Duplicated Code Pattern Mining in Visual Programming Languages*

Miguel Terra-Neves
OutSystems
Portugal
miguel.neves@outsystems.com

João Nadkarni
OutSystems
Portugal
joao.nadkarni@outsystems.com

Miguel Ventura
OutSystems
Portugal
miguel.ventura@outsystems.com

Pedro Resende
OutSystems
Portugal
pedro.resende@outsystems.com

Hugo Veiga
OutSystems
Portugal
hugo.veiga@outsystems.com

António Alegria
OutSystems
Portugal
antonio.alegria@outsystems.com

**ABSTRACT**

Visual Programming Languages (VPLs), coupled with the high-level abstractions that are commonplace in visual programming environments, enable users with less technical knowledge to become proficient programmers. However, the lower skill floor required by VPLs also entails that programmers are more likely to not adhere to best practices of software development, producing systems with high technical debt, and thus poor maintainability. Duplicated code is one important example of such technical debt. In fact, we observed that the amount of duplication in the OutSystems VPL code bases can reach as high as 39%.

Duplicated code detection in text-based programming languages is still an active area of research with important implications regarding software maintainability and evolution. However, to the best of our knowledge, the literature on duplicated code detection for VPLs is very limited. We propose a novel and scalable duplicated code pattern mining algorithm that leverages the visual structure of VPLs in order to not only detect duplicated code, but also highlight duplicated code patterns that explain the reported duplication. The performance of the proposed approach is evaluated on a wide range of real-world mobile and web applications developed using OutSystems.

**CCS CONCEPTS**

- **Software and its engineering → Maintaining software; Software verification and validation; Theory of computation → Automated reasoning.**

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In this work, we aim to aid OutSystems developers manage one important form of technical debt: duplicated code. Duplicated code is commonplace in software developed using traditional text-based languages [14, 23] and may have severe adverse effects that result in higher maintenance costs. For example, if one changes a duplicated code block, it is likely that the same change may need to be applied to most, if not all, duplicates of that block, thus making software harder to evolve and maintain. Code duplication may also exacerbate bug propagation, since a bug in a given code block will also be present in its copies. In our experiments, we observed that the amount of duplicated code in real-world OutSystems code bases can reach as high as 39%, highlighting the importance of addressing code duplication in OutSystems.

In OutSystems, logic is implemented through logic flows. Figure 1 shows an example of a flow that performs some transformations over some input string. The goal is to detect a limited form of type 3 duplicates [45], where near-misses are allowed for node expressions but the graph structure of the duplicated part must be the same. Moreover, this duplicated structure must be visually
highlighted to the user, and thus the duplicated code detector must return the mappings of flow nodes to the duplicated code pattern nodes. These requirements stem from discussions with OutSystems experts, regarding an earlier version of our tool, that exploited data dependencies between nodes in order to find duplicated code with significant syntactic differences. We concluded that such duplicates were hard to analyze and understand, thus negatively impacting the user experience. Figure 2 shows an example of a flow that performs the same transformations as in Figure 1 over some list of strings. The respective duplicated code pattern is highlighted in yellow. In addition to the aforementioned functional requirements, the duplicated code detector must be integrated in a tool that performs static analyses for hundreds of OutSystems code bases every 12 hours. Nonetheless, the detector should process these code bases as fast as possible in order to minimize the computational resources needed to satisfy this time limit, thus optimizing operating costs.

A naive approach for detecting duplicated code in software developed using a VPL could be to translate from the VPL to some text-based language and then apply one of many detectors for such languages [15, 20, 42, 48, 57, 63]. This approach suffers from a severe drawback: it sacrifices the visual structure of the VPL code, which can be leveraged in order to provide helpful explanations of reported duplications by highlighting duplicated code patterns. Such patterns allow the developer to understand and address the sources of code duplication more effectively. Alternatively, some graph-based algorithms for text-based languages [26, 30, 53, 63] or other VPLs [1, 13, 29, 41, 50] could be directly applied to OutSystems logic, but these typically suffer from scalability issues due to the hardness of checking sub-graph isomorphism, and the ones that do address this issue perform some approximated form of sub-graph matching, thus not guaranteeing the consistency of the graph structure.

We propose a duplicated code detector for OutSystems that addresses the aforementioned issues by iteratively mining Maximum Common Sub-graphs (MCSs) of graph representations of OutSystems code. Our main contributions are as follows: a) Several complete graph pre-processing techniques that simplify the MCS extraction task. We use these techniques to improve the efficiency of an MCS algorithm based on Maximum Satisfiability (MaxSAT). b) A novel and scalable greedy algorithm for mining duplicated code patterns in OutSystems code bases. Although the focus of this work is on duplicated code, the proposed algorithm is generic and can thus be used to mine MCSs of arbitrary graph structures. Some techniques are also proposed in order to improve the performance of the mining algorithm. To the best of our knowledge, ours is the first graph-based approach that solves the scalability issue by using an inverted index [48]. c) An extensive experimental evaluation on real-world OutSystems code bases that assess the performance of the proposed techniques. d) A brief evaluation regarding the severity of code duplication in real-world OutSystems code bases.

We start by providing some background on OutSystems, MCSs and MaxSAT in Section 2. Then, the MaxSAT-based MCS algorithm and graph pre-processing techniques are explained in Section 3, followed by the pattern mining algorithm and respective performance improvements in Section 4. Experimental results showing the merits of the proposed techniques are presented in Section 5. Section 6 summarizes related work on duplicated code detection and sub-graph mining. Limitations and design decisions are discussed in Section 7. Finally, Section 8 concludes this paper.

## 2 BACKGROUND

In this section, we introduce the necessary background. Logic flows are explained in Section 2.1, followed by a definition of MCS in Section 2.2 and an explanation of MaxSAT in Section 2.3.

### 2.1 Logic Flows

A logic flow is a directed weakly connected graph \( G = (V, E) \) where each node in \( V \) has one of the following types: Start, End, Instruction, For each, If or Switch. Additionally, each edge in \( E \) can be of type Connector, True, False, Cycle, Condition or Otherwise. We refer to the outgoing edges of a node as branches. \( G \) satisfies the following properties:

- \( G \) does not contain self-loops or parallel edges.
- \( V \) contains only one Start node \( v \), and no edge \((u', v') \in E\) exists such that \( v = v' \).
- Given an End node \( v \in V \), no branch exists in \( E \) for \( v \) and there exists at least one edge \((u', v') \in E\) such that \( u = u' \).
- A Start or Instruction node \( u \in V \) has exactly one Connector branch \((u, v) \in E\).
- An If node \( u \in V \) has exactly one True branch \((u, v) \in E\) and one False branch \((u, v') \in E\).
- A For each node \( u \in V \) has exactly one Connector branch \((u, v) \in E\) and one Cycle branch \((u, v') \in E\) such that there exists a path from \( v \) to itself through \((u, v')\).
- A Switch node \( u \in V \) has at least one Condition branch \((u, v) \in E\) and exactly one Otherwise branch \((u, v') \in E\).

