TEP-GNN: Accurate Execution Time Prediction of Functional Tests using Graph Neural Networks

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ABSTRACT

Predicting the performance of production code prior to actually executing or benchmarking it is known to be highly challenging. In this paper, we propose a predictive model, dubbed TEP-GNN, which demonstrates that high-accuracy performance prediction is possible for the special case of predicting unit test execution times. TEP-GNN uses FA-ASTs, or flow-augmented ASTs, as a graph-based code representation approach, and predicts test execution times using a powerful graph neural network (GNN) deep learning model. We evaluate TEP-GNN using four real-life Java open source programs, based on 922 test files mined from the projects’ public repositories. We find that our approach achieves a high Pearson correlation of 0.789, considerable outperforming a baseline deep learning model. However, we also find that more work is needed for trained models to generalize to unseen projects. Our work demonstrates that FA-ASTs and GNNs are a feasible approach for predicting absolute performance values, and serves as an important intermediary step towards being able to predict the performance of arbitrary code prior to execution.

1 INTRODUCTION

Performance is a critical quality property of many real-life software systems. Hence, performance modeling and analysis have gradually become an increasingly important part of the software development life-cycle. Unfortunately, predicting the performance of real-life production code is well-known to be a difficult problem – predicting the absolute execution time of applications based on code structure is challenging as it is a function of many factors, including the underlying architecture, the input parameters, and the application’s interactions with the operating system [24]. Consequently, works that attempted to predict absolute performance counters (e.g., execution time) for arbitrary applications from source code generally report poor accuracy [21, 23]. However, recent research has shown that predicting performance characteristics is indeed possible in more specialized contexts, via the application of modern machine learning architectures. For example, Guo et al. successfully predict the execution time of a specific untested configuration of a configurable system [7, 8], Samoaa and Leitner have shown that the execution time of a benchmark with specific workload configuration can be predicted [26], and Laaber et al. have shown that a categorical classification of benchmarks into high- or low-variability is feasible [13].

In this work, we demonstrate that another context where performance prediction is possible is the prediction of execution times of functional tests. Test execution times are crucial in agile software development and continuous integration. While individual test cases might have short execution times, software products often have thousands of test cases, which makes the total execution time in the build process high. Researchers have been working on solutions to speed up the testing process by optimizing the code or prioritizing test cases [5, 12, 20, 30]. The goal of this study is to provide the developers with predictions of the execution times of their test cases, and consequently giving them an early indication of the time required to run the cases in the build process. We believe that this would support decisions regarding code optimization and test case selection in early stages of the software life-cycle.

In this paper, we propose an approach dubbed TEP-GNN (Test Execution Time Prediction using Graph Neural Networks) that makes use of structural features of test cases (the abstract syntax tree, AST). In TEP-GNN we enrich the AST with various types of edges representing data and control flow. Following Wang and Jin, we refer to this resulting graph as flow-augmented abstract syntax trees (FA-AST) [33]. We apply a graph neural network (GNN) deep learning model, more specifically GraphConv [22], on the resulting FA-ASTs to predict execution times. We train and test our model on a dataset collected from four well-known open source projects hosted on GitHub: H2 database\(^1\), a relational database, RDF4J\(^2\), a project for handling RDF data, systemDS\(^3\), an Apache project to

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\(^1\)https://github.com/h2database/h2database  
\(^2\)https://github.com/eclipse/rdf4j  
\(^3\)https://github.com/apache/systemds
manage the data science life cycle, and finally the Apache remote procedure call library Dubbo⁴. As labelled ground truth data, we collect 922 real test execution traces from these projects’ publicly available build systems.

We conduct experiments with our TEP-GNN model to answer the following research questions:

- **RQ1**: How accurately can the absolute execution time of a test file consisting of one or multiple test cases be predicted using FA-ASTs and GNNs?
- **RQ2**: Does our usage of GraphConv improve execution time prediction compared to a baseline using Gated Graph Neural Networks (GGNN), as frequently used in previous software engineering research [1, 6]?
- **RQ3**: How well are models trained on a subset of projects transferable to unseen other projects? Can a TEP-GNN model trained on a subset of projects predict the execution time of tests in a project that was not used during training?

