Enabling Open-World Specification Mining via Unsupervised Learning

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Many programming tasks require using both domain-specific code and well-established patterns (such as routines concerned with file IO). Together, several small patterns combine to create complex interactions. This compounding effect, mixed with domain-specific idiosyncrasies, creates a challenging environment for fully automatic specification inference. Mining specifications in this environment, without the aid of rule templates, user-directed feedback, or predefined API surfaces, is a major challenge. We call this challenge Open-World Specification Mining.

In this paper, we present a framework for mining specifications and usage patterns in an Open-World setting. We design this framework to be miner-agnostic and instead focus on disentangling complex and noisy API interactions. To evaluate our framework, we introduce a benchmark of 71 clusters extracted from five open-source projects. Using this dataset, we show that interesting clusters can be recovered, in a fully automatic way, by leveraging unsupervised learning in the form of word embeddings. Once clusters have been recovered, the challenge of Open-World Specification Mining is simplified and any trace-based mining technique can be applied. In addition, we provide a comprehensive evaluation of three word-vector learners to showcase the value of sub-word information for embeddings learned in the software-engineering domain.

1 INTRODUCTION

The continued growth of software in size, scale, scope, and complexity has created an increased need for code reuse and encapsulation. To address this need, a growing number of frameworks and libraries are being authored. These frameworks and libraries make functionality available to downstream users through Application Programming Interfaces (APIs). Although some APIs may be simple, many APIs offer a large range of operations over complex structures (such as the orchestration and management of hardware interfaces).

Staying within correct usage patterns can require domain-specific knowledge about the API and its idiosyncratic behaviors [Robillard and DeLine 2011]. This burden is often worsened by insufficient documentation and explanatory materials for a given API. In an effort to assist developers utilizing these complex APIs, the research community has explored a wide variety of techniques to automatically infer API properties [Lo et al. 2011; Robillard et al. 2013].

This paper contributes to the study of API-usage mining by identifying a new problem area and exploring the combination of machine learning and traditional methodologies to address the novel challenges that arise in this new domain. Specifically, we introduce the problem domain of Open-World Specification Mining. The goal of Open-World Specification Mining can be stated as follows:

Given noisy traces, from a mixed vocabulary, automatically identify and mine patterns or specifications without the aid of (i) implicit or explicit groupings of terms, (ii) pre-defined pattern templates, or (iii) user-directed feedback or intervention.

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Open-World Specification Mining is motivated by the lack of adoption of specification-mining tools outside of the research community. We believe that because Open-World Specification Mining needs no user-supplied input, it will lead to tools that are easier to transition and apply in industry settings. Although this setting reduces the burden imposed on users, it increases the challenges associated with extracting patterns. We address these challenges with a toolchain, called ml4spec:

- We base our technique on a form of intraprocedural, parametric, lightweight symbolic execution introduced by Henkel et al. [2018]. Using their tool gives us the ability to generate abstracted symbolic traces and avoids any need for dynamically running the program.
- To address the lack of implicit or explicit groupings of terms (a challenged imposed by the setting of Open-World Specification Mining) we introduce a technique, *Domain-Adapted Clustering* (DAC), that is capable of recovering groupings of related terms.
- Finally, we remove the need for pre-defined pattern templates by mining specifications using traditional, unrestricted, methods (such as k-Tails [Biermann and Feldman 1972] and Hidden Markov Models [Seymore et al. 1999]). We are able to use these traditional methods by leveraging Domain-Adapted Clustering to "focus" these traditional methods toward interesting patterns.

The combination of both traditional techniques and machine-learning-assisted methods in the pursuit of Open-World Specification Mining raises a number of natural research questions that we consider.

First, we explore the ability of Domain-Adapted Clustering, our key technique, to successfully extract informative and useful clusters of API methods in our Open-World setting:

RESEARCH QUESTION 1: Can we effectively mine useful and clean clusters of API methods in an Open-World setting?

Immediately, we run into the difficulty of judging the utility of clusters extracted from traces. To provide the basis for a consistent and quantitative evaluation, we have manually extracted a dataset of ground-truth clusters from five popular open-source projects written in C.

Next, we compare Domain-Adapted Clustering against several other baselines that do not utilize the implicit structure of the extracted traces:

RESEARCH QUESTION 2: How does Domain-Adapted Clustering (DAC) compare to off-the-shelf clustering techniques?

We also explore how two key choices in our toolchain impact the overall utility of our results:

RESEARCH QUESTION 3: How does the choice of word-vector learner and the choice of sampling technique affect the resulting clusters?

Understanding how different pieces of our toolchain interact provides the ground work for understanding how traditional metrics (co-occurrence statistics) interplay with our machinelearning-assisted additions (word embeddings). To quantify the usefulness of unsupervised learning in our approach, and to validate our central hypothesis, we ask:

RESEARCH QUESTION 4: Is there a benefit from using a combination of co-occurrence statistics and word embeddings?

Finally, we can explore how faithful we are to one of the key tenets of Open-World mining: the lack of user intervention. To do so, we must understand what level of hyper-parameter tuning is required to achieve reasonable results:

RESEARCH QUESTION 5: Does our toolchain transfer to unseen projects with minimal reconfiguration?

The contributions of our work can be summarized as follows:

- We define the new problem domain of Open-World Specification Mining. Our motivation is to increase the adoption of specification-mining techniques by reducing the burden imposed on users (at the cost of a more challenging mining task).
- We create a toolchain based on the key insight that unsupervised learning (specifically word embeddings) can be combined with traditional metrics to enable automated mining in an Open-World setting.
- We introduce a benchmark of 71 ground-truth clusters extracted from five open-source C projects.
- We report on several experiments:
 - In §7.2, we use our toolchain to recover, on average, two thirds of the ground-truth clusters in our benchmark automatically.
 - In §7.3, we compare our Domain-Adapted Clustering technique to three off-the-shelf clustering algorithms; Domain-Adapted Clustering provides, on average, a 30% performance increase relative to the best baseline.
 - In §7.4, we confirm our intuition that sub-word information improves the quality of learned vectors in the software-engineering domain; we also confirm that our Diversity Sampling (§4) technique increases performance by solving the problem of *prefix dominance*.
 - In §7.5, we quantify the impacts of our machine-learning-assisted approach.
 - In §7.6, we find that just two configurations can be automatically tested to achieve performance that is within 10% of the best configuration.

Organization. The remainder of the paper is organized as follows: §2 provides an overview of the ml4spec toolchain. §3 reviews Parametric Lightweight Symbolic Execution. §4 describes Diversity Sampling. §5 introduces Domain-Adapted Clustering. §6 describes trace projection and mining. §7 provides an overview of our evaluation methodology. §7.2-§7.6 address our five research questions. §8 considers threats to the validity of our approach. §9 discusses related work. §10 concludes.

2 OVERVIEW

The ml4spec toolchain consists of five phases: Parametric Lightweight Symbolic Execution, thresholding and sampling, unsupervised learning, Domain-Adapted Clustering, and mining. As input, ml4spec expect a corpus of buildable C projects. As output, ml4spec produces clusters of related terms and finite-state automata (or Hidden Markov Models) mined via traditional techniques.¹ A visualization of the way data flows through the ml4spec toolchain is given in Fig. 1. We illustrate this process as applied to the example in Fig. 2.

Phase I: Parametric Lightweight Symbolic Execution. The first phase of the ml4spec toolchain applies *Parametric Lightweight Symbolic Execution* (PLSE). PLSE takes, as input, a corpus of buildable

¹Although we provide examples based on traditional miners that produce finite-state automata and Hidden Markov Models, we do note that the ml4spec toolchain is miner-agnostic. By using ml4spec as a trace pre-processor, any trace-based miner can be adapted to the Open-World mining setting.



Fig. 1. Overview of the ml4spec toolchain

C projects and a set of abstractions to apply. For our use case, we abstract calls, checks on the results of calls, and return values. §3 describes these abstractions in more detail. Figure 2 presents both an example procedure and a trace resulting from the application of PLSE. Already, examining Fig. 2b, we can see one of the core challenges of Open-World mining: the mixed vocabulary present in the trace from Fig. 2b involves many interesting behaviors but, without user input [Ammons et al. 2002; Lo and Khoo 2006], pre-defined rule templates [Yun et al. 2016], or some pre-described

```
void example() {
  void *A,*B;
  if (!strcasecmp()) {
    addReplyHelp();
  } else if (!strcasecmp()) {
    A = dictGetIterator();
    log();
    while ((B = dictNext(A)) != 0) {
      dictGetKey(B);
      if (strmatchlen(sdslen())) {
        addReplyBulk();
      }
    }
    dictReleaseIterator(A);
  } else if (!strcasecmp()) {
    addReplyLongLong(listLength());
  } else {
    addReplySubcommandSyntaxError();
  }
}
```

(a) Sample procedure, showcasing an iterator usage pattern from the Redis opensource project

```
$START
strcasecmp
strcasecmp != 0
strcasecmp
strcasecmp == 0
dictGetIterator
log
dictGetIterator \rightarrow dictNext
dictNext
dictNext != 0
dictNext \rightarrow dictGetKey
dictGetKey
sdslen
sdslen \rightarrow strmatchlen
strmatchlen
strmatchlen != 0
addReplyBulk
dictGetIterator \rightarrow dictNext
dictNext
dictNext == 0
dictGetIterator
  → dictReleaseIterator
dictReleaseIterator
$END
```

(b) One example trace, taken from the set of traces our Parametric Lightweight Symbolic Executor generates for the example procedure in Fig. 2a

Fig. 2. Example procedure and corresponding trace. The notation $A \rightarrow B$ signifies that the result of call A is used as a parameter to call B.

notion of what methods are related [Le and Lo 2018], we have no straightforward route to separating patterns from noise. We need to *disentangle* these disparate behaviors to facilitate better specification mining.