The logic flow is akin to the control flow graph of a program written in a traditional programming language. Its execution begins at its Start node and terminates at one of its End nodes. Moreover, depending on their types, the nodes/edges can have different attributes. For example, an If node contains a Boolean expression which dictates if the execution is to continue through its True (Cycle) or False (Connector) branch. Similarly, a Condition branch of a Switch node contains a Boolean expression that, if evaluated to true, then the execution continues through that branch. Condition branches also have a pre-specified order of evaluation. If none of those branches evaluate to true, then execution resumes...
through the OTHERWISE branch. A FOREach node contains a reference to a variable of an iterable type (e.g. list). INSTRUCTION nodes can be of various kinds, such as variable assignments, database accesses, calls to other logic flows, among others. Note that, just like functions/methods in text-based languages, logic flows can have input and output parameters.

2.2 Maximum Common Sub-graph

Logic flows are thus a duplicated code pattern is a common sub-graph that occurs across multiple flows. Naturally, the largest common pattern in those flows corresponds to an MCS. Let \( G_1 = (V_1, E_1) \) and \( G_2 = (V_2, E_2) \) be a pair of graphs with labeled nodes/edges. For the purpose of this work, we assume that graphs are directed by default. We use \( L(v) \) to denote the label of some node \( v \). For example, assuming \( v \) is a node of a logic flow, \( L(v) \) can be something as simple as the node’s type (e.g. INSTRUCTION). Given some label \( l \), we use \( V_l \) to denote the subset of nodes \( v \in V_1 \) such that \( L(v) = l \). Analogously, we use \( u \) to denote the label of some edge \((u,v)\) and \( E_l \) to denote the subset of edges \((u,v) \in E_1\) such that \( L(u,v) = l \). For convenience, we use \( L_{comb}(u,v) = (L(u), L(v), L((u,v))) \) to denote the combined label of \((u,v)\) and \( E_{comb}(u,v) \) to denote the subset of edges \((u,v) \in E_1\) such that \( L_{comb}(u,v) = l \). Also, we abuse notation and use \( L_{comb}(E_l) \) to denote the set of combined labels that occur in \( E_l \).

A graph \( G_C = (V_C, E_C) \) is a common sub-graph of \( G_1 \) and \( G_2 \) if there exist mappings \( f_1 : V_C \rightarrow V_1 \) and \( f_2 : V_C \rightarrow V_2 \) such that \( L(v) = L(f_1(v)) = L(f_2(v)) \) for all \( v \in V_C \) and \( L(\ell) = L(f_1(\ell)) = L(f_2(\ell)) \) for all \( (\ell) \in E_C \). \( G_C \) is said to be an MCS if and only if no common sub-graph \( G'_C = (V'_C, E'_C) \) of \( G_1 \) and \( G_2 \) exists containing more nodes or edges than \( G_C \), i.e. such that \( |V'_C| > |V_C| \) or \( |E'_C| > |E_C| \). For convenience, given a node \( v \in V_1 \), we abuse notation and use \( v \in V_C \) to denote that there exists \( v' \in V_C \) such that \( v' \) is mapped to \( v \), i.e. \( f_1(v') = v \). Analogously, given \( (u,v) \in E_1 \), we use \( (u,v) \in E_C \) to denote that there exists \( (u',v') \in E_C \) such that \( f_1(u') = u \) and \( f_1(v') = v \).

2.3 Maximum Satisfiability

MCS computation is well-known to be an NP-hard problem. In recent years, MaxSAT solvers have become a very effective tool for solving such hard combinatorial optimization problems [35–37, 46], thus our approach reduces the MCS problem to MaxSAT.

Let \( X \) be a set of Boolean variables. A literal \( l \) is either a variable \( x \in X \) or its negation \( \neg x \). A clause \( c \) is a disjunction of literals \((l_1 \lor l_2 \lor \cdots \lor l_k)\). If a clause contains a single literal, then it is said to be a unit clause. A propositional logic formula in Conjunctive Normal Form (CNF) \( \phi \) is a conjunction of clauses \( c_1 \land c_2 \land \cdots \land c_n \). A literal \( x \) \((\neg x)\) is said to be satisfied if and only if \( x \) is assigned the Boolean value \( 1 \) \((0)\). A clause is satisfied if and only if at least one of its literals is satisfied. A CNF formula is satisfied if and only if all of its clauses are satisfied. Given a CNF formula \( \phi \), the Boolean Satisfiability (SAT) problem consists of deciding if there exists an assignment \( \alpha : X \rightarrow \{0,1\} \) of Boolean values to the variables of \( X \) that satisfies \( \phi \). If \( \alpha \) exists, then \( \alpha \) is said to be a model of \( \phi \). Otherwise, \( \phi \) is said to be unsatisfiable.

MaxSAT [27] is a generalization of SAT where, in addition to the CNF formula \( \phi \) (referred to as the hard formula), we have a set \( S \) of soft clauses. The goal is to compute a model \( \alpha \) of \( \phi \) that minimizes the number of clauses in \( S \) not satisfied by \( \alpha \).

Example 2.1. Consider the MaxSAT instance with hard formula \( \phi = (\neg x_1 \lor x_2) \) and soft clauses \( S = \{(x_1),(\neg x_2)\} \). The assignment \((\{x_1\},\{\neg x_2\})\) is not a model of \( \phi \). On the other hand, the assignment \((\{x_1\},\{x_2\})\) is a model of \( \phi \) that satisfies the soft clause \((\neg x_2)\). Additionally, it is an optimal model since it is not possible to satisfy more than 1 soft clause for this instance.

3 SINGLE PATTERN EXTRACTION

In order to mine duplicated code patterns, one must be able to extract a maximal pattern from a pair of logic flows \( G_1 = (V_1, E_1) \) and \( G_2 = (V_2, E_2) \). The maximal pattern is an MCS of \( G_1 \) and \( G_2 \). Our approach reduces the problem of finding such an MCS to an instance of MaxSAT. The MaxSAT encoding is presented in Section 3.1. Section 3.2 follows with an explanation of several pre-processing rules used to simplify \( G_1 \) and \( G_2 \) before building the encoding.

3.1 MaxSAT Encoding

Our MaxSAT formulation is inspired by previous work on malware signature synthesis using MaxSAT [16]. It extracts an MCS by mapping the nodes of \( G_2 \) into the nodes of \( G_1 \). The encoding is explained through a running example in which we consider \( G_1 \) and \( G_2 \) to be the logic flows in Figures 1 and 2 respectively. Note that some mappings are not valid, such as mapping an IF to node to an INSTRUCTION. In order to specify such constraints, node and edge labels are used. In the example, the node/edge types are considered as labels for ease of explanation. Additionally, the START and END nodes must appear in every flow, and thus cannot be refactored to a separate flow. Therefore, such nodes are discarded beforehand.

The following three sets of Boolean variables are considered:

- **Inclusion variables.** For each node \( v \in V_1 \), a variable \( o_v \) is introduced to encode if \( v \) is part of the MCS (i.e. \( o_v = 1 \)) or not (i.e. \( o_v = 0 \)). In the running example, three inclusion variables are needed: \( o_{trim}, o_{low}, o_{rep} \).
- **Mapping variables.** For each node pair \( u,v \) such that \( v \in V_1 \) and \( v \in V_2 \), a variable \( f_{u,v} \) is introduced to encode if \( v \) is mapped to \( v \) (i.e. \( f_{u,v} = 1 \)) or not (i.e. \( f_{u,v} = 0 \)). In the example, five variables are needed for each node of \( G_1 \). For the ToLower node, these variables are: \( f_{low,for}, f_{low,trim}, f_{low,low}, f_{low,rep} \) and \( f_{low,list} \).
- **Control-flow variables.** For each edge \((u,v) \in E_1 \), a variable \( e_{u,v} \) is introduced to encode if \((u,v)\) is part of the MCS (i.e. \( e_{u,v} = 1 \)) or not (i.e. \( e_{u,v} = 0 \)). In the example, two control-flow variables are needed: \( e_{trim,low} \) and \( e_{low,rep} \).