Our results show that using TEP-GNN, test execution time can be predicted with a very high prediction accuracy (Pearson correlation of 0.789). Further, we show that our usage of GraphConv indeed improves the model significantly over GGNN. Finally, we show that trained models are not easily transferable. We conclude that test execution times can indeed be predicted using GNN models with high accuracy, even based on performance counters that have been collected “in the wild” by real projects (as opposed to performance measurements collected on a dedicated performance testing machine). Even though test cases are shorter and structurally simpler than arbitrary programs, we see our results as an important stepping stone towards the prediction of the performance of arbitrary software systems prior to execution. However, more work is needed to train general models that can be applied to arbitrary, unseen projects.

## 2 THE TEP-GNN APPROACH

In this section, we introduce TEP-GNN. We first provide a general overview of the model and discuss the problem addressed in this paper, followed by a detailed discussion of the main components of TEP-GNN (FA-ASTs and the machine learning pipeline based on the GraphConv [22] higher order GNN).

### 2.1 Approach Overview

Our goal in this paper is to predict the execution time of test cases based on static code information alone, i.e., without access to prior benchmarking of the test case or dynamic analysis data. The general procedure of our TEP-GNN approach is sketched in Figure 1. To process a test file, we first parse it into its AST. Next, we build a graph representation (FA-AST) by adding edges representing control and data flow to the AST. We then initialize the embeddings of FA-AST nodes and edges before jointly feeding a vectorized FA-AST into a GNN. We use a 3-layer higher order graph convolution neural network to predict the execution time. Each layer is followed by a ReLU activation function. Since GNN learns node embedding, we use global max pooling to compute a graph embedding. Finally, the graph embedding goes into two Linear layers with a ReLU and a sigmoid activation function to perform the prediction of the test execution time. To train our model we use the mean square error loss.

### 2.2 Problem Definition

Given a test file (source code containing one or multiple test cases) $C_i$ and the corresponding run-time value $X_i$ (execution time of all test cases in the file), for a set of test files with known execution times we can build a training set $D = (C_i, X_i)$. We aim to train a deep learning model for learning a function $\phi$ that maps a test file $C_i$ to a feature vector $v$ mapped to the corresponding value $X_i$.

### 2.3 Building Flow-Augmented Abstract Syntax Trees

Recent studies [27] emphasize the importance of the code representation when using deep learning in software engineering. Hence, and given the complexity of predicting performance, prediction based on the syntactical information extracted from ASTs alone is not sufficient to achieve high-quality predictions. In TEP-GNN, the basic structural information provided by the AST is enriched with semantic information representing data and control flow. Consequently, the tree structure of the AST is generalized to a (substantially richer) graph, encoding more information than code structure alone. This idea is based on the earlier work by Wang and Jin [33], who have also introduced the term FA-AST for this kind of source code representation.

```
package org.myorg.weather.tests;

import static org.junit.jupiter.api.Assertions.assertEquals;
import org.myorg.weather.WeatherAPI;
import org.myorg.weather.Flags;

public class WeatherAPITest {
    public void testTemperatureOutput () {
        WeatherAPI api = new WeatherAPI();
        @Test
        public void testTemperatureOutput() {
            double currentTemp = api.getCurrentTemp();
            if(currentTemp <= 3.06)
                assertEquals(Flags.FREEZE, f);
            else
                assertEquals(Flags.THAW, f);
        }
    }
}
```

**Listing 1: A Simple JUnit 5 Test Case**

#### 2.3.1 AST Parsing

We demonstrate our approach for constructing FA-ASTs for test files using the example of a Java JUnit 5 test case (see Listing 1). In this example, a single test case `testTemperatureOutput()` is presented that tests a feature of an (imaginary) API. As common for test cases, the example is short and structurally relatively simple. Much of the body of the test case consists of invocations to the system-under-test and calls of JUnit standard methods, such as `assertEquals`. We speculate that these properties make predicting test execution time a more tractable problem.

