

Grounded Discovery of Coordinate Term Relationships between Software Entities

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Abstract

We present an approach for the detection of coordinate-term relationships between entities from the software domain, that refer to Java classes. Usually, relations are found by examining corpus statistics associated with text entities. In some technical domains, however, we have access to additional information about the real-world objects named by the entities, suggesting that coupling information about the “grounded” entities with corpus statistics might lead to improved methods for relation discovery. To this end, we develop a similarity measure for Java classes using distributional information about how they are used in software, which we combine with corpus statistics on the distribution of contexts in which the classes appear in text. Using our approach, cross-validation accuracy on this dataset can be improved dramatically, from around 60% to 88%. Human labeling results show that our classifier has an F1 score of 86% over the top 1000 predicted pairs.

1 Introduction

Discovering semantic relations between text entities is a key task in natural language understanding. It is a critical component which enables the success of knowledge representation systems such as TextRunner [43], ReVerb [8], and NELL [4], which in turn are useful for a variety of NLP applications, including, temporal scoping [38], semantic parsing [20] and entity linking [25].

In this work, we examine *coordinate* relations between words. According to the WordNet glossary, X and Y are defined as *coordinate terms* if they share a common hypernym [10, 27]. This is a symmetric relation that indicates a semantic similarity, meaning that X and Y are “a type of the same thing”, since they share at least one common ancestor in some hypernym taxonomy (to paraphrase the definition of Snow et al. [37]).

Semantic similarity relations are normally discovered by comparing corpus statistics associated with the

entities: for instance, two entities X and Y that usually appear in similar contexts are likely to be semantically similar [7, 32, 33]. However, in technical domains, we have access to additional information about the real-world objects that are named by the entities: e.g., we might have biographical data about a person entity, or a 3D structural encoding of a protein entity. In such situations, it seems plausible that a “grounded” NLP method, in which corpus statistics are coupled with data on the real-world referents of X and Y , might lead to improved methods for relation discovery.

Here we explore the idea of grounded relation discovery in the domain of software. In particular, we consider the detection of coordinate-term relationships between entities that (potentially) refer to Java classes. We use a software domain text corpus derived from the Q&A website StackOverflow (SO), in which users ask and answer questions about software development, and we extract posts which have been labeled by users as *Java* related. From this data, we collected a small set of entity pairs that are labeled as coordinate terms (or not) based on high-precision Hearst patterns and frequency statistics, and we attempt to label these pairs using information available from higher-recall approaches based on distributional similarity.

We describe an entity linking method in order to map a given text entity to an underlying class type implementation from the Java standard libraries. Next, we describe corpus and code based information that we use for the relation discovery task. Corpus based methods include distributional similarity and string matching similarity. Additionally, we use two sources of code based information: (1) we define the *class-context* of a Java class in a given code repository, and are therefore able to calculate a code-based distributional similarity measure for classes, and (2) we consider the hierarchical organization of classes, described by the Java class type and namespace hierarchies. We demonstrate that using our approach, cross-validation