For ease of explanation, some constraints are shown as at-most-1 constraints, i.e. of the form \( \sum_i e_i \leq 1 \), instead of clauses. Note that these are easily convertible to CNF by introducing the clause \((\neg e_i \lor \neg e_j)\) for each pair \( i,j \) such that \( i \neq j \). The hard formula contains the following constraints:

- **Inclusion clauses.** A node \( v \in V_1 \) is in the MCS if and only if at least one node in \( V_2 \) is mapped to \( v \). If \( v \) is the ToLower
node, we have:
\[(\neg \text{low} \lor \text{flow,for}) \lor \cdots \lor \text{flow,list}) \land \]
\[(\text{low} \lor \neg \text{flow,for}) \land \cdots \land (\text{low} \lor \neg \text{flow,list}). \quad (1)\]

- **One-to-one clauses.** At most one node in \(V_2\) can be mapped to each node \(v \in V_1\). Assuming that \(v\) is the ToLower node:
\[f_{\text{low,for}} + f_{\text{low,trim}} + f_{\text{low,flow}} + f_{\text{low,rep}} + f_{\text{flow,for}} \leq 1. \quad (2)\]

- **Function property clauses.** Each node \(v' \in V_2\) cannot be mapped to more than one node in \(V_1\). If \(v'\) is the ForEach node, we have:
\[f_{\text{trim,for}} + f_{\text{low,for}} + f_{\text{rep,for}} \leq 1. \quad (3)\]

- **Label consistency clauses.** A node \(v' \in V_2\) cannot be mapped to \(v \in V_1\) if \(v\) and \(v'\) do not share the same label:
\[(\neg f_{\text{trim,for}}) \land (\neg f_{\text{trim,list}}) \land \cdots \land (\neg f_{\text{rep,for}}) \land (\neg f_{\text{rep,list}}). \quad (4)\]

- **Control-flow consistency clauses.** Consider some edge \((u, v) \in E_1\) and a pair of nodes \(u', v' \in V_2\). If \(u'\) and \(v'\) are mapped to \(u\) and \(v\) respectively, and \((u', v')\) is not an edge of \(G_2\) or does not share the same label as \((u, v)\), then \((u, v)\) cannot be in the MCS. For example, if \(u\) and \(v\) are the ToLower and Replace nodes of \(G_1\) respectively, since an edge does not exist between the ToLower and Trim of \(G_2\), the following constraint is necessary:
\[(\neg f_{\text{flow,low}} \lor \neg f_{\text{trim,flow}} \lor \neg c_{\text{flow,rep}}). \quad (5)\]

On the other hand, the same constraint is not added when \(u'\) and \(v'\) are the Replace and ListAppend nodes of \(G_2\) respectively, since the edge exists in \(G_2\) and shares the same label as the edge between the ToLower and Replace of \(G_1\).

- **No spurious edge clauses.** An edge \((u, v) \in E_1\) can be part of the MCS only if both \(u\) and \(v\) are as well. If \(u\) and \(v\) are the ToReplace and Replace nodes:
\[(\neg c_{\text{trim,low}} \lor c_{\text{trim,flow}}) \land (\neg c_{\text{trim,low}} \lor c_{\text{low}}). \quad (6)\]

- **No isolate node clauses.** A node \(v \in V_1\) can be part of the MCS only if at least one of its incoming/outgoing edges is in the MCS. Assuming that \(v\) is the ToLower node:
\[(\neg \text{low} \lor c_{\text{low,flow}} \lor c_{\text{low,rep}}). \quad (7)\]

Note that the definition of MCS provided in Section 2.2 does not forbid the inclusion of isolate nodes. However, this is forbidden by the hard formula because such nodes are not desirable for the duplicate code pattern mining use case.

The optimization goal is to maximize the number of edges in the MCS, which is given by the following set of soft clauses:
\[\{(c_{\text{trim,low}}, c_{\text{low,rep}})\}. \quad (8)\]

Although the encoding described here focuses on extracting an MCS of a pair of graphs, it can be easily extended to \(k\) graphs by considering \(k - 2\) extra sets of mapping variables and adding the respective constraints to the hard formula.

### 3.2 Graph Pre-processing

The pattern mining algorithms described in Section 4 rely on solving several MCS instances. Therefore, MCS extraction must be as efficient as possible, since its performance strongly impacts the performance of the pattern miner. MCS instances can become hard to solve as the size of \(G_1\) and \(G_2\) increases. For this reason, several pre-processing rules were implemented in order to reduce the size of \(G_1\) and \(G_2\). The first rule discards edges with combined labels that do not occur in both \(E_1\) and \(E_2\), since it is impossible for an edge to be in the pattern if it does not occur in both graphs. For the running example from Figures 1 and 2, this corresponds to discarding the edges that contain the FOR EACH and List Append nodes.

**Proposition 3.1.** Given a pair of graphs \(G_1 = (V_1, E_1)\) and \(G_2 = (V_2, E_2)\), and an edge \((u, v) \in E_1\) such that \(L_{\text{comb}}(u, v) \notin L_{\text{comb}}(E_2)\), then an MCS of \(G_1\) and \(G_2\) is also an MCS of \(G'_1\) and \(G_2\), where \(V'_1 = V_1\) and \(E'_1 = E_1 \setminus \{ (u, v) \}\), and vice-versa.

**Proof.** Let \(G_C = (V_C, E_C)\) be an MCS of \(G_1\) and \(G_2\). If \(G_C\) is not an MCS of \(G'_1\) and \(G_2\), then \((u, v) \in E_C\) since it is the only edge of \(E_1\) not in \(E'_1\). However, because \(L_{\text{comb}}(u, v) \notin L_{\text{comb}}(E_2)\), no edge \((u', v') \in E_2\) exists such that \(L(u) = L(u')\) or \(L(v) = L(v')\) and \((u, v) = (u', v')\), and thus, by definition, \((u, v)\) cannot be in \(E_C\), resulting in a contradiction. On the other hand, if \(G_C\) is an MCS of \(G'_1\) and \(G_2\) but not of \(G_1\) and \(G_2\), then there must exist edges \((p, q) \in E_1\) and \((p', q') \in E_2\) such that \(L_{\text{comb}}(p, q) = L_{\text{comb}}(p', q')\). By definition, \(E'_1 \setminus E'_2 = \{(u, v)\}\), thus \(L_{\text{comb}}(p, q) = L_{\text{comb}}(u, v)\) which implies that \(L_{\text{comb}}(p, q) \notin L_{\text{comb}}(E_2)\), hence \((p', q')\) does not exist.

