Resolving API Mentions in Informal Documents

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Abstract—Developer forums contain opinions and information related to the usage of APIs. API names in forum posts are often not explicitly linked to their official resources. Automatic linking of an API mention to its official resources can be challenging for various reasons, such as, name overloading. We present a technique, ANACE, to automatically resolve API mentions in the textual contents of forum posts. Given a database of APIs, we first detect all words in a forum post that are potential references to an API. We then use a combination of heuristics and machine learning to eliminate false positives and to link true positives to the actual APIs and their resources.

Index Terms—API traceability; API informal documentation

I. INTRODUCTION

Automatic traceability recovery between an API and its mentions in the forum posts can be useful to mine valuable information about the APIs. An API can be mentioned using its name (e.g., spring framework), its code terms (e.g., PropertiesFactoryBean), or hyperlinks to its resources (e.g., https://spring.io/). The problem of resolving code terms in API-related documents deals with tracing a code term to its API (e.g., linking the type PropertiesFactoryBean to the API it belongs to) [1]–[4]. However, we are aware of no technique to resolve mentions of general API names in the textual contents of the forum posts (see Section III).

We denote a phrase (e.g., spring) resembling an API name in a forum post as a named API mention. We define the problem of resolving such a named API mention as determining whether the mention actually refers to an API and, if so, which exact API it refers to. We present a technique, ANACE (API Name TraCEr), which, given a database of APIs, detects API names in the forum posts and links the names to their resource pages. First, we detect all API mentions, i.e., phrases in a forum post that are potential references to an API in our database. We then use a combination of heuristics and machine learning to eliminate false positives and to link true positives to an actual API.

API names cannot be resolved with simple name-matching, when, for example, a mention can match more than one API name. In fact, in our study of API mentions we observed nine distinct sources of ambiguities in API names that cannot be resolved using trivial name matching (see Section II).

Assigning a mention merely to the most popular API with the same name can also be imprecise (e.g., most used API in Ohloh [5] or downloaded in Sourceforge [6]). For example, such a strategy will always resolve a mention of ‘spring’ or ‘jackson’ to their most popular API namesakes, when the mentions may refer to other APIs or do not refer to any API at all (e.g., jackson as a person or spring as a season). ANACE combines contextual information around an API mention with other features (e.g., contextual and structural cues, API popularity) to determine correct resolutions.

In Figure 1 we show the screenshot of a client UI leveraging ANACE for a StackOverflow thread. Each true mention is highlighted in green and false ones in red. Each true mention is assigned a link. For example, Jackson is resolved to com.fasterxml.jackson.core. The bottom half of the tooltip shows a description of the API. Clicking the mention ‘jackson‘, leads to the API homepage (see the status bar).

II. AMBIGUITY IN API MENTIONS

A mention in a post is a reference to an API. A mention can be one of the following types: (1) Name: A name as a token (e.g., Jackson) or a series of tokens (e.g., PropertiesFactoryBean), or hyperlinks to its resources (e.g., https://spring.io/). The problem of resolving code terms in API-related documents deals with tracing a code term to its API (e.g., linking the type PropertiesFactoryBean to the API it belongs to) [1]–[4]. However, we are aware of no technique to resolve mentions of general API names in the textual contents of the forum posts (see Section III).

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II. AMBIGUITY IN API MENTIONS

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1) Homonymy: Multiple APIs can have the same name.
2) Meronymy: Instead of using an API name, developers may refer to its modules. Consider the following post [7]: “I’m building my first real desktop applications...I’m not sure if I should use SWT or Swing”. Here, ‘SWT’ refers to the SWT module of the Eclipse framework.
3) **Synonymy:** A single API can have more than one name. The GSON API can also be referred to as google-gson. Both org.glassfish.jersey and com.sun.jersey refer to the same 'jersey' framework.
4) **Holonymy:** A framework can interface with third-party APIs through dedicated modules. The Apache camel API offers integration with the Jackson API through its camel-jackson module. The module can still be referred to as: “In apache camel, use Jackson for JSON parsing.”
5) **Hypernymy:** An API from a given framework can be mentioned simply by the framework name. Due to the widespread usage of the JSON processor offered by the com.fasterxml.jackson.core project, the API is mostly referred to by simply ‘jackson’.
6) **Spuriousness:** This ambiguity is a special case of homonymy, where a mention that matches one or more API/module names may not refer to any of those. For example, a mention of ‘jackson’ is spurious if it refers to a non-API entity (e.g., a person).
7) **Aliasing:** A mention of an API is an alias if it differs from the official name of the API. For example, the Google GSON was mentioned as the ‘Google JSON’ API. This is a special case of synonymy, where the synonym does not share any token with the name of the API it refers to (after removing stopwords and organization names).
8) **Demonymy:** When the APIs implementing a specification share similar names with the specification, it is challenging to distinguish between the two. For example, the ‘dao’ reference implementation in the generic-dao API. Apache tomcat is referred to both as a web server and as an open source API in the forum with the same name.
9) **Platform-specificity:** An API can have multiple versions to support different computing platforms. E.g., org.json.me is a mobile-optimized version of the org.json API, but it can still be referred to by org.json (see [8]).