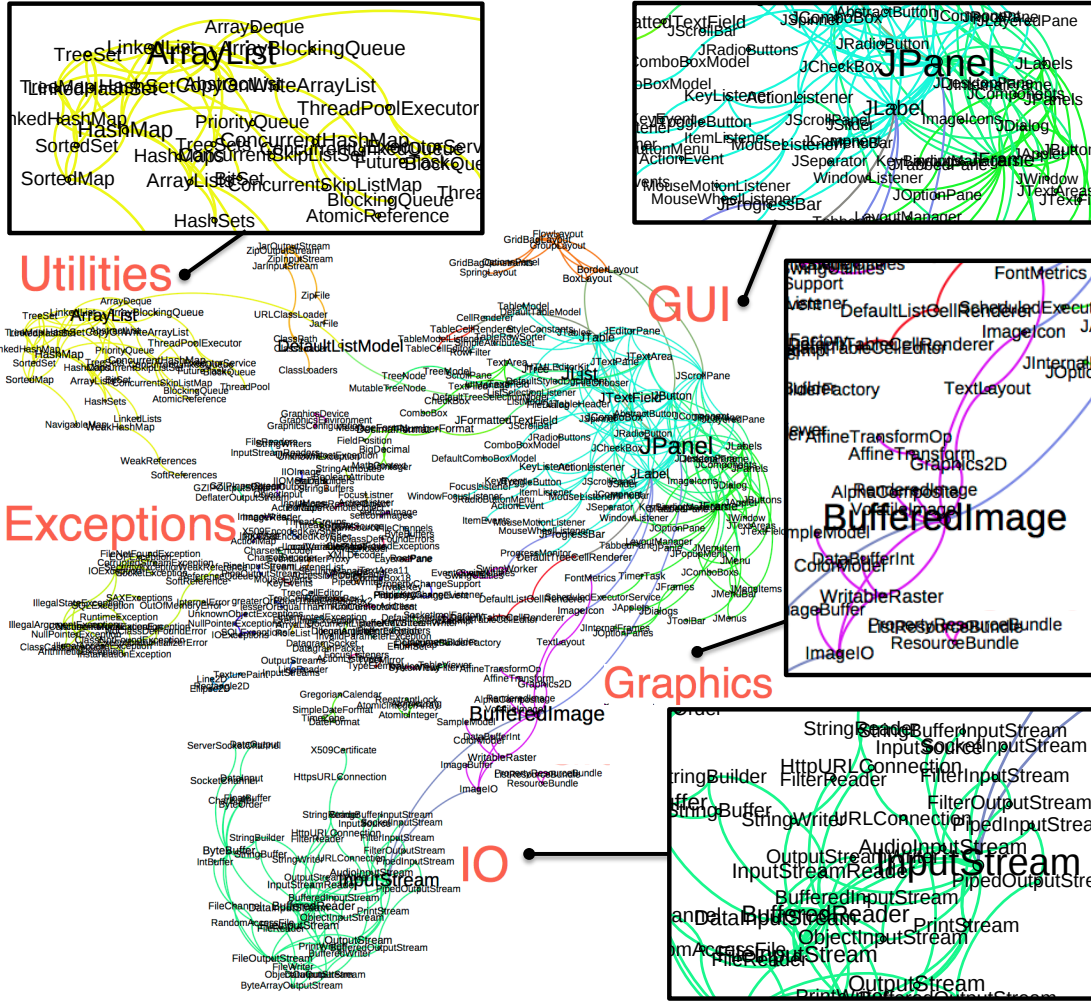


Figure 1: Visualization of predicted coordinate term pairs, where each pair of coordinate classes is connected by an edge. Highly connected components are labeled by edge color, and it can be noted that they contain classes with similar functionality. Some areas containing a functional class group have been magnified for easier readability.

accuracy on this dataset is improved from 60.9% to 88%. According to human labeling, our classifier has an F1-score of 86% over the highest-ranking 1000 predicted pairs.

We see this work as a first step towards building a knowledge representation system for the software domain, in which text entities refer to elements from a software code base, for example classes, methods, applications and programming languages. Understanding software entity relations will allow the construction of a domain specific taxonomy and knowledge base, which can enable higher reasoning capabilities in NLP applications for the software domain [3, 29, 41, 42] and improve a variety of code assisting applications, including code refactoring and token completion [1, 15, 17, 34].

Figure 1 shows a visualization based on coordinate term pairs predicted using the proposed method. Java classes with similar functionality are highly connected in this graph, indicating that our method can be used to construct a code taxonomy.

2 Related Work

Semantic Relation Discovery. Previous work on semantic relation discovery, in particular, coordinate term discovery, has used two main approaches. The first is based on the insight that certain lexical patterns indicate a semantic relationship with high-precision, as initially observed by Hearst [16]. For example, the conjunction pattern “X and Y” indicates that X and Y are coordinate terms. Other pattern-based classifier have

been introduced for meronyms [13], synonyms [24], and general analogy relations [40]. The second approach relies on the notion that words that appear in a similar context are likely to be semantically similar. In contrast to pattern based classifiers, context distributional similarity approaches are normally higher in recall. [7, 32, 33, 36]. In this work we attempt to label samples extracted with high-precision Hearst patterns, using information from higher-recall methods.