Phase II: Thresholding and Sampling. Although our example procedure has a small number of paths from entry to exit, many procedures have thousands of possible paths. Learning from these traces can be challenging due to the number of times the same trace prefix is seen. This problem, which Henkel et al. [2018] term *prefix dominance*, makes downstream learning tasks more challenging. For instance, some terms that occur in multiple traces (e.g., in a common prefix) may occur only a single time in the source program. Off-the-shelf word-vector learners cannot filter for these kinds of rare words because they have no concept of the implicit hierarchy between traces and the procedures they were extracted from. The ml4spec toolchain introduces two novel techniques to address these challenges: Diversity Sampling and Hierarchical Thresholding. Diversity Sampling attempts to recover a fixed number of highly representative traces via a metric-guided sampling

```
dictGetIterator
                          dictGetIterator
                            \rightarrow dictNext
                                                        sdslen
strcasecmp
                          dictNext
                                                          \rightarrow strmatchlen
strcasecmp != 0
                          dictNext == 0
                                                        strmatchlen
strcasecmp == 0
                          dictNext != 0
                                                        strmatchlen != 0
                          dictGetIterator
     (a) Cluster 1
                            → dictReleaseIterator
                                                             (c) Cluster 3
                          dictReleaseIterator
```

```
(b) Cluster 2
```

Fig. 3. Clusters generated via Domain-Adapted Clustering (DAC)

process. Hierarchical Sampling leverages the implicit hierarchy between procedures and traces to remove rare words. Together, these techniques improve the quality of downstream results.

Phase III: Unsupervised Learning. Traditionally, specification and usage mining techniques would define some method of measuring support or confidence in a candidate pattern. Often, these measurements would be based on co-occurrences of terms (or sets of terms). The ml4spec toolchain leverages a key insight: traditional co-occurrence statistics and machine-learning-assisted metrics (extracted via unsupervised learning, specifically word embeddings) can be combined in fruitful ways. Referencing our example in Fig. 2, we might hypothesize, based on co-occurrence, that dictGetIterator and log are related. For the sake of argument, imagine that in each extracted trace we find this same pattern. How can we refine our understanding of the relationship between dictGetIterator and log?

It is in these situations that adding unsupervised learning improves the results. A word-vector learner, such as Facebook's fastText [Bojanowski et al. 2017], can provide us with a measurement of the similarity between dictGetIterator and log. This measurement provides a contrast to the co-occurrence based view of our data. Intuitively, word-vector learners utilize the *Distributional Hypothesis*: similar words appear in similar contexts [Harris 1954]. The global context, captured by co-occurrence statistics, can be supplemented and refined by the local-context information that word-vector learners naturally encode. §7.5 explores the impact and relative importance of both traditional co-occurrence statistics and machine-learning-assisted metrics.

Phase IV: Domain-Adapted Clustering. The trace given in Fig. 2b exhibits several different patterns. The difficulty in mining from static traces like the one in Fig. 2b comes from the need to learn a separation of the various, possibly interacting, patterns and behaviors. To address this challenge, we introduce Domain-Adapted Clustering: a generalizable approach to clustering corpora of sequential data. Domain-Adapted Clustering leverages the insight that it can be useful to combine machine-learning-assisted metrics with co-occurrence statistics captured directly from the target corpus. Using Domain-Adapted Clustering, we can extract the clusters shown in Fig. 3. These clusters allow us to solve the problem of *disentanglement* by projecting the trace in Fig. 2b into the vocabularies defined by each cluster. It is this "focusing" of the mining process that enables the ml4spec toolchain to apply traditional specification-mining techniques in an Open-World setting.

Phase V: Mining. Finally, we can extract free-form specifications by applying traditional mining techniques to the projected traces that ml4spec creates. One powerful aspect of the ml4spec



Fig. 4. Example FSA that was mined by projecting all of the traces extracted from Fig. 2a into the vocabulary defined by Fig. 3b. FSAs for the vocabularies defined by the clusters in Figs. 3a and 3c are also generated, but not shown here.



Fig. 5. Example HMM that was mined by projecting all of the traces extracted from Fig. 2a into the vocabulary defined by Fig. 3b

toolchain is its disassociation from any particular mining strategy. The real challenge of Open-World Specification Mining is extracting, without user-directed feedback, reasonable clusters of possibly related terms. With this information in hand, a myriad of trace-based miners can be applied. Figures 4 and 5 highlight this ability by showing both a finite-state automaton (FSA) mined via the classic k-Tails algorithm and a Hidden Markov Model (HMM) learned directly from the projected traces [Biermann and Feldman 1972; Seymore et al. 1999].

3 PARAMETRIC LIGHTWEIGHT SYMBOLIC EXECUTION

The first phase of the ml4spec toolchain generates intraprocedural traces using a form of parametric lightweight symbolic execution, introduced by Henkel et al. [2018]. Parametric Lightweight Symbolic Execution (PLSE) takes, as input, a buildable C project and a set of abstractions. Abstractions are used to parameterize the resulting traces. In our setting, the abstractions allow us to enrich the output vocabulary. This enrichment enables the final phase of the ml4spec toolchain (mining) to extract specifications that include each of the following types of information:

- **Temporal properties:** the ml4spec toolchain abstracts the sequence of calls encountered on a given path of execution. The temporal ordering of these calls is preserved in the output traces.
- Call-return constraints: often a sequence of API calls can only continue if previous calls succeeded. In C APIs checking for success involves examining the return value of calls. ml4spec abstracts simple checks over return values to capture specifications that involve call-return checks.
- **Dataflow properties:** some specification miners are *parametric*—these miners can capture relationships between parameters to calls and call-returns. To highlight the flexibility that PLSE provides, we include an abstraction that tracks which call results are used, as parameters, in future calls. This call-to-call dataflow occurs in many API usage patterns.
- **Result propagation:** the return value of a given procedure can encode valuable information. Some procedures act as wrappers around lower-level APIs, while other procedures may forward error results from failing calls. In either case, forwarding the result of a call, for any purpose, is abstracted into our traces to aid in downstream specification mining. ml4spec also abstracts constant return values: returning a constant may indicate success or failure, and such information may aid in downstream specification mining.

With these various abstractions parameterizing our trace generation, simple downstream miners, such a k-Tails, are capable of mining rich specifications. However, there is a cost to the variety of abstractions we employ. Each abstraction introduces more words into the overall vocabulary, and, as the size of the overall vocabulary grows, so does the challenge of disentangling traces.

Finally, it is worthwhile to address the limitations of Parametric Lightweight Symbolic Execution. PLSE is intraprocedural and therefore risks extracting only partial specifications. PLSE also makes no attempt to detect infeasible traces. Finally, PLSE enumerates a fixed number of paths. As part of this enumeration, any loops are unrolled for a single iteration only.² In practice these limitations enable the PLSE technique to scale and, for the purposes of the ml4spec toolchain, losses in precision are balanced by the utilization of machine-learning-assisted metrics (which can tolerate noisy data).

4 THRESHOLDING AND SAMPLING

In this section, we outline the techniques used in the ml4spec toolchain to take a corpus of traces, generated via Parametric Lightweight Symbolic Execution (PLSE), and prepare them for word-vector learning and specification mining. In particular, we present two key contributions, Hierarchical Thresholding and Diversity Sampling, which improve the overall quality of our results. In addition, we discuss alternative approaches.

 $^{^{2}}$ This single iteration loop unrolling gives us traces in which the loop never occurred and traces in which we visit the loop body exactly one time. Yun et al. [2016] follow a similar model and argue that most API usage patterns are captured in a single loop unrolling.