We present techniques to resolve the first six ambiguities. The resolution of the other ambiguities is our future work.

III. RELATED WORK

Related work can broadly be divided into three categories: (1) code term tracing, (2) developer forum analysis, and (3) feature location.

**Code Term Traceability Recovery.** Recodoc [1] resolves code terms in the formal documentation of a project to its exact corresponding element in the code of the project. Baker [3] links code terms in the code snippets of Stack Overflow posts to an API/framework whose name was used to tag the corresponding thread of the post. ACE [2] resolves Java code terms in forum textual contents of posts using island grammars [9]. Bacchelli et al. [4] developed Miler to determine whether a development email of a project contains the mention of a given source code element. They compared information retrieval (IR) techniques (LSI [10] and VSM [11]) against lightweight techniques based on regular expressions. Prior to Miler, LSI was also used by Marcus et al. [10], and VSM was compared with a probabilistic IR model by Antoniol et al. [12]. Tools and techniques have been proposed to leverage code traceability techniques, e.g., linking software artifacts where a code term is found [13], associating development emails with the source code in developers’ IDE [14], recommending posts in Stack Overflow relevant to a given code context in the IDE [15].

**Developer Forum Analysis** has been studied extensively, e.g., to find dominant discussion topics [16, 17], to analyze the quality of posts and their roles in the Q&A process [18–23], to analyze developer profiles (e.g., personality traits of the most and low reputed users) [24, 25], and to determine the influence of badges in StackOverflow [26]. Tools have been developed using the knowledge in the forums, such as, auto-comment assistance [27], collaborative problem solving [28], [29], and tag prediction [30].

**Defect and Feature Traceability.** Hayes et al. [31] used three IR algorithms (LSI, VSM, and VSM with thesaurus) to establish links between a high and low-level requirement descriptions. Lormans et al. [32] used LSI to find relationships between requirements, tests, and design documents. Baysal et al. [33] correlated emails in mailing lists and software releases by linking emails with the source code. Types and variable names in the source code were matched against natural language queries to assist in feature location [10, 34, 35]. Given as input a bug report, Hipikat [36] finds relevant source code and other artifacts (e.g., another bug report). Subsequent techniques linked a bug fix report to its related code changes [37, 38], or detected duplicate bug reports [39].

**Discussion.** To the best of our knowledge, no technique other than ANACE exists to resolve API names in forum posts. The code term detection techniques rely on language syntax and naming conventions and thus cannot be adapted to detect API names, because no such structure exists for general API names. As explained in Section II the linking of an API mention to an API is a multi-faceted problem due to diverse sources of ambiguities. Such ambiguities do not come into play in the resolution of code terms [1]–[4]. Similar to the code traceability techniques, ANACE also needs a pre-defined dictionary of entity names. Unlike Recodoc [1] that operates on formal documents, ANACE resolves API names in informal documents. Both Baker [3] and ACE [2] assume a semi-open scope by relying on tags to filter out posts that may not represent an API name of interest. We take an open scope by assuming that a thread can contain discussion about any API.

IV. RESOLUTION FRAMEWORK

Our API database consists of the Java official APIs and the open source Java APIs. Each entry in the database contains a reference to a Java API. For each API, we collect seven fields from online portals: (1) API name (2) module names (3) resource links, e.g., download page, documentation page,
Algorithm 1: The resolution of a mention to an API

Input: (1) Mention Candidate List, MCL, (2) Trained resolution classifier RC

Output: Resolution decision, \( D = (d_{api}, d_{module}, d_{url}) \)

1. \( H = \emptyset \), \( d_{module} = \text{null} \), \( d_{url} = \text{null} \)
2. For each candidate \( c_i \in \text{MCL} \)
3. \( \text{confidence} = \text{getClassifyConf}(\text{mention}, c_i) \)
4. If \( \text{confidence} > \tau \) then \( H = H \cup \{c_i\} \)
5. If \( |H| = 0 \) then \( D = \emptyset \), return \( D \)
6. Else if \( |H| = 1 \) then \( H = \{c_i\}, d_{api} = c_i \)
7. Else \( d_{api} = \text{filter}(H) \)
8. For each module \( s_i \in d_{api} \)
9. If \( \text{Mention} = \text{name}(s_i) \) then \( d_{module} = s_i \), break;
10. If \( d_{module} \neq \text{null} \) then
11. \( d_{url} = \text{getHomepage}(d_{module}) \)
12. Else \( d_{url} = \text{getHomepage}(d_{api}) \)
13. \( D = (d_{api}, d_{module}, d_{url}) \), return \( D \)