Grounded Language Learning. The aim of grounded language learning methods is to learn a mapping between natural language (words and sentences) and the observed world [14, 35, 44], where more recent work includes grounding language to the physical world [19], and grounding of entire discourses [28]. Early work in this field relied on supervised aligned sentence-to-meaning data [12, 45]. However, in later work the supervision constraint has been gradually relaxed [18, 23]. Relative to prior work on grounded language acquisition, we use a very rich and complex representation of entities and their relationships (through software code). However, we consider a very constrained language task, namely coordinate term discovery.

Statistical Language Models for Software. In recent work by NLP and software engineering researchers, statistical language models have been adapted for modeling software code. NLP models have been used to enhance a variety of software development tasks such as code and comment token completion [15, 17, 29, 34], analysis of code variable names [1, 22], and mining software repositories [11]. This has been complemented by work from the programming language research community for structured prediction of code syntax trees [31]. To the best of our knowledge, there is no prior work on discovering semantic relations for software entities.

3 Coordinate Term Discovery

In this section we describe a coordinate term classification pipeline, as depicted at high-level in Figure 2. All the following steps are described in detail in the sections below.

Given a software domain text corpus (StackOverflow) and a code repository (Java Standard Libraries), our goal is to predict a coordinate relation for $\langle X, Y \rangle$, where X and Y are nouns which potentially refer to Java classes.

We first attempt a baseline approach of labeling the pair $\langle X, Y \rangle$ based on corpus distributional similarity. Since closely related classes often exhibit morphological closeness, we use as a second baseline the string similarity of X and Y .

Next, we map noun X to an underlying class imple-

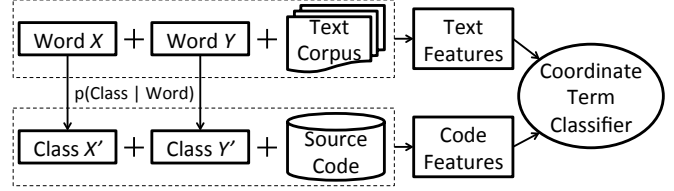


Figure 2: Classification Pipeline for determining whether nouns X and Y are coordinate terms. Each noun is mapped to an underlying class from the code repository with probability, $p(\text{Class}|\text{Word})$. Textual features are extracted based on the input words, code based features are extracted using the mapped classes, and all of these are given to the coordinate term classifier.

mentation from the code repository, named X' , according to an estimated probability for $p(\text{Class } X'|\text{Word } X)$, s.t., $X' = \max_C \hat{p}(C|X)$, for all other classes C . X' is then the code referent of X . Similarly, we map Y to the class Y' . Given a code-based grounding for X and Y we extract information using the class implementations: (1) we define a code based distributional similarity measure, using code-context to encode the usage pattern of a class, and (2) we use the hierarchical organization of classes, described by the type and namespace hierarchies. Finally, we combine all the above information in a single SVM classifier.

3.1 Baseline: Corpus Distributional Similarity.

As an initial baseline we calculate the corpus distributional similarity of nouns $\langle X, Y \rangle$, following the assumption that words with similar context are likely to be semantically similar. Our implementation follows Pereira et al. [33]. We calculate the empirical context distribution for noun X

$$(3.1) \quad p_X = f(c, X) / \sum_{c'} f(c', X)$$

where $f(c, X)$ is the frequency of occurrence of noun X in context c . We then measure the similarity of nouns X and Y using the *relative entropy* or *Kullback-Leibler divergence*

$$(3.2) \quad D(p_X || p_Y) = \sum_z p_X(z) \log \frac{p_X(z)}{p_Y(z)}$$

As this measure is not symmetric we finally consider the distributional similarity of X and Y as $D(p_X || p_Y) + D(p_Y || p_X)$.

3.2 Baseline: String Similarity. Due to naming convention standards, many related classes often exhibit some morphological closeness. For example, classes that

provide Input/Output access to the file system will often contain the suffix `Stream` or `Buffer`. Likewise, many classes extend on the names of their super classes (e.g., `JRadioButtonMenuItem` extends the class `JMenuItem`). More examples can be found in Figure 1 and Table 4. We therefore include a second baseline which attempts to label the noun pair $\langle X, Y \rangle$ as coordinate terms according to their string matching similarity. We use the SecondString open source Java toolkit¹. Each string is tokenized by camel case (such that `ArrayList` is represented as `Array List`). We consider the SoftTFIDF distance of the tokenized strings, as defined by Cohen et al. [6].

