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A Structural and Statistical Approach to Code Similarity Detection

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Abstract

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A Structural and Statistical Approach to Code Similarity Detection

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This thesis introduces a scalable method for detecting code similarity in Python student submissions by combining structural AST paths with TF–IDF–weighted “bag-of-paths” representations. After anonymizing identifiers and extracting root-to-leaf paths, we compute cosine similarities to reveal exact and near-miss clones with over 90 % precision and sub-second runtimes on hundreds of files. Visual heatmaps and clustering help instructors spot reuse patterns, while future work will target deeper semantic equivalences via program-dependence features and dynamic analysis.

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Index

Chapter 1: Introduction

1.1 Background and Motivation

Detecting similar or duplicated code is essential as both class sizes and codebases grow. In educational settings, automated assessments are necessary to handle hundreds of student submissions, yet naive text comparisons break when learners rename variables, adjust formatting, or rearrange logic. While tools like MOSS effectively catch nearly identical copies (Type-1 and Type-2 clones), they struggle with more sophisticated transformations that preserve program structure but mask superficial changes. On the other hand, statistical methods such as TF-IDF treat code tokens like words and compute vector similarities, offering efficiency but overlooking deeper syntactic patterns. Inspired by advances like code2vec, which represents code as multisets of Abstract Syntax Tree (AST) paths, we propose blending structural representations with statistical weighting to catch both overt and subtle similarities.

1.2 Problem Statement

This thesis seeks a scalable, accurate way to assess code similarity that resists superficial edits and distinguishes genuine algorithmic reuse from coincidental common patterns. Focusing on Python, our method must parse and normalize student submissions, extract meaningful structural features, and compare them without exhaustively matching every pair by brute force. Success means flagging snippets that share core logic, despite renaming or reordering, while avoiding false alarms when students independently apply the same standard constructs.

1.3 Research Questions and Objectives

We guide this work with three core questions: first, how can code be represented so that its structure becomes comparable across submissions? Second, does applying

TF-IDF weighting to AST-derived features outperform either textual or purely structural approaches? Third, can our hybrid pipeline reliably uncover plagiarism or natural duplicates in real student data? To answer these, we (1) extract AST paths as structural tokens, (2) transform each submission into a TF-IDF vector of those paths, (3) compute cosine similarity to score every pair, and (4) assess performance on a labeled dataset against existing baselines.

1.4 Proposed Approach and Contributions

Our approach builds a "bag-of-paths" model where each AST path functions like a word in a document. By parsing Python code into an AST, extracting root-to-leaf and other informative paths, and applying TF-IDF, we obtain dense vectors that reflect how distinctive each structural pattern is. Pairwise cosine similarities of these vectors highlight submissions that share deep syntactic structures, even under deliberate obfuscation. Contributions include a largely language-agnostic framework demonstrated in Python, a prototype that handles parsing, anonymization, vectorization, and scoring at scale, and an empirical study showing superior detection of disguised similarities compared to text-only methods.

Chapter 2: Background and Related Work

2.1 Overview of Code Similarity and Clone Detection

Code similarity detection addresses the problem of identifying portions of source code that are identical, nearly identical, or functionally equivalent. In large-scale software projects, copy-and-paste programming, reuse of proven algorithms, or the natural evolution of code through refactoring can lead to duplicated or highly similar code segments. While copying code can speed development, it also propagates defects: a bug discovered in one copy may lurk in its duplicates unless a developer locates and patches every instance. From a maintenance standpoint, clones increase code volume, hinder readability, and complicate efforts like API migration or feature extension. In academic and competitive programming contexts, clone detection underpins plagiarism detection by flagging suspiciously similar submissions across students or contestants.

Over the past three decades, researchers have devised a spectrum of automated clone detection techniques. At one end lie **textual methods**, which operate on raw code strings or token sequences; these are fast and language-agnostic but capture only superficial similarities (Types 1 and 2). In the middle are **structural methods** that parse code into Abstract Syntax Trees (ASTs) or Program Dependence Graphs (PDGs), extracting hierarchical or dependency relationships that endure renaming and minor edits (Types 2 and 3). At the other extreme, **semantic methods**—including graph matching on PDGs and neural code embeddings—aim to recognize functional equivalence (Type 4 clones), albeit at greater computational cost. Recognizing that no single approach suffices for all clone types and code scales, modern tools often compose multiple analyses into **hybrid pipelines** that balance recall (the fraction of true clones found) against precision (the fraction of reported clones that are valid). This chapter surveys these families of techniques, reviews how they are evaluated, and highlights open gaps that motivate our proposed hybrid approach.

2.1.1 Types of Code Clones (Type-1 to Type-4)

The software engineering literature classifies clones into four canonical types, based on how extensively a copied fragment diverges from its source:

- **Type-1 (Exact Clones):** These are verbatim copies of code segments, differing only in non-functional aspects such as whitespace, comments, or formatting. Since the token sequence remains identical, Type-1 clones are the easiest to detect via simple string or token matching.
- **Type-2 (Renamed/Parameterized Clones):** In these clones, the copied code is syntactically identical, but identifiers (variable names, function names) or literal values are systematically renamed. The underlying logic and control flow remain unchanged; only superficial symbols differ. Detecting Type-2 clones requires normalization of tokens (e.g., replacing all identifiers with placeholders) before matching.
- **Type-3 (Near-Miss Clones):** These arise when developers copy a code segment and then introduce small modifications—adding or removing statements, tweaking conditions, or reorganizing a few lines. Though the overall structure and intent mirror the original, gapped similarities appear. Clone detectors must accommodate a bounded number of insertions/deletions or reordering to catch Type-3 clones.
- **Type-4 (Semantic Clones):** The most challenging category encompasses functionally equivalent fragments that implement the same algorithm or behavior, but exhibit different syntactic forms—perhaps using alternative data structures, distinct control constructs (recursion versus iteration), or different API calls. Detecting such clones demands semantic analysis beyond textual or structural similarity.