⁴https://github.com/apache/dubbo
than predicting performance of general-purpose programs, which previous authors have argued to be extremely challenging [21, 23].

FA Next Sibling (c): This connects each node (both terminal and non-terminal) to its next sibling. This allows us to model the order of instructions in an otherwise unordered graph structure. In Figure 2, such an edge would be added, for example, connecting the first usage of api and with the CONSTR node (representing a Java constructor call).

FA Next Use (d): This type of edge connects a node representing a variable to the place where this variable is next used. For example, the variable api is declared in Line 10 in Listing 1, and then used next in Line 14.

Figure 3 shows an example augmenting the AST in Figure 2 (and, consequently, the example test case in Listing 1). Solid black lines indicate the AST parent and child relationships (for simplicity indicated through a single arrow, read from top to bottom). Red dashed arrows refer to the new edges added to represent the data and control flow in the FA-AST, with letter codes indicating the edge type. Terminal nodes are connected with FA Next Token edges (b), modeling the order of terminals in the test case. Similarly, the ordering of siblings is modeled using FA Next Sibling edges (c). Finally, data flow is modeled by connecting each variable to their next usage via FA Next Use edges (d). Edge types (e), (f), and (i) represent a control flow statement, which will be discussed in the following. Multiple edges of different types are possible between the same nodes. For example, the terminal nodes Flags.FREEZE and f are connected via both, an FA Next Token edge (b) and an FA Next Sibling edge (c).

2.3.3 Capturing Control Flow. In a second augmentation step, we now add further edges representing the control flow in the test cases. We currently support if statements, while and for loops, as well as sequential execution. We currently do not support switch statements or do-while loops, as these are less common in test cases. Test files containing these elements will still be parsed successfully, but these control flow constructs will not be captured by the FA-AST. Specifically, the following further edges are added:

FA If Flow (e): This type of edge connects the predicate (condition) of the if-statement with the code block that is executed if the condition evaluates to true. Every if statement contains exactly one such edge by construction.

FA Else Flow (f): Conversely, this edge type connects the predicate to the (optional) else code block. Figure 4 depicts how if-statements are modeled.

FA While Flow (g): A while loop essentially entails two elements - a condition and a
Figure 3: Flow-Augmented AST (FA-AST) for the example presented in Listing 1. Solid lines represent AST parent and child edges, and dashed lines different types of flow augmentations.

Figure 4: Capturing the control flow of if statements.

code block that is executed as long as the condition remains true. We capture this through a FA While Flow (g) edge connecting the condition to the code block, and an FA Next Use (d) edge in the reverse direction. The latter is used to model the next usage of a loop counter. Figure 5 shows this.

FA For Flow (h):
For loops are conceptually similar to while loops. We use FA For Flow (h) edges to connect the condition to the code block, and an FA Next Use (d) edge in the reverse direction. Similar to the modelling of while-loops, FA Next Use (d) relates to the usage (typically incrementing) of a loop counter. This is again illustrated in Figure 6.

FA Next Statement Flow (i):
In addition to the control flow constructs discussed so far, Java of
course also supports the simple sequential execution of multiple statements in a sequence within a code block. FA Next Statement Flow edges (i) are used to represent this case. Different from the constructs discussed so far, a code block can contain an arbitrary number of children, and the FA Next Statement Flow edge is always used to connect each statement to the one directly following it. An illustration is shown in Figure 7.

Referring back to Figure 3, two types of control flow annotations are visible - the modelling of the if-statement in lines 16 to 19 of the test case on the right-hand side, and various sequential executions (FA Next Statement flow (i) ) edges. Further note how flow annotation adds a large number of edges to even a very small AST, transforming the syntax tree into a densely connected graph. This rich additional information can be used in the next step by our GNN model to predict highly accurate test execution times.

