as done in the original study. To this end, we use both the data from the original study and a new larger dataset of 31,960 issues, which we mined from 29 open-source projects. Using more data allows us to strengthen our confidence in the results and further mitigate the threat to the external validity of the study. We also extend the original study by investigating two additional research questions. One evaluates the accuracy of Deep-SE when the training set is augmented with issues from all other projects available in the repository at the time of estimation, and the other examines whether an expensive pre-training step used by the original Deep-SE, has any beneficial effect on its accuracy and convergence speed. The results of our replication show that Deep-SE outperforms the Median baseline estimator and TF-IDF-SE in only very few cases with statistical significance (8/42 and 9/32 cases, respectively), thus confounding previous findings on the efficacy of Deep-SE. The two additional ROs revealed that neither augmenting the training set nor pre-training Deep-SE play a role in improving its accuracy and convergence speed. These results suggest that using semantic similarity is not enough to differentiate user stories with respect to their story points; thus, future work has yet to explore and find new techniques and features that obtain accurate agile software development estimates.

Index Terms—Software Effort Estimation; Story Point Estimation; Deep Learning.

1 INTRODUCTION

In agile development, a software is realized through repeated iterations called sprints (usually 2–4 weeks), and is built in small incremental parts known as releases [1]. In each sprint, the development team designs, implements, tests and delivers a distinct product version or a working release. This allows adaptation to changing requirements at any point during the project life cycle. Accordingly, the development team is required to complete a number of user-valued functionalities, called user stories, in every sprint [2]. User stories are specified in the form of one or two sentences in a user’s everyday language. Because of these small incremental iterations, it is essential for an agile team to focus on estimating the effort required to complete every single user story, rather than the whole project. This allows them to prioritise the user stories, and to organise and manage a successful completion of sprints. The estimation at this granularity is referred to as task-level estimation herein.

Story Point (SP) is commonly used to measure the effort needed to implement a user story [3], [4] and agile teams mainly rely on expert-based estimation [4]. However, similar to traditional software project effort estimation [5], [6], task-level effort estimation is not immune to the expert’s subjective assessment [4]. Subjective assessment may not only lead to inaccurate estimations but also, and more importantly to an agile team, it may introduce inconsistency in estimates throughout different sprints. Thus an intelligent task-level effort estimation technique seems exigent.

Abrahamsson et al. [8] point out the three advantages of using an intelligent task-level effort estimation technique for Agile development. First, an automated technique can use all the project information available from its inception and the history of the previous tasks to produce estimations for new ones. Second, the decision of an automated technique is not influenced nor affected by any pressure from opinions of other individuals. Third, an automated estimation is repeatable and predictable, thus it will always provide a consistent prediction. One of the readily available information that intelligent task-level effort estimation techniques can use is the user story, which is stored in title and description of the issue in an issue-tracking systems. For almost a decade, researchers proposed techniques to predict the effort of a task in SP using features extracted from user stories [5], [8], [9], [10], [11]. In most cases, these studies urged that their model would be a decision support system for expert estimators in Agile teams.

In this paper, we explore the methods introduced to estimate story points for agile development at task-level and we perform a close replication and extension of the study which had introduced the current state-of-the-art, namely Deep-SE [8] (regarded as the “original study” in this paper) [1]. In close replications, the conceptual, methodological, and substantive aspects of the original study are mostly consistent.
kept invariant, and only minor variations are allowed to be introduced [12]. This type of replication serves as an initial check to see if the findings of the original study hold, or can be generalized in slightly varied conditions like the validation against a new dataset. If close replications confirm findings of an original study, an empirical generalization can be established [12], [3], [14].

Deep-SE is an end-to-end deep learning-based approach which accepts user story (i.e., issue title and description of a task recorded in Jira issue management system) as input and estimates story point as an output. In this work, we replicate three out of six research questions investigated in the original study[2]. These research questions compare Deep-SE to three naive baseline techniques, and to another task-level effort estimation technique introduced by Porru et al. [9] (we refer to it as “TF/IDF-SE” herein), and they also investigate the suitability of Deep-SE for cross-project estimation.

Our results show that Deep-SE does not statistically significantly outperform the Median baseline or TF/IDF-SE in at least half of the projects evaluated in the original study, which confirmed the results of the original study [5]. We also observe that Deep-SE’s accuracy in cross-project estimation is not better than within-project estimation, which corroborates the original findings [5].

In addition, we extend the study by evaluating the replicated research questions on an additional larger and more diverse dataset (consisting of 26 projects with 31,960 user stories in total), which we have curated and made publicly available (we refer to it as the Tawosi dataset). The extended evaluation of Deep-SE we carried out, by using the Tawosi dataset, confirmed the findings of our replication, and strengthened the confidence in its results. The results confirmed the conclusion made in the original study only for one research question (cross-project estimation). As for the two other research questions (i.e., sanity check and comparison with TF/IDF-SE), we found variations which led to a different conclusion than that reached by the original study. We discuss the possible origin of the variations in Section 6.

We also pose two new research questions. The first one aims at investigating how using additional user stories from within-company and across different projects based on a realistic chronological order can affect Deep-SE’s prediction performance. The second one explores the effectiveness of an expensive pre-training step used in the original study, on the accuracy of the estimation and on the speed of the convergence of Deep-SE. As stated by the original study, pre-training needs many hours to run and as much as 50,000 issues (without labels) per repository.

The answers to these research questions showed that augmenting the training set with issues from other projects has no appreciable effect on the prediction accuracy of Deep-SE. Also, pre-training the lower levels of Deep-SE does not only not significantly improve its accuracy, but it also does not have tangible impact on its convergence speed towards the best solution; thus, this step can be disregarded.

The rest of the paper is organised as follows. Section 2 presents the related work, and Section 3 briefly describes the structure of Deep-SE and TF/IDF-SE. Section 4 describes the design of our replication study in detail; including the research questions, the data and experimental method used to address them, and threats to validity. Section 5 reports and discusses the results. Further insights on differences between the results of the original study and our replication are discussed in Section 6. Finally, Section 7 concludes the paper with a plausible answer to the question “Why couldn’t Deep-SE outperform the baseline techniques for all the cases?” and suggestions for future work.

2 Related Work

We summarise previous work proposing intelligent techniques to estimate user story points in Table 1 and we describe each of them below in chronological order.

The first study, published in 2011, is the work of Abrahamsson et al. [8]. They proposed to train a prediction model on 17 features extracted from a user stories such as the priority and number of the characters in the user story, and 15 binary variables representing the occurrence of 15 keywords in the user stories. These 15 keywords are the 15 most frequent terms in user stories. They used regression models, Neural Networks (NN), and Support Vector Machines (SVM) to build estimation models for two industrial case studies, one consisting of 1,325 user stories and the other of 13 user stories. The best results were obtained by SVM.

Five years later, Porru et al. [9] proposed to classify user stories into SP classes. Their approach uses features extracted from 4,908 user story descriptions recorded in Jira issue reports, collected from eight open-source projects. Specifically, they extract the type of the issue, the component(s) assigned to it, and the TF-IDF derived from the title and description of the issue. Their study confirmed Abrahamsson et al.’s findings that the user story and its length are useful predictors for story point estimation. Their results also suggest that more than 200 issues are needed for training the classifier to obtain a model with a satisfactory accuracy.

In 2018, Scott and Pfahl [11] used developer-related features alongside the features extracted from 4,142 user stories of eight open-source projects to estimate the story points using SVM. Developer-related features include the developer’s reputation, workload, work capacity, and the number of comments. The results showed that using only developers’ features as input for the SVM estimator leads it to outperform Random Guessing, Mean, and Median baseline estimators. This approach also outperformed two models using only features extracted from the text of the
user story and using a combination of the developers’ and text features.

At the same time, Soares [10] proposed the use of different NLP techniques with auto-encoder neural networks to classify user stories based on the semantic differences in their title in order to estimate their effort in terms of SP. He used TF/IDF and document embedding with four variants of auto-encoders, and evaluated these models on 3,439 issue reports from six open-source projects. The results revealed no significant difference in the SP estimation accuracy of these approaches. Soares speculated that this might be due to the relative semantic simplicity of issue report titles.

In 2019, Choetkiertikul et al. [5] proposed a new approach to SP estimation, based on the combination of two deep learning architectures to build an end-to-end prediction system, called Deep-SE. They used raw user story text as input to their system. A word embedding was used to convert each word in a user story into a fixed-length vector, which is then fed to the deep learning architecture to map it to a space in which the semantically related stories are placed close to each other. In the final step, they used a regressor to map the deep representation into the SP estimate. They evaluated Deep-SE on 23,313 issues from 16 open-source projects and showed that it outperforms both baseline estimators and Porru et al.’s approach [9] based on Mean Absolute Error.

Subsequently, Abadeer and Sabetzadeh [16] evaluated the effectiveness of Deep-SE for SP prediction with a commercial dataset of 4,727 user stories collected from a healthcare data science company. They found that Deep-SE outperforms random guessing, mean and median baselines statistically significantly, however with a small effect size.

3 THE DEEP-SE AND TF/IDF-SE APPROACHES FOR AGILE EFFORT ESTIMATION

This section provides an overview of the two story point effort estimation techniques used in this study, namely Deep-SE [5] and TF/IDF-SE [9], which make up the current state-of-the-art in Agile effort estimation.

Both Deep-SE [5] and TF/IDF-SE [9] leverage the similarity between the target user story and previously estimated user stories to come up with an estimation for the target user story. TF/IDF-SE relies on one of the simplest techniques for text similarity, namely the term frequency-inverse document frequency (TF/IDF) statistic. On the other hand, Deep-SE uses advanced techniques in deep-learning to exploit the semantic similarity between user stories.

When Choetkiertikul et al. [5] proposed Deep-SE, it was natural to compare it with TF/IDF-SE. In the following, we provide a brief description of each approach and refer the reader to the papers where they were proposed originally for a full description [5, 9].