Procedure getClassifierConf \((m, c)\)

14. Return classify \((m, c)\) using RC
15. Procedure filter \((H)\)
16. Return a candidate \( c \) in \( H \) using filters;
17. Procedure getHomepage \((c)\)
18. \( d_{url} = \text{most frequent url in } c \), return \( d_{url} \)

Fig. 2: Partial Mention-Candidate List (MCL) for ‘Jackson’.

Two steps: (1) Given a mention-candidate list, we resolve the mention to one of its candidates (e.g., jackson to com.fasterxml.jackson.core in Figure 1). (2) Given a resolved API, we assign a resource link to the mention (e.g., http://wiki.fasterxml.com/JacksonHome).

V. THE RESOLUTION CLASSIFIER

We used a Naive Bayes classifier (RC in Algorithm 1) to calculate a confidence value for each candidate in a mention candidate list. We compute three types of similarity weights (range [0, 1]) between the mention and each candidate: name (see Section V-A), context (Section V-B), and structural (Section V-C). To produce the confidence value for a candidate, the classifier uses its similarity weights and two popularity counts: its usage and download counts.

A. Name Similarity

A name similarity weight greater than 0 between a mention and an API or its module name was used to include the API in the mention candidate list. An exact match between a mention (M) and a candidate (C) API/module name is considered only if both contained the same series of tokens in the same order. We assigned the similarity a weight of 1. For fuzzy matching, we employ two techniques: (1) Prefix Matching is defined as \( M \) and \( C \) both sharing the same prefix. The weight is 1. (2) Token Sorting is defined as \( M \) and \( C \) both having one or more shared tokens, e.g., \( M = \text{‘jackson’} \) and \( C = \text{com.fasterxml.jackson.core} \). The similarity weight is the Jaccard index [11]:

\[
\begin{align*}
    w & = \frac{|\text{Tokens}(M) \cap \text{Tokens}(C)|}{|\text{Tokens}(M) \cup \text{Tokens}(C)|}
\end{align*}
\]
B. Context Similarity

We analyze the text around a mention to construct a feature context. We compute context similarity by comparing the feature context against the description of each candidate. We compute two types of similarity: noun and verb-based.

**Constructing The Feature Contexts for Mentions.** The feature context is a bag of tokens. We observed that when we find a mention in more than one post of the same thread, all of those occurrences usually referred to one single API. We include the following tokens in the feature context of a mention: (1) **same post:** tokens around it within a window. A window size of 3 takes tokens from 3 sentences right and 3 left (when available). (2) **other posts:** tokens within the window of same mention in other posts. (3) **title:** tokens in the title.

**Constructing Descriptions for Candidates.** The description for each candidate is a bag of tokens except stopwords from selected sentences from its description found (1) in the portal, and (2) in its homepage. Consider the description of the API `com.fasterxml.jackson.core` on its homepage (denoted by $d_H$ afterwards): “Jackson is a high-performance JSON processor. It provides a json parser... This will be the portal page for Jackson”($d_H$). The description of the API in our database as extracted from the portal (denoted by $d_P$): “…It provides ... Add-on module ... to support Joda [http://joda-time.sourceforge.net] data types...” ($d_P$). From the descriptions, we only include a sentence if: (1) starts with the name of the API or its module (e.g., “Jackson is a high-performance JSON processor ...”); (2) contains a subject pronoun referring to the API, and the sentence immediately follows a sentence of type 1 (e.g., “It provides a JSON parser ... ”). (3) contains a reference to another API (e.g., “Add-on module for Jackson to support Joda [http://joda-time.sourceforge.net] data types.”). Here, Joda is a reference to joda-time API.

We consider a link or name as a reference to another API if: (1) the link refers to the resources of another API, or (2) the name is in the list of dependencies of the API. We consider selected sentences based on our observation that not all the sentences are essential to learn about the features of a candidate. For example, the $d_H$ above also contains: “This will be the portal page for Jackson project”.