![Figure 7: Capturing the control flow of sequential execution.](image)

2.4 GNN Model for Test Execution Time Prediction

Once the FA-AST graph has been built for a test file using the three steps discussed above, we use a higher order GNN model to predict the execution time of the Java code.

Graphs are complex structures, verifying if two graphs are identical (also known as isomorphism test) is an important and difficult task. It is unknown if the problem can be solved in polynomial time or it is computationally intractable for large graphs. A fast heuristic to verify if two graph are the same is the k-Weisfeiler-Leman test [34]. The algorithm produces for each graph a canonical form. Then, if the canonical forms of two graphs are not equivalent, the graphs are not considered isomorphic. However, there is the possibility that two non-isomorphic graphs share a canonical form. Thereby, this test might not provide a conclusive evidence that two graphs are isomorphic. Morris et al. [22] prove that a GNN network can be as powerful as the k-Weisfeiler-Leman test with k equal to 1, in which the canonical form propagates the information by nodes. With k greater than 1, the information is propagated among substructures of order k. Morris et al. [22] also propose a higher order graph convolution layer (k-GNN), wherein messages are exchanged among nodes, edges and substructure with tree nodes (triads). Once messages are exchanged among substructures, each node has a latent representation. In order to predict property of the graphs (i.e., the execution time of a graph representing Java code), node embeddings are globally aggregated (pooling step) with an ordering invariant function (i.e. sum, max, mean). In particular, k-GNN is defined as: given is an integer k the k-element subset \( V(G) \) over \( V(G) \). Let \( s = \{s_1, s_2, \ldots \} \) be k-set in \( V(G) \), then the neighborhood of \( s \) is defined as:

\[
N(s) = \{ t \in [V(G)]^k | |s \cup t| = k - 1 \}\]

In Equation 1, the neighbour of a k-set is defined as the set of k-set such that the intersection of their cardinality is equal to \( k - 1 \). The local neighborhood is defined as:

\[
N_L(s) = \{ t \in N(s) | (u, w) \in E(G) \text{ with } u \in s \cup t \text{ and } w \in t \} \]

(2)

The local neighborhood defined in Equation 2 is a subset of the neighbour (eq. 1). Finally, the k-GNN is defined as:

\[
j^{(i)}_{k,L}(s) = \sigma(j^{(i-1)}_{k,L}(s) \cdot W_1^{(t)} + \sum_{u \in N_L(s)} j^{(i-1)}_{k,L}(u) \cdot W_2^{(t)})
\]

(3)

The l-th layer of the k-GNN computes an embedding of \( s \), using the non linear activation function \( \sigma \) of the summation over the substructure itself in the previous layer (i.e., layer \( l - 1 \)) and the summation over the previous layer embedding of each local neighbor of the substructure \( s \). A scheme of the deep learning architecture we use in TEP-GNN is shown in Figure 8. Due to the proven superiority of higher order GNN with respect to classic GNN [22], we adopt GraphConv, a PyTorch-geometric implementation of the higher order Graph Neural Network layer. The GNN is composed of three convolutional layers, each layer has a GraphConv layer with a ReLU activation function and a batch normalization. Then node embeddings are converted into a graph embedding using a global max pooling layer. Finally, the predicted execution time is predicted using two multi-layers perceptrons with ReLU and sigmoid activation functions. We use the Mean Square Error as the loss function. In order to make the learning easier for the neural network, and to reduce the optimization problems, real execution times have been normalized between 0 and 1.

3 EVALUATION

We now present the results of an experimental evaluation of TEP-GNN based on open source Java projects. As training and test data we make use of existing test suite execution traces from the study subjects’ build systems. A replication package containing the scripts used to implement the TEP-GNN approach, all data used in the evaluation, as well as all analysis scripts, are available [9].