To illustrate, consider four Java implementations of a factorial function, each typifying one of these types:

```java
// Original implementation of factorial
public int factorial(int n) {
    int result = 1;
    for (int i = 2; i <= n; i++) {
        result *= i;
    }
    return result;
}

// Type-1 Clone: Identical copy (only whitespace/comments might differ)
public int factorialClone1(int n) {
    int result= 1;
    for (int i= 2; i <= n; i++) {
        result *= i;
    }
    return result;
}

// Type-2 Clone: Only identifiers renamed (structure and logic identical)
public int factorialClone2(int m) {
    int prod = 1;
    for (int j = 2; j <= m; j++) {
        prod *= j;
    }
    return prod;
}

// Type-3 Clone: A small modification added (extra check for n<=1)
public int factorialClone3(int n) {
    if (n <= 1) return 1;        // added check
    int result = 1;
    for (int i = 2; i <= n; i++) {
        result *= i;
    }
    return result;
}

// Type-4 Clone: Different implementation (using recursion instead of loop)
public int factorialClone4(int n) {
    if (n <= 1) return 1;
    return n * factorialClone4(n - 1);
}
```

Figure 1: Example of the 4 Types of Clones

In factorialClone1, the block is an exact duplicate, aside from whitespace differences; detecting it is trivial for text-matching methods. factorialClone2 renames n⟶m, result⟶prod, and i⟶j, but the sequence of operations is unchanged; AST-based or token-normalization methods readily identify such clones. With factorialClone3, the added base-case check (if (n <= 1) return 1;) creates a near-miss clone whose AST or token sequence differs slightly—catching it requires allowance for small edits. Finally, factorialClone4 implements factorial via recursion, yielding a different AST

shape and token sequence; only a semantic or PDG-based approach (or a powerful embedding model) can recognize its equivalence to the loop-based versions.
As clone type increases, detection difficulty grows markedly. Most early tools achieve high recall on Type-1 and Type-2 clones, moderate success on Type-3, and struggle with Type-4. The remainder of this chapter explores a layered spectrum of detection techniques, from structural to statistical to hybrid, and discusses how they perform across clone types.

2.2 Structural Approaches

Structural techniques transform source code into representations that capture its hierarchical or dependency structure, thereby abstracting away surface differences like whitespace or renaming. Two dominant structural forms are Abstract Syntax Trees (ASTs) and Program Dependence Graphs (PDGs).

2.2.1 AST-Based Representations

An Abstract Syntax Tree models the grammatical structure of code: nodes correspond to language constructs (e.g., loops, conditionals, assignments), and leaves represent identifiers, literals, or operators. By comparing AST subtrees rather than raw token sequences, clone detectors can tolerate formatting and renaming, naturally capturing Type-1 and Type-2 clones.
Early AST-based tools parses code into language-specific ASTs, computes hashes of subtrees, and identifies identical or near-identical shapes as clones. CloneDR effectively normalizes away comments and whitespace, and it can detect clones with consistent renaming by abstracting identifiers. However, naive subtree hashing struggles with near-miss edits: an added statement leads to a distinct subtree.
To address scalability and near-miss detection, characteristic-vector approach was introduced. Instead of hashing entire subtrees, It extracts structural features such as subtree node counts, depth, and types into fixed-length vectors. It then applies locality-sensitive hashing (LSH) to group similar vectors, yielding candidate clone

pairs. By tuning similarity thresholds on these vectors, Deckard can detect moderate Type-3 clones. LSH allows to scale to millions of lines of code with reasonable runtime and memory footprints.

Beyond hashing and vectorization, some approaches compute **tree-edit distance**, measuring the minimum number of insert/delete/rename operations to transform one AST into another. While precise, tree-edit algorithms incur O(n3)O(n^3)O(n3) or worse time complexity, making them impractical for large codebases without heuristics or pruning. Parameterized tree matching, where certain subtree edits are discounted or normalized, provides a middle ground, tolerating specific patterns of change.

More recently, machine-learning techniques have been applied directly to ASTs. For instance, **ASTNN** (Zhang et al., 2019) breaks ASTs into statement-level subtrees, embeds each with an RNN, and aggregates them using a gated mechanism to produce function-level vectors. Although ASTNN ultimately yields embeddings, it relies on AST structure to guide its neural architecture.

AST-based methods excel at Types 1 and 2 by design: identical or renamed subtrees hash to the same (or near-identical) values. For Type 3, approaches that allow vector thresholds or edit allowances can catch near-miss clones, though they incur tuning complexity. Detecting Type 4 clones remains beyond pure AST matching, since implementations may have fundamentally distinct tree shapes (as with recursive versus iterative factorial).

2.2.2 Program Dependence Graphs

While ASTs capture syntax, Program Dependence Graphs (PDGs) encode semantic relationships by modeling both data-flow and control-flow dependencies. In a PDG, nodes represent program instructions or predicates, and edges represent how one node depends on another: **data-dependency** edges link definitions to uses, while **control-dependency** edges link predicates (e.g., if or loop conditions) to the statements they guard.

By seeking isomorphic subgraphs within PDGs of two code fragments, a detector can identify pieces that perform equivalent computations—potentially catching Type 4 clones that share dependency patterns despite syntactic divergence.
Komondoor and Horwitz (2001) pioneered PDG-based clone detection by performing program slicing and searching for matching slices across code. Krinke (2001) similarly explored subgraph isomorphism in PDGs, demonstrating that even moderate-sized programs yield many semantically similar slices.
However, exact subgraph isomorphism is NP-complete, and naive matching is infeasible for large graphs. To reduce complexity, modern PDG-based methods employ pruning heuristics (e.g., bounding slice size or focusing on function entry points) or approximate graph comparison via **graph kernels** or **fingerprinting**. For example, **CCGraph** (Xue et al., 2019) computes kernel similarities between PDGs, trading exactness for tractability. Graph-kernel methods implicitly measure substructure overlap without explicit isomorphism enumeration.
PDG construction demands comprehensive program analysis—type checking, control-flow graph derivation, and data-flow analysis—which may require code to compile or undergo static analysis. Tools like CodeSurfer provide PDG extraction but introduce overhead incompatible with on-the-fly IDE integration.
PDG-based detection shines on clones that share underlying computation (Type 4), such as two implementations of the Euclidean GCD algorithm using different loops or API calls. Yet the cost of graph construction and matching limits widespread adoption, relegating PDGs to niche semantic-analysis phases or research prototypes.

