Using Static Analysis Tools to Assist Student Project Evaluation

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ABSTRACT

Code review and static analysis tools are acknowledged as important instruments in software quality control and are used in the industry on a daily basis. In this exploratory study we examine how a well-known static analysis tool can be employed to assess the quality of student solutions to coding assignments. We examine all student solutions submitted to fulfill coding assignments required as part of an introductory programming course taught using Python. We show how teaching staff can evaluate the progress of individual students and how coding mistakes common to many students can be highlighted. We also show how teaching staff can improve their own understanding of perceived assignment complexity by evaluating the aggregate quality of student submitted source code.

CCS CONCEPTS

• **Social and professional topics** → **Student assessment**.

KEYWORDS

static analysis, student evaluation, Computer Science education

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1 INTRODUCTION

We know that source code quality has an important influence on the software development process as a whole. While experience plays a central role in writing quality code, at the same time the principles of code quality should be taught early on. This leads to many introductory programming courses also addressing issues related to code quality in the form of observing coding guidelines, following a set of established best practices, and even adopting methodologies such as feature-driven or test-driven development.

Code review and static analysis tools support this approach by allowing automatic detection of many types of quality deficiencies such as software defects, security vulnerabilities, or the breaking of best practices in early development phases. These tools are widely used in the industry and their efficiency in development and maintenance has been proven to be significant, with existing research [14] showing average defect detection of up to 55% to 60%. However, the usage of these tools in an educational setting is usually limited to quality control as a software engineering process, or within coursework dedicated to software quality, which is usually taught at a more advanced level.

As such, the main objective of our work is to *"assist teaching staff in monitoring the learning evolution of students in a programming language course"*. As many academic courses touch upon the most important issues of programming style and best practices, we believe that special attention should be dedicated to corresponding learning outcomes and the way they are assessed. At the same time, evaluating the quality of student code is a tedious and time consuming activity, reasons for which it is often overlooked. This can be changed through automation, which brings additional advantages such as the ability to track student progress through all completed assignments, compare student performance for a certain assignment as well as build an overall assessment of the student projects themselves, and improve the understanding teaching staff have about the aspects students found most difficult to address.

We study how our main objective can be fulfilled through an experience report that covers all student solutions to the coding assignments required within the *Fundamentals of Programming* introductory course that is taught using Python 3 and is attended by 200 first-year undergraduate students in computer science from the Babeş-Bolyai University in Cluj-Napoca, Romania.

2 TOOLS FOR STATIC ANALYSIS

Static code analysis allows developers to gain important insight into source code without having to run it. Its benefits are the subject of notable recent studies, mainly caused by the growth of static code analysis tools [10] and their tight link with software quality through implementation of known quality models such as SQALE [12] and QMOOD [3].

Current static analysis tools are considered to belong to the third generation [11], with the major shift in the fact that analysis is performed on the target program's abstract syntax tree. Focusing on the logic of the code allows improved tool efficiency in detecting existing issues. Most of the widely used tools are available for several programming languages and can be easily integrated into development environments in the form of plug-ins such as those for Pylint [16] and SonarQube [20]. Static analysis tools such as SonarQube were also used to characterize quality of large-scale code bases in recent research targeting software quality [8, 15]. The tight integration between well-known software quality models and static analysis tools have helped promote increased formalism in the study of software quality [1]. Boehm et al. [6] have shown that

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Table 1: Pylint message types

Message Type	Abbrev	Usage
Information	I	Information message
Refactor	R	Bad code smell
Convention	C	Programming standard violation
Warning	W	Python specific problems
Error	E	Probable bugs
Fatal	F	Errors that block further processing

early detection of defects lowers software development costs. This was corroborated by more recent research [5, 6], which showed that feedback received early on allowed correcting errors and problems before they could make a large impact during the latter stages of the software development life cycle.

From a teaching viewpoint, static analysis tools can provide the following valuable features:

- They allow imposing coding standards uniformly and automatically; this reduces the time requirements from teaching staff and frees them from a task that can easily be perceived as tedious.
- Perform source code analysis in order to identify code defects, code smells, performance issues and dependencies [9].
- Enhance code comprehension by encouraging the creation of shorter, easier to read methods [9].
- They are available at all times, and students can use them to perfect the assignments they are currently working on [2].