3.1 Dataset

Related studies in performance engineering frequently collect their own performance data, for example by repeated execution of the projects on a researcher’s laptop [28], in cloud virtual machines [14], or on controlled hardware [29]. To increase the realism of the study we have chosen a different approach – we harvest existing execution traces from an open source build system (GitHub), and extract test execution times from this public data. This data represents actual, real-life test execution times. However, we do not have the option to collect more data on-demand, and we do not know what precise hardware has been used to collect the data.

To collect the data, we searched for projects to serve as study subjects. We applied the following selection criteria: (i) projects written in Java; (ii) available on GitHub; (iii) include test results published on GitHub; and (iv) use GitHub shared runners as build system.
Based on these criteria, we selected four projects of diverse application domains, i.e., databases, web servers, and data science life-cycle (systemDS, H2, Dubbo, and RDF4J). These are depicted in Table 1. The first column shows the project’s name, the second provides a brief description of the project. The third column shows the number of distinct test files extracted from the project. As for the fourth column, it shows the total number of runs performed in the testing job. The last two columns show the total number of tokens in the entire project test files and the vocabulary size (the number of distinct nodes in the graphs). We observe that RDF4J, a triplestore database used in semantic web contexts [25], contains more test files than the other projects. For the H2 relational database and systemDS we were able to collect the most test runs. Finally, it should be noted that H2 has the highest code density as measured by the number of nodes and the resulting vocabulary size by a wide margin. This indicates that H2 tests are generally larger and more complex than the test cases in the other study subjects.

All data was extracted from GitHub-hosted runners, which are virtual machines hosted by GitHub with the GitHub Actions runner application installed. All shared runners can be assumed to use the same hardware resources, which is available at GitHub’s website, and each job runs in a fresh instance of the virtual machine. Additionally, all jobs from which the data is extracted uses the same operating system, specifically Ubuntu 18.04. This allows us to minimize bias introduced by variations in execution environment or hardware.

For collecting test execution traces we looked at the latest successful action workflow run for each project. We then extracted the run times from the test report in the workflow, and mined the corresponding source code files from the respective project repositories in order to feed them to the parser. For H2, some test cases are run several times during the same build job. In these cases, we recorded the average of the run times. As the execution times of tests can vary dramatically between and within projects, to increase the efficiency of the model training, we normalize each execution time to interval $[0; 1]$. Hence, our final dataset includes distinct test files, each associated with one runtime value between 0 and 1. Then after model training, we denormalize the runtime value and present the results based on the original values.

Table 2 indicates how prevalent different control flow nodes were in the test cases of our study subjects. For all projects, block statements are the most frequent control flow construct, since sequential executions widely exist in nearly all programs. For loops are substantially more common than while loops, and if statements are frequent. Do-while loops and switch statements, which are currently unsupported by TEP-GNN, are both quite rare in the tests of our subjects (not shown in the table).

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Table 1: Overview of study subjects.

| Project | Description                                      | Test files | Test runs | Number of nodes | Vocabulary size |
|---------|--------------------------------------------------|------------|-----------|-----------------|----------------|
| systemDS | Apache Machine Learning system for data science lifecycle | 127        | 1321      | 110631          | 3161           |
| H2      | Java SQL database                                | 194        | 1391      | 405706          | 17972          |
| Dubbo   | Apache Remote Procedure Call framework           | 123        | 524       | 75787           | 4499           |
| RDF4J   | Scalable RDF processing for Java                 | 478        | 1055      | 214436          | 10755          |
| **Total** |                                                | **922**    | **4291**  | **806580**      | **36387**      |

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6https://docs.github.com/en/actions/using-github-hosted-runners/about-github-hosted-runners#supported-runners-and-hardware-resources
Table 2: Occurrences of Control Flow Nodes in Each Project

| Control Flow Statement | systemDS | H2 | Dubbo | RDF4J |
|------------------------|----------|----|-------|-------|
| If Statement           | 166      | 1322 | 53    | 161   |
| While Loop             | 2        | 222  | 3     | 22    |
| ForStatement           | 196      | 1114 | 42    | 158   |
| Block Statement        | 293      | 2900 | 116   | 395   |
| Total                  | 707      | 5612 | 214   | 736   |

3.2 Results

In this section, we investigate the results of applying TEP-GNN to our dataset, answering RQ1 – RQ3 introduced in Section 1.

