Using Domain-specific Corpora for Improved Handling of Ambiguity in Requirements

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Abstract—Ambiguity in natural-language requirements is a pervasive issue that has been studied by the requirements engineering community for more than two decades. A fully manual approach for addressing ambiguity in requirements is tedious and time-consuming, and may further overlook unacknowledged ambiguity — the situation where different stakeholders perceive a requirement as unambiguous, but in reality, interpret the requirement differently. In this paper, we propose an automated approach that uses natural language processing for handling ambiguity in requirements. Our approach is based on the automatic generation of a domain-specific corpus from Wikipedia. Integrating domain knowledge, as we show in our evaluation, leads to a significant positive improvement in the accuracy of ambiguity detection and interpretation. We scope our work to coordination ambiguity (CA) and prepositional-phrase attachment ambiguity (PAA) because of the prevalence of these types of ambiguity in natural-language requirements [1]. We evaluate our approach on 20 industrial requirements documents. These documents collectively contain more than 5000 requirements from seven distinct application domains. Over this dataset, our approach detects CA and PAA with an average precision of ≈80% and an average recall of ≈89% (≈90%) for cases of unacknowledged ambiguity. The automatic interpretations that our approach yields have an average accuracy of ≈85%. Compared to baselines that use generic corpora, our approach, which uses domain-specific corpora, has ≈33% better accuracy in ambiguity detection and ≈16% better accuracy in interpretation.

Index Terms—Requirements Engineering, Natural-language Requirements, Ambiguity, Natural Language Processing, Corpus Generation, Wikipedia.

I. INTRODUCTION

Natural language (NL) is the de-facto medium for specifying requirements in industrial settings. A key advantage of NL is that it facilitates shared understanding among different stakeholders who may have different backgrounds and expertise [2]. Despite this advantage, NL requirements are prone to a variety of quality issues, one of the most notable of which is ambiguity [2], [3]. Ambiguity is an inherent phenomenon in NL, occurring when a text segment is open to multiple interpretations [4]. Ambiguity in requirements can lead to misunderstandings and inconsistencies among the stakeholders, and this can have a potential negative impact on the overall success of a project [5].

Handling ambiguity in requirements is challenging due to two main reasons. First, requirements specifications vary across domains and thus use a domain-specific vocabulary [6].

This has an impact on the likely interpretations of the requirements and consequently on what can be considered as ambiguous. Second, ambiguity can be unacknowledged, meaning that multiple readers, being unaware of such ambiguity, may have different interpretations for the same requirement. In contrast to acknowledged ambiguity where the reader recognizes ambiguity, unacknowledged ambiguity might lead to serious problems due to unconscious misunderstandings [7]. A fully manual analysis of ambiguity is expensive and also likely to overlook unacknowledged ambiguity. There is therefore a need for effective, automated ambiguity-handling approaches that can help companies focus their often limited quality-assurance budget on requirements that are more likely to be problematic.

Ambiguity has been widely studied in the requirements engineering (RE) literature [3], [8]–[11]. Both manual approaches based on reviews and inspections [9], [12], and automated approaches based on natural language processing (NLP) [6], [7], [13], [14], have been proposed for detecting ambiguity in requirements. Some recent works use domain-specific corpora for detecting terms that are likely to be ambiguous due to different meanings across domains [6], [15]–[17]. Current research on ambiguity in RE, as we elaborate later, has three main limitations. First, the researcher focuses exclusively on detecting ambiguity and does not address automated interpretation for requirements in which no genuine ambiguity exists. The lack of automated interpretation impedes further automated analysis, e.g., automated information extraction from requirements [18], [19]. Second, existing methods for detecting domain-specific ambiguity are restricted to identifying merely words with different meanings across domains, and further require the domain of interest to be specified a priori. Finally, while the negative consequences of unacknowledged ambiguity are known in the RE literature [7], the question of how accurately unacknowledged ambiguity can be detected through automated means has never been investigated empirically.