3.3 Entity Linking. In order to draw code based information on text entities, we define a mapping function between words and class types. Our goal is to find $p(C|W)$, where C is a specific class implementation and W is a word. This mapping is ambiguous, for example, since users are less likely to mention the qualified class name (e.g., `java.lang.String`), and usually use the class *label*, meaning the name of the class not including its package (e.g., `String`). As an example, the terms `java.lang.String` and `java.util.Vector` appears 37 and 1 times respectively in our corpus, versus the terms `String` and `Vector` which appear 35K and 1.6K times. Additionally, class names appear with several variations, including, case-insensitive versions, spelling mistakes, or informal names (e.g., `array` instead of `ArrayList`).

Therefore, in order to approximate $p(C, W)$ in

$$(3.3) \quad p(C|W) = \frac{p(C, W)}{p(W)}$$

We estimate a word to class-type mapping that is mediated through the class label, L , as

$$(3.4) \quad \hat{p}(C, W) = p(C, L) \cdot p(L, W)$$

Since $p(C, L) = p(C|L)p(L)$, this can be estimated by the corresponding MLEs

$$(3.5) \quad \begin{aligned} \hat{p}(C, L) &= \hat{p}(C|L) \cdot \hat{p}(L) \\ &= \frac{f(C)}{\sum_{C' \in L} f(C')} \cdot \frac{f(L)}{\sum_{L'} f(L')} \end{aligned}$$

where $f()$ is the frequency function. Note that since $\sum_{C' \in L} f(C') = f(L)$ we get that $\hat{p}(C, L) = \hat{p}(C)$, as the class label is uniquely determined by the class qualified name (the opposite does not hold since multiple class types may correspond to the same label). Finally, the term $p(L, W)$ is estimated by the symmetric string

ARG-Method: `Class` is being passed as an argument to `Method`. We count an occurrence of this context once for the method definition

`Method(Class class, ...)`

as well as for each method invocation

`Method(class, ...)`

For example, given the statement

`str = toString(i);`

where i is an Integer, we would count an occurrence for this class in the context ARG-toString.

API-Method: `Class` provides the API method `Method`. We count an occurrence of this context once for the method definition, and for every occurrence of the method invocation, e.g. `class.Method(...)`.

For example, given the statement

`s = map.size();`

where `map` is a `HashMap`, we would count an occurrence for this class in the context API-size.

Table 1: Definition of two types of code-contexts for a class type, `Class`, or an instantiation of that type (e.g., `class`).

distance between the two strings, as described in Section 3.2. We consider the linking probability of $\langle X, Y \rangle$ to be $\hat{p}(X'|X) \cdot \hat{p}(Y'|Y)$, where X' is the best matching class for X s.t. $X' = \max_C \hat{p}(C|X)$ and similarly for Y' .

3.4 Code Distributional Similarity. Corpus distributional similarity evaluates the occurrence of words in particular semantic contexts. By defining the *class-context* of a Java class, we can then similarly calculate a *code distributional similarity* between classes. Our definition of class context is based on the usage of a class as an argument to methods and on the API which the class provides, and it is detailed in Table 1. We observe over 23K unique contexts in our code repository. Based on these definitions we can compute the distributional similarity measure between classes X' and Y' based on their code-context distributions, as previously described for the corpus distributional similarity (Section 3.1, following Pereira et al. [33]). For the code-based case, we calculate the empirical context distribution of X' (see Equation 3.1) using $f(c, X')$, the occurrence frequency of class X' in context c , where c is one of the ARG-Method or API-Method contexts (defined in Table 1) for methods observed in the code repository. The distributional similarity of $\langle X', Y' \rangle$ is then taken, using the relative entropy, as $D(p_{X'} || p_{Y'}) + D(p_{Y'} || p_{X'})$.