3.2.1 RQ1: Quality of Predictions. In order to answer the first research question, we combine the collected data for all projects into one dataset entailing 922 code fragments and associated normalized execution times. After that, we apply TEP-GNN as discussed in Section 2. For model training, we split the dataset into train and test sets using 80% and 20%, respectively. Each network is trained for 100 epochs. As optimizer we use Adam [11] with a learning rate = 0.001. To evaluate the results of our model, we use a Pearson correlation metric, a measure of linear correlation between two sets of data. In addition, as a loss function, we use mean squared error, which is the average squared difference between the estimated and actual values. All experiments have been executed in a machine equipped with a GeForce 940MX graphics card and 16GB of RAM.

Table 3: Results of the TEP-GNN on the entire dataset

|                      | Pearson correlation | Mean squared error |
|----------------------|---------------------|--------------------|
|                      | 0.789               | 0.017              |

Results are shown in Table 3. Our model trained on FA-AST is able to predict test execution times with a very high accuracy, as can be seen in the Pearson correlation (between predicted and actual execution times in the test data set) of 0.789, and a mean squared error of 0.017. These results substantially outperform the accuracy values reported in previous studies that attempted to predict absolute software performance counters [21, 23]. We argue that the key innovation that enables this high accuracy is the combination of FA-AST as a powerful code representation model and GraphConv as a modern GNN.

3.2.2 RQ2: Comparison of TEP-GNN Against a Baseline GNN. To validate the suitability of our approach and the selected GNN model, we compare it to a commonly used GNN baseline, called Gated Graph Neural Networks (GGNN) [17]. GGNNs are widely used in studies that attempt to learn code semantics [1, 6]. We compare the methods at two levels – for the entire dataset (similar to the analysis presented for RQ1) and at the level of individual projects.

Comparison for the entire dataset. We first apply both TEP-GNN and the baseline method to the dataset consisting of all projects. Figure 9 depicts the respective results. Our model outperforms the baseline, with a Pearson correlation that is higher almost up to 0.1 (i.e., 0.789 versus 0.697). Hence, we conclude that our model and GNN architecture is indeed more appropriate to predict the execution time of test cases than a more standard GGNN approach.

![Figure 9: Comparison of TEP-GNN and a baseline (applying GGNN to the same FA-AST graphs). Dot points show real (y axes) and predicted (x axes) execution times produced by our model. The dash line refers to the perfect prediction.](image)

Analyzing the results, we observe that TEP-GNN is able to achieve highly accurate predictions in most cases. However, there are rare outliers where our prediction model misses by approximately 20%. The baseline GGNN method, on the other hand, has a tendency to predict fairly uniform execution times between $10^2$ and $10^3$, almost independent of what the actually observed test execution time is. Hence, it suffers from lower accuracy scores.

Comparison for individual projects. In the next step, we conduct a similar analysis, but focused on individual projects. This study answers the question of how well TEP-GNN works if trained on and used by a single project. Thus, we train and test TEP-GNN and the baseline on each of the four projects individually. The results for each project are depicted in Figure 10.

We observe that in general the prediction quality is substantially lower if the model is trained on individual projects, both for TEP-GNN and the baseline. TEP-GNN still outperforms the baseline for each project, but only with negligible prediction performance differences in the case of H2 and Dubbo. For RDF4J, which contains the largest number of test cases (and, consequently, the largest number of graphs to learn from), the difference between our approach and the baseline remains larger.

From these results we conclude that (a) TEP-GNN indeed outperforms the baseline in all the settings we tested, but (b) our approach works best if sufficient training graphs are available in comparison to the size of the graphs and vocabulary (if graphs are complex and/or training data is sparse the difference between our approach and the baseline is insignificant); (c) finally, we conclude that both approaches appear to learn some transferable knowledge even when training on graphs that originate from a different project.
3.2.3 RQ3: Evaluation of Models Trained on Different Projects.