3.1 Deep-SE

Choetkiertikul et al. [5] proposed Deep-SE as a deep learning model to estimate story point of a single software task, which is represented by an issue report, containing the title and description of the issue.

Their model is composed of four components: (1) Word Embedding, (2) Document representation using Long-Short Term Memory (LSTM) [22, 23], (3) Deep representation using Recurrent Highway Network (RHWN) [24], and (4) Differentiable Regression.

The first component converts each word in the title and description of issues (i.e., user story) into a fixed-length vector (i.e., word embedding). These word vectors serve as an input sequence to the LSTM layer, which computes a vector representation for the whole document. The document vector is then fed into the RHWN, which transforms the document vector multiple times, before outputting a final vector which represents the text. The vector serves as input to the regressor, which predicts the output story-point. The word embedding and LSTM layers are pre-trained without using SP values to come up with a proper parameter initialization for the main deep structure (referred to as the pre-trained language models) which helps achieve a faster convergence of the model.

Pre-training leverages two sources of information: the predictability of natural language, and the availability of free texts without labels (e.g., issue reports without story points). The first source comes from the property of languages that the next word can be predicted using previous words, thanks to grammars and common expressions [5]. As per Choetkiertikul et al.’s [5] suggestion, we used the pre-trained language models that they shared given that this step takes long to execute. The pre-trained language models are trained on a corpus of 50,000 issues selected from each repository. The issues are not required to have SP estimation to be included in the pre-training stage and may also come from projects that are not considered for SP-estimation study.

The use of the Fibonacci series or the Planning Poker card set [4] for SP scales is usually recommended and applied by expert estimation and planning poker practitioners [1]. However, as Deep-SE uses a regressor in the last layer, the estimated SP can be a real number, hence, its estimations would not follow a Fibonacci scale, and the authors did not round the predicted SP to the nearest SP value on the Fibonacci scale.

3.2 TF/IDF-SE

Porru et al. [9] treat SP estimation as a classification problem. Their idea is to use the title and description of issues (i.e., user stories) and issue related data available at the estimation time (i.e., issue type and component), to build a machine learning classifier for estimating the story points required to address an issue. They extract TF/IDF statistics and user story length from issue reports, and use issue type and the component of the issue to build a dataset in which rows represent issues and columns are the TF/IDF values alongside the binary values representing the association of an issue to a type or component. Specifically, they concatenate the title and description of the issue reports and call it context. They separate the code snippets (if any) from natural language text in the context and analyse two chunks

3. No explanation is given in the original study on how the 50,000 issues are selected. We noticed that their pre-training dataset takes into use every issue available in a repository until the number of issues reach 50,000.

4. Planning Poker card set includes the following numbers: 0, 0.5, 1, 2, 3, 5, 8, 13, 20, 40, 100, and ∞.
| Reference                         | Approach                                      | Baseline | Measure             | Data                                                                 | Results                                                                 |
|----------------------------------|-----------------------------------------------|----------|---------------------|----------------------------------------------------------------------|------------------------------------------------------------------------|
| Abrahamsson et al. [8], 2011, IEEE Int. Symp. on Empirical Software Engineering and Measurement | Regression-based ML (Regression, NN, SVR) | expert estimation | MMRE, MMER, PRED(25%) | 17 features extracted from 1,338 issue reports from two industrial projects | In one project the developers' subjective estimates work better than the proposed approach (SVR), in the other project the accuracy of SVR lies in the range of subjective estimates of developers |
| Porru et al. [9], 2016, Int. Conf. on Predictive Models and Data Analytics in Software Engineering | Classification-based ML (KNN, NB, DT, SVM), The SVM variant is referred to as “TF/IDF-SE” in this paper | ZeroR (always selects as the outcome the most represented class) | MMRE | TF/IDF features and length of the title and description, and type and component of 4,908 issue reports from eight open-source projects | Estimating SP using an automated tool is feasible. SVM results in an MMRE between 0.16 and 0.61 after an initial training of more than 200 issues |
| Scott and Pfahl [11], 2018, Int. Conf. on Software and System Process | Classification-based ML (multiple two-class SVMs) | Mean, Median, and Random baselines | MAE and SA | TF/IDF features, length, and five developer-related features extracted from 4,142 issue reports from eight open-source projects | SVM classifier with only five developer-related features outperforms SVM with textual features or a combination of textual and developers’ features |
| Soares [10], 2018, IEEE Int. Joint Conf. on Neural Networks | Classification-based ML (AutoEncoder NN) | TF/IDF with SVM | Precision, Recall and F-measure | Distributed memory paragraph vector and distributed bag-of-words paragraph vector extracted from the title of 3,439 issue reports from six open-source projects | Found no significant difference among the different variants of AutoEncoders used in the study regarding SP estimation accuracy |
| Choetkiertikul et al. [5], 2019, IEEE Transactions on Software Engineering | Regression-based deep-learning called Deep-SE (word embedding + LSTM + RHWN + regression) | Mean, Median, and Random baselines, and KNN | MAE, MdAE, and SA | Title and description of 23,313 issue reports from 16 open-source projects, and dataset used by Porru et al. [9] | Deep-SE outperforms the baselines and TF/IDF-SE in all cases |
| Abadeer and Sabetzadeh [16], 2021, IEEE 29th International Requirements Engineering Conference Workshops (REW) | Deep-SE (word embedding + LSTM + RHWN + regression) | Mean, Median, and Random baselines | MAE, MdAE, and SA | Title and description of 4,727 issue reports from one industrial project | Deep-SE outperforms the baselines |
| This Study                       | Deep-SE (word embedding + LSTM + RHWN + regression) and TF/IDF-SE (SVM) | Mean, Median, and Random baselines | MAE, MdAE, and SA | Title, description, type and component of 31,960 issue reports from 26 open-source projects, in addition to the datasets used by Choetkiertikul et al. [5] | Deep-SE does not outperform the baselines and TF/IDF-SE statistically significantly in all cases |

**Note:** SVM = Support Vector Machine / SVR = Support Vector Regression / NN = Neural Network / KNN = K-Nearest-Neighbour / NB = Naive Bayes / DT = Decision Tree / LSTM = Long-Short Term Memory / RHWN = Recurrent Highway Network / MAE = Mean Absolute Error / MdAE = Median Absolute Error / SA = Standard Accuracy / MMRE = Mean Magnitude of Relative Error / MMER = Mean Magnitude of Error Relative to Estimation (a.k.a estimation MMRE) / PRED(25%) = Prediction at level 25%

4 Empirical Study Design

In this section, we provide a detailed description of the research questions investigated for the replication and extension of the original study [5], together with the data, benchmarks, and evaluation methods used to answer these questions. To carry out both the replication and extended study, we use the implementation and configuration made publicly available by Choetkiertikul et al. [5] for both Deep-SE and TF/IDF-SE, subject to some alterations needed to fix some errors. To allow the replication of our work, our scripts and data are publicly available [28].

4.1 Research Questions

The first research question asked by Choetkiertikul et al. [5] investigates whether Deep-SE is a suitable method to estimate story points. To this end they assess whether it is

5. Since Porru et al. [9] did not provide any public implementation for TF/IDF-SE, we use the one provided by Choetkiertikul et al. [5]. Moreover, the link to the replication package provided in Porru et al. [9] is no longer maintained by the authors and when contacted the authors were not able to provide us with more data nor tools.
able to outperform simpler baseline estimators for within-project estimation (i.e., building a prediction model by using past issues of a given project, and using such a model to predict the story points for new issues within the same project).

Specifically, they compare Deep-SE with the Mean and Median baselines and they also report the SA values for all three techniques. SA is a measure of their accuracy performance against Random Guessing (see Sections 4.3 and 4.4 for the definition of the benchmarks and the evaluation method). Therefore, in our replication we investigate the same research question:

**RQ1. Sanity Check: Is Deep-SE suitable for story points estimation?**

We evaluate this research question through two sub-questions. We first replicate the original study by evaluating Deep-SE on the same data used by Choetkiertikul et al. [5]: **RQ1.1. Sanity Check - Replication**, where we compare Deep-SE’s accuracy with baseline estimators and the results reported in the original study.

Second, we extend RQ1.1 by evaluating Deep-SE on a larger dataset comprising 26 projects (see Section 4.2 for detail) to further strengthen the confidence in the results of RQ1: **RQ1.2. Sanity Check - Extension**.

If we find that Deep-SE outperforms the baseline techniques for both RQ1.1 and RQ1.2, then we can confirm the conclusion made in the original study.

Choetkiertikul et al. [5] also compared Deep-SE to previous state-of-the-art for within-project estimation proposed by Porru et al. [9] (i.e., TF/IDF-SE). This motivates our second research question:

**RQ2. Deep-SE vs. TF/IDF-SE: How does Deep-SE perform against TF/IDF-SE in story point estimation?**

Similarly to RQ1, we investigate two sub-questions for RQ2 by replicating the same experiment with the same data used in the original study (**RQ2.1. Deep-SE vs. TF/IDF-SE - Replication**) and by extending it and experimenting with a larger dataset (**RQ2.2. Deep-SE vs. TF/IDF-SE - Extension**). Deep-SE outperforming TF/IDF-SE for both RQ2.1 and RQ2.2 will further confirm the conclusion made in the original study.