¹<http://secondstring.sourceforge.net/>

3.5 Code Hierarchies and Organization. The words X and Y are defined as coordinate terms if they have the same hypernym in a given taxonomy, meaning they have at least one common ancestor in this taxonomy [36]. For the purpose of comparing two class types, we therefore define an ancestry relation between them using two taxonomies based on the code namespace and type hierarchies.

Package Taxonomy: A package is the standard way for defining namespaces in the Java language. It is a mechanism for organizing sets of classes which normally share a common functionality. Packages are organized in a hierarchical structure which can be easily inferred from the class name. For example, the class `java.lang.String`, belongs to the `java.lang` package, which belongs to the `java` package.

Type Taxonomy: The inheritance structure of classes and interfaces in the Java language defines a type hierarchy, such that class A is the ancestor of class B if B extends or implements A .

We define type-ancestry and package-ancestry relations between classes $\langle X', Y' \rangle$, based on the above taxonomies. For the type taxonomy,

$$A_{type}^n(X', Y') = \{\# \text{ of common ancestors } X' \text{ and } Y' \text{ share within } n \text{ higher up levels in the type taxonomy}\}$$

for n from 1 to 6. $A_{package}^n$ is defined similarly for the package taxonomy. As an example,

$$A_{package}^2(\text{ArrayList}, \text{Vector}) = 2$$

as these classes both belong in the package `java.util`, and therefore their common level 2 ancestors are: `java` and `java.util`. Moreover,

$$A_{type}^1(\text{ArrayList}, \text{Vector}) = 5$$

since both classes extend the `AbstractList` class, and also implement four joint interfaces: `List`, `RandomAccess`, `Cloneable`, and `Serializable`.

4 Experimental Settings

4.1 Data Handling. We downloaded a dump of the interactions on the StackOverflow website² from its launch date in 2008 and until 2012. We use only the 277K questions labeled with the user-assigned *Java* tag, and their 629K answers.

Text from the SO html posts was extracted with the Apache Tika toolkit³ and then tokenized with the

²<http://www.clearbits.net/creators/146-stack-exchange-data-dump>

³<http://tika.apache.org/>

High PMI	Low PMI
<code><JTextField,JComboBox></code>	<code><threads,characters></code>
<code><yearsPlayed,totalEarned></code>	<code><server,user></code>
<code><PostInsertEventListener,PostUpdateEventListener></code>	<code><code,design></code>
<code><removeListener,addListener></code>	<code><Java,client></code>
<code><MinTreeMap,MaxTreeMap></code>	<code><Eclipse,array></code>

Table 2: Sample set of word pairs with high and low *PMI* scores. Many of the high *PMI* pairs refer to software entities such as variable, method and Java class names, whereas the low *PMI* pairs contain more general software terms.

Mallet statistical NLP package [26]. In this study, we use only the text portions of the SO posts, and exclude all raw code segments, as indicated by the user-labeled `<code>` markup. Next, the text was POS tagged with the Stanford POS tagger [39] and parsed with the MaltParser [30]. Finally, we extract noun pairs with the conjunction dependencies: *conj* or *inv-conj*, a total of 255,150 pairs, which we use as positive training samples.

We use the Java standard libraries code repository as a grounding source for Java classes, as we expect that users will often refer to these classes in the *Java* tagged SO posts. This data includes: 7072 source code files, the implementation of 10562 class and interface types, and 477 packages. The code repository is parsed using the Eclipse JDT compiler tools, which provide APIs for accessing and manipulating Abstract Syntax Trees.

4.2 Classification. We follow the classification pipeline described in Figure 2, using the LibLinear SVM classifier [5, 9] with the following features:

Corpus-Based Features

- *Corpus distributional similarity* (Corpus Dist. Sim.) - see Section 3.1.
- *String similarity* (String Sim.) - see Section 3.2.

Code-Based Features

- *Text to code linking probability* (Text-to-code Prob.) - see Section 3.3.
- *Code distributional similarity* (Code Dist. Sim.) - see Section 3.4.
- *Package and type ancestry* ($A_{package}^1$ - $A_{package}^6$ and A_{type}^1 - A_{type}^6) - see Section 3.5.