For Noun-based Similarity, we compute how the tokens tagged as nouns in the context of a mention ($M$) are similar to the tokens tagged as nouns in the description of each of its candidates using Equation 1

**Verb-based Similarity** uses the same approach, but analyzes the verbs instead of the nouns.

C. Structural Similarity

We heuristically link the code terms around a mention to its candidates. The more code terms are associated with a candidate, the more structurally it is similar to the mention.

**Constructing Code Context for Mentions.** We identify types (class, interface) in each post using Java naming conventions, similar to previous approaches [1, 2] (e.g., camel case, etc.). We collect types that are most likely not declared by the user. Consider the following example [40]:

```java
import com.fasterxml.jackson.databind.ObjectMapper;
ObjectMapper mapper = new ObjectMapper();
Wrapper wrapper = mapper.readValue(...);
```

We add `ObjectMapper` into our code context, but not the type `Wrapper`. This is because the same post later declares the type `Wrapper` as public class `Wrapper`. We parse code snippets using the ANTLR parsing framework [41]. We discard two types of snippets that the ANTLR Java parser cannot parse: (1) Non-java snippets (e.g., .NET), and (2) Malformed Java snippets (e.g., a mix of Java and XML, etc.).

In a post with only one mention, we assign all types in the post to the code context of the mention. In the presence of multiple mentions in the same post, we define a window to assign types (explained in Figure 3).

**Linking Types to the Candidates (Algorithm 2).** The input is a type name found in the code context of a mention, its candidate APIs, and the code snippets from the same post. The output is a one or more candidate APIs to which the type may belong to. If the type name is fully-qualified (FQN) (e.g., `com.fasterxml.jackson.databind.ObjectMapper`), we associate it to the candidate whose type name matches it exactly (line 4). For an unqualified type name in the code context (e.g., `ObjectMapper`), we analyze the import statements (when available) in the input code snippets (lines 7-9). For example, the above code snippet imports the package `com.fasterxml.jackson.databind.*` from the API `..jackson.core`. There is an FQN in `..jackson.core` by the name `..jackson.databind.ObjectMapper`. We thus associate `ObjectMapper` to only `..jackson.core`. In the absence of import statements, we associate the type to all of the APIs whose type names (unqualified) matched the type (lines 6, 10). We compute the structural similarity between a mention $M$ and a candidate $C$ as:

$$\text{simscore}(structure) = \frac{|\text{Types}(M) \cap \text{Types}(C)|}{|\text{Types}(M)|}$$

(2)

$\text{Types}(M)$ is the list of types for $M$ in its context. When code terms are not found for a given mention, we assign $\text{Types}(M) = \emptyset$, i.e., $|\text{Types}(M) \cap \text{Types}(C)| = 0$.

VI. CANDIDATE FILTERING HEURISTICS

We considered candidates with a confidence value $> 0.5$ from the resolution classifier as potential hits. We observed that it can be erroneous to trivially select the candidate with the highest confidence value because more than one candidate or their extension can offer similar features, and the description
input : (1) Mention Candidate List, \( MCL = \{c_1, \ldots, c_n\} \),
(2) A type name \( t \) from a code context, (3) All code snippets \( S \) in the post.
output: Linking decision \( D_T = \{c_1, \ldots\} \)
1 \( D_T = \emptyset, H[c_i] = \emptyset, \ldots, H[c_n] = \emptyset, A = \emptyset; \)
2 \( \text{foreach} c_i \in MCL \) do
3 \( \text{foreach} t_i \in c_i \) do
4 \( \text{if} \ FQN(t_i) = T \ \text{then} \ D_T = D_T \cup \{c_i\}; \)
5 \( \text{else} \text{ if} \ \text{UnqualifiedName}(t_i) = T \ \text{then} \)
6 \( H[c_i] = H[c_i] \cup \{t_i\}, A = A \cup \{c_i\}; \)
7 \( \text{foreach} c_i \in H \) do
8 \( \text{foreach} t_i \in H[c_i] \) do
9 \( \text{if} \ \text{isInImported}(T, t_i) \ \text{then} \)
10 \( D_T = D_T \cup \{c_i\}; \)
11 \( \text{if} \ |D_T| = 0 \ \text{then} D_T = A; \)
12 return \( D_T; \)
13 \( \text{procedure} \ \text{isInImported}(T, t_i) \)
14 \( \text{foreach} \ \text{Import} \ \text{statement} \ i \in S \) do
15 \( T = \text{getProcessed}(i) + \ldots + \emptyset; \)
16 \( \text{if} \ t_i = T \ \text{then} \text{return true}; \)
17 \( \text{procedure} \ \text{getProcessed}(i) \)
18 \( \text{foreach} \ t \in \{\text{import}, \ldots, \text{*}\} \) do \text{remove} \ t \text{from} i ;
19 return \( i; \)
Algorithm 2: The linking of a type name to a candidate

of the most likely candidate are insufficient or incomplete. We apply the following three filters in sequence as listed below to pick the best hit. We do not apply a second intrinsic filter if the mention is already resolved using another filter.