4.1 Hierarchical Thresholding

When preparing data for a word-vector learner, it is common to select a vocabulary minimum threshold, which limits the words for which vectors will be learned. Any word that appears fewer times than the threshold is removed from the training corpus. Through this process extremely rare words, which may be artifacts of data collection, typos, or domain-specific jargon, are removed. In the domain of mining specifications, we have a similar need. We would like to pre-select terms, from our overall vocabulary, that occur enough times to be used as part of a pattern or specification. We could simply set an appropriate vocabulary minimum threshold using our word-vector learner of choice; however, this approach ignores a unique aspect of our traces. The traces we have, which are used as input to both the word-vector learner and specification miner, are intra-procedural traces extracted from a variety of procedures. To select terms that occur frequently does not necessarily select for terms that are used across a variety of procedures. Because our traces are paths through a procedure, it is possible to have a frequently occurring term (with respect to our traces) that only occurs in one procedure. To achieve our desire for terms that are used in a variety of diverse contexts, we developed a modified thresholding approach: Hierarchical Thresholding. Hierarchical Thresholding counts how often a term occurs across procedures instead of traces. This simple technique, with its utilization of the extra level of hierarchical information that exists in the traces, reduces the possibility of selecting terms that are rare at the source-code level but frequent in the trace corpus.

4.2 Diversity Sampling

The corpus of symbolic traces that we obtain, via lightweight symbolic execution, can be a challenging artifact to learn from. The symbolic executor, at execution time, builds an execution tree and it is from this tree that we enumerate traces. Any attempt to learn from such traces can be thought of as an attempt to indirectly learn from the original execution trees. The gap between the tree representation and trace representation introduces a challenge: terms that co-occur at the start of a large procedure (with many branches) will be repeated hundreds of times in our trace corpus. This prefix duplication, which Henkel et al. [2018] term *prefix dominance*, adversely affects the quality of word embeddings learned from traces.

As part of the ml4spec toolchain, we introduce a novel trace-sampling methodology, which seeks to resolve the impact of *prefix dominance*. We call this sampling methodology *Diversity Sampling* because it samples a diverse and representative set of traces by using a similarity metric to drive the sample-selection process.

Alg. 1 provides the details of our Diversity Sampling technique. Because we work with intraprocedural traces, we can associate each trace with its source-code procedure. Consequently, the sampling routine can sample maximally diverse traces for each procedure independently. (For a simple reason, our algorithm treats the trace corpus as a collection of sets: each set holds the intra-procedural traces for one source procedure.) To begin Diversity Sampling, we either return all traces (if the number of traces for a given procedure is less than our sampling threshold), or we begin to iterate over the available traces and make selections. At each step of the selection loop, on lines 8–19, we identify a trace that has the maximum average Jaccard distance when measured against our previous selections. Jaccard distance is a measure computed between sets and, in our setting, we use the set of unique tokens in a given trace to compute Jaccard Distances. We take the average Jaccard distance from the set of currently sampled traces to ensure that each new selection differs from all of the previously selected traces. Finally, when we have selected an appropriate number of samples, we return them and proceed to process traces from the next procedure. Algorithm 1: Diversity Sampling

input : A trace corpus TR **output**: A down-sampled trace corpus

```
1 outputs \leftarrow [];
 2 for T \in \mathbb{TR} do
       if |T| \leq SAMPLES then
 3
           outputs = outputs \cup T;
 4
           continue;
 5
       end
 6
       choices \leftarrow T[0];
 7
       while | choices | < SAMPLES do
 8
           D^* = 0.0;
 9
           S = null;
10
           for t \in T – choices do
11
                D = AverageJaccardDistance(t, choices);
12
                if D \ge D^* then
13
                    S = t:
14
                    D^* = D;
15
                end
16
            end
17
           choices = choices \cup S
18
       end
19
20
       outputs = outputs \cup choices;
   end
21
22 return outputs;
```

4.3 Alternative Samplers

Although Diversity Sampling is rooted in the intuition of extracting the most representative set of traces for each procedure, it may not make a difference in the quality of downstream results. It is for this reason that we also consider, in our ml4spec toolchain, two alternative approaches to trace sampling: no sampling and random sampling. We include the option of no sampling because word-vector learners thrive on both the *amount* and *quality* of data available. It is reasonable to ask whether the training data lost by downsampling our trace corpus has enough negative impact to offset possible gains. We also include random sampling as a third alternative; our motivation for this inclusion is to assess the impact of our metric-guided selection. §7.4 evaluates the sampling strategies discussed here.

5 DOMAIN-ADAPTED CLUSTERING

§3 outlined how ml4spec makes use of Parametric Lightweight Symbolic Execution (PLSE) to generate rich traces. In §4, we presented innovations that improved the traces generated by PLSE, and addressed some of the challenges associated with learning from traces. In this section, we introduce Domain-Adapted Clustering, our solution to the challenge of clustering related terms. We seek to cluster related terms (words) to simplify the Open-World Specification Mining task. Traditional specification miners often use either rule templates or some form of user-directed

input (the API surface of interest, or perhaps a specific class or selection of classes from which specifications should be mined). In our Open-World setting, none of this information is available. Therefore, we have developed a methodology for extracting clusters of related terms that harnesses the power of unsupervised learning (in the form of word embeddings). With these clusters in hand, the task of mining specifications is greatly simplified.

5.1 Motivation

To motivate Domain-Adapted Clustering, it is revealing to consider the relationships among the following ideas:

- **Co-occurrence:** word–word co-occurrence can be a powerful indicator of some kind of relationship between words. Co-occurrence is, by its nature, a global property that can, optionally, be associated with a sense of direction (word *A* appears to the left/right of word *B*).
- **Analogy:** analogies are another way in which words can be related. The words that form an analogical relationship encode a kind of information that is subtly different from the information that co-occurrence provides. Given the analogy *A* is to *B* as *C* is to *D*, one would find that *A* and *B* often co-occur, as do *C* and *D*; however, there may be no strong relationship (in terms of co-occurrence) between *A*/*B* and *C*/*D*.
- **Synonymy:** synonyms are, in some sense, encoding strictly local structure. Two synonymous words need not co-occur; instead, synonyms are understood through the concept of replaceability: if one can replace *A* with *B* then they are likely synonyms.

We can now attempt to codify which of these concepts are of value for Open-World Specification Mining. To do so, we will introduce a simple thought experiment: consider an extremely simple specification that consists of a call to foo and a comparison of the result of this call to 0. In our traces this pattern would manifest in one of two forms: (i) foo foo==0 or (ii) foo foo!=0. For the sake of our thought experiment, also assume that, by chance, print follows foo in our traces 95% of the time. What kinds of relationships do we need to use to extract the cluster of terms: foo, foo==0, and foo!=0? We could use co-occurrence, however using co-occurrence will likely pick up on the uninformative fact that foo frequently co-occurs with print. Furthermore, co-occurrence may struggle to pick up on the relationship between foo and the check on its result: because each check is encoded as a distinct word, neither check will co-occur with extremely high frequency. We could, instead, use synonymy, but it is trivial to imagine words, such as malloc and calloc, that are synonyms but not related in the sense of a usage pattern or specification.

It is the insufficiency of both co-occurrence and synonymy that forms the basis of Domain-Adapted Clustering. Because neither metric covers all cases, Domain-Adapted Clustering forms a parameterized mix of two metrics: one based on left and right co-occurrence, and another based on unsupervised learning. Because both of these metrics encode a distance (or similarity) of some sort, Domain-Adapted Clustering can be thought of as computing the pair-wise distance matrices and then mixing them via a parameter $\alpha \in [0, 1]$. Figure 1 provides a visual overview of the mixing process Domain-Adapted Clustering employs.

5.2 The Co-occurrence Distance Matrix

Domain-Adapted Clustering utilizes co-occurrence statistics extracted directly from the (sampled and thresholded) trace corpus. To capture as much information as possible, Domain-Adapted Clustering walks each trace and computes, for each word pair (A, B), the number of times that A follows B and the number of times that B follows A. These counts are converted to percentages and these percentages represent a kind of similarity between A and B. The higher the percentages, the

more often *A* and *B* co-occur. To turn the percentages into a distance, we subtract them from 1.0 and store the average of the left-distance and right-distance in our co-occurrence distance matrix.

5.3 The Word-Embedding Distance Matrix

To incorporate unsupervised learning, Domain-Adapted Clustering utilizes word-vector learners. The use of word-vector learners in the software-engineering domain is not a new idea [DeFreez et al. 2018; Henkel et al. 2018; Nguyen et al. 2017a; Pradel and Sen 2018; Ye et al. 2016b]. Many recent works have explored the power of embeddings in the realm of understanding and improving software. What we contribute is, to the best of our knowledge, the first thorough comparison of three of the most widely used word-vector learners in the application domain of software engineering. We do this comprehensive evaluation to test an intuition that *sub-word information improves the quality of embeddings learned from software artifacts.* We base this intuition on the observation that similarly named methods have similar meaning. §7.4 provides the details of this evaluation.