Since the validity of the code based features above is directly related to the success of the entity linking phase,

Method	<i>Coord</i>	<i>Coord-PMI</i>
Code & Corpus	85.3	88
<i>Baselines:</i>		
Corpus Dist. Sim.	57.8	58.2
String Sim.	65.2	65.8
Corpus Only	64.7	60.9
Code Only	80.1	81.1
<i>Code Features:</i>		
Code Dist. Sim.	67 (60.2)	67.2 (59)
$A^1_{package}$	64.2 (63.8)	64.3 (63.9)
$A^2_{package}$	64.2 (63.8)	61.2 (64.8)
$A^3_{package}$	65.8 (64.3)	66 (64.6)
$A^4_{package}$	52.5 (52)	64.7 (58.7)
$A^5_{package}$	52.5 (52)	52.6 (58.7)
$A^6_{package}$	50.4 (51.6)	52.3 (52)
A^1_{type}	51.4 (51.4)	55.1 (53.7)
A^2_{type}	54 (53.9)	55.5 (54.3)
A^3_{type}	56.8 (56.7)	57 (56.9)
A^4_{type}	57.1 (56.9)	57.3 (57.1)
A^5_{type}	57.4 (57.6)	58 (57.9)
A^6_{type}	57.2 (57.4)	57.5 (57.5)
Text-to-code Prob.	55.7	55.8

Table 3: Cross validation accuracy results for the coordinate term SVM classifier (Code & Corpus), as well as baselines using corpus distributional similarity, string similarity, all corpus based features (Corpus Only), or all code based features (Code Only), and all individual code based features. The weighted version of the code based features (see Section 4.2) is in parenthesis. Results are shown for both the *Coord* and *Coord-PMI* datasets.

each of the code based features are used in the classifier once with the original value and a second time with the value weighted by the text to code linking probability.

Of the noun pairs $\langle X, Y \rangle$ in our data, we keep only pairs for which the linking probability $\hat{p}(X'|X) \cdot \hat{p}(Y'|Y)$ is greater than 0.1. Note that this guarantees that each noun must be mapped to at least one class with non-zero probability. Next, we evaluate the string morphology and its resemblance to a camel-case format, which is the acceptable formatting for Java class names. We therefore select alphanumeric terms with at least two upper-case and one lower-case characters. We name this set of noun pairs the *Coord* dataset.

A key assumption underlying statistical distributional similarity approaches is that “high-interest” entities are associated with higher corpus frequencies, therefore, given sufficient statistical evidence “high-interest” relations can be extracted. In the software domain, real

world factors may introduce biases in a software-focused text corpus which may affect the corpus frequencies of classes: e.g., users may discuss classes based on the clarity of their API, the efficiency of their implementation, or simply if they are fundamental in software introduced to novice users. Another motivation for using grounded data, such as the class implementation, is that it may highlight additional aspects of interest, for example, classes that are commonly inherited from. We therefore define a second noun dataset, *Coord-PMI*, which attempts to address this issue, in which noun pairs are selected based on their pointwise mutual information (*PMI*):

$$(4.6) \quad PMI(X, Y) = \log \frac{p(X, Y)}{p(X)p(Y)}$$

where the frequency of the pair $\langle X, Y \rangle$ in the corpus is positive. In this set we include coordinate term pairs with high *PMI* scores, which appear more rarely in the corpus and are therefore harder to predict using standard NLP techniques. The negative set in this data are noun pairs which appear frequently separately but do not appear as coordinate terms, and are therefore marked by low *PMI* scores.

To illustrate this point, we provide a sample of noun pairs with low and high *PMI* scores in Table 2, where pairs highlighted with bold font are labeled as coordinate terms in our data. We can see that the high *PMI* set contains pairs that are specific and interesting in the software domain while not necessarily being frequent words in the general domain. For example, some pairs seem to represent variable names (e.g., $\langle yearsPlayed, totalEarned \rangle$), others likely refer to method names (e.g., $\langle removeListener, addListener \rangle$). Some pairs refer to Java classes, such as $\langle JTextField, JComboBox \rangle$ whose implementation can be found in the Java code repository. We can also see examples of pairs such as $\langle PostInsertEventListener, PostUpdateEventListener \rangle$ which are likely to be user-defined classes with a relationship to the Java class `java.util.EventListener`. In contrast, the low *PMI* set contains more general software terms (e.g., *code*, *design*, *server*, *threads*).