1. Betweenness: We apply this filter, if the feature context of the mention contains the keywords ‘extension’, ‘wrapper’, ‘plugin’, or variants thereof (e.g., ‘plug-in’). We determine whether a candidate \( c_i \) in the hit-list is a direct extension of another hit \( c_2 \) (i.e., direct incoming edge from \( c_i \)). If so, we put the extension (i.e., \( c_1 \)) into a bucket. Consider the sentence: “Use the gson extension easy gson ...”. Given a hit-list for the mention ‘easy gson’ with two candidates (gson and easy-gson), we put easy-gson in the bucket, because it depends on gson. For only one candidate in the bucket, we assign the mention to the candidate. For more than one extension, we select the one with the highest name similarity.

2. Centrality: We compute the influence of each candidate in a hit-list on the rest of the candidates in the same mention candidate list. For the mention ‘jackson’ in the sentence “I use Jackson to parse JSON messages” (see Figure 2) and given a hit-list with two APIs (com.fasterxml.jackson.core and org.apache.camel.jackson.datatype), we compare which one of the two candidates is used the most by the other candidates in the mention candidate list. We compute the influence of a hit on other candidates by taking the proportion of the number of other APIs in the mention candidate list that are dependent on a hit versus the number of other APIs that the hit is dependent on. We assign the mention to the hit with the highest influence score. If we have ties for the highest score, we assign the mention to the hit on which most other APIs are dependent on. Otherwise, we move to the next filter.

3. Closeness. We compute how close a hit of type ‘core’ is with other candidates in the mention candidate list and assign the mention to the hit with the lowest ‘closeness’ value.

Closeness \( c = \frac{1}{\text{# Other APIs in MCL dependent on (c) + 1}} \)

The constant 1 is used as a smoothing value, loosely adapted from the definitions of Laplace smoothing [11].

A. Extrinsic Filters

We determine whether and how a mention relates to the surrounding other mentions in the same post. We apply the following three filters in sequence: composition, aggregation, and projection. We stop processing a mention if we can make a decision using a filter. For a given forum post, the input to each filter is a list of all hit-lists and the mentions found in the post as produced by the resolution classifier, even when the mentions may already be resolved by the intrinsic filters. If we can make a decision using the extrinsic filters, but the mention is already resolved through intrinsic filters, we overwrite the previous decision (explained below). Therefore, for these filters to be applicable to a mention, we require at least one true mention immediately preceding and one following the mention in the same post already resolved.

1. Composition: We determine whether the candidate API can be a module of an API mentioned immediately before the candidate. For the mention ‘jackson’ in the sentence “In apache-camel, Jackson can deserialize JSON”, suppose the hit-list includes two candidates: com.fasterxml.jackson.core and org.apache.camel.jackson.

We assign ‘jackson’ to org.apache.camel because one of its module named camel-jackson which offers JSON processing features and the previous mention apache-camel was resolved to the API org.apache.camel. For the above hit-list, the influence intrinsic filter will erroneously assign the mention ‘jackson’ to the ..jackson.core, because ..apache.camel depends on it. By applying this filter, we overwrite the resolution to ..apache.camel API.

2. Aggregation: We determine whether the immediately preceding or following other mentions are dependent on the candidate. For the mention ‘jackson’ in “Since spring packages Jackson, we used JSON-based messages”, and a hit-list with com.fasterxml.jackson.core and ..jackson.datatype, we assign jackson to ..jackson.core, because the nearest mention to Jackson in the post is Spring, which is resolved to org.springframework and depends on ..jackson.core.

3. Projection: We determine whether the candidate API is dependent on any of the surrounding mentions in the same post. Consider the sentence: “I can serialize Joda-time with the Jackson JSON processor”. Given com.fasterxml.jackson.core and ..jackson.datatype as hits, we assign jackson to ..datatype, because it depends on the joda-time API.
VII. SUMMARY

The resolution of API names in the developer forums can be challenging when a mention can exhibit ambiguities, e.g., more than one API exist with the same name. We presented ANACE, a technique that can resolve API mentions in forum posts. Our ongoing work focuses on the following directions:

- **Evaluation**: The effectiveness of ANACE compared to the baselines (e.g., search engines, etc.)
- **Empirical Study**: Analysis of the prevalence of the ambiguities in the forum post.
- **Extension**: The extension of ANACE to handle API name resolution from different other programming languages.

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