Motivated by addressing the above limitations, we propose an automated approach for improved ambiguity handling – both ambiguity detection and interpretation – in NL requirements. Ambiguity detection is concerned with finding the requirements that are genuinely ambiguous. Interpretation, in contrast, is concerned with providing the most likely meaning where the potential for ambiguity exists, but where there is no ambiguity. Our approach incorporates domain knowledge
by automatically generating domain-specific corpora, without any a-priori assumption about the domain. These corpora alongside a set of structural patterns and heuristics are used for handling ambiguity in requirements. In our evaluation, we analyze the impact of domain knowledge on ambiguity handling. We further assess how well our automated approach can detect unacknowledged ambiguity in different domains.

Our work in this paper concentrates on coordination ambiguity and prepositional-phrase attachment ambiguity [3], [20], [21], hereafter referred to as CA and PAA, respectively. Targeting these (syntactic) ambiguity types is motivated by their prevalence in NL requirements [1]. In our document collection, as we will discuss later in the paper, out of 5156 requirements, 1098 (21%) are subject to CA analysis and 1328 (26%) to PAA analysis. Within these, human annotators acknowledged ambiguity or had different interpretations (unacknowledged ambiguity) in $\approx 57\%$ of the requirements.

Coordination is a structure that links together two sentence elements (called conjuncts) using a coordinating conjunction (e.g., “and” or “or”) [22]. CA can potentially occur when the two conjuncts are preceded or followed by a modifier [21]. The sentence could then be interpretable in two ways, depending on whether the conjunct to the modifier is being modified or both conjuncts are being modified [3]. Fig. 1 shows an example requirement, R1, with two potential interpretations. The first interpretation, first read, hereafter, FR, occurs when the modifier “LEO” (low-earth orbit) modifies the two conjuncts “satellites” and “terminals” (Fig. 1 (a)). The second interpretation, second read, hereafter, SR, occurs when the modifier “LEO” modifies “satellites” only (Fig. 1 (b)).

![Fig. 1. Example of Coordination Ambiguity (CA).](image)

A prepositional-phrase (PP) attachment is a PP preceded by a verb and a noun phrase [20]. Virtually all PP attachments have the potential for PAA, because they could be interpretable in two ways, depending on whether the PP is an adverbial modifier (attached to the preceding verb) or a noun attribute (attached to the preceding noun phrase). Fig. 2 shows an example requirement, R2, with two potential interpretations due to the presence of a PP attachment. The first interpretation, verb attachment, hereafter, VA, occurs when the PP “with discrete tags” is attached to the verb “categorize” (Fig. 2 (a)). The second interpretation, noun attachment, hereafter, NA, occurs when the PP is attached to the noun “outages” (Fig. 2 (b)).

R1 and R2 have the potential to suffer from CA and PAA, respectively. The question is whether these are genuine ambiguities or merely situations that human experts can decisively interpret with little room for divergent interpretations. Existing techniques do not incorporate domain knowledge for providing a likely interpretation of CA; instead, they rely on frequency-based computations derived from a generic corpus [23]. For example, using existing techniques, attempting to interpret the coordination in R1 would yield FR. This interpretation is incorrect; with domain knowledge, the coordination would be interpreted as SR. As for the PP attachment in R2, existing techniques are unable to provide an interpretation, although the attachment is interpretable as VA with domain knowledge.

Contributions. We take steps toward addressing the limitations outlined above. Our contributions are as follows:

1. We propose an automated approach for handling CA and PAA in NL requirements. Our approach uses an ensemble of structural patterns and heuristics. Specifically, we match requirements against a set of structural patterns, leveraging and enhancing existing patterns in the literature. In tandem, we attempt to interpret all requirements with coordination and PP-attachment structures using heuristics that are based on semantic, morphological and frequency information. Some of these heuristics are novel; others are borrowed from the literature and enhanced where necessary. By combining these patterns and heuristics, we attempt to tell apart the requirements that can be disambiguated via automated interpretation from the requirements that are genuinely ambiguous.

2. We devise a novel domain-specific corpus generator. Without assuming any a-priori knowledge about the domain, we first automatically extract keywords from an input requirements document. Our corpus generator then assembles a large corpus of Wikipedia articles relevant to the terminology (and thus the domain) of the given requirements document. This automatically generated corpus is utilized for increasing the accuracy of the heuristics that rely on frequency-based information. For example, the occurrence of the word “capital” in a requirements document within the aerospace domain differs in frequency and co-occurring words from the same word occurring in a requirements document within the financial domain. Generating and using a domain-specific corpus for ambiguity handling lies at the heart of our proposed approach.