Based on the third conclusion above, we now raise the question if it is possible to build a generic model trained on a subset of projects and apply it to a new (unseen) project. Hence, we now train new TEP-GNN models using three of the projects in our dataset, and test on the fourth one. The results for all four combinations are shown in Figure 11.

We observe that the quality of predictions in this setting is in general rather disappointing, ranging from a Pearson correlation of 0.381 when testing on the H2 database to -0.02 when testing on systemDS. Interestingly, H2, which has the structurally most complex test cases in our study subjects, seems to perform better with a transferred model than the other projects, where test cases tend to be simpler. This is likely due to the test cases in projects such as systemDS mainly consisting of calls to the specific system-under-test, about which a transferred model clearly cannot learn any execution time properties.

Despite these results, we conclude that the models that achieve the highest prediction performance are trained with data across multiple projects, including ones with both complex and simpler test cases. A more general model, i.e., a model that has been trained using data of multiple projects (including the one that it is being applied to) is able to outperform a "pure" model that is trained and tested on a single, individual project.

4 DISCUSSION

Our study results show that the accurate prediction of execution times of test suites is possible. This gives developers an early indication of the time required to run the cases in the build process, deciding in the process if techniques such as test case selection are required.

4.1 Lessons Learned

FA-ASTs are a promising approach to represent source code for performance prediction. Unlike previous work [21, 23, 35], our goal in this study was to treat performance prediction as a regression rather than a classification (slow or fast) problem. Our results in Section 3.2 indicate that using flow augmentation we are able to achieve good prediction quality. Furthermore, more information could be added to the FA-AST, such as program dependency graphs. We speculate that this approach is also promising to predict the performance of more complex, arbitrary code; however, more specific experiments in this direction need to be carried out as future research.
GraphConv substantially outperforms the more common GGNN models in performance prediction as long as sufficient data is available. As discussed in Section 3.2, our GraphConv based GNN model substantially outperforms GGNN, which is a currently commonly used graph neural network model in software engineering research [1, 6]. However, this is only true if sufficient data is available – when training models for individual projects, we observed that, due to the limited amount of training data available in these cases, the performance difference between our GraphConv based model and the GGNN baseline was minimal. We conclude that, as long as sufficient data is available, GraphConv should also be investigated in other software engineering contexts that make use of GNNs.

TEP-GNN in its current form is not able to generalize to unseen projects. While TEP-GNN can effectively predict the execution time of unseen test files, it can only do so if other test cases from the same project have been used to build the model. This implies that much of what the model learns about test case performance during training is project-specific and does not generalize to other projects. This is not surprising, given that the core of test cases consist of invocations to the system-under-test, which will be different from project to project. However, our results also demonstrate that training a model on test cases originating from a range of different projects leads to better predictions than training on a single project. This indicates that some cross-project learning indeed happens. Evidently, for practitioners a general model that can be applied to any project, without the need to train first based on historical executions from the same project, would be much more directly useful. Hence, future research should investigate whether approaches such as meta-learning [31] could be used to build more transferable models. At the very least, we hypothesize that general prediction models for project families, such as Apache or Eclipse projects, could be built.

4.2 Threats to Validity

Similar to other experimental studies in software engineering, our work is subject to certain limitations and threats to validity, which we elaborate in the following.

Internal Validity Threats. A key design choice in our study was the usage of existing, real-world data from GitHub’s build system, rather than collecting performance data ourselves (e.g., on a dedicated experiment machine). This has obvious advantages with regards to the realism of our approach, but raises the threat that our training and test data may be subject to confounding factors outside of our knowledge. In particular, prior research has shown that even identically configured cloud virtual machines can vary significantly in performance [15]. However, the high accuracy achieved by our prediction models indicates that this is not a major concern with the data we used. That said, we expect that TEP-GNN would perform even better on the performance data that has been measured more rigorously.