Another important question tackled by the original study is the performance of Deep-SE for cross-project estimation, i.e., building a prediction model by using issues from another project, and using such a model to predict the story points for the issues of a new target project, for which there are not enough issues to train an accurate model [5, 9]. Cross-project estimation is generally deemed as a more difficult task than within-project estimation, since the training and target projects might be heterogeneous [29], [30], [31]. Thus, our third research question assesses the ability of Deep-SE in cross-project estimation, as posed in the original study:

**RQ3. Cross-project Estimation. Is Deep-SE suitable for cross-project estimation?**

We tackle this question by replicating the two experiments done by Choetkiertikul et al. [5] in our first sub-question **RQ3.1. Cross-project Estimation - Replication**. Specifically, in the first experiment to train Deep-SE we use a project belonging to the same repository of the target project (i.e., cross-project within-repository estimation). In the second experiment, we use as training data the issues from a project belonging to repository different from that of the target project (i.e., cross-project cross-repository estimation). We replicate this research question with the same set of the source and target projects and compare the results of Deep-SE to the Mean and Median baselines, as done in the original study. We observe that Choetkiertikul et al. [5] did not consider the temporal ordering of the issues’ creation time in collecting issues for their training and testing sets for this research question. However, previous work on software engineering prediction models showed that neglecting contextual details (like the temporal ordering of the data) is a potential threat to the conclusion stability of the study [32], [33], [34]. In a real-world scenario, one would be able to use only the issues from the past projects to train the model. Thus, all the issues in the training (and validation) set should precede, in creation time, the earliest created issue from the test set. Surprisingly, for 11 out of 16 experiments, more than 97% of the issues used to train the models in RQ3.1 were created after the start date of the target project, thus making the use of Deep-SE in practice infeasible. Therefore, we extend the original analysis in order to assess Deep-SE’s performance in a realistic scenario, which takes into account the chronological order of the data used for cross-project estimation. This motivates, our second sub-question: **RQ3.2. Cross-project Estimation - Extension**, where we only use the issues created before the start date of the target project as the cross-project training data for Deep-SE. We compare the results of Deep-SE with Mean and Median baseline techniques.

Our next research question, focuses on another practical usage scenario: the case in which there is not enough historical data from the target project to train an accurate prediction model, and as a result, the data would need to be augmented with the use of external sources. This is a very common case for deep learning models, which need an abundance of training data to perform well, and previous study investigates how to augment the training set in different application domains [35], [36]. Our research question aims at analysing if augmenting the training set (composed of a few instances from target project) with a larger number of issues from other projects, helps Deep-SE produce more accurate estimations:

**RQ4. Augmented Training. How does Deep-SE perform when using a training set augmented with other projects issues?**

To answer RQ4, we use the same data splits used for RQ1.2, but we modify the training sets by adding to them past issues from all the other projects available, yet respecting the chronological order of the issues. In particular, we include in the training set the issues from other projects (belonging to the same repository as the target project) that are created before the earliest created issue in the validation set. Therefore, we augment the target project training data with every issue that a company already had in their repository.

6. Among the five remaining projects, for two of them, 75% and 37% of the issues were created after the start date of the target projects, and for three (in which MULESOFT was used as the source or target project) we could not determine the percentage as the start/end time of the MULESOFT project is not known as this project repository is no longer accessible.
at the time of predicting the story points for new issues of the target project.

Our fifth and last research question, investigates a technical aspect of the deep learning approach proposed by Choetkiertikul et al. [5]: The utility of pre-training for Deep-SE. Pre-training is described as a way to come up with a good parameter initialization for Deep-SE without using the labels (i.e., story points). Choetkiertikul et al. [5] pre-train the lower layers of Deep-SE (i.e., embedding and LSTM layers), which operate at word and sentence level. In the absence of pre-training, the parameters are typically initialized randomly, but Choetkiertikul et al. [5] stated that a good initialization (through pre-training of embedding and LSTM layers) allows a faster convergence towards good solutions. However, their study did not compare the performance of Deep-SE with and without using such a pre-training step. In this work, we investigate the actual benefit of using such a pre-training step since pre-training is very expensive both in terms of running time and amount of data required (Choetkiertikul et al. reports that their pre-training step needs around 50,000 issues to work properly and took 46 hours and 48 minutes for nine repositories to run [5]). Given these limitations, if the use of pre-training does not improve the estimation performance (accuracy-wise and execution time-wise), its usage would not be advisable. This motivates our next research question:

RQ5. Pre-Training Effectiveness. Does pre-training Deep-SE’s lower levels improve its accuracy and/or convergence speed?

To answer this question, we compare Deep-SE with random weight initialization to Deep-SE initialized with weights tuned by pre-training (i.e., the pre-training step used by Choetkiertikul et al. [5]).

The comparison is performed on estimation accuracy, running time, and the number of epochs each of them performs before converging to an optimal solution. We perform this analysis on the dataset used in both RQ1.1 and RQ1.2.

4.2 Data

To execute a close replication of the research questions to that of the original study, we adopted the datasets made publicly available by Choetkiertikul et al. [5]. Moreover, we also gather our own dataset in order to strengthen our confidence in the results and further mitigate the threat to the external validity of the study. We explain each of these datasets in the following, while a summary of the descriptive statistics of all three datasets is in Table 2.

4.2.1 The Choetkiertikul Dataset

Choetkiertikul et al. [5] mined 16 open-source projects from nine different repositories (namely Apache, Appcelerator, DuraSpace, Atlassian, Moodle, Lsstcorp, MuleSoft, Spring, and Talendforge) and gathered a total number of 23,313 issues (i.e., user stories) with recorded story points, after filtering out all those issues that had assigned a story point of zero, or negative, or an unrealistically large value (i.e., greater than 100). Choetkiertikul et al. collected their dataset on August 8, 2016, and made it publicly available [13]. We refer to this dataset as the Choet dataset and we use it to answer RQs 1.1, 3.1, and 5.

4.2.2 The Porru Dataset

Choetkiertikul et al. [5] also collected eight open-source projects stored in six open-source repositories, aiming at benchmarking Deep-SE against Porru’s TF/IDF-SE approach using a common dataset.

In total, the Porru dataset, as collected by Choetkiertikul et al. [5], [15], contains 4,904 issues. Among these eight projects, six are common with the Choet dataset (i.e., TIMOB, TISTUD, APSTUD, MESOS, MULE, and XD), although they contain a different subset of issues as Porru et al. applied a set of more restrictive filtering criteria than those used by Choetkiertikul et al. in building the Choet dataset [5]. These criteria are as follows: (1) Story points must have been assigned once and never updated afterwards. Updated story points may mean that the information provided in the issue report had misleading information, and they do not want to confuse the classifier with noisy input. (2) The issue must be addressed. Issues not addressed are likely to be unstable; hence they might also confuse the classifier. (3) Once the story points are assigned, the informative fields of the issue (i) must be already set and (ii) their value must not have been changed afterwards. They define informative fields used as dependent variables for classification, including Issue Type, Description, Summary, and Component(s). (4) The values in the story points field must correspond to one of those included in the Planning Poker cards set.

Choetkiertikul et al. made their version of the Porru dataset publicly available [13]. We refer to this dataset as the Porru dataset. We used this dataset to answer RQ2.1.

4.2.3 The Tawosi Dataset

In this study, we collected 31,960 issues from 26 projects stored in 13 different open-source repositories. We will refer to this data as the Tawosi dataset. We have made our dataset publicly available at [28] and used it to answer RQs 1.2, 2.2, 3.2, 3.1, and 4.

In the following, we describe in more detail how we curated the Tawosi dataset and its differences with respect to the Choet and Porru datasets.

The Tawosi dataset contains data collected from 26 open-source software projects that used Agile development methodologies and estimated story points for issues. Each of these projects use the Jira software [37] as a platform to manage their issues, and contains at least 200 issues with recorded SP estimation.

In order to collect the above data, we analysed 13 major open source repositories used in previous work. Eleven of these repositories were used by either Choetkiertikul et al. [5] or Porru et al. [9] and other previous work [10], [11], and the two additional ones, Hyperledger and MongoDB, were used in related work [38]. These 13 repositories contained a total of 904 projects, from which we extracted all those projects having the SP estimation recorded. This resulted in 44 projects. After this step 69,191 issues were retrieved from the 44 projects. Then we applied the issue filtration criteria recommended by Porru et al. [9] (see

7. The dataset used in Porru et al. [9] is not publicly available, so Choetkiertikul et al. [5] re-collected it by closely following the approach described in their paper [9]. This dataset slightly differs from the original dataset in the number of issues.
Section 4.2.2 as they are more restrictive than those used by Choetkertikul et al. [5], and thus their use seems like a more sensible choice to remove those data points that are more likely to be noisy [9]. After this filtering step, we retained in our final dataset only those projects that had more than 200 issues (i.e., 26 out of 44 projects). This resulted in a final number of 31,960 issues contained in our dataset. We used the Representational State Transfer (REST) API, provided by Jira [39], to query and collect the issue reports.

Twelve of the projects in the Tawosi dataset are in common with the Choet dataset but they have a different number of issues, as we collected the data more recently and applied Porru’s filtration criteria. In addition, the Tawosi dataset includes 14 more projects (namely, ALOY, CLI, DAEMON, TIDOC, CONFCLOUD, CONFSERVER, DNN, FAB, STL, COMPASS, SERVER, EVG, NEXUS, and TDP) with a total of 10,506 issues. Four projects in the Choet dataset (with a total of 2,087 issues) are not included in our dataset (with a total of 11,029 more issues). Moreover, the MULESTUDIO project was no longer available on Jira when we collected our data.

Finally, for RQ4 (augmented training set), we use the mean or median story point of the past issues as used in the predicted story point for a new issue.

### 4.3 Benchmarks

As done in the original study, we use three commonly used baseline estimation techniques, i.e., Random Guessing, Mean, and Median estimators to benchmark Deep-SE.

**Random Guessing (RG)** is a naive method that simply assigns story point of a randomly selected issue to the target issue [25]. More formally, Random Guessing predicts a story point value $y$ for the target case $issue_t$ by randomly sampling (with equal probability) all the remaining $n - 1$ cases and taking $y = r$, where $r$ is the story point of the randomly drawn $issue_r$ from $1...n \mid issue_r \neq issue_t$ [25]. This method does not need any parameter estimation and any prediction system is expected to outperform it over time, otherwise, the prediction system would not be using any information about the target case. The results for RG are in the on-line appendix [28].