2.3 Statistical and NLP-Inspired Methods

Statistical and NLP-inspired methods eschew deep structural parsing in favor of representations that treat code as “text plus tokens,” applying classic information-retrieval and machine-learning techniques.

2.3.1 Token n-grams and TF-IDF

One foundational approach views code as a sequence of lexical tokens (identifiers, keywords, operators) and analyzes contiguous subsequences **n-grams** to measure overlap. For instance, the snippet

```python
for i in range(5):
    print(i)
```

Figure 2: Snippet of a a for loop

yields tokens [for, i, in, range, (, 5,), :, print, (, i,)] and trigrams like [for, i, in], [i, in, range], etc. If another code fragment shares numerous identical n-grams, a token-based clone detector may flag them as duplicates.

Suffix-tree algorithms over normalized token streams enable efficient longest common subsequence searches. **CCFinder** (Kamiya et al., 2002) normalizes identifiers into placeholders, builds a suffix tree of token sequences, and extracts maximal matching substrings to detect Type 1 and Type 2 clones, with adjustable gap tolerance for Type 3 detection.

A complementary strategy employs **TF-IDF** vectorization: treat each code fragment as a "document" and each token (or token bigram) as a "term." Term Frequency–Inverse Document Frequency downweights ubiquitous tokens ({, }, ;, for) and highlights domain-specific identifiers. Fragments become high-dimensional vectors, and **cosine similarity** between vectors estimates clone likelihood. **SourcererCC** (Sajnani et al., 2016) scales this model by constructing an inverted index of token bags with IDF weights, performing fast candidate retrieval across hundreds of millions of lines. SourcererCC demonstrates linear or near-linear scalability and achieves high recall on Types 1–2 and strong Type 3 clones.

Statistical methods excel in simplicity and speed, requiring only tokenization—not full parsing. They are language-agnostic (modulo lexers) and integrate readily into code-search infrastructures. However, they struggle with token reordering, coincidental vocabulary overlap, and purely semantic clones that share few tokens.

2.3.2 Vector Embeddings for Code

Inspired by word embeddings in NLP, recent work learns dense vector representations—**code embeddings**—for entire fragments. A well-trained embedding model places semantically similar code snippets close in vector space, enabling clone detection via nearest-neighbor search.

Early efforts, such as **White et al. (2016)**, applied recursive neural networks over ASTs to learn embeddings that distinguish clones from non-clones. Wei and Li (2017) proposed **CDLH**, an LSTM-based "learning to hash" model that maps token sequences and AST paths into compact binary codes optimized via supervised clone-pair training.

The **code2vec** framework (Alon et al., 2019) decomposes ASTs into a multiset of paths (ordered node sequences between leaf pairs), embeds each path via learned vectors, and aggregates them through an attention mechanism into a single representation per method. Code2vec has shown success in code summarization tasks and can be repurposed for clone detection by comparing method vectors.

Transformer-based pretraining extends these ideas at scale. **CodeBERT** (Feng et al., 2020) and **GraphCodeBERT** (Guo et al., 2020) leverage bilingual (comment/code) and graph structural objectives to learn deep contextual embeddings from massive GitHub corpora. Fine-tuning these models on clone detection benchmarks yields state-of-the-art results on Type 3 and Type 4 clones, albeit at the cost of heavy computation and large training datasets.

Graph Neural Networks (GNNs) further combine structural and learned representations, embedding PDG or AST graphs via message passing to capture dependencies. The flexibility of GNNs allows the incorporation of semantic edges (data- and control-flow) into embedding learning.

Embedding approaches mitigate the brittleness of token-based methods and the computational expense of graph matching, but they shift the challenge to data collection (gathering labeled clone/non-clone pairs), model interpretability, and efficient similarity search in high dimensions.

2.4 Hybrid Methods

Because each detection family offers distinct trade-offs, **hybrid pipelines** merge them to maximize overall effectiveness. A prototypical hybrid detector comprises three phases:

1. **Lexical Pre-Filtering:** A fast token-based index (e.g., TF-IDF or n-gram inverted index) retrieves a broad set of candidate pairs with minimal computational overhead. This stage prioritizes recall—ideally catching all Type 1–2 clones and many Type 3s—while tolerating false positives.
2. **Structural Verification:** Candidates pass through AST-based checks (e.g., subtree hash alignment or tree-edit distance thresholds) that prune false positives, improving precision. Tools like **NiCad** (Roy and Cordy, 2008) exemplify this stage by normalizing code and running longest-common-subsequence comparisons on the normalized AST or token stream.
3. **Semantic Refinement:** The hardest Type 4 candidates, or borderline Type 3 cases filtered out or retained ambiguously, undergo deeper analysis via PDG comparison, embedding similarity, or neural classifiers. Limited in scale, this phase focuses on a small set of high-value clone suspects.

Finally, results merge into coherent clone classes: overlapping detections are consolidated, and clone groups (more than pairwise) are constructed. Thresholds at each phase are tuned on validation datasets to balance precision and recall according to application needs—high precision for IDE warnings, high recall for security audits or large-scale refactoring.

Hybrid detectors achieve near-linear scalability by confining expensive analyses to a subset of candidates. They exploit the speed of token-based retrieval, the accuracy of structural matching, and the semantic power of embeddings or PDGs. This architectural pattern underlies many state-of-the-art systems and motivates our own structural-statistical hybrid design.

2.5 Evaluation Metrics and Benchmarks

Quantifying clone detector performance relies on classic metrics from information retrieval and classification: **precision** (the proportion of reported clones that are true clones), **recall** (the proportion of true clones that are reported), and their harmonic mean, **F1-score**. In clone detection, one can evaluate at the **pair** level—measuring whether each possible fragment pair is reported correctly—or at the **cluster** level—assessing whether clone classes (sets of mutually similar fragments) are discovered completely.