Our choice of word-vector learners as an unsupervised learning methodology is a deliberate one. Earlier, we saw how synonymy could be a useful (albeit incomplete) property to capture. Furthermore, we already have a notion of distance between words (given to us via our co-occurrence distance matrix). Word-vector learners mesh well with both of these pre-existing criteria: word vectors encode local context and are able to capture synonymy. Additionally, word–word distance is encoded in the learned vector space. These properties make word-vector learners a convenient choice for Domain-Adapted Clustering. To extract a distance matrix from a learned word embedding, Domain-Adapted Clustering computes, for each word pair (A, B), the cosine distance between the embedding of A and the embedding of B (here, we use cosine distance because it is the distance of choice for word vectors).

5.4 Cluster Generation

To generate clusters, Domain-Adapted Clustering applies the insight that the clusters we seek should be expressed in concrete usages. This idea leads us to invert the problem of clustering instead of clustering all of the terms in the vocabulary, we take a more bottom-up approach. We start with an individual trace from our corpus of sampled traces. Within the trace, we find topics or collections of terms that are related under our machine-learning-assisted metric: we use the combined distance matrix we created previously and apply a threshold to detect words that are related. Within a trace, any two words whose distance is below the threshold are assigned to the same intra-trace cluster. The next step uses the set of all intra-trace clusters to create a set of reduced traces: each trace in the corpus of traces is projected onto each of the intra-trace clusters to create a new corpus of reduced traces. To form final clusters, we apply a traditional clustering method (DBSCAN [Ester et al. 1996]) to the collection of reduced traces as the distance metric.

One distinctive advantage of Domain-Adapted Clustering, for our use case, is its ability to generate overlapping clusters. Most off-the-shelf clustering techniques produce disjoint sets but, in the realm of Open-World Specification Mining, it is easy to conceive of multiple patterns that share common terms (opening a file and reading versus opening a file and writing). Finally, it is worthwhile to note that the clustering step we have outlined here introduces two hyper-parameters: the threshold to use for intra-trace clustering (which we will call β) and DBSCAN's ϵ , which controls how close points must be to be considered neighbors. This leaves Domain-Adapted Clustering with a total of three tunable hyper-parameters: α , β , ϵ .

```
$START
                                         dictGetIterator
strcasecmp
                                         dictGetIterator
strcasecmp != 0
                                            → dictNext
strcasecmp
                                         dictNext
strcasecmp == 0
                                         dictNext == 0
dictGetIterator
                                         dictNext != 0
log
                                         dictGetIterator
dictGetIterator
                                            → dictReleaseIterator
  \rightarrow dictNext
                                         dictReleaseIterator
dictNext
                                                (b) Example cluster
dictNext != 0
dictNext \rightarrow dictGetKey
dictGetKey
                                         dictGetIterator
sdslen
                                         dictGetIterator
sdslen \rightarrow strmatchlen
                                            \rightarrow dictNext
strmatchlen
                                         dictNext
strmatchlen != 0
                                         dictNext != 0
addReplyBulk
                                         dictGetIterator
dictGetIterator
                                            \rightarrow dictNext
  \rightarrow dictNext
                                         dictNext
dictNext
                                         dictNext == 0
dictNext == 0
                                         dictGetIterator
dictGetIterator
                                            → dictReleaseIterator
  → dictReleaseIterator
                                         dictReleaseIterator
dictReleaseIterator
                                       (c) Result of projecting the trace in Fig. 6a
$END
                                       into the vocabulary defined by the cluster
                                       in Fig. 6b
     (a) Example trace
```

Fig. 6. Example of trace projection

6 MINING

The final phase of the ml4spec toolchain is mining. To mine specifications in an Open-World setting, ml4spec applies several insights, described in the preceding sections, to create a corpus of rich traces and a collection of clusters. These two artifacts are used, in the mining phase, to create a new corpus of *projected traces* that can be fed to any pre-existing trace-based mining technique. To create projected traces, ml4spec takes each cluster and each trace and generates a new projected trace by removing, from the original trace, any word that is not in the currently selected cluster. This projection process is shown in Fig. 6. After projection, traces can be de-duplicated (if desired) and then passed to any trace-based miner. The ml4spec toolchain is unique in its non-reliance on any particular trace-based miner. It is the dissociation from specific mining techniques that makes ml4spec a toolchain for Open-World mining and not just another trace-based mining technique.

Table 1. Grid search parameters

Name	Values	Purpose	Phase
learner	{fastText, GloVe, word2vec}	Word-vector learner to use	II (Learning)
sampler	{Diversity, Random, None}	Sampling method to use	III (Sampling)
alpha	$\{0.00, 0.25, 0.50, 0.75, 1.00\}$	Weight for combined distance matrix	IV (DAC)
beta	$\{0.20, 0.25, \ldots, 0.45, 0.50\}$	Threshold for intra-trace clustering	IV (DAC)
epsilon	$\{0.10, 0.30, 0.50, 0.70, 0.90\}$	Parameter to DBSCAN	IV (DAC)

7 EVALUATION

In this section we introduce our evaluation methodology and address each of our five research questions. For the purposes of evaluation we ran the ml4spec toolchain on five different open source projects:

- Curl: a popular command-line tool for transferring data.
- Hexchat: an IRC client.
- Ngnix: a web server implementation.
- Nmap: a network scanner.
- Redis: a key-value store.

These projects were selected because they exhibit a wide variety of usage patterns across diverse domains. For each of these five projects, we performed a grid search to gain an understanding of our various design decisions. §7.1 details this search.

7.1 Grid Search

To facilitate a comprehensive evaluation of ml4spec, we performed a grid search across thousands of parameterizations of the ml4spec toolchain. The grid search serves two purposes. First, the results of the grid search provide a firmer empirical footing for understanding the efficacy and impacts of different aspects of our toolchain (in particular, the grid search aids in quantifying the impacts of different word-vector learners and sampling methodologies). Second, the Open-World Specification Mining task emphasizes a lack of user-directed feedback—to meet this standard we must ensure, via the data gleaned from the grid search, that the hyper-parameters associated with the ml4spec toolchain can be set, globally, to good default values. Table 1 outlines the parameters in play and the ranges of values investigated for each parameter. Upper and lower limits for each search range were carefully chosen, based on the results of smaller searches, to reduce the computational costs of the larger search over the parameters presented in Tab. 1.

7.2 RQ1: Can we effectively mine useful and clean clusters in an Open-World setting?

Research Question 1 asked whether we can mine useful and clean clusters. The difficulty with mining such clusters lies in the setting of our mining task. We seek to solve the problem of mining specifications in an Open-World setting: one in which implicit and explicit sources of hierarchical or taxonomic information are unavailable. It is this Open-World setting that creates a unique need for disentangling the many different topics that may exist in an abstracted symbolic trace. The purpose of Research Question 1 is to understand the efficacy of the techniques described earlier (specifically, Domain-Adapted Clustering) against a key challenge of Open-World Specification Mining: learning correct and clean clusters.

To measure the quality of our learned clusters we found the need for a benchmark. Unfortunately, to the best of our knowledge, the problem of Open-World Specification Mining has not been

hashTypeInitIterator hashTypeNext hashTypeReleaseIterator

(a) Cluster in the vocabulary of simple call names

```
hashTypeInitIterator
hashTypeInitIterator
	→ hashTypeNext
hashTypeNext
hashTypeNext == -1
hashTypeNext != -1
hashTypeInitIterator
	→ hashTypeReleaseIterator
hashTypeReleaseIterator
```

(b) Cluster in our enriched vocabulary

Fig. 7. Comparison between two clusters

previously addressed and, therefore, there is no ground truth to evaluate our learned clusters against (due to the lack of need for gold standard clusters). One possible avenue of evaluation and source of implicit clusters exists in source-code documentation. Many thoroughly documented and heavily used APIs include information on the associations between functions (most commonly in the form of a "See also…" or "Related methods…" listing). Another possible source of implicit information comes from projects that have made the transition from a language like C to a language like C++. In such a transition methods are often grouped into classes and this signal could be used to induce a clustering. Finally, there is the implicit clustering induced by the locations where various API methods are defined: even in C, functions defined in the same header are likely related.

Despite these various sources of implicit clusters, we have identified a need for manually defined gold standard clusters. We use manually extracted ground truth clusters for two reasons. First, the sources of information listed above are indications of relatedness but not necessarily indications of a specification or usage pattern. For example, several different methods are commonly defined for linked lists, such as length(), next(), prev(), and hasNext() but not all of these methods are necessarily used together in a pattern. Second, the vocabulary we are working over includes more than simple call names—we also have information related to the path condition and information about dataflow between calls. For example, compare the two clusters given in Fig. 7. The cluster in Fig. 7a consists only of call names, while the cluster in Fig. 7b includes call names, return value checks, and dataflow information. In comparing these two clusters, it becomes clear that a cluster over words in our enriched vocabulary (induced by the abstractions we choose) is strictly more informative than a cluster over a vocabulary of simple call names.

