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ABSTRACT
We present a method for source code plagiarism detection that is independent of the programming language. Our method EsaGst combines Explicit Semantic Analysis and Greedy String Tiling. Using 25 cases of source code plagiarism in C++, Java, JavaScript, PHP, and Python, we show that EsaGst outperforms a baseline method in identifying plagiarism across programming languages.

CCS CONCEPTS
• Information systems–Information retrieval–Specialized information retrieval

KEYWORDS
Source Code Plagiarism Detection, Explicit Semantic Analysis, Greedy String Tiling

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1 Introduction & Related Work
Source code plagiarism detection (SCPD) is an effective deterrent to undue reuse of code in programming assignments, which are common in computer science and related study programs. Many SCPD methods focus on specific programming languages by employing approximate string matching to identify similar programs [1]. Other methods additionally analyze the structure or semantics of source code [2]. Some methods addressed the cross-language SCPD task using Latent Semantic Analysis [3]. We presume that plagiarists trying to obfuscate reused code preserve the semantics of the identifiers, comments, and other tokens. Thus, we see a semantic analysis as promising for devising a language-independent SCPD method. Therefore, we adapt Explicit Semantic Analysis (ESA) [4], a well-established semantic analysis method, and Greedy String Tiling to the SCPD use case. ESA models text as concept vectors. The concepts are the topics in a knowledge base, which is typically Wikipedia or another encyclopedia. The vector components reflect the relevance of the modeled text for each of the concepts. Greedy String Tiling (GST) is an algorithm with near-linear complexity to find all individually longest substring matches in two strings [5].

2 Method
To perform ESA, we used the EsaPlag system [6] and thirty thousand articles from the categories “Computer programming” and “Fields of mathematics” in the English Wikipedia. Using the title of articles as concepts, we represented each document, i.e., a computer program, by deriving a concept vector for each term in the document. To maintain all semantic information of documents, we only removed line breaks before forming the vectors. To compute the similarity of documents, we devised the Scored GST algorithm that determines the longest sequence of semantically similar terms. Other than GST, Scored GST matches not only identical elements but all elements whose similarity is above a threshold. Here, the concept vectors for document terms are the elements, whose similarity we computed via the cosine measure. We set the cosine similarity above which we consider concept vectors a match to 50% and the final score above which we report results to 5% as this value maximized the F1 score.

3 Experiments
To evaluate our SCPD method, we created a dataset of simulated source code plagiarism. We implemented a basic programming assignment—a calculator supporting basic arithmetic operations—in the five most common languages on GitHub, i.e., C++, Java, JavaScript, PHP, and Python. For each language-specific implementation, we created four plagiarized versions using the following obfuscation methods: (1) renaming identifiers, (2) renaming identifiers by converting camelCase to snake_case, (3) restructuring the code, and (4) reusing half of the code. To test for false positives, we used unrelated code with no semantic matches. As a baseline, we used the text matching system Anton [5].
Anton computes the similarity of documents as the ratio of hashed 5-word chunks occurring in both documents to the chunks in the first document. Since the score is asymmetric, so are the baseline results in Figure 1. We used Anton’s default threshold for reporting results, i.e., a 20% overlap in chunks.

4 Results and Discussion

Figure 1 shows the results. Cells colored in green indicate correct detections, i.e., true positive and true negatives. Red fill denotes false positives and false negatives. Boldface font emphasizes cases, in which EsaGst identified a case that the baseline missed.

The baseline identified many monolingual cases and some cross-lingual cases involving syntactically similar languages like Java and JavaScript and, to a lesser extent, Java and C++. For syntactically different languages, EsaGst achieved much better results. Particularly, EsaGst yielded high similarity scores for the documents with a semantic similarity of 100% (x0, x2, x3). For monolingual plagiarism cases, the average EsaGst score is 99.2%, and for cross-lingual cases 89.0%. These results show that EsaGst is more robust to syntactic variations of the programming languages than the baseline method. Nonetheless, the similarity scores for cross-lingual cases involving Python are often low due to syntactic peculiarities of Python. For example, Python’s keyword elif is expressed by two words (else if) in all other languages. Moreover, Python is an untyped language, which leads to shorter word sequences omitting words corresponding to the data types. This is why Python yielded the highest similarity with Javascript, which is an untyped language as well.

In our experiments, EsaGst could distinguish plagiarized documents from unrelated documents in all cases using a reporting threshold of 5%. However, a limitation of our small-scale test set is that it does not include non-plagiarized documents on related programming tasks, which would likely yield higher similarity scores and potentially false positive detections.

5 Conclusion

This poster presents preliminary results on using ESA and Scored GST to identify cross-language source code plagiarism in a small set of test programs. Important questions we plan to investigate in our future research include: (1) the effect of varying parameters like the dimensionality of concept vectors, the similarity thresholds, and the minimum substring lengths for GST, (2) the influence of the ESA knowledgebase dataset, and (3) the results of EsaGst and more cross-language SCPD methods on a larger, more diverse test set. The test set should include programs that different developers implemented for the same task to distinguish plagiarized from topically related content.

Despite the limitations of our initial experiments, we see Explicit Semantic Analysis combined with Scored Greedy String Tiling as a promising method for revealing semantically equivalent source code in different programming languages.

REFERENCES


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