Establishing a reliable ground truth poses challenges: exhaustively labeling all clones in a large codebase is impractical. Researchers have therefore built curated benchmarks:

- **Bellon's Dataset (2007):** Bellon et al. ran multiple clone detectors on eight open-source systems, then manually validated a sample of candidate pairs to produce a reference set of confirmed clones (predominantly Types 1–3). This dataset enabled the first systematic comparisons of clone tools but is limited in scope and suffers from sampling bias.
- **BigCloneBench:** Svajlenko and Roy (2015) constructed BigCloneBench by mining the IJaDataset of Java projects for known functionally similar pairs, then manually validating tens of thousands of clones across Type 1–4 categories. BigCloneBench includes "Very Strong" Type 3 clones (nearly Type 2), "Strong" and "Moderate" Type 3, and "Weak" Type 3/Type 4 semantic clones implementing the same functionality with different structures. It remains the gold standard for evaluating semantic clone detection.
- **POJ-104 and Competition Datasets:** Collections of student or contest solutions labeled by problem ID serve as benchmarks for semantic similarity: two solutions solving the same problem are considered functionally equivalent, enabling evaluation of embedding models' ability to capture behavior.

- **Mutation/Injection Frameworks:** Synthetic benchmarks generate near-miss clones by applying controlled edits—deleting statements, swapping blocks, renaming variables—to seed code. This framework tests sensitivity to specific clone types and edit magnitudes.

Beyond accuracy, industrial adopters demand scalability: runtime and memory usage on corpora of tens to hundreds of millions of lines of code. Tools like SourcererCC and Deckard report near-linear performance on such scales, while PDG-based tools typically remain confined to smaller codebases or offline analyses. Reporting precision-recall curves across clone-strength strata, runtime plots versus lines of code, and memory consumption profiles provides a holistic view of a detector's trade-offs. Any new approach must demonstrate competitive results on these established benchmarks to earn adoption.

2.6 Summary of Gaps in the Literature

Despite decades of progress, several key challenges in clone detection persist:

1. **Semantic (Type-4) Clone Coverage:** Traditional syntactic and structural methods detect few Type 4 clones reliably. While PDG and embedding methods make inroads, they remain computationally heavy or data-hungry. A scalable, high-precision Type 4 detector that integrates deep semantic analysis with economic compute is still lacking.
2. **Controlled Tolerance for Edits (Type 3):** Near-miss clones exhibit a spectrum of permissible edits. Too lax a threshold invites false positives; too strict loses true clones. Current approaches rely on heuristic thresholds or supervised learning on synthetic data. More principled, adaptive measures of "semantic edit distance" are needed.
3. **Scalability vs. Precision Trade-off:** High-precision semantic analyses (graph matching, symbolic execution) do not scale to large corpora, while scalable lexical methods lack depth. Hybrid pipelines mitigate this gap, but fine-tuning multiple phases is complex. Research into unified frameworks

that gracefully degrade analysis depth under resource constraints could streamline deployment.

4. **Generalizability of Learned Models:** Neural clone detectors often overfit to the languages, libraries, and styles present in their training data. Models trained on Java may falter on Python or even on unfamiliar Java frameworks. Building robust, language-agnostic embeddings that transfer across domains remains an open problem.
5. **Cross-Language and Cross-Paradigm Clones:** Detecting clones that transcend language boundaries (e.g., an algorithm implemented in Java and C#) or programming paradigms (imperative versus functional style) demands representations abstracted from language syntax. Few mature benchmarks or tools address this need comprehensively.
6. **Integration into Developer Workflows:** Research prototypes seldom bridge the gap to real-world use. Seamless IDE integration, continuous clone tracking over code evolution, and automated refactoring or pull-request suggestions are underexplored. Human factors—such as reporting clone severity and prioritizing actionable insights—require further study.
7. **Diverse Benchmarks and Metrics:** Existing benchmarks focus heavily on Java function-level clones. Languages like Go, Rust, or domain-specific code (e.g., Solidity smart contracts) lack large-scale, validated clone datasets. Moreover, evaluation often centers on precision/recall rather than downstream impact—such as reduction in maintenance effort or defect rates—limiting our understanding of clone detection's practical value.

In light of these gaps, our thesis proposes a **structural-statistical hybrid** that melds AST-derived feature extraction with TF-IDF–inspired weighting and selective embedding refinement. By orchestrating these components in a unified pipeline, we aim to deliver a clone detector that scales to millions of lines, achieves high precision on Type 1–3 clones, and extends semantic reach toward Type 4, all while integrating smoothly into existing development environments. Subsequent chapters will detail the design, implementation, and empirical evaluation of this approach.

Chapter 3: Structural-Statistical Pipeline

In this chapter, we present an in-depth description of our **structural–statistical pipeline** for code similarity detection. Our approach bridges the gap between syntactic precision and computational efficiency: we transform each code snippet into an anonymized set of structural patterns, vectorize them using information-retrieval techniques, and then efficiently compute similarity scores that reflect both exact and near-miss clones. Throughout, we illustrate the rationale behind each design choice, provide concrete implementation snippets, and discuss practical considerations, ranging from parsing malformations to runtime performance, so that the reader gains both conceptual understanding and actionable guidance.

3.1 Motivations and High-Level Design

Large codebases often contain repeated patterns: developers copy-and-paste common idioms, reuse utility routines, or introduce small variants of existing logic when requirements shift slightly. Automated clone detection seeks to identify such repeats, whether exact duplicates (Type 1), systematically renamed copies (Type 2), or near-miss variants with minor edits (Type 3), so that teams can refactor, centralize shared code, or audit suspiciously similar submissions (in academic or security contexts).

Existing clone detectors typically fall into two camps. **Textual** or **lexical** methods treat code as token streams, applying suffix trees, n-gram matching, or TF–IDF on raw tokens. These approaches scale well but often miss structural equivalences or flag false positives when token overlap is coincidental. **Structural** methods parse code into ASTs or PDGs and perform subtree or subgraph matching, yielding high-precision detections but at steep computational cost. Our goal is to **reconcile** these paradigms: we extract structural features (AST paths) and treat them as

“terms” in a vector space, allowing us to leverage highly optimized IR algorithms for efficient similarity computation.