**Mean and Median Effort** are two baseline benchmarks commonly used for effort estimation techniques [40], [41], [42]. Specifically, the mean or median story point of the past issues is used as the predicted story point for a new issue.

### 4.4 Evaluation Measures and Statistical Analysis

Several measures have been used in the software effort estimation literature to measure the accuracy of the estimation models. These measures are generally built upon the error estimation literature to measure the accuracy of the estimation models. These measures are generally built upon the error estimation literature to measure the accuracy of the estimation models. These measures are generally built upon the error estimation literature to measure the accuracy of the estimation models.

Similarly to the original study, we discuss all results of our study based on the MAE measure, while we report the MdAE and SA values in our on-line appendix for completeness [28].

These measures (defined in Equations 1 and 2) are standardised measures which are not biased towards under- or over-estimates and which have been recommended in previous work [25], [26], [42]. Specifically, the mean or median story point of the past issues is used as the predicted story point for a new issue.

Across $n$ projects, the MAE and MdAE are computed as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |actual_i - predicted_i|$$

$$MdAE = \text{Median} \left\{ |actual_i - predicted_i| \right\}$$

where $actual_i$ is the actual effort, $predicted_i$ is the predicted effort and $n$ is the number of projects.

$SA$ is recommended as a standard measure to compare multiple prediction models against each other [25]. It is based on MAE and is defined as follows:

$$SA = \left( 1 - \frac{MAE_p}{MAE_p} \right) \times 100$$

where $MAE_p$ is the $MAE$ of the approach $p$, when being evaluated and $MAE_p$ is the $MAE$ of a large number (usually 1,000 runs) of random guesses.

For a prediction model $p$, which outperforms random guessing in terms of accuracy, $SA$ will produce a number in the range $[0, 1]$. An $SA$ value closer to zero means that the predictor $p$ is performing just a little better than random guessing [25], [42]. For a prediction model which is outperforming random guessing, $SA$ will produce a negative
value. For a high-performance prediction model MAE and MDAE should be lower and $S_A$ should be higher than the competitors.

To check if the difference in the results achieved by two methods is statistically significant, we performed the Wilcoxon Ranked-Sum test (a.k.a. Mann–Whitney U test) on the distribution of the absolute errors produced by the methods under investigation. Specifically, we tested the following null hypothesis: $H_0$: The absolute errors produced by the prediction model $P_1$ are higher than those produced by the prediction model $P_2$. We used the one-way Wilcoxon test; hence, if the test rejects the Null Hypothesis, the alternative hypothesis would be accepted: $H_1$: The absolute errors produced by the $P_1$ are lower than those provided by the $P_2$. We correct the confidence level of $\alpha = 0.05$ for multiple hypothesis testing according to Bonferroni ($\alpha / K$, where $K$ is the number of hypotheses). Using this correction mitigates the risk of incorrectly rejecting the Null Hypothesis (i.e., Type I error) [42].

We also use a standardised non-parametric effect size measure (i.e., the Vargha Delaney’s $\hat{A}_{12}$ statistic) to assess the practical magnitude of the difference between two methods, as recommended in previous work [42, 43]. For two algorithms $A$ and $B$, the $\hat{A}_{12}$ measures the probability of $A$ performing better than $B$ with respect to a performance measure. $\hat{A}_{12}$ is computed using Equation (4), where $R_1$ is the rank sum of the first data group being compared, and $m$ and $n$ are the number of observations in the first and second data sample, respectively.

\[ \hat{A}_{12} = \frac{(R_1 - m + \frac{1}{2})}{n} \]  

Based on Equation (4), if two algorithms are equally good, $\hat{A}_{12} = 0.5$. Respectively, $\hat{A}_{12}$ higher than 0.5 signifies that the first algorithm is more likely to produce better predictions. The effect size is considered small for $0.6 \leq \hat{A}_{12} < 0.7$, medium for $0.7 \leq \hat{A}_{12} \leq 0.8$, and large for $\hat{A}_{12} \geq 0.8$, although these thresholds are not definitive [42]. We do not transform the $\hat{A}_{12}$ as we are interested in any improvement achieved by the methods [42, 44].

To perform the above analyses, we used the Wilcoxon Rank-Sum test and Vargha Delaney’s $\hat{A}_{12}$ effect size available from the stats library in R v. 4.0.1 [45].

4.5 Threats to Validity

Our study is a close replication and extension of a previous work on task-level software effort estimation [5]. Thus, it shares some of the threats to the validity of the original study, but also has implemented further mitigation. We followed best practice for designing the replication and reporting finding in a sound way [12, 13, 14, 46, 47].

In the original study, the authors expressed their concern about basing their ground truth on the most likely biased human-estimated story points. However, they argued that Deep-SE is trained to imitate human beings with respect to estimations by reproducing an estimate that human engineers would be able to derive. For this aim, story points sufficiently serve the purpose. Moreover, whenever an unbiased ground truth is available, Deep-SE can be trained on the new target variable.

To minimize threats to conclusion validity, the original study, and similarly our study, used unbiased accuracy performance measures and applied statistical tests by checking all the required assumptions. Besides, in our study, we checked by performing peer-code-review that the implementation of all estimation approaches and the computation of the accuracy measures adhere to their original definitions.

To mitigate the external validity, like the original study, we collected data from real-world open-source projects to evaluate the methods. Although these projects differ greatly in size, complexity, and developers community, we cannot claim that they are representative of all kinds of...
software projects. Specially, there are differences between open-source and commercial software projects. A key difference, that may affect the estimation of story points, is the behaviour of contributors, developers, and the project’s stakeholders. It is expected that in an industrial setting for a commercial software project, the user stories are written in a more cohesive and disciplined manner, thus, providing more useful information and containing less noise. Hence, further investigation for commercial projects from industrial software companies is needed to strengthen the conclusions made in this study.

Santos et al. [14] showed that sampling error and (un)intentional contextual modifications in experimental settings can produce different results, leading to an unsuccessful reproduction of results. To avoid such errors and modifications, we made sure that for the replicated RQs we use the same data and train-validation-test as the ones used in the original study. We also made sure that all the projects have more than 200 observations, thus mitigating the threat of obtaining unstable p-values and effect sizes due to undersampling [14]. To ensure that we keep the experimental setting consistent with the original study, we followed the procedures outlined in their paper. Furthermore, for both Deep-SE and TF/IDF-SE, we used the implementation provided by Choetakierikul et al. [5]. The only changes we made are to amend and fix errors found in the implementation of the baseline techniques and evaluation metrics according to the definition recommended in the literature (see Section 6).

Our scripts and dataset are publicly available [28].

5 RESULTS
This section presents the results and discusses the answers to the research questions.

5.1 RQ1. Sanity Check
5.1.1 RQ1.1. - Replication

Results: In Table 3, under the column “Rep”, we report the results obtained by Deep-SE and the baseline estimators (i.e., Mean and Median) on the Choet dataset in our replication study. Below we analyse and discuss the results based on the MAE measure.

We can observe that Deep-SE generally outperforms the Mean baseline estimator obtaining lower MAE values on 14 out of the 16 projects (i.e., 88%) investigated in our replication study. The differences on 11 of them (i.e., 69%) is statistically significant with two projects having a medium effect size, six having small, and three having negligible ones as shown in Table 3. However, when Deep-SE is compared to the Median estimator, results reveal that the former obtains lower MAE values on 8 out of the 16 projects under study (i.e., 50%) with the differences being statistically significant in only 4 cases (25%) with the effect size being small.

Discussion: These results are not in complete accordance with those obtained in the original study, where it is shown that Deep-SE achieves lower MAE values than both baseline techniques for all 16 projects (see the Orig column in Table 3) with statistically significant differences in 14 and 15 out of the 16 cases when compared to the Median and Mean estimators, respectively.

Variation in the results due to use of stochastic techniques, such as deep learning, can be acceptable to some extent [15]. In fact, the variation we observed in the MAE values achieved for Deep-SE in the original study and this replication can be attributed to such a stochastic nature. However, the difference observed between the results of the baseline techniques reported in the the original study and this replication suggests unjustifiable discrepancies, since the baseline techniques are deterministic and should always yield the same results given the same datasets. Therefore, we further investigated the origin of such discrepancies by analysing the results and code provided in the original study’s replication package and by contacting the authors. We found that the likely cause for these discrepancies is a fault in the computation of the MAE and MdAE of the baseline estimators, and the original study’s use of a possibly different approach for random guessing. Section 6 provides a detailed explanation of these causes.

Moreover, while investigating the implementation provided for Deep-SE, we noticed that Deep-SE performs a transformation on the distribution of the SPs in the preprocessing stage (see Section 6 for more details). This transformation is applied on the SP distribution of each project, before being split into training/validation/test sets, however this pre-processing is not mentioned in the paper.

To further investigate the effect of such a transformation on the results, we used Deep-SE with the original SPs (i.e., without transforming its distribution) and we report the results in Table 5 under the ‘Cut’ column. Our results show that in this case all estimators perform generally worse. Specifically Deep-SE obtains worse MAE values than those it obtains when the transformation is applied in our replication study (Rep) in 15 cases (94%) with the difference being statistically significant in four of them (27%) and the effect size being small in one and negligible in the remaining three. While the Mean and Median estimators perform worse in 16 (100%) and 14 (88%) cases, respectively with the remaining two cases being equivalent. The difference is statistically significant in 12 cases when compared to the Mean estimator with medium effect size in 2 of them, small in 7, and negligible in 2 cases. While, when compared to the Median estimator, the difference is not statistically significant for any of the cases.

We also observe differences between the results shown in Table 5/Cut and the original study (Orig). Deep-SE performs worse without applying the SP transformation in all 16 cases considered; whereas, the Mean and Median estimators obtain worse MAE values in 6 (38%) and 4 (25%) cases, respectively.