Taken together, these two issues (the weak signal of the aforementioned sources and the lack of labels for some words in our enriched vocabulary) make manually extracted clusters more desirable. For the purpose of this evaluation we have extracted 71 gold standard clusters from five open source projects. We have placed no explicit limit on the sizes of the clusters we included, thereby increasing the challenge of recovering all the clusters in our benchmark correctly.

Using our set of 71 gold standard clusters we are able to perform a quantitative evaluation by measuring the Jaccard similarity³ of our extracted clusters and our gold standard clusters. Because our toolchain does not mine a fixed number of clusters, we need some way to "pair" an extracted cluster with the gold standard cluster it most represents. To do this, we look for a pairing of extracted clusters with gold standard clusters that maximizes the average Jaccard similarity. This

³Jaccard similarity between sets A and B is $\frac{|A \cap B|}{|A \cup B|}$. Jaccard distance is one minus the Jaccard similarity.

	Benchmark				
Measurement	curl	hexchat	nginx	nmap	redis
Top-1 (Jaccard)	62.8%	52.8%	44.9%	49.1%	71.9%
Top-1 (Intersection)	79.7%	78.7%	67.6%	70.1%	83.5%
Top-5 (Jaccard)	62.1%	51.8%	43.7%	47.3%	69.3%
Top-5 (Intersection)	77.9%	73.8%	70.1%	67.2%	81.0%

Table 2. Best scoring configurations for each of the five target projects

provides us with a way to have a consistent evaluation regardless of the number of total clusters we extract. (One might argue that this allows for extracting an unreasonable amount of clusters in an attempt to game this metric. However, this kind of "metric hacking" is unachievable in our toolchain due to the use of DBSCAN to extract clusters from reduced traces. Clustering our reduced traces, using the Jaccard distance between sets of tokens within a trace, removes the possibility that our tool is simply enumerating all possible clusters to achieve a high score.)

In addition to Jaccard similarity, which penalizes both omissions and spurious inclusions, we also measure the percent intersection between our extracted clusters and the clusters in our gold standard dataset. Table 2 provides both of these measurements for each of the five open-source projects we examined. To provide a robust understanding of performance, and reduce variance in our measurements, we provide both the best (Top-1) results and an average of the five best results (Top-5) for both similarity measures. (We use the data from our grid search, described in §7.1, to compute these averages.) Examining Tab. 2, we observe that the ml4spec toolchain retrieves clusters that have a strong agreement with the clusters in our gold standard dataset. Furthermore, the intersection similarity results show that our extracted clusters contain, on average, over two thirds of the desired terms from the clusters in our gold standard dataset. Together, these results answer Research Question 1 in the affirmative: ml4spec is capable of extracting clean and useful clusters in an Open-World setting.

7.3 RQ2: How does DAC compare to off-the-shelf clustering techniques?

In this section, we explore how our Domain-Adapted Clustering (DAC) technique (a key piece of our Open-World specification miner) compares to traditional clustering approaches. To understand the relationship between DAC and more traditional clustering methods, it is instructive to consider the input data we have available to use in the clustering process. Prior to clustering, we have access to a pairwise distance matrix (created via a combination of co-occurrence statistics and word–word cosine distance), our learned word vectors, and our original traces.

Most clustering methods accept either vectors of data or pair-wise distance matrices. In principle, this leaves our choices for clustering methods to compare to quite open. However, using our word vectors as the input to clustering ignores our earlier insight about the advantage of combining word embeddings and co-occurrence statistics. Therefore, we focus on clustering algorithms that accept pre-computed pair-wise distances as input. From this class of clustering methods we have selected the following techniques to compare against: DBSCAN [Ester et al. 1996], Affinity Propagation [Frey and Dueck 2007], and Agglomerative Clustering.

To compare the selected traditional techniques to DAC we use the benchmark we introduced in RQ1 as a means of consistent evaluation. Both DAC and our selection of traditional techniques require some number of hyper-parameters to be set. To ensure a fair evaluation, we have searched over a range of hyper-parameters for each of the selected techniques and compare between the

	Benchmark				
Clustering	curl	hexchat	nginx	nmap	redis
DBSCAN	49.9%	36.7%	34.9%	36.5%	59.6%
Agglomerative	38.9%	15.8%	25.8%	12.7%	8.6%
Affinity Prop.	12.1%	10.2%	11.9%	10.3%	11.5%
DAC (Rel. Increase)	+25.9%	+41.2%	+24.1%	+34.5%	+25.7%

Table 3. DAC compared to off-the-shelf clustering techniques

Table 4. DAC compared to off-the-shelf clustering techniques boosted by our machine-learning-assisted metric

	Benchmark				
Clustering	curl	hexchat	nginx	nmap	redis
DBSCAN	49.9%	38.0%	38.1%	37.9%	64.4%
Agglomerative	40.7%	21.6%	39.2%	19.7%	26.7%
Affinity Prop.	15.3%	12.5%	13.4%	15.3%	15.5%
DAC (Rel. Increase)	+25.9%	+36.9%	+10.6%	+29.7%	+16.5%

best configurations for each technique. Table 3 provides performance measurements for each of the three off-the-shelf clustering baselines across each of our five target projects. In addition, Tab. 3 provides the relative performance increase gained by using DAC in place of these baselines.⁴ For this comparison we have made only the co-occurrence distance matrix available to our off-the-shelf baselines as one of DAC's key insights was the importance of a machine-learning-assisted metric. Table 4 follows the same format but provides each off-the-shelf technique access to the combined matrix DAC uses for clustering. In either case, we see that DAC outperforms each of the baselines by a wide margin.

7.4 RQ3: How does the choice of word vector learner and the choice of sampling techniques affect the resulting clusters?

Research Question 3 seeks to understand the impact of two choices made in the earlier portion of our toolchain: the choice of word vector learner and the choice of trace sampling technique. For the choice of word vector learner we argued that fastText with its utilization of sub-word information (in the form of character level n-grams) would provide embeddings better suited to the task of extracting clean clusters. We based this prediction on the observation, made by many, that similarly named methods often have similar meaning. When it came to the choice of trace sampling we sought to reduce the impact of a problem, identified by Henkel et al. [2018], called *prefix dominance*. To address this issue of *prefix dominance* in our specification mining setting we introduced a trace sampling methodology termed Diversity Sampling.

To understand the interplay and effects of these choices we have evaluated the ml4spec toolchain in nine configurations. These nine configurations are defined by two choices: a choice of word vector learner (either fastText [Bojanowski et al. 2017], GloVe [Pennington et al. 2014], or word2vec [Mikolov

 $^{^4}$ We compute the relative performance increase by comparing to the best overall off-the-shelf technique on a per-project basis.

	Learner			
Sampler	word2vec	GloVe	fastText	
Diversity Sampling	50.3%	47.1%	52.2%	
Random Sampling	42.0%	41.5%	50.0%	
No Sampling	44.9%	44.4%	48.6%	

Table 5. Top-5 performance (geometric mean across our five target projects). The shaded row and column represent the best sampler and learner, respectively.

Table 6. Top-1 performance (geometric mean across our five target projects). The shaded row and column represent the best sampler and learner, respectively.

	Learner			
Sampler	word2vec	GloVe	fastText	
Diversity Sampling	52.7%	48.6%	54.9%	
Random Sampling	44.5%	43.6%	53.0%	
No Sampling	47.7%	46.3%	50.7%	

et al. 2013]) and a choice of trace sampling technique (either Diversity Sampling, random sampling, or no sampling). By evaluating our full toolchain with varying choices of embedding and sampling methodology we can either confirm or refute our intuitions. We leverage the gold standard clusters introduced in RQ1 to provide a consistent benchmark for comparison between the nine configurations we've outlined.

First, we examine top-5 performance (measured against our benchmark) across all of the configurations we established in §7.1. We look at averages of the top-5 configurations (with sampler and learner fixed to one of the nine choices outlined earlier) to understand effects of our choices of interest (the sampler and learner) and to reduce any variance from other sources. Table 5 provides top-5 performance measurements for each of our nine possible configurations. We can see that fastText is superior (regardless of sampling choice) to any of the other word vector learners by a wide margin. We also observe that fastText paired with Diversity Sampling is the most performant combination. However, fastText with no sampling is not far behind—this is perhaps indicative of both the impact of word embeddings and the need for larger corpora to learn suitable embeddings.

Although top-5 averages provide a robust picture of the performance of our selected configurations, we also would like to understand which configurations have the best peak (top-1) performance. To assess top-1 performance, we examine Tab. 6 which shows the geometric mean (across our five target projects) of the best performing configuration identified via the data from our grid search (§7.1). These results affirm the impact of Diversity Sampling and fastText as the superior word-embedding learner for this use case. Finally, we observe that the combination of fastText and Diversity Sampling again produces the best overall performance.