The application of Proposition 3.1 may cause either \(G_1\) or \(G_2\) to become disconnected. More specifically, some edges may become what we refer to as orphan edges, i.e., an edge \((u, v) \in E_1\) such that \(u\) and \(v\) do not appear in any edges of \(E_1\) other than \((u, v)\). In other words, no other edge \((p, q) \in E_1\) exists such that \(p \in \{u, v\}\) or \(q \in \{u, v\}\). Let \(O_{\text{comb}}^{(i)}\) denote the subset of orphan edges in \(E_{\text{comb}}^{(i)}\). If \(|O_{\text{comb}}^{(1)}| > |E_{\text{comb}}^{(2)}|\), then \(G_1\) is said to contain an excess of orphan edges with combined label \(\ell\). The second rule discards orphan edges responsible for excesses in \(G_1\) and \(G_2\) until this no longer the case. It is safe to do this because the MCS can contain at most \(|E_{\text{comb}}^{(2)}|\) edges with combined label \(\ell\).

**Proposition 3.2.** Given a pair of graphs \(G_1 = (V_1, E_1)\) and \(G_2 = (V_2, E_2)\), and an orphan edge \((u, v) \in E_1\), if \(G_1\) contains an excess of orphan edges with combined label \(L_{\text{comb}}(u, v)\), then there exists an MCS \(G_C = (V_C, E_C)\) of \(G_1\) and \(G_2\) such that \((u, v) \notin E_C\).

**Proof.** Let \(G'_C = (V'_C, E'_C)\) be an MCS of \(G_1\) and \(G_2\) such that \((u', v') \in E'_C\), and let \((p, q) \in E'_C\) be the edge of \(G'_C\) such that \(f_i(p) = u\) and \(f_i(q) = v\). Because \((u, v)\) is an orphan edge, by definition \((p, q)\) must also be an orphan edge. Moreover, since \((u, v)\) is in excess, we have that \(|O_{\text{comb}}^{(1)}(u, v)| > |m_{\text{comb}}^{(2)}(u, v)|\) and thus there exists at least one edge \((u', v') \in O_{\text{comb}}^{(1)}(u, v)\) such that \((u', v') \notin E'_C\). Consequently, there exists a mapping \(f_i\) identical to \(f_i\), with the exception that \(f_i(p) = u'\) and \(f_i(q) = v'\), thus \(G_C\) exists.

\(\square\)
The aforementioned rules may also cause some of the connected components of some graphs to become simple paths, i.e. a subgraph of $G_i$ with node set $V_S = \{v_1, v_2, \ldots, v_n\}$ such that $(v_i, v_{j+1}) \in E_i$, for all $1 \leq j < n$, and no other edge exists in $E_i$ with nodes from $V_S$. Assuming $i = 1$, let $P'_{1}^{L_{\text{comb}}(v_i, v_{j+1})} = P_{1}^{L_{\text{comb}}(v_i, v_{j+1})}$ denote the set of all simple path components $V'_S = \{v'_1, v'_2, \ldots, v'_n\}$ in $G_1$ such that $L_{\text{comb}}(v_i, v_{j+1}) = L_{\text{comb}}(v'_i, v'_{j+1})$ for all $1 \leq j < n$. The third rule discards $v_1 (v_n)$ if there exist more components in $P'_{1}^{L_{\text{comb}}(v_i, v_{j+1})} \cup L_{\text{comb}}(v_i, v_{j+1})$ than nodes in $V_2^{L_{\text{comb}}(v_i, v_{j+1})}$. Similarly to Proposition 3.2, this is allowed because the MCS can contain at most $\vert V_2^{L_{\text{comb}}(v_i, v_{j+1})} \vert$ nodes with label $L(v_1)$,$L(v_n)$. We prove the correctness of this rule just for $v_1$, but note that the same reasoning applies for $v_n$.

Proposition 3.3. Given a pair of graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ such that $G_1$ contains a simple path component $V_S = \{v_1, v_2, \ldots, v_n\}$, if $\sum_{i,j} c_{\text{comb}}(u_i, v_j) > \sum_{i} c_{\text{comb}}(u_i, v_j)$, then there exists an MCS $G_C = (V_C, E_C)$ of $G_1$ and $G_2$ such that $v_1 \not\in V_C$.

Proof. Let $G'_C = (V'_C, E'_C)$ be an MCS of $G_1$ and $G_2$ such that $v_1 \in V'_C$. We have that $\sum_{i,j} c_{\text{comb}}(u_i, v_j) > \sum_{i} c_{\text{comb}}(u_i, v_j)$ $\Rightarrow$ $\sum_{i} c_{\text{comb}}(u_i, v_j)$. Without loss of generality, assume that $G'_C$ contains two simple path components $U_S = \{u_1, u_2, \ldots, u_n\}$ and $U'_S = \{u'_1, u'_2, \ldots, u'_n\}$ such that $f'_j (u_j) = u_j$ for all $1 \leq j \leq n$ and $f'_j (u'_j) = u'_j$ for all $2 \leq k \leq n$. By definition, we have that $L_{\text{comb}}(u_i, u_{j+1}) = L_{\text{comb}}(u'_i, u'_{j+1}) = L_{\text{comb}}(u'_i, u'_{j+1})$ for all $2 \leq j < n$ and $L_{\text{comb}}(u_i, u_2) = L_{\text{comb}}(u'_i, u'_2)$. Therefore, there exists a mapping $f'_j$ identical to $f'_j$, with the exception that $f'_j (u_j) = f'_j (u'_j)$ and $f'_j (u'_j) = f'_j (u'_j)$ for all $2 \leq j \leq n$, and $f'_j (u_1) = u'_1$, thus $G'_C$ exists.

The three rules are repeatedly used to simplify $G_1$ and $G_2$ until a fixpoint is reached, i.e. all the rules are no longer applicable. At each iteration, isolate nodes are also discarded since our MaxSAT encoding forbids the inclusion of such nodes in the MCS, and doing so may enable further simplifications through Proposition 3.3.

4 PATTERN MINING
This section focuses on the problem of mining duplicated code patterns from a set of graphs $G_1, G_2, \ldots, G_n$. We start by describing a greedy pattern mining algorithm in Section 4.1, followed by its lazy version in Section 4.2. In Section 4.3, we propose an optimization that relies on de-duplicating the initial set of graphs before mining patterns. Lastly, in Section 4.4 we describe how an inverted index can be used in order to further reduce the algorithm’s runtime.

4.1 Greedy Algorithm
We propose a pattern mining algorithm that follows a greedy approach. The algorithm iteratively picks the graph pair $G, G'$ with the highest priority, according to some custom priority function, extracts a pattern $G_C$ of $G, G'$ and replaces $G, G'$ with $G_C$. This process is repeated until there are no more graph pairs left to consider.