When we compare the performance of Deep-SE to that of Mean and Median when no transformation is applied i.e., ‘Cut’, we observe that Deep-SE outperforms Mean and Median in 15 and 6 cases, respectively. Out of the 15 cases, the difference between Deep-SE and Mean is statistically significant in 12 cases, with a medium effect size in 3 and a small one in the remaining 9 cases. As for the Median estimator, out of the 6 cases, only 2 cases show statistically significant difference with small effect size in one and negligible effect size in the other.

We conclude that the transformation induces the techniques to produce a lower absolute error by reducing the
range of the SP distribution of the entire dataset (including the test set), therefore suggesting more optimistic results than the ones that could be achieved in practice, where the test set is not available at prediction time. Indeed, when we train Deep-SE while correctly applying the transformation on the training set only (column CutTrain in Table 6), we find that in the majority of the cases (12 out of 16) its performance deteriorates, however the difference is statistically significant in only one of these 12 cases with a negligible effect size.

In this study, we apply the transformation on the SP distributions for research questions RQ1.1 and RQ5 for replication purposes, while we use the original SP values to answer the remaining RQs.

5.1.2 RQ 1.2 - Extension.

To answer RQ 1.2, we benchmark Deep-SE against the Mean and Median estimators using the Tawosi dataset.

The results reported in Table 7 show that Deep-SE outperforms Mean in 20 out of 26 cases (77%). However, the difference in absolute error is statistically significant in 16 (62%) with 13 cases having a small effect size and the remaining three having a large effect size as shown in Table 8. When compared to the Median estimator, Deep-SE obtains lower (better) MAE values in 10 out of the 26 cases investigated (38%) and only four (15%) show statistically significant differences with one having a large effect size and only one (NEXUS) has a medium effect size.

Overall, the results obtained for RQs 1.1-RQ1.2 show:

Answer to RQ1: Deep-SE statistically significantly outperform the baseline estimators in only 38% of the cases for within-project estimation, and therefore does not pass the sanity check.

5.2 RQ2. Deep-SE vs. TF-IDF-SE

5.2.1 RQ2.1 - Replication

The original study evaluated Deep-SE and TF-IDF-SE on the Porru dataset and found that Deep-SE outperformed TF-IDF-SE for all the eight projects under investigation.

To answer RQ2.1, we replicate the same experiment with the same data used in the original study.

Table 7 shows the results we obtained in our replication study using Deep-SE (i.e., Deep-SE (Rep)) and TF-IDF-SE (Rep)), together with the results obtained by the original study (Deep-SE (Orig) and TF-IDF-SE (Orig), shaded in grey).

First of all, we observe that in our replication of TF-IDF-SE we obtain exactly the same results as Choeokkietkikul et al. [5] (i.e., the TF-IDF-SE results are fully reproducible), whereas the results we obtained for Deep-SE are different from those obtained in the original study [5]. Deep-SE outperforms TF-IDF-SE in six out of eight projects (75%) and, among these, the difference is statistically significant in four projects (i.e., MULE, XD, DNN and NEXUS), out of which three have negligible effect size (MULE, XD, DNN) and only one (NEXUS) has a medium effect size (Table 8).
TABLE 4: RQ1.1 and RQ5. Results of the Wilcoxon test (\( \hat{A}_{12} \) effect size in parentheses) comparing Deep-SE vs. baselines (Mean, Median), vs. Deep-SEpre-train, and vs. Deep-SEcut, on the Choet dataset.

| Project | Deep-SE vs. | Deep-SEpre-train | TF/IDF-SE | Mean | Median |
|---------|-------------|------------------|-----------|------|-------|
| MESOS   | 0.139 (0.52)| 0.182 (0.52)     | 0.592 (0.51)| 0.526 (0.50) |
| USERGRID | 0.440 (0.51) | 0.955 (0.43)     | 0.318 (0.48) | 0.419 (0.51) |
| TISTUD  | 0.015 (0.54) | 1.000 (0.39)     | 0.734 (0.51) | 0.622 (0.49) |
| APSTUD  | 0.597 (0.44) | 0.960 (0.45)     | 0.953 (0.55) | 0.352 (0.51) |
| TIMOB   | 0.001 (0.60) | 0.999 (0.44)     | 0.893 (0.52) | 0.947 (0.47) |
| BLM     | 0.001 (0.64) | 0.866 (0.45)     | 0.617 (0.51) | 0.566 (0.49) |
| CLOV    | 0.001 (0.68) | 0.063 (0.57)     | 0.782 (0.54) | 0.678 (0.48) |
| ESWSERVER | 0.018 (0.60) | 0.003 (0.65)     | 0.366 (0.48) | 0.637 (0.48) |
| DURACLOUD | 0.002 (0.50) | 0.936 (0.45)     | 0.503 (0.51) | 0.334 (0.54) |
| DM      | 0.001 (0.66) | 0.013 (0.53)     | 0.007 (0.47) | 0.019 (0.53) |
| MDL     | 0.001 (0.75) | 0.517 (0.50)     | <0.001 (0.42)| <0.001 (0.59) |
| MULE    | 0.572 (0.49) | 0.656 (0.49)     | 0.532 (0.50) | 0.160 (0.53) |
| MULESTUDIO | 0.428 (0.51) | 0.442 (0.50)     | 0.362 (0.51) | 0.370 (0.51) |
| XD      | <0.001 (0.58)| 0.266 (0.51)     | 0.991 (0.54) | 0.590 (0.50) |
| TDQ     | <0.001 (0.70)| 0.009 (0.56)     | 0.219 (0.48) | <0.001 (0.60) |
| TESB    | <0.001 (0.62)| 0.017 (0.52)     | 0.233 (0.48) | 0.019 (0.56) |

5.2.2 RQ2.2 - Extension

Table[5] shows the results obtained by Deep-SE and TF/IDF-SE on the Tawosi dataset.

We observe that Deep-SE performs better than TF/IDF-SE on 14 out of 26 projects (54%) and worse on nine projects (34%). Both perform equally good on the remaining three projects (12%). However, in the cases where Deep-SE outperforms TF/IDF-SE, the difference in absolute errors is statistically significant in only five out of 14 cases (19% of all cases). Among those, the effect size is large in only one case, medium in two, and small in two other cases (see Table[5]). For the cases where Deep-SE performs worse than TF/IDF-SE, the difference in absolute errors is significant in four out of nine cases (15% of all cases), one having a small effect size and the remaining three having a negligible one.

Overall, these results strengthen our confidence in the conclusion of RQ2.1 by confirming a small difference between the results of these two techniques.

Answer to RQ2: Deep-SE statistically significantly outperforms TF/IDF-SE in only five out of 26 cases (19%), whereas it provides statistically significantly worse results in four cases (15%). Therefore, we cannot conclude that Deep-SE outperforms TF/IDF-SE for all projects herein.

5.3 RQ3. Cross-project Estimation

5.3.1 RQ3.1 - Replication

Following the original study, we performed two different types of experiments in order to investigate the effectiveness of Deep-SE for cross-project SP estimation.

The first experiment is characterised by the fact that Deep-SE is trained by using SP contained only in projects belonging to a same repository of the target project (i.e., within-repository), for example Deep-SE trained on MESOS and tested on USERGRID, where both belong to Apache repository, while in the second experiment we train Deep-SE by using SPs contained only in projects belonging to a
TABLE 7: RQ2.1. Results of the Deep-SE and TF/IDF-SE replication (Rep), original study (Orig), and the baselines on the Porru dataset. Best results (among all methods but Deep-SE (Orig) and TF/IDF-SE (Orig)) in bold.

| Project | Deep-SE (Rep) | TF/IDF-SE (Rep) | Mean       | Median     | Deep-SE (Orig) | TF/IDF-SE (Orig) |
|---------|---------------|-----------------|------------|------------|---------------|-----------------|
| TIMOB   | 7.36          | 1.76            | 20.08      | 1.76       | 1.44          | 1.76            |
| TISTUD  | 1.36          | 1.28            | 1.87       | 1.26       | 1.04          | 1.28            |
| APSTUD  | 5.52          | 5.69            | 5.59       | 5.69       | 2.67          | 5.69            |
| MESOS   | 1.08          | 1.23            | 1.24       | 0.84       | 0.76          | 1.23            |
| MULE    | 3.27          | 3.37            | 3.22       | 3.07       | 2.32          | 3.37            |
| XD      | 1.23          | 1.86            | 1.24       | 1.34       | 1.00          | 1.86            |
| DNN     | 0.69          | 1.08            | 0.72       | 1.08       | 0.47          | 1.08            |
| NEXUS   | 0.30          | 0.39            | 0.72       | 0.39       | 0.21          | 0.39            |

TABLE 8: RQ2.1. Results of the Wilcoxon test (Δ12 effect size in parentheses) comparing Deep-SE vs. TF/IDF-SE, Deep-SE vs. baselines (Mean, Median), and TF/IDF-SE vs. baselines (Mean, Median) on the Porru dataset.

| Project | Deep-SE vs. TF/IDF-SE | Mean       | Median     | Mean       | Median     |
|---------|------------------------|------------|------------|------------|------------|
| TIMOB   | 0.968 (1.00)           | <0.001 (0.99) | 0.968 (0.43) | <0.001 (1.00) | 0.500 (0.50) |
| TISTUD  | 1.000 (0.64)           | <0.001 (0.67) | 1.000 (0.36) | <0.001 (0.64) | 0.500 (0.50) |
| APSTUD  | 0.866 (0.48)           | 0.413 (0.52)  | 0.366 (0.52)  | 0.666 (0.48)  | 0.500 (0.50) |
| MESOS   | 0.486 (0.66)           | 0.087 (0.57)  | 0.996 (0.37)  | <0.001 (0.66) | 0.999 (0.40) |
| MULE    | 0.043 (0.43)           | 0.039 (0.56)  | 0.080 (0.55)  | 0.990 (0.43)  | 0.997 (0.41) |
| XD      | 0.005 (0.41)           | 0.280 (0.53)  | 0.238 (0.53)  | 0.987 (0.41)  | 0.995 (0.39) |
| DNN     | <0.001 (3.38)          | 0.150 (0.53)  | <0.001 (0.62) | 1.000 (0.38)  | 0.500 (0.50) |
| NEXUS   | <0.001 (0.76)          | <0.001 (0.91) | <0.001 (0.64) | <0.001 (0.76) | 0.501 (0.50) |

different repository (i.e., cross-repository; for example Deep-SE trained on MESOS from Apache repository and tested on MULE, which belongs to MuleSoft repository).