These results support two conclusions. First, fastText, with its use of sub-word information, outperforms GloVe and word2vec in the cluster extraction task we have benchmarked. Second, Diversity Sampling both improves the performance of our toolchain and word vector learner (by reducing the amount of input data) and provides an increase in performance compared to the other baseline choices of sampling routine. These results also support further examination of the advantages of sub-word information in the software-engineering domain; specifically, we note that



Fig. 8. Average benchmark performance for varying values of α

fastText has no concept of the ideal boundaries between sub-tokens that naturally exist in program identifiers. A word vector learner equipped with this knowledge may produce even more favorable results.

7.5 RQ4: Is there a benefit to using a combination of co-occurrence statistics and word embeddings?

One of the key insights from §5 was that word embeddings and co-occurrence statistics capture subtly different information. Word embeddings excel at picking up on local context (a direct result of being based on the distributional hypothesis which asserts that similar words appear in similar contexts). This focus on local context makes word embeddings well-suited for tasks like word similarity and analogy solving. For specification mining, co-occurrence information is often used, in some form, to capture the "support" for a candidate rule or pattern. These co-occurrence statistics encode a global relationship between words that is more far-reaching than the relationship captured by word vectors.

Research Question 4 attempts to precisely quantify the impact of these two different sources of information. This effort is made somewhat easier by the choice to include a tunable parameter in our toolchain that represents the relative weight of word–word distance and co-occurrence distance in our final pair-wise distance matrix. By evaluating our full toolchain with a gradation of weight values we can pinpoint the mix of metrics that lead to optimal performance on the benchmark we introduced earlier.

Figure 8 plots average benchmark scores for different values of the α parameter. Here we take an average, with α fixed, over all configuration explored in §7.1. We observe a clear trend of increasing performance as more weight is applied to the word embeddings (and less to the co-occurrence statistics). In addition, we note that this performance increase reaches a peak at $\alpha = 0.75$ for each



Fig. 9. Peak benchmark performance for varying values of α

of the five projects. As we did in Research Question 3, we also examine top-1 performance. The results for top-1 performance, given in Fig. 9, paint a clearer picture of the relationship between word embeddings and co-occurrence statistics. In Fig. 9 we observe that, for all five projects, adding word embeddings to our distance matrix produces a pronounced increase in performance. Again we are able to validate that, for each project, this increase in performance peaks at $\alpha = 0.75$. These results suggests an affirmative answer to Research Question 4: there is a quantifiable benefit to using both co-occurrence statistics and word embeddings; furthermore, a combination that favors the distances produced via word embeddings yields maximum performance across each of the projects we examined.

7.6 RQ5: Does our toolchain transfer to unseen projects with minimal reconfiguration?

Research Question 5 asked if our toolchain can be easily adapted to unseen projects. More precisely, we would like to evaluate whether the few parameters in our tool can use reasonable defaults without sacrificing too much performance. To do this we can re-examine some of the results from the grid search in §7.1 to develop an understanding of the performance impact choosing defaults would have when transferring to unseen data.

We can rank configurations by enumerating the top-20 configurations for each of our five target projects and counting the number of times any given configuration occurs in the top-20 for any project. This ranking reveals that two configurations each produce top-20 results in four out of the five projects we considered. Examining these two configurations further, we find that exploring just these two configurations allows ml4spec to find clusters that are within ten percent of the best performing configuration for each of our five projects. Therefore, we can answer Research

Question 5 in the affirmative, with the knowledge that running in just two default configurations allows for full automation with no more than a ten percent performance decrease.

8 THREATS TO VALIDITY

Our usage of Parametric Lightweight Symbolic Execution (PLSE) provides us with a way to quickly extract rich traces from buildable C programs; however, PLSE is imprecise. It is possible that a more precise symbolic-execution engine would provide our downstream mining techniques with more accurate information and, in turn, reveal more correct specifications. In addition, it is likely that an execution engine capable of generating interprocedural traces would improve the quality of our results.

Our ground-truth clustering benchmark was manually extracted with the goal of providing a quantitative benchmark in the rich vocabulary available to the ml4spec toolchain. This manual process is susceptible to bias. To mitigate this risk, each cluster was validated against the source program to confirm that the set of terms within the cluster appeared in a concrete usage. Furthermore, the gold-standard clusters were created with no bounds on their size: this variance in cluster size greatly increases the difficulty of recovering correct clusters while matching the reality of usage patterns which can range from simple checks to complex iterators or initialization routines. It is our hope that the release of the ground-truth dataset will provide the groundwork for a larger, more comprehensive, gold-standard dataset curated by the community.

We chose to focus on a collection of five open-source C projects. It is possible that our selection of projects is not representative of the wider landscape of API usages in C. Furthermore, our technique, while language agnostic in theory, may not easily transfer to other languages. Fortunately, the PLSE implementation uses the GCC toolchain as a front end, which makes cross-language mining a possibility for future work.

9 RELATED WORK

There exists a wide variety of related works from the specification mining, API misuse, program understanding, and entity embedding communities. For comprehensive overviews of specification mining and misuse we refer the reader to Lo et al. [2011] and Robillard et al. [2013]. For efforts in machine learning and its application in the software-engineering domain Allamanis et al. [2017a] provide an excellent survey. In addition, there exists a listing of machine learning on code resources maintained by the community [source{d} 2019]. For details on embeddings and their use in the software-engineering domain Martin Monperrus [2019] provide an up-to-date listing. In the following sections, we discuss related works in the realms of specification mining and embeddings of software artifacts in greater detail.

Specification Mining

There is a rich history of work on mining specifications, or usage patterns, from programs. Earlier approaches, such as Li and Zhou [2005], provided relatively simple specifications. Going forward in time, a growing body of work attempted to produce richer FSA-based specifications [Acharya and Xie 2009; Ammons et al. 2002; Dallmeier et al. 2006; Gabel and Su 2008; Lo and Khoo 2006; Lorenzoli et al. 2008; Pradel and Gross 2009; Quante and Koschke 2007; Shoham et al. 2008; Walkinshaw and Bogdanov 2008; Walkinshaw et al. 2007]. Some recent work such as Deep Specification Mining and Doc2Spec, has incorporated NLP techniques [Le and Lo 2018; Zhong et al. 2009]. DeFreez et al. [2018] use word-vector learners to bolster traditional support-based mining via the identification of *function synonyms*. In the broader field of non-FSA-based specification mining techniques, there exist several novel techniques: Nguyen et al. [2009] mine graph-based specifications; Sankaranarayanan et al. [2008] produce specifications as Datalog rules; Acharya et al. [2007] create a partial order

over function calls and Murali et al. [2017] develop a Bayesian framework for learning probabilistic specifications. In addition to mining, several works focus on the related problem of detecting misuses [Engler et al. 2001; Livshits and Zimmermann 2005; Monperrus and Mezini 2013; Wasylkowski et al. 2007; Yun et al. 2016].

The ml4spec toolchain is agnostic to the choice of trace-based mining technique used to generate specifications. This miner-agnostic perspective makes ml4spec a front end that enables prior trace-based miners to work in the Open-World setting we have described. In addition, ml4spec's use of Parametric Lightweight Symbolic Execution makes it possible to mine, via traditional methods, specifications that involve both control-flow and data-flow information.

Embeddings of Software Artifacts

Recently, several techniques have leveraged learned embeddings for artifacts generated from programs. Nguyen et al. [2016, 2017b] leverage word embeddings (learned from ASTs) in two domains to facilitate translation from Java to C#. Le and Lo [2018] use embeddings to bootstrap anomaly detection against a corpus of JavaScript programs. Gu et al. [2016] leverage an encoder/decoder architecture to embed whole sequences in their DEEPAPI tool for API recommendation.

Pradel and Sen [2017] use embeddings (learned from custom tree-based contexts built from ASTs) to bootstrap anomaly detection against a corpus of JavaScript programs. Gu et al. [2016] leverage an encoder/decoder architecture to embed whole sequences in their DEEPAPI tool for API recommendation. API2API by Ye et al. [2016a] also leverages word embeddings, but it learns the embeddings from API-related natural-language documents instead of an artifact derived directly from source code. Alon et al. [2018b] learn from paths through ASTs to produce general representations of programs; in [Alon et al. 2018a] they expand upon this general representation by leveraging attention mechanisms. Ben-Nun et al. [2018] produce embeddings of programs that are learned from both control-flow and data-flow information. Zhao et al. [2018] introduce type-directed encoders, a framework for encoding compound data types via a recursive composition of more basic encoders. Using input/output pairs as the input data for learning, Piech et al. [2015] and Parisotto et al. [2016] learn to embed whole programs. Using sequences of live variable values, Wang et al. [2017] produce embeddings to aid in program repair tasks. Allamanis et al. [2017b] learn to embed whole programs via Gated Graph Recurrent Neural Networks (GG-RNNs) [Li et al. 2015]. Peng et al. [2015] provide an AST-based encoding of programs with the goal of facilitating deep-learning methods.