5 Results

5.1 Classification and Feature Analysis. In Table 3 we report the cross validation accuracy of the coordinate term classifier (*Code & Corpus*) as well as baseline classifiers using corpus distributional similarity (*Corpus Dist. Sim.*), string similarity (*String Sim.*), all corpus features (*All Corpus*), or all code features (*All Code*). Note that using all code features is significantly more successful on this data than any of the corpus baselines (corpus baselines’ accuracy is between 57%-

Code Dist. Sim	$A^3_{package}$	A^5_{type}
$\langle \text{FileOutputStream}, \text{OutputStream} \rangle$	$\langle \text{KeyEvent}, \text{KeyListener} \rangle$	$\langle \text{JMenuItem}, \text{JMenu} \rangle$
$\langle \text{AffineTransform}, \text{AffineTransformOp} \rangle$	$\langle \text{StyleConstants}, \text{SimpleAttributeSet} \rangle$	$\langle \text{JMenuItems}, \text{JMenu} \rangle$
$\langle \text{GZIPOutputStream}, \text{DeflaterOutputStream} \rangle$	$\langle \text{BlockQueue}, \text{ThreadPoolExecutor} \rangle$	$\langle \text{JMenuItems}, \text{JMenus} \rangle$
$\langle \text{OutputStream}, \text{DataOutputStream} \rangle$	$\langle \text{BufferedImage}, \text{WritableRaster} \rangle$	$\langle \text{JLabel}, \text{DefaultTreeCellRenderer} \rangle$
$\langle \text{AtomicInteger}, \text{AtomicIntegerArray} \rangle$	$\langle \text{MouseListener}, \text{MouseWheelListener} \rangle$	$\langle \text{JToggleButton}, \text{JRadioButtonMenu} \rangle$
$\langle \text{ResourceBundle}, \text{ListResourceBundle} \rangle$	$\langle \text{DocumentBuilderFactory}, \text{DocumentBuilder} \rangle$	$\langle \text{JFrame}, \text{JDialogs} \rangle$
$\langle \text{setIconImages}, \text{setIconImage} \rangle$	$\langle \text{ActionListeners}, \text{FocusListeners} \rangle$	$\langle \text{JTable}, \text{JTableHeader} \rangle$
$\langle \text{ComboBoxModel}, \text{DefaultComboBoxModel} \rangle$	$\langle \text{DataInputStream}, \text{DataOutputStream} \rangle$	$\langle \text{JTextArea}, \text{JEditorPane} \rangle$
$\langle \text{JTextArea}, \text{TextArea} \rangle$	$\langle \text{greaterOrEqualThan}, \text{lessOrEqualThan} \rangle$	$\langle \text{JTextPane}, \text{JEditorPane} \rangle$
$\langle \text{ServerSocketChannel}, \text{SocketChannel} \rangle$	$\langle \text{CopyOnWriteArrayList}, \text{ConcurrentLinkedQueue} \rangle$	$\langle \text{JTextArea}, \text{JTable} \rangle$

Table 4: Top ten coordinate terms predicted by classifiers using one of the following features: code distributional similarity, package hierarchy ancestry ($A^3_{package}$), and type hierarchy ancestry (A^5_{type}). All of the displayed predictions are *true*.

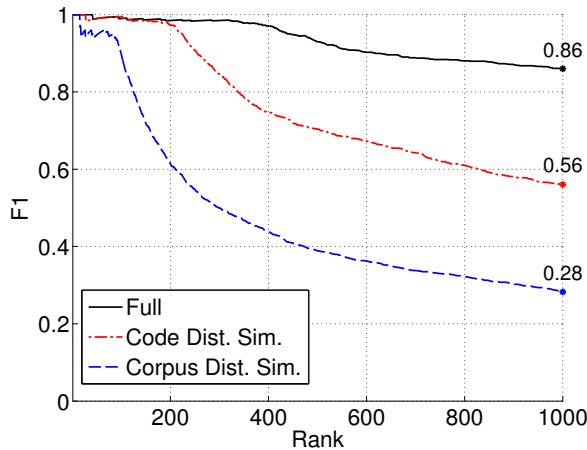


Figure 3: Manual Labeling Results. F1 results of the top 1000 predicted coordinate terms by rank. The final data point in each line is labeled with the F1 score at rank 1000.