For the duplicated code use case, the priority function is based on the notion of refactor weight of a graph. Given some graph $G = (V, E)$, each node $v \in V$ has an associated refactor weight $\omega_v$, which depends on its type and the kind of operations it performs. We consider a refactor weight of 1 for all nodes except INSTRUCTION nodes that correspond to database accesses. The weight of such nodes is given by the respective number of database tables, and filter and sort conditions. Similarly, we consider a refactor weight of 0 for all edges $u \in E$. Let $G_{V_1} = (V_{W_1}, E_{W_1})$, $G_{W_2} = (V_{W_2}, E_{W_2}, \ldots, G_{W_p} = (V_{W_p}, E_{W_p})$ denote the $p$ weakly connected components of $G$. A weakly connected component $G_{W_i}$ is a maximal sub-graph of $G$ such that, for all node pairs $u, v \in V_{W_i}$, $v$ reachable from $u$ in the undirected counterpart of $G$. The refactor weight $\omega_G$ of $G$ is given by:

$$\omega_G = \max_{i \in \{1, \ldots, p\}} \left\{ \sum_{v \in V_{W_i}} \omega_v + \sum_{(u, v) \in E_{W_i}} \omega_{u, v} \right\}. \tag{9}$$

We consider the maximum weight across $G$’s components instead of the sum because, from a refactoring perspective, patterns with less but bigger components are preferable. Given a graph pair $G, G'$, its priority is an upper bound of the refactor weight of an MCS of $G$ and $G'$. Given two components $G_{W_i}, G_{W'_j}$ of $G, G'$, respectively, the upper bound $\text{comp}_\text{ub}(G_{W_i}, G_{W'_j})$ for $G_{W_i}, G_{W'_j}$ is given by:

$$\sum_{f \in \text{comb}(E_{W_i})/\text{comb}(E_{W'_j})} \min_{E_W \in \{E_{W_i}, E_{W'_j}\}} \left\{ \sum_{(u, v) \in E_W} (\omega_{u, v} + \omega_u + \omega_v) \right\}. \tag{10}$$

Assuming $G'$ has $q$ components, the refactor weight upper bound $\text{ub}(G, G')$ for $G$ and $G'$ is given by:

$$\text{ub}(G, G') = \max_{i, j \in \{1, \ldots, p\} \times \{1, \ldots, q\}} \left\{ \text{comp}_\text{ub}(G_{W_i}, G'_{W'_j}) \right\}. \tag{11}$$

Ties in Equation (11) are broken using an upper bound of the number of edges of an MCS of $G$ and $G'$, given by:

$$\sum_{f \in \text{comb}(E)/\text{comb}(E')} \min \left\{ \left| E_{\text{comb}(f)} \right|, \left| E'_{\text{comb}(f)} \right| \right\}. \tag{12}$$

The greedy pattern mining algorithm is presented in Algorithm 1. It receives as input a set of $n$ graphs $G_1, G_2, \ldots, G_n$ and a minimum refactor weight threshold $\beta$, and returns a set $R$ of maximal patterns with a refactor weight of at least $\beta$ (line 2). Then, it initializes a priority queue $Q$ with all possible pairs of graphs in $A$ (lines 3 and 4). While $Q$ is not empty (line 5), it repeatedly pops a pair $G$ and $G'$ from the queue (line 6), and, if the upper bound for $G$ and $G'$ satisfies the threshold $\beta$ and both graphs are still active (line 7), it extracts an MCS $G_C$ of $G$ and $G'$ using the approach described in Section 3 (line 8). If the refactor weight of $G_C$ satisfies the threshold $\beta$ (line 9), then $G$ and $G'$ are removed from the active set $A$ (line 10), $G_C$ is stored in $R$ (line 11), new pairs with $G_C$ and the remaining active graphs are added to $Q$ (lines 12 and 13), and $G_C$ is added to the active graph set (line 14).

Due to its greedy nature, one can extend the algorithm in order to obtain a tree hierarchy of the patterns. Let $G$ and $G'$ be duplicated...
4.2 Lazy Greedy Algorithm

Recall that the pattern miner must return a response within a given time budget. If said budget expires, the miner should still return a subset of maximal patterns. Algorithm 1 may incur a long delay until the first pattern extraction due to the eager initialization of the priority queue (line 3), which requires computing refactor weight upper bounds for $O(n^2)$ candidate graph pairs. For example, for one of our test code bases, the miner needs to handle about 13K flows, which corresponds to almost 85M pairs. Queue initialization can take up to a couple of hours for such large code bases.

To solve this issue, we propose a lazy version of Algorithm 1, based on the observation that, given a graph pair $G_i, G_j$, such that $i \neq j$, and $ub(G_i, G_j) \geq ub(G_i, G_k)$ and $ub(G_i, G_j) \geq ub(G_j, G_k)$ for all $1 \leq k \leq n$, where $ub$ is the refactor weight upper bound from Equation (11), then we can safely extract an MCS for $G_i$ and $G_j$ before performing any further upper bound computations. This property comes as a consequence of the monotonicity of $ub$.

**Proposition 4.1.** Given three graphs $G_1 = (V_1, E_1), G_2 = (V_2, E_2)$ and $G_3 = (V_3, E_3)$, and an MCS $G_C = (V_C, E_C)$ of $G_1$ and $G_2$, we have that $ub(G_1, G_3) \geq ub(G_C, G_3)$ and $ub(G_2, G_3) \geq ub(G_C, G_3)$.

**Proof.** Without loss of generality, assume that $G_1, G_2, G_3$ and $G_C$ contain a single weakly connected component. By definition, $G_C$ is a sub-graph of $G_1$. Consequently, we have that $L_{comb}(E_C) \subseteq L_{comb}(E_1)$, implying that $L_{comb}(E_C) \cap L_{comb}(E_3) \subseteq L_{comb}(E_1) \cap L_{comb}(E_3)$. Additionally, we have that $E_C^\ell \subseteq E_3^\ell$ for any label $\ell$, thus:

$$ub(G_C, G_3) = \sum_{(u, v) \in E_C^\ell} \min_{E \in \{E_C^\ell, E_3^\ell\}} \left( \sum_{(u, v) \in E} \omega_{u, v} + \omega_{u, \ell} \right) \leq \sum_{(u, v) \in E_3^\ell} \min_{E \in \{E_C^\ell, E_3^\ell\}} \left( \sum_{(u, v) \in E} \omega_{u, v} + \omega_{u, \ell} \right) = ub(G_1, G_3).$$

Same goes for $G_2$.

The lazy greedy pattern mining algorithm is presented in Algorithm 2. It shares many similarities with Algorithm 1, the main difference being the management of the priority queue $Q$ and active graph set $A$. Initially, $Q$ and $A$ are empty (line 9) and a set of inactive graphs $I$ is initialized with all graphs with a refactor weight that satisfies the threshold $\beta$ (line 10). At each iteration, the algorithm starts by checking if $Q$ is empty (line 12). If so, then a graph $G \in I$ is activated (line 13). This corresponds to moving $G$ from $I$ to $A$ (lines 3 and 6) and adding new pairs to $Q$ containing $G$ and each
Algorithm 3: Isomorphic pattern mining algorithm.
\[
\begin{array}{l}
\text{Input: } G_1, G_2, \ldots, G_n
\\
D \leftarrow \emptyset
\\
\text{for } i \leftarrow 1 \text{ to } n \text{ do}
\\
\quad \text{key} \leftarrow \text{Sort}([I_{\text{comb}}(u,v) : (u,v) \in E_i])
\\
\quad \text{foreach } G \in D[\text{key}] \text{ do}
\\
\quad \quad \text{if IsIsomorphic}(G_i,G) \text{ then}
\\
\quad \quad \quad G_C \leftarrow \text{GetIsomorphicPattern}(G_i,G)
\\
\quad \quad \quad D \leftarrow (D \setminus \{(\text{key},G_i)\}) \cup \{(\text{key},G_C)\}
\\
\quad \quad \quad \text{break}
\\
\quad \quad \text{if } \exists G \in D[\text{key}] \text{IsIsomorphic}(G_i,G) \text{ then}
\\
\quad \quad \quad D \leftarrow D \cup \{(\text{key},G_i)\}
\\
\text{return GetPatterns}(D)
\end{array}
\]

remaining inactive graph (lines 4 and 5). Next, if necessary, additional graphs are activated until the pair in Q with the highest upper bound no longer contains inactive graphs (lines 14 to 17). The rest of the algorithm (lines 18 to 26) behaves in the same way as Algorithm 1, with the exception that each new MCS $G_C$ is added to the inactive set I instead of A (line 26). This process is repeated until Q becomes empty and at most 1 inactive graph is left (line 11).