In contrast to prior work on the embedding of software artifacts, we provide both a novel use of embeddings in the software-engineering domain (in the form of Domain-Adapted Clustering and its machine-learning-assisted metric) and a comprehensive comparison between three state-of-the-art word embedding techniques (fastText [Bojanowski et al. 2017], GloVe [Pennington et al. 2014], and word2vec [Mikolov et al. 2013]). Furthermore, we make an insight into a future line of work involving the utilization of refined sub-token information to improve embeddings in the software-engineering domain.

10 CONCLUSION

With a growing number of frameworks and libraries being authored each day, there is an increased need for industrial-grade specification mining. In this paper, we introduced the problem of Open-World Specification Mining with the hope of fostering new mining tools and techniques that focus on reducing burdens on users. The challenge of mining is amplified in an Open-World setting. To address this challenge, we introduced ml4spec: a toolchain that combines the power of unsupervised learning (in the form of word embeddings) with traditional techniques to successfully mine specifications and usage patterns in an Open-World setting.

Our work also provides a new dataset of ground-truth clusters which can be used to benchmark attempts to extract related terms from programs. We provided a comprehensive evaluation across three different word-vector learners to gain insight into the value of sub-word information in the software-engineering domain. Lastly, we introduced three new techniques: Hierarchical Thresholding, Diversity Sampling, and Domain Adapted Clustering each solving a different challenge in the realm of Open-World Specification Mining.

REFERENCES

- Mithun Acharya and Tao Xie. 2009. Mining API Error-Handling Specifications from Source Code. In *Fundamental Approaches* to Software Engineering (Lecture Notes in Computer Science), Marsha Chechik and Martin Wirsing (Eds.). Springer Berlin Heidelberg, 370–384.
- Mithun Acharya, Tao Xie, Jian Pei, and Jun Xu. 2007. Mining API Patterns As Partial Orders from Source Code: From Usage Scenarios to Specifications. In Proceedings of the the 6th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The Foundations of Software Engineering (ESEC-FSE '07). ACM, New York, NY, USA, 25–34. https://doi.org/10.1145/1287624.1287630
- Miltiadis Allamanis, Earl T Barr, Premkumar T Devanbu, and Charles A Sutton. 2017a. A Survey of Machine Learning for Big Code and Naturalness. *CoRR* abs/1709.0 (2017). http://arxiv.org/abs/1709.06182
- Miltiadis Allamanis, Marc Brockschmidt, and Mahmoud Khademi. 2017b. Learning to Represent Programs with Graphs. *CoRR* abs/1711.0 (2017). arXiv:1711.00740 http://arXiv.org/abs/1711.00740
- Uri Alon, Meital Zilberstein, Omer Levy, and Eran Yahav. 2018a. code2vec: Learning Distributed Representations of Code. CoRR abs/1803.09473 (2018). arXiv:1803.09473 http://arxiv.org/abs/1803.09473
- Uri Alon, Meital Zilberstein, Omer Levy, and Eran Yahav. 2018b. A General Path-based Representation for Predicting Program Properties. In Proceedings of the 39th ACM SIGPLAN Conference on Programming Language Design and Implementation (PLDI 2018). ACM, New York, NY, USA, 404–419. https://doi.org/10.1145/3192366.3192412
- Glenn Ammons, Rastislav BodÄŋk, and James R. Larus. 2002. Mining Specifications. In Proceedings of the 29th ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (POPL '02). ACM, New York, NY, USA, 4–16. https://doi.org/10.1145/503272.503275
- Tal Ben-Nun, Alice Shoshana Jakobovits, and Torsten Hoefler. 2018. Neural Code Comprehension: A Learnable Representation of Code Semantics. *CoRR* abs/1806.07336 (2018). arXiv:1806.07336 http://arxiv.org/abs/1806.07336
- A. W. Biermann and J. A. Feldman. 1972. On the Synthesis of Finite-State Machines from Samples of Their Behavior. IEEE Trans. Comput. C-21, 6 (June 1972), 592–597. https://doi.org/10.1109/TC.1972.5009015
- Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching Word Vectors with Subword Information. *Transactions of the Association for Computational Linguistics* 5 (2017), 135–146. https://transacl.org/ojs/index.php/tacl/article/view/999
- Valentin Dallmeier, Christian Lindig, Andrzej Wasylkowski, and Andreas Zeller. 2006. Mining Object Behavior with ADABU. In Proceedings of the 2006 International Workshop on Dynamic Systems Analysis (WODA '06). ACM, New York, NY, USA, 17–24. https://doi.org/10.1145/1138912.1138918
- Daniel DeFreez, Aditya V. Thakur, and Cindy Rubio-GonzÄąlez. 2018. Path-based Function Embedding and Its Application to Error-handling Specification Mining. In Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2018). ACM, New York, NY, USA, 423–433. https://doi.org/10.1145/3236024.3236059 event-place: Lake Buena Vista, FL, USA.
- Dawson Engler, David Yu Chen, Seth Hallem, Andy Chou, and Benjamin Chelf. 2001. Bugs As Deviant Behavior: A General Approach to Inferring Errors in Systems Code. In *Proceedings of the Eighteenth ACM Symposium on Operating Systems Principles (SOSP '01)*. ACM, New York, NY, USA, 57–72. https://doi.org/10.1145/502034.502041
- Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. 1996. A Density-based Algorithm for Discovering Clusters a Density-based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD'96)*. AAAI Press, 226–231. http: //dl.acm.org/citation.cfm?id=3001460.3001507
- Brendan J. Frey and Delbert Dueck. 2007. Clustering by Passing Messages Between Data Points. *Science* 315, 5814 (2007), 972–976. https://doi.org/10.1126/science.1136800 arXiv:http://science.sciencemag.org/content/315/5814/972.full.pdf
- Mark Gabel and Zhendong Su. 2008. Javert: Fully Automatic Mining of General Temporal Properties from Dynamic Traces. In *Proceedings of the 16th ACM SIGSOFT International Symposium on Foundations of Software Engineering (SIGSOFT '08/FSE-16)*. ACM, New York, NY, USA, 339–349. https://doi.org/10.1145/1453101.1453150
- Xiaodong Gu, Hongyu Zhang, Dongmei Zhang, and Sunghun Kim. 2016. Deep API Learning. In Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering (FSE 2016). ACM, New York, NY, USA, 631–642. https://doi.org/10.1145/2950290.2950334