65% whereas code-based accuracy is over 80%). When using both data sources, performance is improved even further (to over 85% on the *Coord* dataset and 88% on *Coord-PMI*).

We provide an additional feature analysis in Table 3, and report the cross validation accuracy of classifiers using each single code feature. Interestingly, code distributional similarity (*Code Dist. Sim.*) is the strongest single feature, and it is a significantly better predictor than corpus distributional similarity, achieving around 67% v.s. around 58% for both datasets.

5.2 Evaluation by Manual Labeling. The cross-validation results above are based on labels extracted using Hearst conjunction patterns. In Figure 3 we provide an additional analysis based on manual human labeling of samples from the *Coord-PMI* dataset, following a procedure similar to prior researchers exploring semi-supervised methods for relation discovery [4, 21]. After all development was complete, we hand labeled the top 1000 coordinate term pairs according to the ranking by our full classifier (using all code and corpus features) and the top 1000 pairs predicted by the classifiers based on code and corpus distributional similarities only. We report the F1 results of each classifier by the rank of the predicted samples. According to our analysis, the F1 score for the text and code distributional similarity classifiers degrades quickly after the first 100 and 200 top ranked pairs, respectively. At rank 1000, the score of the full classifier is at 86%, whereas the code and text classifiers are only at 56% and 28%.

To highlight the strength of each of the code based features, we provide in Table 4 the top ten coordinate terms predicted using the most successful code based features. For example, the top prediction using type hierarchy ancestry (A^5_{type}) is $\langle \text{JMenuItem}, \text{JMenu} \rangle$. Since *JMenu* extends *JMenuItem*, the two classes indeed share many common interfaces and classes. Alternatively, all of the top predictions using the package hierarchy ancestry ($A^3_{package}$) are labels that have been matched to pairs of classes that share at least 3 higher up package levels. So for example, *BlockQueue* has been matched to *java.util.concurrent.BlockingQueue* which was predicted as a coordinate term of *ThreadPoolExecutor* which belongs in the same package. Using code dis-

tributional similarity, one of the top predictions is the pair `<GZIPOutputStream, DeflaterOutputStream>`, which share many common API methods such as `write`, `flush`, and `close`. Many of the other top predicted pairs by this feature have been mapped to the same class and therefore have the exact same context distribution.

5.3 Taxonomy Construction. We visualize the coordinate term pairs predicted using our method (with all features), by aggregating them into a graph where entities are nodes and edges are determined by a coordinate term relation (Figure 1). Graph edges are colored using the Louvain method [2] for community detection and an entity label’s size is determined by its betweenness centrality degree. We can see that high-level communities in this graph correspond to class functionality, indicating that our method can be used to create an interesting code taxonomy.

Note that our predictions also highlight connections within functional groups that cannot be found using the package or type taxonomies directly. One example can be highlighted within the GUI functionality group. `Listener` classes facilitate a response mechanism to GUI `Actions`, such as *pressing a button*, or *entering text*, however, these classes belong in different packages than basic GUI components for historical reasons. In our graph, Action and Listener classes belong to the same communities of the GUI components they are normally used with.

6 Conclusions

We have presented an approach for grounded discovery of coordinate term relationships between text entities representing Java classes. Using a simple entity linking method we map text entities to an underlying class type implementation from the Java standard libraries. With this code-based grounding, we extract information on the usage pattern of the class and its location in the Java class and namespace hierarchies. Our experimental evaluation shows that using only corpus distributional similarity for the coordinate term prediction task is unsuccessful, achieving prediction accuracy of around 58%. However, adding information based on the entities’ software implementation improves accuracy dramatically to 88%. Our classifier has an F1 score of 86% according to human labeling over the top 1000 predicted pairs. We have shown that our predictions can be used to build an interesting code taxonomy which draws from the functional connections, common usage patterns, and implementation details that are shared between classes.

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