We observe that the results we obtained by using Deep-SE both for the within-repository and cross-repository experiments are different from those recorded in the original study. Specifically, the MAE values obtained in our within-repository replication are higher (worse) than those reported in the original study in seven out of the eight (88%) projects (see Table 7a). Whereas, the MAE values we obtain in the cross-repository replication are higher than those reported in the original study only for four out of eight (50%) projects (see Table 7b). The difference between the MAE values achieved by the Mean estimator and those of Deep-SE are higher for the cases in which the difference in the mean MAE values of the source and target projects is larger (see Table 7a). In the cross-repository training scenario, Deep-SE statistically significantly outperforms the Mean estimator in six out of eight cases (75%), with a large effect size in three of them, medium in one, and small in two cases. This is due to the distribution of the SP values in the source and target project. The difference between the MAE values achieved by the Mean estimator and those of Deep-SE are higher for the cases in which the difference in the mean SP values of the source and target projects is larger (see Table 7a). While, when compared to the Median estimator, our results show that Deep-SE obtains better MAE values in two cases out of eight (25%) with the difference being statistically significant and the effect size being small in both cases. Overall, for both scenarios, Deep-SE outperforms the Mean and Median estimators with a statistically significant difference in 10 and 4 out of 16 cases (63% and 25%), respectively.

Finally, we comment on the use of Deep-SE for within-project estimation versus its use for cross-project estimation by observing that, overall, Deep-SE is more effective for the former. In fact, the estimation accuracy achieved by Deep-SE on the same set of target projects (i.e., USERGRID, MESOS, APSTUD, TIMOB, TISTUD, MULESTUDIO, MULE when trained based on within-project – see Table 3) is always higher than the accuracy of Deep-SE when trained with cross-project with both within- or cross-repository (see Table 7). This confirms the findings of the original study: Deep-SE is more suitable for within-project estimation than for cross-project estimation.

5.3.2 RQ3.2 - Extension

For this research question, we exploit issues from projects belonging to the same repository as the target project to form a training/validation set. Therefore, we can only use those repositories in the Tawosi dataset that contain more than one project (i.e., Appcelerator, Atlassian, Hyperledger, MongoDB, and Talendforge). These repositories contain 18 projects, in total. For each of these 18 projects (as target projects), we combine all the issues from all the other projects belonging to the same repository to form the training/validation set (as the training source). We then remove the issues that are created after the start date of the target project from the training/validation set. For 13 out of 18 target projects, this leaves us with a source issue set containing less than 200 issues. We remove these target projects from our experiments, as previous work showed training with less than 200 issues may not result in a stable model [9].
Thus, we investigate five projects for this research question, namely, ALOY with 1,620 issues as the training source, CLI with 3,383 issues, DAEMON with 5,587 issues, TIDOC with 335 issues, and TDP with 1,410 issues. We split these source issue sets into 75%-25% train-validation sets and use them to train Deep-SE. The resulting model is used to estimate all the issues in the target projects.

Table 10 reports the results of our experiments. We can observe that, based on the MAE, Deep-SE always provides better results than the Mean estimator but with a statistically significant difference only in three of them. Whereas, Deep-SE performs worse than the Median estimator in all five cases, with the difference being statistically significant in two cases (TIDOC and TDP), and the effect size being small.

These results corroborate the conclusion drawn in RQ3.1: Deep-SE does not always provide more accurate cross-project SP estimations than baseline estimators. Moreover, our results for RQ3.2 highlight that when Deep-SE is used in a realistic scenario, taking into account the chronological order of the issues, its prediction performance worsens.

9. Note that we only include those issues from other projects that are resolved before the creation of the first issue in the test set.

5.4 RQ4. Augmented Training Set

To augment the training sets used in RQ1.2, we exploit issues from projects belonging to the same repository as the target project in the Tawosi dataset. Similarly to RQ3.2, this limits us to 18 projects in the Appcelerator, Atlassian, Hyperledger, MongoDB, and Talendforge repositories.

Applying the augmentation resulted in an increase in the size of the training set for all 18 target projects, ranging between 63.2 times for TIDOC and 1.4 times for SERVER (10.5 times on average over 18 projects). This experiment mimics a real-world scenario in which a company uses issues from all its projects (past and present) to train Deep-SE and use it for story point estimation of new issues.

Note that, this is different from RQ3.2, where Deep-SE did not use any issues from the target project for training, while herein, we keep the original 60%-20% train-validation sets from the target project and only augment the training set with available issues from other project. The purpose of this is to examine whether Deep-SE’s estimation performance will increase, if more training data were available.

Table 11 shows the results we obtained after augmenting the training set for 18 projects (indicated by “AUG” as the column header). This table also shows the results of Deep-SE estimating SP for the same projects by only using within-project issues (under WP column). We also report the results of the baseline estimators, to verify whether augmenting the training set helps Deep-SE outperform the baselines on those projects in which Mean and Median had previously performed better in within-project estimation. Results show that Deep-SE performs better on only five out of 18 projects (28%), when the training set is augmented. On the other

Answer to RQ3: Deep-SE is less effective for cross-project SP estimation with respect to within-project SP estimation.

| Source       | Target       | Method        | MAE   | Deep-SE (Rep) vs. |
|--------------|--------------|---------------|-------|-------------------|
| MESOS (ME)   | USERGRID (UG)| Deep-SE (Orig)| 1.07  |                   |
|              |              | Deep-SE (Rep) | 1.16  |                   |
|              |              | Mean          | 1.02  | 1.00 (0.42)       |
|              |              | Median        | 0.89  | 1.00 (0.37)       |
| USERGRID (UG)| MESOS (ME)   | Deep-SE (Orig)| 1.14  |                   |
|              |              | Deep-SE (Rep) | 1.51  |                   |
|              |              | Mean          | 1.52  | 0.262 (0.51)      |
|              |              | Median        | 1.50  | 0.802 (0.49)      |
| TISTUD (AS)  | APSTUD (AP)  | Deep-SE (Orig)| 2.75  |                   |
|              |              | Deep-SE (Rep) | 4.37  |                   |
|              |              | Mean          | 4.27  | 0.918 (0.48)      |
|              |              | Median        | 4.38  | 0.573 (0.50)      |
| TISTUD (AS)  | TIMOB (TI)   | Deep-SE (Orig)| 1.99  |                   |
|              |              | Deep-SE (Rep) | 3.38  | <0.001 (0.54)     |
|              |              | Mean          | 3.45  | 1.000 (0.45)      |
|              |              | Median        | 3.17  |                   |
| APSTUD (AP)  | TISTUD (AS)  | Deep-SE (Orig)| 2.85  |                   |
|              |              | Deep-SE (Rep) | 2.79  |                   |
|              |              | Mean          | 3.38  | <0.001 (0.59)     |
|              |              | Median        | 3.17  | <0.001 (0.56)     |
| APSTUD (AP)  | TIMOB (TI)   | Deep-SE (Orig)| 3.41  |                   |
|              |              | Deep-SE (Rep) | 3.51  |                   |
|              |              | Mean          | 4.36  | <0.001 (0.64)     |
|              |              | Median        | 4.19  | <0.001 (0.62)     |
| MULE (MU)    | MULESTUDIO (MS)| Deep-SE (Orig)| 3.14  |                   |
|              |              | Deep-SE (Rep) | 3.64  |                   |
|              |              | Mean          | 3.34  | 0.775 (0.49)      |
|              |              | Median        | 3.26  | 0.997 (0.46)      |
| MULESTUDIO (MS)| MULE (MU)| Deep-SE (Orig)| 2.31  |                   |
|              |              | Deep-SE (Rep) | 2.77  |                   |
|              |              | Mean          | 3.05  | 0.004 (0.54)      |
|              |              | Median        | 2.60  | 0.997 (0.46)      |

Table 9: RQ3.1. Comparing Deep-SE cross-project SP estimation replication results (Rep) to the original study results (Orig) [5], and to the baselines. The results of the Wilcoxon test (A12 effect size in parentheses) for Deep-SE (Rep) vs. Mean and Median baselines are shown in the last column. Best results (among all approaches but Deep-SE (Orig)) per project are highlighted in bold.

(a) Within-Repository Training

(b) Cross-Repository Training
TABLE 10: RQ3.2. Comparing the cross-project prediction accuracy (in terms of MAE) of Deep-SE and the baselines Mean and Median. The last column shows the result of the Wilcoxon statistical test ($A_{12}$ Effect size in parentheses) for Deep-SE. Best results in bold.

| Source Target | Method | MAE | Deep-SE vs. |
|---------------|--------|-----|-------------|
| APSTUD        | ALOY   | Deep-SE 2.15 Mean 2.83 <0.001 (0.67) |
|               |        | Median 2.10 0.770 (0.48) |
| TIDOC, TIMOB  |        | Deep-SE 2.72 Mean 2.80 0.089 (0.53) |
|               |        | Median 2.38 0.940 (0.46) |
| TISTUD        |        | Deep-SE 2.95 Mean 3.04 0.166 (0.53) |
|               |        | Median 2.89 0.526 (0.50) |
| APSTUD, TIDOC |        | Deep-SE 2.53 Mean 2.91 <0.001 (0.64) |
|               |        | Median 2.45 0.006 (0.53) |
| TISTUD        |        | Deep-SE 1.60 Mean 2.46 <0.001 (0.75) |
|               |        | Median 1.53 0.021 (0.54) |
| TIDOC         |        | Deep-SE 2.47 Mean 2.62 0.83 2.74 2.74 |
|               |        | Median 2.53 2.75 0.65 0.68 |
| TDP           |        | TDP 1.63 Mean 2.46 0.99 1.51 1.51 |
|               |        | Median 2.32 2.77 0.65 0.69 |
| TESB          |        | TDP 1.00 Mean 1.29 1.33 1.33 |
|               |        | Median 1.22 1.39 1.48 1.59 |

Answer to RQ4: Augmenting the training set with issues from within-company projects had no steady positive or negative effect on Deep-SE’s accuracy.