In our previous experiments [24], static analysis of Python code revealed students had a tendency to create code with excessive cyclomatic complexity due to superfluous branching statements, as well as methods having different return types depending on code path, which often resulted in hard to identify defects. Modern tools also help consummate professionals by detecting software defects and security vulnerabilities, such as the use of uninitialized resources, checking for software vulnerabilities such as unused network connections, use of low-security pseudo-random number generators and so on.

In this study we used the Pylint open-source analysis tool to scan all student submitted assignments. Pylint can be used both in command-line mode or integrated as a plugin into several development environments. Pylint itself can be extended using a plugin system to detect additional issues. The default rule set checks code against a large collection of known code smells and enforces Python's PEP-8 default coding convention [17].

For each Python module, the tool reports detected issues in the form of messages. Each message has one of the types presented in Table 1, contextualizing the identified issue. Messages in the *information* or *fatal* categories are not classified as source code defects; the former are used to provide additional information, while the latter preclude further processing from taking place. In addition, each message has a unique code and associated description, which can be used to automatically aggregate issues across Python modules or projects, as well as to help developers understand and fix reported issues.

Table 2: Student assignment descriptions, their deadlines and the number of individually submitted solutions for each assignment.

Code	Description	Deadline (week)	Count
A1	Multi-week assignment targeting procedural programming	5	149
A2	Introductory assignment for object-oriented programming	6	158
A3	Multi-week assignment for elements of layered architecture in an object-oriented context	9	129
A4	Board game implementation that tests most of the concepts studied during the semester	13	100
A5	Programming techniques such as backtracking	14	106

A project's Pylint score is calculated once all source code modules are scanned. It is determined as a weighted linear computation with respect to the type and the number of occurrences for each issue. The score values are computed using Formula (1), where E_{count} represents the number of error issues found; remaining notations follow the abbreviations found in Table 1. Issues identified as errors carry the highest weight, while other message types describing issues are equally weighted. The score is upper bounded by 10 and has no lower bound.

$$score = 10 - 10 * \frac{5 * E_{count} + W_{count} + R_{count} + C_{count}}{Statement_{count}} \quad (1)$$

3 APPROACH TO STUDENT EVALUATION

3.1 Methodology

Our experience report covers the introductory *Fundamentals of Programming* course, which is taught in English and taken by first-year undergraduate students in computer science. Course material is designed so that it can be completed without previous programming experience. In practice, most students already have programming experience using the C language at high-school level. However, our experience has shown that the switch to the Python language, and the introduction of software engineering elements have an equalizing effect, as very few students bring previous experience that is relevant in the given context. In addition, the choice of language and course material keep students motivated to successfully complete it. This is evidenced by the consistent positive feedback that is anonymously provided by students at the end of each semester.

The course is designed as an introduction to programming and covers lower-level topics such as searching, sorting and computational complexity. However, introductory topics in software engineering such as modular programming, layered architecture and unit testing are also covered. Furthermore, in contrast to most students' previous experience, emphasis is placed on code readability,

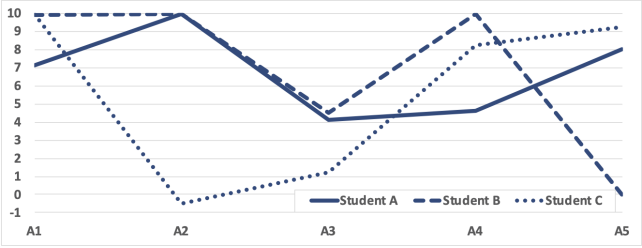

Figure 1: History of Pylint error scores recorded for the submissions of three students (A,B and C) over the semester's course. Maximum score is 10, with no lower bound.

composition and testing. Principles of layered architecture are also introduced and elaborated upon. The course syllabus for the semester covered in our evaluation is publicly available [23] and presents in detail course objectives, targeted competencies and technical content. Several of the course objectives and competences can be linked to measurable code quality, which can be evaluated using the available tooling detailed in Section 2.