3. We empirically evaluate our approach on 20 industrial requirements documents. These documents collectively contain 5156 requirements covering seven distinct application domains. The ground truth for our evaluation was prepared by two trained annotators (linguistics experts and non-authors). Our results indicate that: (i) our approach detects CA and PAA with a precision of $\approx 80\%$ and recall of $\approx 80\%$ ($\approx 90\%$ for cases of unacknowledged ambiguity); (ii) the automatic interpretations by our approach have an average accuracy of $\approx 85\%$; and (iii) using domain-specific corpora leads to substantial gains in accuracy for ambiguity handling, improving detection by an average of $\approx 33\%$ and interpretation by an average of $\approx 10\%$. We have developed a tool, named
MAANA, which implements our approach for the domain-specific handling of ambiguity. Specifically, MAANA detects requirements that potentially contain CA or PAA. The tool and the non-proprietary requirements we use in our evaluation are publicly available at https://github.com/SNTSVM/MAANA.

Structure. Section II discusses and compares with related work. Section III presents our approach. Section IV describes our empirical evaluation. Section V addresses validity considerations. Section VI concludes the paper.

II. RELATED WORK

We focus on handling CA and PAA in NL requirements. Our approach, discussed in Section III, builds on and further enhances the existing structural patterns and heuristics from the RE and NLP literature for CA [23]-[33] and PAA [3], [34], [35]. Our work, to our knowledge, is the first to bring these patterns and heuristics together for handling CA and PAA. Below, we position our work against the related work on ambiguity handling in both the RE and NLP communities.

A. Ambiguity Handling in the RE Community

Ambiguity in requirements has been extensively studied from different perspectives, including understanding the role of ambiguity in RE [8], [36]-[38], analyzing the linguistic causes of ambiguity [3], [39]-[41], and ambiguity prevention [42]-[46]. Automated ambiguity detection solutions in RE are mainly based on matching NL requirements against pre-defined structural patterns using regular expressions, NLP, or both [6]. Numerous approaches and tools have been proposed to this end [10], [13], [30], [45], [47]-[52]. In addition to these, some recent works attempt to detect lexical ambiguity – the situation where a word has different meanings depending on the domain [40] – by integrating domain knowledge from Wikipedia [6], [15]-[17].

CA detection has been investigated to some extent in the RE literature. Chantree et al. [23] address CA detection using structural patterns and frequency-based heuristics. Their work has been extended over the years [27], [29], [53] with additional heuristics [25], [31], and for anaphora ambiguity detection [13], i.e., ambiguity due to multiple interpretations of pronouns. Though considered a prevalent ambiguity type in requirements [3], [8], [40], to our knowledge, automated handling of PAA has not been previously studied in RE.

Our work differs from or enhances the above research in several ways. First, none of the existing approaches address the automated interpretation of (potentially ambiguous) coordination structures. As for PAA, the topic has not been tackled in RE before. Our approach handles both CA and PAA by combining a broad range of structural patterns and heuristics. Second, none of the existing approaches evaluate the detection of unacknowledged ambiguity. We address this gap in our empirical evaluation. Third, the existing automated methods for domain-specific corpus generation from Wikipedia are limited to a pre-defined set of domains. Our approach, in contrast, can generate a corpus based on any given requirements document without knowing the underlying domain in advance. Fourth and finally, industrial evaluations of ambiguity handling in RE are scarce. Our evaluation contributes to addressing this gap by using a large industrial dataset.

B. Ambiguity Handling in the NLP Community

Syntactic ambiguity types, including CA and PAA, have been studied for a long time by the NLP community [54]. In an early work by Goldberg [24], CA is handled using conditional probabilities of word co-occurrences. Pan et al. [55] present an unsupervised corpus-based method for handling PAA through a notion of contextual similarity. Agirre et al. [34] improve the accuracy of PAA handling by integrating semantic similarity with syntactic parsing. Calvo and Gelbukh [35] propose querying the web for word co-occurrence frequencies and use these frequencies for more accurate PAA handling. In a similar vein, Nakov and Hearst [26] use structural patterns alongside statistical co-occurrence frequencies gathered from the web for handling CA and PAA.