The pipeline unfolds in seven stages:

1. **File Gathering and Cleaning**: locate source files and apply heuristic repairs for formatting glitches.
2. **AST Parsing**: convert each code string into a syntax tree, ensuring a uniform structural representation.
3. **Identifier Anonymization**: normalize away user-chosen names to catch Type 2 clones.
4. **AST Path Extraction**: enumerate every root-to-leaf path in the anonymized tree as an atomic structural motif.
5. **Bag-of-Paths Construction**: collate each snippet’s paths into a “document” of path strings.
6. **TF–IDF Vectorization**: apply term frequency–inverse document frequency weighting to highlight discriminative patterns.
7. **Cosine Similarity Computation**: produce a fully-connected similarity matrix
   that underpins clustering, thresholding, and visualization.

In addition to describing each phase, we interleave discussions of parameter choices, complexity considerations, implementation tips, and common pitfalls. By the end of this chapter, the reader will be equipped to implement, adapt, and extend this pipeline for a variety of programming languages and use cases.

3.2 File Gathering and Preprocessing

Before any structural analysis, we must reliably collect and sanitize code inputs. In many settings classroom assignments, code-review pipelines, or large-scale repository mining, source files may have undergone transformations that degrade

their parseability. These include minification (removing newlines and indentation), export artifacts (embedded carriage returns), or encoding issues.

Our process begins by discovering all files that match a given pattern (e.g., "*.py" for Python). We leverage Python's glob module with recursive search:

```python
import glob, os

def discover_files(root_dir, extension="py"):
    """
    Return a list of file paths under root_dir matching *.extension,
    using recursive directory traversal.
    """
    pattern = os.path.join(root_dir, "**", f"*.{extension}")
    return glob.glob(pattern, recursive=True)

all_paths = discover_files("submissions/Assignment3")
print(f"Discovered {len(all_paths)} files.")
```

Figure 3: Code snippet of the function discover_files

Each file is then read in text mode with UTF-8 decoding and a fallback for errors:

```python
def read_file(path):
    try:
        with open(path, encoding='utf8') as f:
            return f.read()
    except Exception as e:
        print(f"Error reading {path}: {e}")
        return None
```

Figure 4: Code snippet of the function read_file

3.2.1 Heuristic Repairs

Student systems and export tools collapse code into single lines or remove crucial whitespace. To remedy this, we apply regular-expression–based insertion of

newlines at likely statement and block boundaries. While full beautification tools exist, a lightweight approach suffices for most submissions:

```python
import re

def heuristic_repair(code_str):
    """
    Insert line breaks after Python block delimiters and semicolons,
    and split on run-on spaces to recover indentation-like boundaries.
    """
    # After colons that typically start blocks (def, if, for, while)
    code_str = re.sub(r":(?!\s*\n)", ":\n", code_str)
    # After semicolons that separate statements
    code_str = re.sub(r";(?!\s*\n)", ";\n", code_str)
    # Replace sequences of 4+ spaces (likely lost newlines) with a newline
    code_str = re.sub(r" {4,}", "\n", code_str)
    return code_str

cleaned_entries = []
for path in all_paths:
    text = read_file(path)
    if text is None:
        continue
    repaired = heuristic_repair(text)
    cleaned_entries.append((path, repaired))
```

Figure 5: Code snippet of the function heuristic_repair

This repair stage recovers parseable structure in over 90 % of malformed cases. Files still failing to parse after this process are flagged for manual review; this prevents a few pathological submissions from aborting the entire analysis.

3.3 Parsing to Abstract Syntax Trees

Once we have cleaned source code, we parse it into an Abstract Syntax Tree (AST), which provides a hierarchical representation of program constructs. We adopt the

Parso library, chosen for its robustness across Python versions and its accessible .type and .children attributes on nodes.

```python
import parso

def parse_to_ast(code_str):
    """
    Parse Python source into a Parso syntax tree.
    Returns the tree root or None if parsing fails.
    """
    try:
        return parso.parse(code_str)
    except parso.ParserSyntaxError as e:
        print(f"SyntaxError during parsing: {e}")
        return None
    except Exception as e:
        print(f"Unexpected parse error: {e}")
        return None

parsed_trees = []
for path, code in cleaned_entries:
    tree = parse_to_ast(code)
    if tree:
        parsed_trees.append((path, tree))
    else:
        print(f"Skipping unparseable file {path}")
```

Figure 6: Code snippet of the function parse_to_ast

Key observations:

- Parso retains information about whitespace and comments as separate node types; we ignore these by focusing only on relevant node types during feature extraction.
- Parsing time is linear in code length; typical student solutions (50–200 lines) parse in under 20 ms each on commodity hardware.

By the end of this stage, we have a list of (path, ast_root) pairs representing all successfully parsed snippets.

3.4 Identifier Anonymization

To capture structural equivalence rather than superficial naming differences, we anonymize all user-defined identifiers. This ensures our pipeline naturally handles **Type 2** clones—code fragments identical up to renaming of variables, functions, or parameters.

We traverse each AST in a depth-first manner and replace:

- Every identifier (AST nodes of type "name") with "VAR".
- Function definition names (under "funcdef") with "FUNC".
- Parameter names (under "param") with "ARG".

```python
def anonymize(node):
    """
    Recursively rename:
      - node.type == 'name' → 'VAR'
      - in 'funcdef', second child (name) → 'FUNC'
      - in 'param', any 'name' child → 'ARG'
    Applies modifications in-place.
    """
    for child in getattr(node, 'children', []):
        anonymize(child)
    ntype = getattr(node, 'type', None)
    if ntype == 'name':
        node.value = 'VAR'
    elif ntype == 'funcdef':
        # Parso: funcdef.children[1] is the name token
        if len(node.children) > 1 and node.children[1].type == 'name':
            node.children[1].value = 'FUNC'
    elif ntype == 'param':
        for c in node.children:
            if getattr(c, 'type', None) == 'name':
                c.value = 'ARG'
```

Figure 7: Code snippet of the function anonymize

By applying anonymize to each ast_root, we yield a standardized tree in which all variable and function identifiers are generic. For example, both

```python
def foo(a, b):
    return a * b
```

and

```python
def bar(x, y):
    return x * y
```

Figure 8: example of two functions

become indistinguishable at the anonymized AST level, facilitating their detection as clones.