Another design choice was that we predict execution times for entire test classes (files). More fine-grained predictions (e.g., for individual test cases in a class) would of course be doable, for instance by constructing the FA-AST with test methods as entry points rather than for an entire class as compilation unit. However, individual test cases often have very short execution times in relation to the precision with which build systems typically measure execution times (milliseconds), and the resulting graphs would be very small. We argue that our choice of test class granularity constitutes a good trade-off that is still useful for developers.

External Validity Threats. An obvious question raised by our work is how well the results reported in Section 3.2 would generalize to other projects. To mitigate this threat, we have chosen four relatively different Java projects as study subjects following a diversity sampling strategy [2]. However, our study does not allow us to conclude whether the TEP-GNN approach would generalize to other programming languages or closed-source software.

5 RELATED WORK

Predicting software performance. Predicting the absolute value of a performance counter, such as execution time, based on the source code alone is challenging, as application performance is a function of several unknowns stemming from the application runtime and interactions between the OS and underlying hardware. This makes the problem notoriously challenging for any machine
learning model, including deep learning techniques. Hence, existing studies often struggle with poor prediction accuracy [21, 23]. One way to simplify the problem (and hence make it more tractable) is to convert it into a classification problem. Examples of this approach include Zhou et al. [36], who predict if a program from a programming competition website exceeds the time limit, Ramadan et al. [24], who predict whether a performance change is introduced by a code structure change, or Laaber et al. [13], who have shown that a categorical classification of benchmarks into high- or low-variability is feasible.

However, recent research has shown that predicting absolute performance values can be feasible in more specialized contexts. For example, Guo et al. successfully predict the execution time of a specific untested configuration of a configurable system [7, 8], and Samoza and Leitner have shown that the execution time of a benchmark with a specific workload configuration can be predicted [26]. In this work, our core contribution is we demonstrate that predicting absolute performance values is possible in another context, namely for the execution time of test files.

**Graph neural networks for software engineering.** Graph Neural Networks (GNNs) constitute an up-and-coming machine learning model in the context of software engineering research [27]. Graphs are mathematical structures used to model pairwise relations between objects. A graph can be used to model a wide number of different domains, ranging from biology [10], face-to-face human interactions [18, 19], or digital contact tracing [4]. Li et al. [17] use a GRU cell in gated graph neural networks (GGNNs) for updating the nodes’ states. To evaluate their model they run the model on a basic program and try to detect null pointers. Instead of having the whole program as an input Li et al. [17] use the memory heap states of the program to the model. Since the original work by Li et al. [17], GGNNs have become a commonly used tool for applying GNNs in software engineering. One challenge that needs to be solved before any GNN approach can be applied for code-based software engineering research is how to represent a program as graph.

Phan et al. [32] use graph convolutional networks (GCNs) based on compiled assembly code to detect defects on control flow graphs in C. Another application of control flow graphs is using graph matching networks (GMN) between two graphs of binary functions proposed by Li et al. [16]. Other researchers propose the creation of program graphs based on the AST, Allamanis et al. [1] and Brockschmidt et al. [3] use GGNN in C# for naming variables and generating program expressions for code completion respectively.

### 6 CONCLUSION AND FUTURE WORK

In this work we presented TEP-GNN, an effective method for predicting the execution time of Java test files. Our approach leverages explicitly capturing control and data flow information as augmentations to the program AST. Further, our approach applies high order convolution graph neural networks over this flow-augmented AST (FA-AST). By building FA-AST using original ASTs and flow edges, our approach can directly capture the syntax and semantic structure of test classes. Experimental results on four diverse test subjects demonstrate that by combining graph neural networks and control/data flow information, we can predict absolute test execution times with high accuracy.

As the future work, we plan to further extent the FA-AST model currently used by TEP-GNN, as well as explore other ways of program representation to capture more syntactic and semantic code features. Additionally, we plan to apply our approach to the execution time of general-purpose programs rather than test cases. Finally, we would like to extend our current labeled data set by applying active learning to increase the amount of training data in a systematic way.

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