- Zellig S. Harris. 1954. Distributional Structure. WORD 10, 2-3 (1954), 146–162. https://doi.org/10.1080/00437956.1954. 11659520
- Jordan Henkel, Shuvendu K. Lahiri, Ben Liblit, and Thomas Reps. 2018. Code Vectors: Understanding Programs Through Embedded Abstracted Symbolic Traces. In Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2018). ACM, New York, NY, USA, 163–174. https://doi.org/10.1145/3236024.3236085
- Tien-Duy B. Le and David Lo. 2018. Deep Specification Mining. In Proceedings of the 27th ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA 2018). ACM, New York, NY, USA, 106–117. https://doi.org/10.1145/ 3213846.3213876
- Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard S Zemel. 2015. Gated Graph Sequence Neural Networks. CoRR abs/1511.0 (2015). arXiv:1511.05493 http://arxiv.org/abs/1511.05493
- Zhenmin Li and Yuanyuan Zhou. 2005. PR-Miner: Automatically Extracting Implicit Programming Rules and Detecting Violations in Large Software Code. In Proceedings of the 10th European Software Engineering Conference Held Jointly with 13th ACM SIGSOFT International Symposium on Foundations of Software Engineering (ESEC/FSE-13). ACM, New York, NY, USA, 306–315. https://doi.org/10.1145/1081706.1081755
- Benjamin Livshits and Thomas Zimmermann. 2005. DynaMine: Finding Common Error Patterns by Mining Software Revision Histories. In Proceedings of the 10th European Software Engineering Conference Held Jointly with 13th ACM SIGSOFT International Symposium on Foundations of Software Engineering (ESEC/FSE-13). ACM, New York, NY, USA, 296–305. https://doi.org/10.1145/1081706.1081754 event-place: Lisbon, Portugal.
- David Lo and Siau-Cheng Khoo. 2006. SMArTIC: Towards Building an Accurate, Robust and Scalable Specification Miner. In Proceedings of the 14th ACM SIGSOFT International Symposium on Foundations of Software Engineering (SIGSOFT '06/FSE-14). ACM, New York, NY, USA, 265–275. https://doi.org/10.1145/1181775.1181808
- David Lo, Siau-Cheng Khoo, Jiawei Han, and Chao Liu. 2011. *Mining Software Specifications: Methodologies and Applications*. CRC Press. Google-Books-ID: VAzLBQAAQBAJ.
- D. Lorenzoli, L. Mariani, and M. PezzÃĺ. 2008. Automatic generation of software behavioral models. In 2008 ACM/IEEE 30th International Conference on Software Engineering. 501–510. https://doi.org/10.1145/1368088.1368157
- Zimin Chen Martin Monperrus. 2019. Embeddings for Source Code. https://www.monperrus.net/martin/embeddings-forcode
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed Representations of Words and Phrases and their Compositionality. In Advances in Neural Information Processing Systems 26, C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger (Eds.). Curran Associates, Inc., 3111–3119. http://papers.nips.cc/ paper/5021-distributed-representations-of-words-and-phrases-and-their-compositionality.pdf
- Martin Monperrus and Mira Mezini. 2013. Detecting Missing Method Calls As Violations of the Majority Rule. ACM Trans. Softw. Eng. Methodol. 22, 1 (March 2013), 7:1–7:25. https://doi.org/10.1145/2430536.2430541
- Vijayaraghavan Murali, Swarat Chaudhuri, and Chris Jermaine. 2017. Bayesian Specification Learning for Finding API Usage Errors. In Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering (ESEC/FSE 2017). ACM, New York, NY, USA, 151–162. https://doi.org/10.1145/3106237.3106284
- Trong Duc Nguyen, Anh H. T. Nguyen, Hung Dang Phan, and Tien N. Nguyen. 2017a. Exploring API Embedding for API Usages and Applications. 2017 IEEE/ACM 39th International Conference on Software Engineering (ICSE) (2017), 438-449.
- Trong Duc Nguyen, Anh Tuan Nguyen, and Tien N. Nguyen. 2016. Mapping API Elements for Code Migration with Vector Representations. In Proceedings of the 38th International Conference on Software Engineering Companion (ICSE '16). ACM, New York, NY, USA, 756–758. https://doi.org/10.1145/2889160.2892661
- Trong Duc Nguyen, Anh Tuan Nguyen, Hung Dang Phan, and Tien N Nguyen. 2017b. Exploring API Embedding for API Usages and Applications. In *Proceedings of the 39th International Conference on Software Engineering (ICSE '17)*. IEEE Press, Piscataway, NJ, USA, 438–449. https://doi.org/10.1109/ICSE.2017.47
- Tung Thanh Nguyen, Hoan Anh Nguyen, Nam H. Pham, Jafar M. Al-Kofahi, and Tien N. Nguyen. 2009. Graph-based Mining of Multiple Object Usage Patterns. In Proceedings of the the 7th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The Foundations of Software Engineering (ESEC/FSE '09). ACM, New York, NY, USA, 383–392. https://doi.org/10.1145/1595696.1595767
- Emilio Parisotto, Abdel-rahman Mohamed, Rishabh Singh, Lihong Li, Dengyong Zhou, and Pushmeet Kohli. 2016. Neuro-Symbolic Program Synthesis. *CoRR* abs/1611.0 (2016). arXiv:1611.01855 http://arxiv.org/abs/1611.01855
- Hao Peng, Lili Mou, Ge Li, Yuxuan Liu, Lu Zhang, and Zhi Jin. 2015. Building Program Vector Representations for Deep Learning. In Proceedings of the 8th International Conference on Knowledge Science, Engineering and Management - Volume 9403 (KSEM 2015). Springer-Verlag New York, Inc., New York, NY, USA, 547–553. https://doi.org/10.1007/978-3-319-25159-2_49
- Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global Vectors for Word Representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for

Computational Linguistics, Doha, Qatar, 1532-1543. http://www.aclweb.org/anthology/D14-1162

- Chris Piech, Jonathan Huang, Andy Nguyen, Mike Phulsuksombati, Mehran Sahami, and Leonidas Guibas. 2015. Learning Program Embeddings to Propagate Feedback on Student Code. In *Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37 (ICML'15)*. JMLR.org, 1093–1102. http://dl.acm.org/citation. cfm?id=3045118.3045235
- Michael Pradel and Thomas R. Gross. 2009. Automatic Generation of Object Usage Specifications from Large Method Traces. In Proceedings of the 2009 IEEE/ACM International Conference on Automated Software Engineering (ASE '09). IEEE Computer Society, Washington, DC, USA, 371–382. https://doi.org/10.1109/ASE.2009.60
- Michael Pradel and Koushik Sen. 2017. *Deep Learning to Find Bugs*. Technical Report TUD-CS-2017-0295. Technische Universität Darmstadt, Department of Computer Science.
- Michael Pradel and Koushik Sen. 2018. DeepBugs: a learning approach to name-based bug detection. *PACMPL* 2 (2018), 147:1–147:25.
- J. Quante and R. Koschke. 2007. Dynamic Protocol Recovery. In 14th Working Conference on Reverse Engineering (WCRE 2007). 219–228. https://doi.org/10.1109/WCRE.2007.24
- M. P. Robillard, E. Bodden, D. Kawrykow, M. Mezini, and T. Ratchford. 2013. Automated API Property Inference Techniques. *IEEE Transactions on Software Engineering* 39, 5 (May 2013), 613–637. https://doi.org/10.1109/TSE.2012.63
- Martin P. Robillard and Robert DeLine. 2011. A field study of API learning obstacles. Empirical Software Engineering 16, 6 (Dec. 2011), 703–732. https://doi.org/10.1007/s10664-010-9150-8
- Sriram Sankaranarayanan, Franjo IvanÄŊiÄĞ, and Aarti Gupta. 2008. Mining Library Specifications Using Inductive Logic Programming. In Proceedings of the 30th International Conference on Software Engineering (ICSE '08). ACM, New York, NY, USA, 131–140. https://doi.org/10.1145/1368088.1368107
- Kristie Seymore, Andrew Mccallum, and Ronald Rosenfeld. 1999. Learning Hidden Markov Model Structure for Information Extraction. (1999).
- S. Shoham, E. Yahav, S. J. Fink, and M. Pistoia. 2008. Static Specification Mining Using Automata-Based Abstractions. IEEE Transactions on Software Engineering 34, 5 (Sept. 2008), 651–666. https://doi.org/10.1109/TSE.2008.63
- source{d}. 2019. Cool links & research papers related to Machine Learning applied to source code (MLonCode): src-d/awesome-machine-learning-on-source-code. https://github.com/src-d/awesome-machine-learning-on-source-code original-date: 2017-06-20T13:35:45Z.
- N. Walkinshaw and K. Bogdanov. 2008. Inferring Finite-State Models with Temporal Constraints. In 2008 23rd IEEE/ACM International Conference on Automated Software Engineering. 248–257. https://doi.org/10.1109/ASE.2008.35
- N. Walkinshaw, K. Bogdanov, M. Holcombe, and S. Salahuddin. 2007. Reverse Engineering State Machines by Interactive Grammar Inference. In 14th Working Conference on Reverse Engineering (WCRE 2007). 209–218. https://doi.org/10.1109/ WCRE.2007.45
- Ke Wang, Rishabh Singh, and Zhendong Su. 2017. Dynamic Neural Program Embedding for Program Repair. CoRR abs/1711.07163 (2017). arXiv:1711.07163 http://arxiv.org/abs/1711.07163
- Andrzej Wasylkowski, Andreas Zeller, and Christian Lindig. 2007. Detecting Object Usage Anomalies. In Proceedings of the the 6th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The Foundations of Software Engineering (ESEC-FSE '07). ACM, New York, NY, USA, 35–44. https://doi.org/10.1145/1287624.1287632 event-place: Dubrovnik, Croatia.
- X Ye, H Shen, X Ma, R Bunescu, and C Liu. 2016a. From Word Embeddings to Document Similarities for Improved Information Retrieval in Software Engineering. In 2016 IEEE/ACM 38th International Conference on Software Engineering (ICSE). 404-415. https://doi.org/10.1145/2884781.2884862
- Xin Ye, Hui Shen, Xiao Ma, Razvan C. Bunescu, and Chang Liu. 2016b. From Word Embeddings to Document Similarities for Improved Information Retrieval in Software Engineering. 2016 IEEE/ACM 38th International Conference on Software Engineering (ICSE) (2016), 404–415.
- Insu Yun, Changwoo Min, Xujie Si, Yeongjin Jang, Taesoo Kim, and Mayur Naik. 2016. APISAN: Sanitizing API Usages Through Semantic Cross-checking. In *Proceedings of the 25th USENIX Conference on Security Symposium (SEC'16)*. USENIX Association, Berkeley, CA, USA, 363–378. http://dl.acm.org/citation.cfm?id=3241094.3241123
- Jinman Zhao, Aws Albarghouthi, Vaibhav Rastogi, Somesh Jha, and Damien Octeau. 2018. Neural-augmented Static Analysis of Android Communication. In Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2018). ACM, New York, NY, USA, 342–353. https://doi.org/10.1145/3236024.3236066
- H. Zhong, L. Zhang, T. Xie, and H. Mei. 2009. Inferring Resource Specifications from Natural Language API Documentation. In 2009 IEEE/ACM International Conference on Automated Software Engineering. 307–318. https://doi.org/10.1109/ASE.2009.94