### 4.3 Isomorphic Logic Flows

In practice, we observed that it is common for some of the logic flows to be fully duplicated. For example, among the 13K flows in the test code base mentioned at the start of the previous section, about 2K of them ($\approx 15\%$) are full duplicates. Finding full duplicates is much cheaper than mining MCSs, hence we propose an algorithm for de-duplicating the code base in order to significantly reduce the number of refactor weight upper bound computations.

Given two graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ and an MCS $G_C = (V_C, E_C)$ of $G_1$ and $G_2$, we say that $G_1$ and $G_2$ are isomorphic if and only if, for all $u \in V_1 \cup V_2, v \in V_C$, and for all $(u,v) \in E_1 \cup E_2$ and $(u,v) \in E_C$. When this is the case, we refer to $G_C$ as an isomorph-isomorphic duplicated code pattern. The MaxSAT encoding presented in Section 3.1 can be adapted to extract only isomorphism patterns by adding the following hard clauses:

- Unit clauses containing each of the inclusion and control-flow variables.
- A clause $(\forall v \in V_1 f_u v')$ for each node $v' \in V_2$.
- A clause $(\neg f_{u'} v \lor \neg f_u v')$ for each edge $(u',v') \in E_2$ and nodes $u,v \in V_1$ such that $(u,v) \not\in E_1$ or $L(u,v) \neq L(u',v')$.

This variant is a decision problem, which can be solved much more efficiently than its optimization version. In fact, in many practical scenarios, one can quickly conclude that $G_1$ and $G_2$ are isomorphic by checking if $|V_1| \neq |V_2|$ or $|E_1| \neq |E_2|$, or if any of the pre-processing rules in Section 3.2 is applicable.

The isomorphic pattern mining algorithm is presented in Algorithm 3. It maintains a dictionary $D$ of lists of graphs where the isomorphic patterns are stored. Initially, $D$ is empty (line 1). For each graph $G_i$, the algorithm starts by computing the key for $G_i$, which is the sorted concatenation of the combined labels of the edges in $E_i$ (line 3). Next, it checks if there exists a graph $G$ in $D$ with the same key as $G_i$, such that $G$ and $G_i$ are isomorphic (lines 4 and 5). Note that $G_i$ and $G_i$ will have the same key if and only if each combined label appears the exact same number of times in both graphs, which is a necessary condition in order for $G_i$ and $G_i$ to be isomorphic. If such $G$ exists, then an isomorphic pattern $G_C$ is extracted for $G_i$ and $G_i$ (line 6), and $G_i$’s entry in $D$ is replaced with $G_C$ (line 7). Otherwise, $G_i$ is added to $D$ (lines 9 and 10). Finally, the isomorphic patterns in $D$ are returned by the algorithm (line 11).

### 4.4 Inverted Index

Although de-duplication helps, the number of candidate graph pairs can still be prohibitively high. For example, de-duplicating the test code base reduces the number of flows to 11K, which still results in about 61M pairs. In order to further reduce this number, we use a partial inverted index like the one proposed in SOURCERERCC [48]. In the context of our work, the inverted index is a mapping of combined edge labels to lists of graphs that those labels appear in. The index is deemed partial because it contains entries only for a subset of combined labels that occur with the most frequency.

Algorithm 4 describes the process of creating the index for a given set of graphs $G_1, G_2, \ldots, G_n$. For each graph $G_i$, it starts by creating a bag $B$ of the combined labels that appear in $E_i$, sorted in decreasing order of their global frequency (line 3). The global frequency of some combined label $I \in I_{\text{comb}}(E_i)$ is given by:

\[
\frac{\sum_{j=1}^n |E_{ij}|}{\sum_{j=1}^n |E_j|}
\]

Lastly, entries containing $G_i$ are added to $I$ for a prefix of $B$ (lines 4 and 5). The prefix size is controlled through the $\delta$ input parameter, which represents the fraction of a graph’s combined labels to include in the index. For example, if $\delta = 0.2$, then the 20% most frequent combined labels in $B$ are included in $I$.

Algorithm 1 requires the following changes in order to integrate the inverted index: (1) During queue initialization (line 3), only pairs of graphs that occur in the same index list are considered. (2) A new pattern $G_C$ is added to the index before the queue update (lines 12 and 13), and the respective new queue pairs should contain only graphs that occur in the same index lists as $G_C$. The same reasoning applies to the queue updates in lines 4, 5, 24 and 25 of Algorithm 2.

### 5 EXPERIMENTAL EVALUATION

In this section, the performance of the pattern mining algorithms and optimizations proposed in Section 4 is evaluated. The pattern
miners were executed on benchmark sets of logic flows from a random sample of 800 real-world code bases written in OutSystems\textsuperscript{2}. The 800 code bases were sampled uniformly from the full world of 1491 code bases that existed at experimentation time. Note that an OutSystems code base contains multiple web/mobile applications, typically hundreds. In order to protect sensitive data, the code bases are anonymized at the source, including the replacement of string literals with hashes. Two performance indicators are considered: mining time, i.e. elapsed time since the start of the mining algorithm until termination, and duplicated refactor weight found, i.e. total refactor weight of the nodes and edges that appear in the patterns returned by the algorithm. Note that the same node/edge may appear multiple times across different patterns, but the respective refactor weight is counted only once. Precision/recall is not considered because the respective results depend heavily on the node/edge labels, and the focus of this work is algorithm scalability.

Before running the mining algorithms, nodes that cannot be refactored to a separate logic flow, such as START and END nodes, are discarded. Flows with refactor weight lower than the threshold \(\beta\) (5 in our experiments) are also discarded. Lastly, only benchmarks for which there exists a noticeable difference in results are considered in the evaluation, i.e., we ignore benchmarks for which the mining time and duplicated refactor weight across all pattern miner configurations does not vary by more than 1 second and 0.1\% respectively. This results in a final collection of 693 benchmarks\textsuperscript{3}. Table 1 summarizes several statistics regarding the number of flows and nodes in these benchmarks. Flows/nodes considered corresponds to the flows/nodes that are not discarded before mining.

Table 2 shows some statistics regarding the amount of duplication found in the benchmark sets. For each benchmark set and parameter, the maximum value obtained across all evaluated pattern mining configurations is considered. The \(p \times x\) columns show the \(x\)-percentile values for each parameter. For example, a value of 15.8\% in the \(p = 0.75\) column of the 'Flows with duplicated code' row indicates that, in 75\% of the benchmarks, 15.8\% or less of the flows are found to contain duplicated code. Note that these percentages consider the full universe of flows/nodes present in these benchmarks before pre-processing.