Student evaluation is a continuous activity that covers the entire semester. As part of practical work, each student completes five individual coding assignments where they practice important concepts from procedural, modular and object-oriented programming. In addition to required functionalities, instructor feedback and grading are based on code attributes such as code readability, complexity and coupling at both method and class levels. Table 2 illustrates the five main coding assignments students had to implement during the fourteen-week semester, together with their deadlines and the number of actual student submitted solutions included in our study.

Assignments are graded by experienced teaching staff during face-to-face laboratory sessions, in which students demonstrate running programs and sustain a discussion regarding implementation decisions. Students send assignment source code to a designated email address using their faculty email. Submissions are downloaded and pre-processed using in-house developed tooling. This allows detecting invalid submissions, such as those not accompanied by source code, or where students submitted code written in a different programming language, or for a different course altogether. Valid submissions are screened for plagiarism using Stanford's MOSS system [22], which uses winnowing to analyze the similarity between source code submissions at the abstract syntax tree level [19].

Our study was enabled by the creation of an additional software tool that enables analysis and visualization of student progress. Geared towards use by experienced teaching staff, it enables both cross-sectional as well as longitudinal visualization of the Pylint scores assigned to a single, or a group of students. This empowers teaching staff to check the progress of individual and groups of students, as well as to identify assignments that pose too much, or too little difficulty for enrolled students. Furthermore, it allows delving into specific issues reported by Pylint, in order to determine what types of issues are most difficult for students to resolve.

Table 3: Distribution of submissions according to Pylint score

	Pylint score		
	$= 10$	$\in [0-10)$	< 0
A1	41.61%	42.95%	15.44%
A2	52.23%	40.76%	7.01%
A3	7.75%	85.27%	6.98%
A4	22.00%	73.00%	5.00%
A5	10.38%	87.74%	1.89%

3.2 Evaluation

We carry out our study by running Pylint on all 642 student submissions. Each of them represents a successfully completed assignment. As shown in Table 2, their number follows a decreasing trend due to the increased complexity, with A4 and A5 being completed by around half of the 200 students enrolled in the course. We then evaluate the suitability of using static analysis to monitor and evaluate the performance and progress of students in successfully carrying out progressively more difficult coding assignments.

3.2.1 Analysis and visualization of a single student's performance over a semester's course. Monitoring the progress for a given student is possible by making a longitudinal evaluation regarding their progress in learning. Our developed tooling provides visualizations such as illustrated in Figure 1, showing the score history for three selected students. Let's consider the student whose assignments are represented using the uninterrupted blue line. Some variability within the scores can be observed and is expected. However, all assignments are scored above 0.

Teaching staff can consult Pylint reports for singular or groups of assignments. Table 4 illustrates the analyzer output in the case of one student submission. Each table row represents one detected issue. This helps teaching staff to improve their understanding of issues common for many students, or to examine a single student's submissions in more detail.

We must note that in order to have the complete picture, teaching staff must take into consideration each assignment's level of complexity and difficulty, as each assignment is based on, and at the same time more complex, than the previous one.

3.2.2 Analysis and visualization of a given assignment. The objective is to provide the means for a cross-sectional evaluation that targets all student submissions for a particular assignment. This approach provides relevant information regarding the learning level of all the students based on the computed average value for all analyzed source code submissions. This can be achieved for all Pylint message types illustrated in Figure 1. We illustrate the results obtained within our experimental study using Table 3. We partition student submissions for each assignment into one of three categories, based on their Pylint score. Submissions scored with 10 did not trigger any of the analyzer rules. Those having a positive score are in a separate classification, while we consider submissions having a negative score those that require most attention to following best practices.