5.5 RQ5. Pre-Training Effectiveness

Tables 3 and 5 show the performance of Deep-SE with and without pre-training (Deep-SE vs Deep-SE!pre-train) on the Choet and the Tawosi datasets, respectively. We can observe that using pre-training does not always improve Deep-SE’s estimation accuracy. Specifically, Deep-SE with random initialization (i.e., Deep-SE!pre-train) obtained better MAE values, although with a small difference, for six out of 16 (38%) projects from the Choet dataset (TIMOB, APSTUD, BAMB, CLOV, MESOS, XD).

The results of the Wilcoxon test (Table 4) show that the difference in the estimation accuracy of Deep-SE with and without pre-training is statistically significant (in favour of pre-training) for two of the projects (DM and MDL) with a negligible effect size.[9] On the Tawosi dataset (Table 5), Deep-SE without pre-training performs similarly or better than Deep-SE in 13 out of 26 projects (50%) among which the difference in errors produced by the two variants is statistically significant on four projects only (TISTUD, TIDOC, MDL, TDQ) with a negligible/small effect size (Table 6).

Having seen the trivial effect of pre-training in improving the accuracy of Deep-SE for SP estimation, we checked whether it at least helps Deep-SE converge faster to the best solution. To this end, we compare the running time and the number of epochs (Table 12) required by the two variants to converge to the best solution on the validation set before the early stopping criterion is met (i.e., ten consecutive epochs with no improvements in the validation loss function).

We can observe that the running time of Deep-SE with random initialization (i.e., Deep-SE!pre-train) is slightly smaller than its pre-trained variant in 33 out of the 42 cases (79%) studied. When checking for statistical difference between the distribution of the running time of the two variants, the results of the Wilcoxon test show $p-value = 0.956$.
for the Choet dataset and \( p - value = 0.791 \) for the Tawosi dataset, indicating that we cannot accept the alternative hypothesis that these results are stastically significant different. Similarly, the comparison between the number of epochs does not reveal any significant difference (\( p - value = 0.83 \)), although on average, Deep-SE without pre-training took slightly fewer epochs to converge (see Table 12).

Overall, the results show that using the pre-trained embedding weights and LSTM layer do not enhance Deep-SE’s accuracy or convergence speed; thus, it can be skipped to save the high cost required by such a pre-training procedure.

**Answer to RQ5:** Pre-training the lower layer of Deep-SE with user stories from other projects has a negligible effect in improving its SP estimation accuracy or convergence speed; thus, it can be skipped.

### 6 Discrepancies

Our replication of the work by Choetkiertikul et al. [5] provided different results from the original study in some cases. In RQ1.1, we found that the results we achieved for Deep-SE and the baselines are different from that of the original study. Moreover, in RQ2.1, although the results obtained in our study for TF/IDF-SE matched those reported in the original study, we found differences in the results of Deep-SE between the two studies. Finally, in RQ3.1, we observed differences in the results of Deep-SE between our replication and the original study, although they support the same conclusion as the one made in the original study.

In order to investigate the causes of the discrepancies we: (i) peer-reviewed the modifications and fixes we performed on the original source code and results to make sure it is correct (i.e., the second author reviewed the code written by the first author, and double-checked the results), (ii) check the source code and results included in the replication package provided by the authors [15]; (iii) contact the authors of the original study. We discuss below the possible reasons for observing different results.

First of all, we notice a discrepancy in the results reported for the baseline estimators, namely Mean and Median. These naive baselines are deterministic, and therefore we do expect them to achieve the same results when applied to the same data. However, this was not the case, and further investigation suggests that there may have been a misuse of these estimators in the original study. Indeed, the results of the original study are reproducible only by adding one (1.0) to the Mean and Median point estimates. Since this addition modifies the original estimates of the baselines, it leads to an incorrect absolute error computation on the test set. This modification of the original estimates is not described or justified in the original paper, neither in the more general effort estimation literature, and as such we conclude that it should not be used. Therefore, for all the RQs investigated in this paper, we report the correct results for the Mean and Median estimators based on the definition given in the literature as described in Section 4.4.

By investigating the source code made publicly available by the authors [15], we also found a discrepancy between the description of Deep-SE provided in the paper and its implementation as included in their replication package. In fact the Python implementation for Deep-SE applies a transformation on the SP distribution before using it for training, validation, and testing. Through this transformation, all the original results of Deep-SE are different from those reported in the original study. Indeed, the results of the original study are reproducible only by adding one (1.0) to the Mean and Median point estimates. Since this addition modifies the original estimates of the baselines, it leads to an incorrect absolute error computation on the test set. This modification of the original estimates is not described or justified in the original paper, neither in the more general effort estimation literature, and as such we conclude that it should not be used. Therefore, for all the RQs investigated in this paper, we report the correct results for the Mean and Median estimators based on the definition given in the literature as described in Section 4.4.

| Project          | Running Time (Seconds) | Epochs |
|------------------|------------------------|--------|
|                  | Deep-SE | Deep-SE/pre-train | Deep-SE | Deep-SE/pre-train |
| MESSOS           | 757     | 702               | 113     | 109              |
| ALLOY            | 144     | 159               | 111     | 113              |
| TISTUD           | 1,641   | 1,576             | 106     | 106              |
| APSTUD           | 317     | 251               | 122     | 111              |
| TIMOB            | 226     | 164               | 130     | 108              |
| BAM              | 198     | 149               | 131     | 128              |
| CLOV             | 601     | 486               | 108     | 115              |
| DURACLOUD        | 239     | 217               | 125     | 111              |
| DM               | 179     | 150               | 117     | 108              |
| MDL              | 303     | 261               | 112     | 109              |
| MULE             | 1,193   | 892               | 117     | 106              |
| TISTUD           | 272     | 217               | 137     | 147              |
| FAB              | 214     | 172               | 118     | 107              |
| STL              | 161     | 143               | 116     | 115              |
| DM               | 2,942   | 2,711             | 110     | 110              |
| COMPASS          | 259     | 166               | 171     | 117              |
| CONSERVER        | 276     | 307               | 107     | 129              |
| EVG              | 2,421   | 1,967             | 173     | 175              |
| MDL              | 822     | 719               | 112     | 126              |
| MULE             | 1,586   | 1,495             | 111     | 115              |
| NEXUS            | 604     | 626               | 106     | 106              |
| XD               | 466     | 380               | 110     | 109              |
| TDP              | 312     | 259               | 110     | 110              |
| TDB              | 409     | 434               | 115     | 117              |
| TESB             | 466     | 350               | 119     | 110              |
| Total            | 19,273  | 16,564            | 3,115   | 3,041            |
| Mean             | -       | -                 | 119.81  | 114.81           |

Table 12: RQ5. Comparing running time and number of epochs that each of the methods (i.e., Deep-SE when used with initialization of weights through pre-training (Deep-SE) and Deep-SE with random initialization (Deep-SE/pre-train)) needs to converge, on the (a) Choet and (b) Tawosi datasets. Best results in bold.
The following caveats arise using such a transformation: (i) it is not mentioned in the original paper [5], which can render future replications and/or adoption of the method non-consistent or unreliable; (ii) our results (RQ1) show that without applying the pre-processing step, an estimation technique tends to perform generally worse. (iii) the current source code applies the pre-processing step to the entire dataset (i.e., before splitting it into training, validation, and test sets). However, while applying such a transformation on the training set might be acceptable, it should not be applied on the test set since it can undermine the validation process by inflating its accuracy, given that in real world settings, the test set is unknown and such a transformation cannot be applied at prediction time. The corresponding author of the original study explained to us that they performed this pre-processing to investigate the effect of eliminating outliers from the training set, but it was not their intention to apply it to the test set.

Therefore, we conclude that using the code as provided in the replication package might lead users, unaware of the application of such a transformation in the code, to unjustly/unfairly compare Deep-SE with other approaches which do not include this pre-processing step.

This may be the case of a recent work by Abadeer and Sabetzadeh [16] that used Deep-SE with a dataset of industrial projects. Using the Deep-SE’s implementation as provided in the replication package, will automatically apply the transformation to the entire dataset before training, validation, and testing, and it will replace all those SPs with a value of 13 (which are 4% of the issues) with the value 8. Therefore, Deep-SE may produce a lower (better) MAE than the baselines in case they are used on non-transformed data.

Based on the above observations, for replication purposes we reported the result of Deep-SE both with and without transformed SPs for RQ1.1, and with transformation for RQ5. Whereas, for RQ1.2, RQ2, RQ3, and RQ4, we report the results of Deep-SE without transformation.

7 Conclusion

Considering the variations observed between the replication and the original study [5], we cannot confirm the same conclusions made in the original study for RQs1-2: Deep-SE did not outperform the Median baseline for all projects (RQ1) and was not always better than TF/IDF-SE (RQ2) with statistical significance. Moreover, the statistical test on the distribution of the absolute errors showed that, for both Deep-SE and TF/IDF-SE, the difference with the Median estimator is not significant in at least half of the projects investigated (RQ2.1). A broader experiment with the Tawosi dataset (RQ2.2), which contains a larger number of projects and issues, showed that the results of the two methods are significantly different in only one-fifth of the cases.