In order to solve the MCS MaxSAT instances, the PySAT\textsuperscript{18} implementation of linear search [25] is used. Each MCS extraction is run with a timeout of 10 seconds. When the timeout is triggered, an approximate MCS is retrieved from the best solution found by the linear search algorithm. In order to prevent the pattern miner from becoming stuck due to occasional huge flows that result in hard MaxSAT instances, the respective graphs are always removed from the active graph set whenever linear search fails to prove optimality, regardless of the refactor weight of the approximate MCS. In our experiments, we observed that timeouts are a rare occurrence: 0.1\% of a total of 267481 MCS extractions for one of the configurations with graph pre-processing (Section 3.2) and inverted index (Section 4.4) enabled. To solve the isomorphic pattern SAT instances, we run PySAT with a timeout of 10 seconds as well. In our experiments, PySAT was configured to use the Glucose SAT solver (version 4.1) [2]. All experiments were run on an AWS m5a.12xlarge instance with 128 GB of RAM.

### 5.1 Algorithm Comparison

Table 3 compares the maximum and total mining time for the Greedy (Section 4.1) and Lazy (Section 4.2) algorithms. Both algorithms were executed with graph pre-processing enabled. Lazy shows better performance than the original non-lazy version, being able to process all the benchmarks in 10.5\% less time. Figure 3 shows a distribution plot comparing the mining times of the algorithms. For a given algorithm, each \((x, y)\) point in the plot indicates that, for \(x\) benchmarks, the mining time of that algorithm is at most \(y\). For example, the \((600, 200)\) point in the line that corresponds to Lazy indicates that 600 of the benchmarks are processed in 200 seconds or less by that algorithm. Overall, we can see a small but noticeable reduction in mining times for Lazy compared to Greedy.

The performance improvement in terms of mining time was expected, since Lazy adds graph pairs to the queue on an as-needed basis, resulting in a lower overhead incurred by queue updates. Recall that the main advantage of Lazy is a much shorter time-to-first-pattern, since, unlike Greedy, it does not suffer from the major initialization overhead incurred by the eager initialization of the queue. We observed an average time-to-first-pattern of 1 second for Lazy versus 96 seconds for Greedy, and maximum values of 25 seconds and over 1 hour and 12 minutes respectively.

### 5.2 Impact of De-duplication

Table 3 and Figure 3 show the impact, in terms of mining time, of applying de-duplication (Section 4.3) before running the Lazy algorithm. Note that the time spent on de-duplication is accounted for in the reported mining times. Overall, we can see that the performance boost is quite significant. In particular, DedupThenLazy achieves a reduction of 34.6\% in total mining time compared to Lazy. Additionally, the reduction for the hardest benchmark is 42.3\%. This reduction makes sense because, as we observed in our experiments, DedupThenLazy spends, on average, 13.8\% of mining time on de-duplication and removes about 19.4\% of the flows before running the pattern mining algorithm.

### 5.3 Impact of Inverted Index

Table 3 and Figure 3 also compare the performance of DedupThenLazy with and without the inverted index. For this experiment, the \(\delta\) parameter of the inverted index was set to 1.0. We can see that, compared to lazyfication and de-duplication, the inverted index has, by far, the largest overall positive impact in the performance of the pattern mining algorithm, achieving a reduction of 67.2\%.
Table 2: Maximum amounts of duplicated code found per benchmark set.

| Parameter                        | min   | p = 0.25 | p = 0.5 | p = 0.75 | p = 0.90 | p = 0.95 | p = 0.99 | max     | total   |
|----------------------------------|-------|----------|---------|----------|----------|----------|----------|---------|---------|
| Flows with duplicated code       | 0.7%  | 8.8%     | 12.1%   | 15.8%    | 20.6%    | 23.4%    | 32.3%    | 42.9%   | -       |
| Duplicated nodes found           | 0.7%  | 6.9%     | 9.9%    | 13.2%    | 18.1%    | 22.0%    | 30.9%    | 39.0%   | -       |
| Duplicated weight found          | 14    | 1185.00  | 3623.00 | 9956.00  | 22632.00 | 40896.40 | 101675.72| 270756  | 6817353 |

Figure 3: Distribution of mining time, in seconds, for different configurations of the pattern mining algorithms.

Table 3: Maximum and total mining time for different configurations of the pattern mining algorithms.

| Algorithm                  | max          | total         |
|----------------------------|--------------|---------------|
| GREEDY                     | 2h09m12s     | 1d09h52m39s   |
| LAZY                       | 2h07m22s     | 1d06h20m08s   |
| DedupThenLazy              | 1h13m32s     | 19h49m41s     |
| DedupThenLazy+Index        | 48m39s       | 6h30m45s      |

in total mining time. The performance improvement observed for the hardest instance is not as significant: a reduction of 33.8%. This performance boost was expected since, with the inverted index, the algorithm only needs to compare each graph with a much smaller subset of graphs with overlapping combined edge labels, versus comparing all possible pairs. Overall, the combination of lazyfication, de-duplication and the inverted index results in a total mining time reduction of 80.8% compared to the original GREEDY algorithm.

Additional experiments were performed in order to evaluate the impact of the δ parameter on the performance of the mining algorithm. We tested values of δ ranging from 0.1 to 1.0 in increments of 0.1. We observed that, in the best case, a value of δ = 0.1 resulted in a small total mining time reduction of 4.5% compared to δ = 1.0. Detailed results regarding mining time for the different values of δ are not shown due to space limitations.

Figure 4 shows a distribution plot of duplicated refactor weight found for the different values of δ. These values are normalized against the largest duplicated refactor weight values found for each benchmark. For a given value of δ, each (x, y) point in the plot indicates that, for x benchmarks, the duplicated refactor weight found with δ is at least a fraction y of the best value. We can see that decreasing δ can have a significant negative impact on the amount of duplication that the algorithm is able to detect, particularly with δ ≤ 0.3. The impact is much less significant for δ ≥ 0.6. However, using δ = 0.6 results in a total mining time reduction of just 1.1%. Overall, such a small mining time reduction does not compensate the negative impact on the algorithm’s detection capabilities.

5.4 Impact of Graph Pre-processing

Table 4 compares the performance of the lazy algorithm, with and without graph pre-processing, in terms of time spent solving MaxSAT instances in addition to the total mining time. Note that the time spent building the encoding and on pre-processing is accounted for in the reported times. In both scenarios, the algorithm was executed with the inverted index enabled. Enabling pre-processing results in the generation of 897 extra MaxSAT instances. This increase makes sense because pre-processing leads to the generation of smaller, and thus easier MaxSAT instances. Consequently, linear search is able to find larger MCSs before the timeout, resulting in more MCSs being generated before triggering the β threshold of the pattern miner. Note that, with pre-processing, optimality of the MCS is proven for 1073 additional instances, which is more than the 897 extra ones. Moreover, despite these extra instances, 37% less time is spent in total solving MaxSAT instances. Overall, this translates to a reduction in total mining time of 11.7%.

Figure 5 shows a distribution plot comparing the duplicated refactor weight found with and without graph pre-processing. In order to improve readability, only benchmarks for which there was a variation of at least 0.1% are considered. We can see that a moderate
improvement is achieved by enabling graph pre-processing. This is expected since, as mentioned previously, more and larger MCSs are generated when pre-processing is enabled.