Table 4: Pylint result statistics for a single submitted assignment

Code	Description	Count
C0116	Missing function or method docstring (missing-function-docstring)	24
C0103	Function/argument name "*xxx*" doesn't conform to snake_case naming style (invalid-name)	15
C0301	Line too long (103/100) (line-too-long)	9
C0114	Missing module docstring (missing-module-docstring)	4
C0411	standard import "*xxx*" should be placed before "*from domain import* *" (wrong-import-order)	2
C0304	Final newline missing (missing-final-newline)	1
C0123	Using *type()* instead of *isinstance()* for a typecheck; (unidiomatic-typecheck)	1
	Total Convention messages	56
W0104	Statement seems to have no effect (pointless-statement)	4
W0108	Lambda may not be necessary (unnecessary-lambda)	2
W0401	Wildcard import domain (wildcard-import)	2
W0614	Unused import create from wildcard import (unused-wildcard-import)	2
W0703	Catching too general exception Exception (broad-except)	1
W0702	No exception type(s) specified (bare-except)	1
	Total Warning messages	12
R1705	Unnecessary "*elif*" after "return" (no-else-return)	3
R1720	Unnecessary "*elif*" after "raise" (no-else-raise)	1
	Total Refactor messages	4
E0702	Raising int while only classes or instances are allowed (raising-bad-type)	2
	Total Error messages	2

The data in Table 3 shows a general decrease in negative scores through the semester's duration, which we attribute to students gradually improving their coding skills, and having a better understanding of stated requirements and best practices. We also note that introductory assignments A1 and A2 have the largest share of submissions with a score of 10, while their number decreases for the more complex assignments.

Teaching staff can use this data to complete their mental picture regarding assignment complexity and fine tune assignment difficulty in order to maximize learning potential. One such example is the introduction of assignment A2, where students are required to create an object-oriented program that handles a single domain entity. The main reason for its existence was the observation that the introduction of *classes*, *class and object methods* and *attributes* was initially confounding for many students.

3.2.3 Analysis and visualization of assignments corresponding to multiple students. Given that many classes, including the one presented in this study have high enrollment, many activities, including seminars and laboratory work are carried out in smaller formations. Many times, these are coordinated by several instructors. As such, we believe it is important to enable analyzing the results for the students found in a seminar or laboratory formation. Figure 2 illustrates a selection made in our tooling that reveals the Pylint scores for the assignments submitted by 25 students (student identities are protected according to European GDPR). This allows course coordinators to check the progress of each formation and identify those issues that several students have trouble with. Figure 3 illustrates the score range for all submitted assignments using box-plots. We note that while most scores were above 0, for each assignment Pylint identified problematic submissions that required additional attention from the instructors.

3.3 Benefits

The benefits of this approach can be summarized as:

- Assesses quality and programming principles for source code. It provides different perspectives for Python code, including defects and code smells, offering the possibility of focusing on different criteria to be monitored.
- Reduces time spent by teaching staff on repetitive issues. Student source code is inspected automatically, and results are available immediately.
- Allows to process projects for classes with high enrollment. This is extremely useful in case of courses with numerous participants, and especially when there are several instructors who evaluate student work. The tool acts as a guideline that provides a uniform measure for all submissions.
- Allows to observe student progress during the entire semester. This is one of the scenarios proposed in our approach and can offer tutors valuable measurements about student effort, their results for each assignment, but also can show trends for the entire semester.
- Provides an overall view of student performance, as described in Section 3.2.2. It can provide valuable insight about the entire activity associated with a course, and can be used for further developing and improving course materials and requirements.

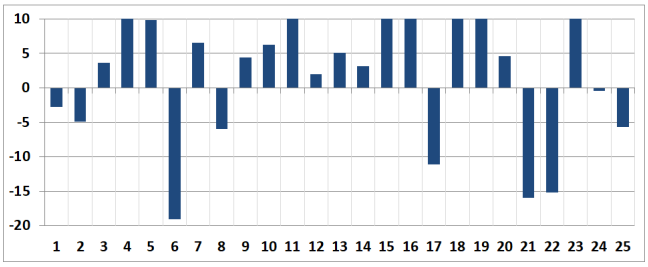

Figure 2: Pylint scores for 25 submissions of assignment A1.

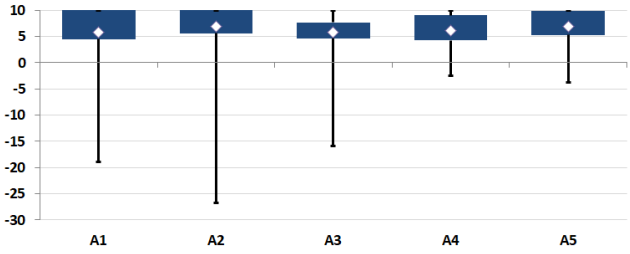

Figure 3: Pylint scores for each assignment represented as box plots. Whiskers represent lowest and highest scores, and boxes showcase the inter-quartile range.