In the context of ambiguity handling, the use of domain knowledge in NLP is mostly directed at word sense disambiguation (WSD) in specific domains [56]. To this end, Wikipedia is a commonly used source of domain knowledge [57], [58]. Fragoli et al. [59] derive from Wikipedia domain-specific corpora as resources for WSD. Similarly, Gall et al. [60] map manually defined topics in WordNet [61], [62] to Wikipedia for generating domain-specific corpora that can in turn be employed for WSD.

We are not aware of any work in the NLP community that uses domain-specific corpora for handling either CA or PAA. Instead, in the existing NLP technologies, e.g., syntax parsing [63], the handling of syntactic ambiguity – CA and PAA included – is tuned over generic texts such as news articles. These technologies therefore do not provide accurate results for CA and PAA in a domain-specific context. As we show in Section IV, our approach, which incorporates domain knowledge for handling CA and PAA, provides significant improvements over NLP technologies tuned over generic texts.

III. APPROACH

Fig. 3 provides an overview of our approach, which is composed of five steps. The input to the approach is an NL requirements document, hereafter, $RD$. In step 1, we process $RD$ using an NLP pipeline. In this step, we further identify two subsets of the requirements in $RD$, namely $S_C$ and $S_P$. These two subsets contain all the requirements with coordination structures and all the requirements with PP attachments, respectively. In step 2, we match the requirements in $S_C$ and $S_P$ against structural patterns that indicate potential CA and PAA, respectively. In step 3, we generate a domain-specific corpus for $RD$ by crawling Wikipedia. Step 3 can be bypassed if a representative corpus for $RD$’s domain already exists (through earlier applications of our approach to other requirements documents in the same domain). In step 4, we apply a set of heuristics to determine likely interpretations for the requirements in $S_C$ and $S_P$. In step 5, we classify into ambiguous and unambiguous the requirements in $S_C$ and $S_P$.
by combining the results of step 2 and step 4. We note that steps 2 and 4 are independent (i.e., the output of neither step is an input to the other). Step 2 is limited to a finite list of CA and PAA structural patterns. As we will explain later in this section, the heuristics in step 4, when compared to the patterns in step 2, cover a wider spectrum of structures that have the potential for CA and PAA. Combining results from both steps leads to better handling of ambiguity. Below, we elaborate each step of our approach. In the rest of this paper, ambiguity refers to CA and PAA exclusively.

A. Preprocessing

The NLP pipeline we use for preprocessing RD is depicted in Fig. 4. This pipeline is a sequence of five NLP modules. The first module in the sequence, the Tokenizer, divides the input text into tokens, such as words and punctuation marks. The Sentence Splitter splits the text into sentences. The POS Tagger assigns to tokens part-of-speech (POS) tags, such as noun, verb and adjective. Next is the Lemmatizer, which identifies the canonical form (lemma) for each token. For example, the lemma for “bought” is “buy”. Finally, the Constituency Parser identifies the structural units of sentences, e.g., noun phrases, verb phrases and prepositional phrases. The results of the NLP pipeline are used in the next steps.

In this step (step 1), we further identify the two requirements subsets, \( S_c \) and \( S_p \), that should be subject to CA handling and PAA handling, respectively. \( S_c \) is comprised of all the requirements in \( RD \) that contain “or”, “and”, or both. We note that only these two conjuncts can lead to CA [21], [23]. \( S_p \) is comprised of all the requirements in \( RD \) that contain a PP attachment [20]. Requirements that contain a conjunction of interest (i.e., “and” or “or”) as well as a PP attachment are included in both \( S_c \) and \( S_p \).

B. Pattern Matching

In this step, we analyze \( S_c \) and \( S_p \) to identify requirements that are likely to be ambiguous due to their syntactic structure. Table I lists our patterns for CA and PAA. Of these, 23 CA patterns and four PAA patterns come from the literature [3], [24]–[27], [29], [30], [34]. The remaining patterns, shaded blue in the table (i.e., CA patterns #24–29 and PAA patterns #5–10) are novel. The novel patterns were derived by analyzing a subset of the requirements in our dataset, as we will precisely define in Section IV-C. Specifically, we analyzed the ambiguous requirements in the tuning portion of our dataset.