6 RELATED WORK

Many duplicated code detection techniques have been proposed in the literature for text-based programming languages. Rattan et al. [43] wrote an extensive survey on this topic, where they classify these techniques into five main categories: text-based [4, 5, 11, 14, 15, 21], token-based [17, 22, 28, 42, 48, 54], tree-based [8, 20, 52], graph-based [24, 26, 30, 49, 53, 63] and metrics-based [6, 32, 40]. Recently, several detectors based on machine learning have also emerged [47, 55–57, 60–62]. These techniques (except most graph-based) only support duplicated code detection at a pre-defined granularity, i.e., are able to report, for example, groups of methods as duplicated, but are unable to do so for relatively small but frequent duplicated code patterns contained within said methods. For example, such techniques may miss duplicated patterns like the one from Figures 1 and 2 since only 60% of those flow’s logic is duplicated.

Graph-based detectors analyse the Program Dependence Graphs (PDGs) of the code blocks in order to detect duplicated code. Typically, these approaches also rely on searching for isomorphic subgraphs [24, 26, 30, 53]. Because such detectors consider the PDG of the graph, these are able to detect semantic duplicates with many syntactic changes. However, scalability is an issue due to the hardness of checking sub-graph isomorphism. Some graph-based detectors mitigate this by using heuristics in order to avoid some of these checks [30, 53], applying some limited form of pre-processing to the PDGs [53] or using approximate graph matching [63]. To the best of our knowledge, ours is the first graph-based approach that solves the scalability issue by means of an inverted index.

Some approaches exist in the literature for detecting duplicated code in Simulink models [1, 13, 29, 41, 50]. SIMONE [1] applies the NiCad [11, 15] text-based detector on textual representations of the models, thus sacrificing visual structure. ConQAT [13] uses heuristics to mine large duplicated code patterns from promising pairs of graphs and then group these patterns into clusters. Due to the heuristic nature of the algorithm, it does not ensure intra-cluster consistency of the graph structure of the patterns. Additionally, it is not able to detect smaller more frequent duplicated code patterns contained within larger less frequent ones. eScan [41] solves these issues by using a combination of frequent sub-graph mining and maximal clique covering instead. However, it has been shown that this approach does not scale in practice [12, 50]. SCANQAT [50] mitigates this issue by combining ConQAT and eScan, but the reported results show a modest improvement over the latter.

MCS extraction is a well-known problem with several important applications besides duplicated code detection [16, 39, 44, 59]. Classical approaches solve the MCS problem via reduction to maximum clique [7]. Our approach is closely related to more recent work that translates the problem to a constraint satisfaction [33, 51] or an integer linear programming problem [3]. An alternative solution, proposed by McCreesh et al. [34], uses branch and bound to search for MCSs. A later iteration of this approach exploits reinforcement learning in order to learn a more effective branching heuristic [51].

Figure 6: The labeled graph for the logic flow in Figure 2.

Frequent sub-graph mining is closely related to the duplicated code pattern mining problem addressed in this work. The typical solution is to follow a top-bottom approach that starts with a set of very small high frequency candidate common sub-graphs and iteratively extends them with new nodes/edges until their frequency falls below a given threshold [9, 10, 19, 38, 58]. By nature, this approach maximizes sub-graph size while maintaining a pre-specified minimum frequency. We decided to implement our own custom mining algorithms for duplicated code because, if a timeout is triggered, it is preferable to return a set of large high-impact patterns than a set of high frequency patterns with very few nodes/edges.

7 LIMITATIONS AND DISCUSSION

The precision and recall of the proposed approach strongly depends on the quality of the node and edge labels. These were defined based on extensive iterative feedback from expert OUTSYSTEMS developers. The edge labels are set to their respective types in the logic flows, with the exception of SWITCH branches which consider the variable types and function calls that appear in the respective SWITCH condition. Node labels, however, can be quite sophisticated depending on their type. A simple example is the If node label, which considers what kind of condition is being checked (e.g. null check) in addition to the respective variable types and function calls. On the other hand, the label of an INSTRUCTION node that performs a database access considers several characteristics, such as which tables are being accessed and which filters are being applied over which table columns. Some normalizations were also performed, such as swapping the branches of an IF node if the condition is a negation of some Boolean expression. Overall, the labels were tuned with the goal of maximizing the detection of type 3 duplicates that share the same graph structure. Figure 6 shows the labeled version of the logic flow from Figure 2.

Duplicated IF and SWITCH nodes can only be refactored if at least one of their branches is also part of the duplicated code pattern. However, the proposed mining algorithms do not capture this kind of constraint. To circumvent this, some post-processing is applied to the patterns, immediately after extraction, in order to discard occurrences of such nodes. Another option would be to sacrifice generality by adding additional clauses to the MaxSAT encoding that enforce this constraint.

As discussed in Section 1, in earlier versions of our system, we used a graph representation more similar to PDGs that included data dependencies instead of just the syntactic structure of the logic flows. This representation enabled the pattern miners to find semantic duplicates with significant syntactic differences, but discussions with OUTSYSTEMS experts led to the conclusion that such duplicates were hard to analyse and understand. For this reason,
we focused on detecting type 3 duplicates with the same graph structure, but note that the proposed approach is agnostic to the graph representation and can be seamlessly applied on PDGs in order to detect syntactically dissimilar duplicated code.

Recall from Section 1 that the following requirements must be satisfied in order to provide a good user experience: (1) the graph structure of the duplicated code must be the same across its corresponding logic flows; (2) the duplicated code detector must return the mappings of flow nodes to the duplicated code pattern in order for the tool to visually highlight the duplicated structure. Most state-of-the-art detectors do not satisfy these requirements. For example, SIMONE [1] applies text-based detection to Simulink models, thus losing the information needed for requirement 2. The same applies to all non-graph based detectors for text-based languages, and even some of the graph-based like CCGRAPH [63], which performs approximate graph matching using graph kernels. On the other hand, COQAT [13], eSCAN [41], SCANQAT [50] and CChSAPR [53] come close to satisfying these requirements. However, we do not compare with these approaches for the reasons that follow: COQAT’s and SCANQAT’s source code is not publicly available. COQAT’s clustering step ignores the connections between nodes, thus not satisfying requirement 1. Changing this requires replacing several list comparisons with isomorphism checks, which incurs a significant performance overhead. Lastly, CChSAPR applies some filtering rules that are specific to PDGs. Moreover, CChSAPR implements heuristics that prevent it from finding certain types of duplicated code patterns, such as duplicated sub-flows within large dissimilar flows or flows with dissimilar names.

8 CONCLUSIONS AND FUTURE WORK

Duplicated code is an important form of technical debt that incurs a significant negative impact on software maintenance and evolution costs. For this reason, for the past few decades, a large body of research has been dedicated to studying and addressing code duplication in text-based programming languages. We propose a novel duplicated code detector for OUTSYSTEMS that leverages the code’s visual structure in order to provide helpful explanations of reported duplications. Scalability is achieved by using an inverted index to avoid many unnecessary comparisons. An extensive experimental evaluation carried out on real-world OUTSYSTEMS code bases show the effectiveness and scalability of the proposed solution. This solution is currently deployed in the Architecture Dashboard4, a production static analysis tool for the OUTSYSTEMS VPL.

In the future, we plan to design and implement an incremental version of the pattern mining algorithm. Incrementality has the potential to considerably reduce mining time, cutting down on computational resource costs and enabling real-time duplicated code detection. Algorithms for mining duplicated code patterns that occur frequently within a single flow are being considered as well. Lastly, we plan to exploit the tree structure of the patterns in order to provide a guided refactoring experience to the user, and eventually pursue full automation of the refactoring process.

4https://www.outsystems.com/platform/architecture-dashboard/

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