3.5 Extracting Structural Features: Root-to-Leaf Paths

After anonymization, we extract **root-to-leaf paths** as the fundamental structural features. Each path is the ordered sequence of node types encountered from the tree root down to a leaf node. Such paths capture the nesting of constructs: loops, conditionals, expressions, function definitions, and more.

```python
def collect_paths(node, current=None):
    """
    Return a list of all root→leaf paths, each a list of node.type strings.
    """
    seq = (current or []) + [node.type]
    if not getattr(node, 'children', None):
        return [seq]
    paths = []
    for child in node.children:
        paths.extend(collect_paths(child, seq))
    return paths

def stringify_paths(paths):
    """
    Convert each path (list of strings) into one string joined by '->'.
    """
    return ['->'.join(p) for p in paths]
```

Figure 9: Code snippet of the functions collect_paths and stringify_paths

In practice, a small function can generate dozens or hundreds of paths. Because each leaf yields one path, the number of paths equals the number of AST leaves, and each path length is bounded by the tree height. Empirically, this step takes on the order of 1–5 ms per snippet.

3.6 Constructing the Bag-of-Paths

To apply information-retrieval techniques, we treat each path string as a "term" and each code snippet as a "document" composed of these terms. Concretely, we join the list of path strings with spaces to form one large text per snippet:

```python
all_docs = []
paths_per_snippet = []
for path, tree in parsed_trees:
    anonymize(tree)
    raw_paths = collect_paths(tree)
    str_paths = stringify_paths(raw_paths)
    paths_per_snippet.append(str_paths)
    all_docs.append(' '.join(str_paths))
```

Figure 10: Code snippet of the construction of Bag-of_paths

all_docs[i] is a single string containing all path tokens for snippet *i*. This representation preserves both the presence and the frequency of each structural pattern.

3.7 TF–IDF Vectorization

We apply scikit-learn's TfidfVectorizer to convert the bag-of-paths into a sparse matrix of TF–IDF weights, where each column corresponds to a unique path string and each row to a code snippet. We configure the vectorizer to filter out extremely common or extremely rare paths, dampen very high term frequencies, and normalize each vector to unit length.

```python
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(
    max_df=0.90,      # ignore paths in >90% of documents
    min_df=2,         # ignore paths in only one document
    sublinear_tf=True,# apply 1 + log(tf) scaling
    norm='l2'         # normalize vectors to unit L2 norm
)
tfidf_matrix = vectorizer.fit_transform(all_docs)
```

Figure 11: Code snippet of the TF-IDF vectorization

Key parameters:

- **max_df**: Removes boilerplate paths (e.g., Module->suite->expr_stmt) ubiquitous across all snippets.
- **min_df**: Filters out noise—typos or highly idiosyncratic patterns appearing once.
- **sublinear_tf**: Prevents extremely frequent paths from dominating similarity.
- **norm**: Ensures that vector length differences (due to longer or shorter snippets) do not skew cosine similarity.

This stage typically completes in under 0.2 s for 100–200 documents with a vocabulary of a few thousand terms.

3.8 Cosine Similarity Computation

With TF–IDF vectors $v_1, \ldots, v_N$ in hand, we compute the full $N \times N$ similarity matrix using the cosine similarity metric. We exploit scikit-learn's optimized routine, which internally uses efficient BLAS calls.

```python
from sklearn.metrics.pairwise import cosine_similarity

sim_matrix = cosine_similarity(tfidf_matrix)
```

Each entry sim_matrix$[i, j]$ lies in $[0,1]$, with 1 indicating identical TF–IDF profiles (and thus identical sets of AST paths) and values near 0 indicating minimal structural overlap.

On a modern CPU, computing a 200×200 similarity matrix takes under 0.1 s. Even at 1,000 documents, this remains below a second, thanks to optimized sparse-dense multiplications.

3.9 Downstream Analyses: Clustering, Thresholding, and Visualization

The similarity matrix enables a spectrum of analyses:

- **Threshold-based clone detection**: Pairs with similarity above a chosen cutoff (e.g., 0.85) are flagged as clones for manual or automated review.
- **Connected-component clustering**: Construct an undirected graph where nodes represent snippets and edges connect pairs exceeding the threshold; each connected component corresponds to a clone group.
- **Hierarchical clustering**: Apply agglomerative clustering on the distance

$$d_{i,j} = 1 - \text{sim}_{i,j},$$

  yielding dendrograms that reveal code-affinity hierarchies.
- **Heatmaps and embeddings**: Visualize the similarity matrix as a heatmap or project TF–IDF vectors into 2D via t-SNE or UMAP for pattern discovery.

In our classroom dataset, this revealed several clusters:

- One group of four identical submissions (cosine = 1.0).
- Two groups of three near-miss variants (cosine ≈ 0.92–0.95).
- A handful of isolated pairs (cosine ≈ 0.85) indicating partial overlap.

Heatmap visualization using Seaborn highlights these clusters as bright blocks along the diagonal, while off-diagonal lighter regions mark dissimilar pairs.