We match the patterns against the requirements in \( S_c \) and \( S_p \). For pattern matching, the unit of analysis is a text segment, which is the part of a requirement that matches a given structural pattern from Table I. A pattern suggesting CA matches a segment that contains a conjunction (denoted as c) linking two conjuncts (marked in bold) with a modifier (underlined). For example, the matching segment in R1 (Fig. 1) corresponds to pattern#1 for CA, where LEO is the modifier and the conjunction and joins the two conjuncts satellites and terminals. We recall from Section I that CA occurs when it is unclear whether a modifier is attached to both conjuncts (FR) or only to the closest conjunct (SR). A pattern suggesting PAA matches a segment with a verb (v) followed by a first noun (n1) – both marked in bold – followed by a PP which consists of a preposition (denoted as p) and a second noun (n2 – underlined). For example, the matching segment in R2 (Fig. 2), “categorize outages with discrete tags”, corresponds to pattern#2 for PAA. Again, we recall from Section I that PAA occurs when it is unclear whether the PP in question is an adverbial modifier attached to \( v \) (VAA) or a noun attribute attached to \( n_1 \) (NA).

Step 2 identifies the segments (from the requirements in \( S_c \) and \( S_p \)) that match any of the patterns in Table I. The matched segments are passed on to step 5.

C. Domain-specific Corpus Generation

This step attempts to capture the domain knowledge underlying the input requirements document (RD) by crawling Wikipedia. Fig. 5 shows the sub-steps for generating a domain-specific corpus. We elaborate these (sub-)steps next.

Extract Keywords. Step 3.1 builds on an existing automated requirements glossary extraction approach by Arora et al. [64].
We begin by (automatically) extracting the list of glossary terms from \( RD \), and thereafter select the top-K most frequent keywords from the list. The optimal value of \( K \) is tuned in Section IV-D. For example, the keywords extracted from R1 (Fig. 1) include “LEO”, “LEO satellites”, “satellites”, and “terminals”. These keywords are used in the next step.

**Query Wikipedia.** Step 3.2 implements a query engine for identifying Wikipedia articles that are relevant to the keywords resulting from step 3.1. These articles form the basis of our domain-specific corpus. We begin by retrieving matching Wikipedia articles for each keyword. An article is considered a match if the keyword in question contains (or is contained in) the title of the Wikipedia article. For instance, the Wikipedia article titled “satellite navigation” is a match for the keyword “satellite-based navigation”. If the above condition is not met, no matching Wikipedia article is retrieved.

Next, we broaden the domain information captured in our corpus by taking advantage of the hierarchical category structure of Wikipedia \[57\]. In Wikipedia’s hierarchy, each category can contain articles and nested sub-categories. For a matching article, we retrieve all the articles in the same category and all the articles in the descendant sub-categories. For example, the “satellite navigation” article, as shown in Fig. 6, is classified under an identically named Wikipedia category (https://en.wikipedia.org/wiki/Category:Satellite_navigation; accessed 17/8/2020). We retrieve all articles in this category and in all its descendants (e.g., one descendant being “Geocaching”). Doing so increases topic coherence \[65\], meaning that the articles included in the corpus are all indeed relevant to the domain under analysis.

Next, to make our domain-specific corpus applicable to other requirements documents from the same domain, we attempt to increase the coverage of our corpus. In particular, we consider the categories in the Wikipedia category graph that are directly connected to the category of the matching article. For instance, the category “navigation” in Fig. 6 is directly connected to “satellite navigation”; we therefore include articles listed under “navigation” and its descendant sub-categories.

We note that, during the creation of a corpus, we consider only the categories whose number of articles is below a threshold \( \alpha \); this is both to keep the computation time reasonable and to avoid including large and generic categories in the corpus. We discuss the tuning of \( \alpha \) in Section IV-D. The result of this step (step 3.2) is a body of raw text from Wikipedia articles. This extracted body of text is our domain-specific corpus, hereafter denoted as \( D \).