Furthermore, we observed that Deep-SE is not so effective for cross-project estimation (RQ3), thus confirming the conclusion made in the original study. Using other additional projects for training Deep-SE or augmenting the training set with issues from other projects developed within the same repository does not improve its prediction performance statistically significantly (RQ4). We also showed that the pre-training of the lower layers of Deep-SE, which demands a large number of issues and takes a long time to execute, does not have a significant effect on its accuracy nor convergence (RQ5).

Overall, our study reveals that both sophisticated techniques like Deep Learning (Deep-SE) and simpler ones like TF/IDF-SE, which in essence try to find semantic similarities between user stories to estimate effort, very often fail to provide statistically significantly better estimations than a naïve baseline technique like the Median estimator. This suggests that semantic similarity between user stories might not be sufficient, or even effective, for issue-level effort estimation. For instance, it is possible that two user stories that discuss the same concept (thus are semantically related) demand different amounts of effort to be resolved (e.g., one asks for a new feature to be implemented and the other requires a small change in an already implemented feature).

Table 13 shows an example of five semantically related user stories from the Spring XD project. As we can see, these semantically similar user stories are estimated to have different story points. It means that, the distribution of the story points in the groups of semantically related user stories is not necessarily different from the distribution of the story points in the set of all user stories in the project. In other words, the semantic similarity is not enough to discriminate user stories with regard to their story point worth of effort. That is a possible explanation for why methods like Deep-SE and TF/IDF-SE, that rely on semantic similarities between user stories to make a mapping between the groups of similar user stories and their story points, fail to perform better than the Median estimator. Future work demands an exploration to devise new effort drivers from issue reports and exploit them for more accurate effort estimation.

Acknowledgments

Vali Tawosi, Rebecca Moussa and Federica Sarro are supported by the ERC Advanced fellowship grant no. 741278. We would like to thank the authors of the original papers [3], [9] for being cooperative, replying to our queries, and supporting this replication.

References

[1] M. Cohn, Agile estimating and planning. Pearson Education, 2005.
[2] A. Trendowicz and R. Jeffery, “Software project effort estimation,” Foundations and Best Practice Guidelines for Success, Constructive Cost Model—COCOMO II, pp. 277–293, 2014.
[3] K. Beck and M. Fowler, Planning Extreme Programming, 1st ed. Boston, MA, USA: Addison-Wesley Longman Publishing, 2000.
[4] M. Usman, E. Mendes, F. Weidt, and R. Britto, “Effort estimation in agile software development: a systematic literature review,” in PROMISE, 2014, pp. 82–91.
[5] M. Choetkiertikul, H. K. Dam, T. Tran, T. Pham, A. Ghose, and T. Menzies, “A deep learning model for estimating story points,” IEEE TSE, vol. 45, no. 7, pp. 637–656, 2019.
[6] M. Jørgensen, “A review of studies on expert estimation of software development effort,” JSSE, vol. 70, no. 1-2, pp. 37–60, 2004.
[7] F. Sarro, R. Moussa, A. Petrozziello, and M. Harman, “Learning from mistakes: Machine learning enhanced human expert effort estimates,” IEEE Transactions on Software Engineering, 2020.
[8] P. Abrahamsson, I. Fronza, R. Moser, J. Vlasenko, and W. Pedrycz, “Predicting development effort from user stories,” in ESEM. IEEE, 2011, pp. 400–403.
[9] S. Porru, A. Murgia, S. Demeyer, M. Marchesi, and R. Tonelli, “Estimating story points from issue reports,” in PROMISE, 2016, pp. 1–10.
| Issue Key | Title | Description | Story Point |
|-----------|--------|-------------|-------------|
| XD-2347  | Document Kafka message bus | As a user, I’d like to refer to documentation in wiki so that I can setup and configure Kafka as a message bus as recommended. | 2 |
| XD-2361  | Pre-allocate partitions for Kafka message bus | As a user, I want Spring XD’s message bus to be able to pre-allocate partitions between nodes when a stream is deployed, so that rebalancing doesn’t happen when a container crashes and/or it’s redeployed. | 8 |
| XD-3164  | Kafka bus defaults configurable at producer/consumer level | As a developer, I want to be able to override Kafka bus defaults for module consumers and producers, so that I can finely tune per topic configuration and behaviour. Such properties should include -autoCommitEnabled, queueSize, maxWait, batchSize, and fetchSize for consumers-batchSize, batchTimeout for producers. | 3 |
| XD-3516  | Document partitioning through deployment properties | As an s-e-d user, I’d like to have documentation on deployment manifest, so I could refer to the relevant bits on partitions. I’d like to understand how stream with e... | 2 |
| XD-3740  | Kafka message bus maxWait property is not set up | The maxWait property from server.xml in the message bus section for kafka is not propagated through the code, it is ignored. | 1 |

[10] R. G. Soares, “Effort estimation via text classification and autoencoders,” in 2018 International Joint Conference on Neural Networks (IJCNN). IEEE, 2018, pp. 01–08.

[11] E. Scott and D. Pfahl, “Using developers’ features to estimate story points,” in ICSSP, 2018, pp. 106–110.

[12] M. D. Uncles and S. Kwok, “Designing research with in-built differentiated replication,” Journal of Business Research, vol. 66, no. 9, pp. 1398–1405, 2013.

[13] N. Juristo and O. S. Gómez, “Replication of software engineering experiments,” in Empirical software engineering and verification. Springer, 2010, pp. 60–88.

[14] A. Santos, S. Vegas, M. Oivo, and N. Juristo, “Comparing the results of replications in software engineering,” Empir. Softw. Eng, vol. 26, no. 2, pp. 1–41, 2021.

[15] “DeepSE Source Code - GitHub.” [Online]. Available: https://github.com/SEAnalytics/datasets/tree/master/storypoint/IEEETSE2018

[16] M. Abadeer and M. Sabetzadeh, “Machine learning-based estimation of story points in agile development: Industrial experience and lessons learned,” in REW. IEEE, 2021, pp. 106–115.

[17] S. Suthaharan, in Machine Learning Models and Algorithms for Big Data Classification. Springer, 2016, pp. 207–235.

[18] A. Corazza, S. Di Martino, F. Ferrucci, C. Gravino, F. Sarro, and E. Mendes, “Using tabu search to configure support vector regression for effort estimation,” Empir. Softw. Eng, vol. 18, no. 3, pp. 506–546, 2013.

[19] D. F. Specht, “Probabilistic neural networks,” Neural networks, vol. 3, no. 1, pp. 109–181, 1990.

[20] M. Shepperd and C. Schofield, “Estimating software project effort using analogies,” IEEE Transactions on software engineering, vol. 23, no. 11, pp. 736–743, 1997.

[21] I. Rish et al., “An empirical study of the naive bayes classifier,” in IJCAI 2001, vol. 3, no. 22, 2001, pp. 41–46.

[22] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[23] F. A. Gers, J. Schmidhuber, and F. Cummins, “Learning to forget: Continual prediction with lstm,” Neural computation, 1999.

[24] T. Pham, T. Tran, D. Phung, and S. Venkatesh, “Faster training of very deep networks via n-porm gates,” in ICPR. IEEE, 2016, pp. 3542–3547.

[25] S. Shepperd and S. MacDonell, “Evaluating prediction systems in software project estimation,” IST, vol. 54, no. 8, pp. 820–827, 2012.

[26] W. B. Langdon, J. Dolado, F. Sarro, and M. Harman, “Exact mean absolute error of baseline predictor, marpt,IST,” IST, vol. 73, pp. 16–18, 2016.

[27] B. A. Kitchenham, L. M. Pickard, S. C. MacDonell, and M. J. Shepperd, “What accuracy statistics really measure,” IEEE Software, vol. 148, no. 3, pp. 81–85, 2001.

[28] “DeepSE, fixed Python source code, TF/IDF-SE Python source code, and the datasets used in this study.” [Online]. Available: https://highshare.com/s/7097e1e15e524266b570

[29] E. Mendes, M. Kalinowski, D. Martins, F. Ferrucci, and F. Sarro, “Cross- vs. within-company cost estimation studies revisited: an extended systematic review,” in EASE, 2014, pp. 121–1210.

[30] L. Minku, F. Sarro, E. Mendes, and F. Ferrucci, “How to make best use of cross-company data for web effort estimation?” in ESEM. IEEE, 2015, pp. 1–10.

[31] F. Ferrucci, E. Mendes, and F. Sarro, “Web effort estimation: The value of cross-company data set compared to single-company data set,” in PROMISE. ACM, 2012, pp. 29–38.

[32] A. A. Bangash, H. Sahar, A. Handlee, and K. Ali, “On the time-based conclusion stability of cross-project defect prediction models,” Empir. Softw. Eng, vol. 25, no. 6, pp. 5047–5083, 2020.

[33] M. Jimenez, R. Rwemalika, M. Papadakis, F. Sarro, Y. L. Traon, and M. Harman, “The importance of accounting for real-world labelling when predicting software vulnerabilities,” in ESEC/SIGSOFT FSE. ACM, 2019, pp. 679–685.

[34] D. Falesi, J. Huang, L. Narayana, J. T. Thai, and B. Turhan, “On the need of preserving order of data when validating within-project defect classifiers,” Empir. Softw. Eng, vol. 25, no. 6, pp. 4805–4830, 2020.

[35] L. Taylor and G. Nitschke, “Improving deep learning using generic data augmentation,” arXiv preprint arXiv:1708.06020, 2017.

[36] A. Cichocki, K. W. Jagan, and G. Grochowski, “Data augmentation for improving deep learning in image classification problem,” in 2018 international interdisciplinary PhD workshop (IIPhDW). IEEE, 2018, pp. 117–122.

[37] “Jira — Issue & Project Tracking Software — Atlassian.” [Online]. Available [https://www.atlassian.com/software/jira]