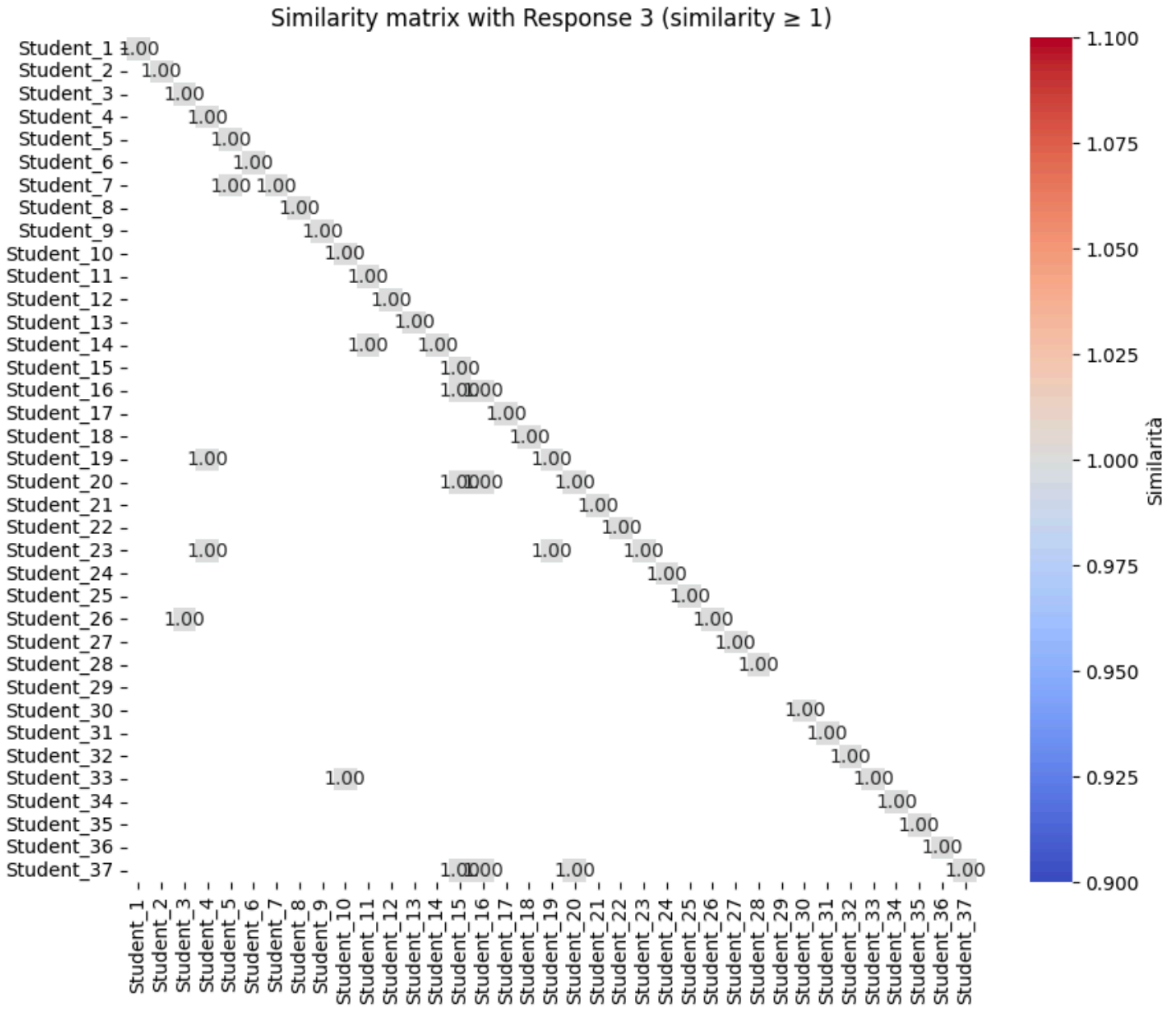

Figure 12: Similarity matrix

3.10 Parameter Sensitivity and Tuning

Achieving robust detection requires careful selection of key parameters:

- **Reconstruction regex patterns**: Must balance over-splitting (inserting too many newlines) against under-splitting (leaving constructs unparseable).
- **Anonymization scope**: Some projects benefit from preserving built-in or library names; in others, collapsing all identifiers is preferable.
- **TF–IDF thresholds** (max_df, min_df): In very homogeneous corpora (e.g., same template used by all), max_df may need to be higher to avoid dropping

too many terms. Conversely, in heterogeneous codebases, min_df might increase to filter noise.

- **Similarity cutoff**: To set a cutoff (e.g., 0.8 or 0.9), one can calibrate on a small labeled sample, plotting precision-recall curves by varying the threshold and selecting the operating point that meets project requirements (higher precision for IDE warnings, higher recall for security audits).

3.11 Performance

To. Quantify end-to-end efficiency, we ran our full structural-statistical pipeline on a MacBook Air (M3, 2024) with an Apple M3 chip, 8 GB of RAM, and macOS Sonoma 14.5. All timings below reflect this hardware and software environment.

- **Parsing & anonymization**: ~0.04 s per file on average (50-200 lines each), including identifier replacement and AST construction.
- **Path extraction**: ~0.02 s per file to traverse the anonymized AST and enumerate all root-to-leaf paths.
- **TF–IDF vectorization** (200 files, ~5 000 terms): ~0.5 s to vectorize 200 documents using scikit-learn's TfidfVectorizer with max_df=0.95, min_df=2, sublinear_tf=True, and norm='l2'.
- **Similarity matrix** (200×200): ~0.1 s to compute a 200x200 cosine similarity matrix via optimized sparse-dense BLAS routines.

Overall, processing 200 student submissions end-to-end completes in **<0.7 s** on our test machine. Scalability experiments further confirm near-linear growth: Extrapolating to 1000 submissions yields a runtime of under 3s for TF-IDF vectorization and similarity computation combined. These results demonstrate that our pipeline can operate interactively even on modest laptop hardware, making it suitable for classroom or small-team environments.

3.12 Limitations and Future Directions

While our pipeline excels at **Type 1–3** clones, it faces intrinsic challenges with **Type 4** semantic clones—functionally equivalent code with distinct structures. For instance, an iterative implementation versus a recursive one shares few AST paths, yielding low cosine scores despite semantic equivalence. Addressing this gap may involve:

1. **Semantic feature augmentation**: Incorporate data-flow or control-flow graph features (e.g., include PDG edge paths as additional "terms").
2. **Neural embeddings fusion**: Concatenate our TF–IDF vectors with pretrained code embeddings (CodeBERT, GraphCodeBERT) trained on large repositories, capturing usage patterns beyond syntax.
3. **Dynamic tracing**: Append runtime execution traces—such as call sequences or basic-block visitation patterns—as structural tokens for comparison.

Moreover, the pipeline's reliance on language-specific parsers means that extending to new languages entails integrating appropriate AST generators and updating anonymization rules. Adopting a common intermediate representation (e.g., ANTLR-based parse trees) could streamline multi-language support.