- Allows to objectively assess student performance for a given task, providing additional insight on the perceived difficulty of the assignment. This is elaborated in Section 3.2.3.

3.4 Threats to Validity

We evaluated the threats that might influence the validity of our study according to existing best practices [18] at each of the steps in our process: data collection, integration with Pylint, and result analysis.

Threats to internal validity were addressed in several steps. We validated each student submission to ensure it was valid for the course and given assignment, removed duplicated submissions and enforced a standardized naming scheme. Submission analysis using Pylint was automated and results were verified for accuracy.

With regards to external validity, we believe our approach is amenable for application to software engineering courses where students received substantial multi-week assignments. We must note that results from static analysis will be skewed in the case of submissions that were previously checked by students themselves using the same, or other analysis tools. In addition, the scores reported using static analysis only paint a partial picture, as program functionality and actual reliability cannot be adequately tested. As such, we must account for the fact that reported scores are only an imperfect approximation of true software quality with regards to both its functional and non-functional requirements.

We addressed threats to construct validity by limiting our exploration to well-known issues. We employed a popular static analyzer and limited our study to the span of a single semester, to eliminate the influence inter-semester changes may have on course rules and materials.

Code review automation brings important benefits in terms of time, but cannot replace human expertise. Issues like logical error problems, requirements misunderstanding, missing functionalities [4] cannot be detected by such tools. So, such a tool must be used to complement student and instructor effort, in order to save time.

4 RELATED WORK

Although the benefits of code review and static analysis tools have been clearly recognized and such tools are part of everyday life in software development, their applicability in software engineering education did not reach its full potential. Some contributions have been reported especially in the case of students using these tools to improve their programming skills.

A study conducted about the use of code review by students at an introductory course in Software Engineering [21] was based on an evaluation of comments from the tool and a survey given to the students. The conclusion was that including code review at undergraduate level can enhance program comprehension and improve programming ability and enforcement of coding standards.

PyTA was introduced in [13] as a wrapper for Pylint. Authors used it in programming exercises to first year students in computer science. They reported that the tool helped students solve errors in less time, and complete programming assignments quicker.

An approach in which Pylint is used for student assessment is presented in [7], which compares traditional, instructor-driven grading with Pylint scores for a data set consisting of 44 student submissions for one programming assignment of medium complexity. Although the experiment was a reduced scale one, the conclusions highlighted the accuracy of the tool in detecting several source code issues, but also reported a lower score than the one given by the instructor.

While [13, 21] show the application of code review based on static analysis in the learning process, and [7] in the assessment of student work, our approach brings at least two benefits: tracking student progress across all course assignments and being able to select several aspects of the code, not only a general score, which might provide more detailed feedback about which aspects students need to improve. While other research studies on this topics concentrates mainly on benefits for the students, our approach has the unique feature of providing insights for teaching staff, helping them in improving project requirements and complexity.

5 CONCLUSIONS AND FUTURE WORK

Code quality is an essential attribute for all software systems, and it should be included in introductory courses teaching programming and software engineering. We conducted a study on how a popular code review and static analysis tool can be used to assist instructors in evaluating these aspects, and highlighted a number of possible benefits of such an approach, especially in case of courses having a large number of enrolled students.

In conclusion, we believe our approach is valuable for monitoring student progress and shows that some activities associated with assessment can be automated. The experimental study is based on real data gained from 200 enrolled students and 642 analyzed submitted assignments which point to solid results that emphasize the

actual situation from the presented course. The study also showed that Pylint provides meaningful information regarding different aspects of code style or logical errors that can be further processed and properly analyzed.

Future plans associated with this project include a more comprehensive analysis of the messages returned by Pylint, in order to detect common errors or misuse of programming artefacts. Furthermore, we plan to extend the study to cover several academic years. Integrating the use of such tools into the course itself, and encouraging students to use it during their programming sessions is also a future goal.

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