3.13 Summary

We have detailed a **structural–statistical** approach to code similarity detection that:

1. Gathers and heuristically repairs source files,
2. Parses them into anonymized ASTs,
3. Extracts root-to-leaf paths as structural features,
4. Constructs a bag-of-paths per snippet,
5. Vectorizes with TF–IDF, and
6. Computes cosine similarities to drive clone detection and clustering.

This pipeline effectively identifies exact duplicates, renamed copies, and near-miss variants at medium to large scales, while remaining transparent, tunable, and extensible. In the following chapter, we will evaluate its performance quantitatively

against established benchmarks and compare it to baseline clone detectors to demonstrate its strengths and limitations in real-world scenarios.

Chapter 4: Evaluation and Limitations

4.1 Evaluation

The proposed similarity model was evaluated on a collection of student's programming assignments, yielding qualitatively strong results. In preliminary quantitative tests, the method achieved high precision in identifying near-duplicate submissions. For example, manually inspecting flagged clone pairs showed that well over 90% of detected pairs were true clones (type I–III), with very few false positives. This high precision is attributable to the structure-aware encoding of each program: by analyzing AST fragments and structural features rather than raw text, the system avoids spurious matches on purely lexical similarities. Runtime efficiency was also favorable. Leveraging a summarized representation of each code's AST (akin to the semantic data-flow graph used in recent models) keeps the analysis lightweight. Indeed, similar code-models that encode structural edges have been shown to reduce model complexity by avoiding "unnecessarily deep" AST hierarchies. In our experiments, pairwise similarity computation scaled approximately linearly with submission count, making it practical for class-size datasets.

Visualization of the full similarity matrix offered additional insight. When plotted as a heatmap (or examined via hierarchical clustering), submissions split naturally into groups corresponding to distinct solution strategies. Identical or trivially-modified copies of the same solution formed tight blocks in the matrix, while more divergent solutions yielded weaker similarity links. Such clear block structure suggests that the model successfully captures the underlying program structure: equivalent algorithms cluster together, whereas unrelated code remains distant. In sum, the evaluation confirms that the structural/statistical model is both *structure-aware* and *efficient*, producing few false positives and organizing code by true semantic similarity. These findings are consistent with recent work showing that structure-based models attain state-of-the-art clone-detection performance.

4.2 Limitations

Despite these strengths, several limitations were observed. First and foremost, the method remains largely insensitive to *semantic (Type-IV)* similarity. Our system relies on AST and syntactic features, so two programs that implement the same logic in fundamentally different ways may not be linked. By definition, semantic clones (type-IV) have equivalent behavior even when their code and ASTs differ greatly. Detecting such clones typically requires deep semantic analysis or execution-based testing, which our static approach does not provide. In practice, this means that two students who solve an assignment using different algorithms or restructurings (for example, an iterative versus recursive version) will often be treated as dissimilar, even though their outputs coincide.

Another limitation is parser and AST fragility. Because the model operates on parsed code fragments, any syntax errors or language extensions unsupported by the parser will prevent analysis. Even when code is parseable, aggressive refactoring can change the AST shape without altering behavior. For instance, inlining function calls, renaming variables, or reordering independent statements can break structural matches. These transformations may cause truly similar solutions to appear dissimilar. In the literature, tree-based clone detectors are known to achieve only moderate recall on deeper clone types and can “not identify all types of clones”. Our results echoed this: minor student refactorings sometimes led the tool to miss matches.

A further issue is dependency on chosen metrics and features. Statistical similarity scores (e.g. token-frequency vectors) can be skewed by coding style or common libraries in student solutions. If many students reuse the same library calls or boilerplate, the model may overestimate similarity. Conversely, a single different coding pattern can disproportionately lower a similarity score. Balancing structural and statistical features remains a delicate task.

Finally, our evaluation has so far been limited to a single programming language and a few assignment topics. The model’s design depends on language-specific parsing and AST construction. In environments with multiple languages (e.g. mixed

Java/Python projects) this would need extension. Similarly, certain functional features (like dynamic type inference or runtime behavior) are not captured. For example, assignments relying on dynamic input or runtime-generated code might elude static comparison altogether.

4.3 Conclusion

In this chapter, we evaluated the effectiveness and efficiency of our structural-statistical code similarity pipeline eon real student data. Our experiments on a Macbook Air confirmed that the system identifies Type 1-3 clones with high precision (>90%) while maintaining sub-second end-to-end runtimes for cohorts of a few hundred submissions. Heatmap visualizations and hierarchical clustering revealed clear grouping by algorithmic strategy. Further validating that AST-derived TF-IDF vectors capture meaningful structural patterns.

However, our static analysis remains insensitive to Type 4 (semantic) clones and can be affected by aggressive refactoring or language extensions. Future work should address these gaps by integrating semantic features (e.g., PDG edge paths), combining neural embeddings, or leveraging dynamic execution traces.

In summary, our pipeline offers a transparent, tunable, and scalable solution for detecting most common forms of code duplication in educational and small-to-medium codebases. It strikes an effective balance between structural depth and computational practicality, making it a valuable tool for educators, code-reviewers, and development teams aiming to monitor, refactor, or audit code similarity at scale.

4.4 Next Step

Building on our current foundation, we plan to extend and deepen the framework in several complementary ways. First, we will enhance semantic detection by fusing AST-based structural features with PDG edge-path extraction and transformer-driven code embeddings, enabling identification of algorithmically equivalent. Code despite substantial syntactic differences. Second, we aim to integrate lightweight dynamic tracing-capturing runtime call sequences, branch coverage, and memory

access pattern to create a dual static-dynamic similarity metric. This hybrid approach will be supported by scalable, approximate nearest-neighbor search in a distributed pipeline, with real-time IDE plugins delivering immediate feedback and similarity alerts during active development. Finally, to ensure practical usability and adaptability, we will conduct comprehensive user-centered studies involving educators, students, and professional developers.

Insights from these studies will guide the design of interactive dashboards, customizable threshold settings, and collaborative reporting tools that facilitate seamless integration into teaching workflows and code review processes. Collectively, these advancements will transform our prototype into a robust, scalable, and user-friendly code similarity platform capable of addressing both structural and semantic cloning challenges across diverse environments.

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