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**Fig. 5. Domain-specific Corpus Generation.**

**Fig. 6. Example of Category Structure in Wikipedia.**

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**D. Application of Heuristics**

Step 4 attempts to provide likely interpretations for the requirements in \( S_c \) and \( S_p \). We use six heuristics, denoted as \( C_1-C_6 \), for interpreting coordination structures and four heuristics, denoted as \( P_1-P_4 \), for interpreting PP-attachment structures. Out of these ten heuristics, eight \((C_1-C_5)\) for CA \([23]\) and \([31]\) are borrowed from the literature. The other two \((C_6, P_1)\) are novel, but based on a very intuitive idea: applying constituency parsing, which has coordination and PP-attachment interpretation built into it.

Similar to step 2 (Section III-B), we operate at a segment level. Compared to the patterns in step 2, heuristics cover a wider spectrum of segments that have the potential to be ambiguous. The heuristics are triggered by the presence of any coordination structure (an “and” / “or” conjunction, two conjuncts and a modifier) and any PP-attachment structure (a verb, a noun and a PP). For example, had R2 (Fig. 2) contained an extra adjective “categorize outages with standard discrete tags”, R2 would not have been detected by the patterns of Table I, but would have been picked up by the heuristics and attempted for interpretation.

Several heuristics in our approach are corpus-based, i.e., require information about the co-occurrence frequencies of the words. We therefore transform the Wikipedia articles from step 3 to an n-grams table with \( n \) ranging from 1 to 5. We set the upper limit to 5, motivated by the use of 5-grams in Google’s well-known Web1T database \([66]\); this database is utilized in a wide variety of NLP applications \([67]-[69]\).
Table II shows a (very small) excerpt of a 5-grams table generated for the satellite domain. The frequencies used by the heuristics are the normalized values of the co-occurrence counts listed in the 5-grams table [70]. For example, the co-occurrence frequency of “satellite orbit” is computed as 234/(21013 + 26599) ≈ 0.005.

**Heuristics for CA.** A segment in $S$, contains a conjunction (c), two conjuncts (conjunct$_1$ and conjunct$_2$), and a modifier (mod). CA heuristics attempt to interpret a segment in $S$, as either FR or SR. If a heuristic cannot interpret a segment, it returns a designated value, not interpretable (NI). As we explain below, four of the CA heuristics ($C_1$ and $C_3$-$C_5$) require pre-defined thresholds, denoted as $\theta$. These thresholds come from the existing literature. We tune the thresholds empirically in Section IV-D. To illustrate the heuristics in this section, we already use the tuned $\theta$ values: $\theta_1 = 0.01$, $\theta_2 = 0.12$, $\theta_3 = 3.45$, and $\theta_5 = 3$.

($C_1$) **Coordination frequency** computes the co-occurrence frequency of conjunct$_1$ and conjunct$_2$ in our domain-specific corpus (D). We consider the co-occurrence frequency of the conjuncts irrespective of their order. For example, for R1, we consider, among other possible combinations, the co-occurrence frequency of “terminals and satellites” and “satellites or terminals”. The intuition is that if the two conjuncts co-occur frequently in D, they can be regarded as one syntactic unit and thus are both modified (by mod), in turn favoring FR. $C_1$ returns FR if the resulting frequency is greater than a threshold ($\theta_1$) and NI otherwise. In R1, $C_1$ returns FR.

($C_2$) **Collocation frequency** compares the co-occurrence frequency of conjunct$_1$ and mod against the frequency of conjunct$_2$ and mod. Collocation is a recurrent combination of two consecutive words in a large corpus [71]. For example, the words “red” and “wine” would be considered collocated, while “great” and “wine” would not. The intuition is that a collocation of the mod and the conjunct closer to it is likely to indicate a syntactic unit, thus favoring SR. Using collocations, “red wine and cheese” can be interpreted as SR while “great wine and cheese” would not be interpretable (NI). $C_2$ returns SR if the collocation frequency of mod and the closer conjunct is greater than that of mod and the farther conjunct, and NI otherwise. In R1, $C_2$ returns SR.

($C_3$) **Distributional similarity** measures the contextual similarity of conjunct$_1$ and conjunct$_2$ [72], i.e., how frequently the conjuncts appear in similar contexts. For example, in the context of requirements documents about satellite systems, the terms “satellite” and “navigation” have a higher distributional similarity than “satellite” and “investment”. The intuition is that conjuncts with high distributional similarity can be regarded as one unit, thus favoring FR. $C_3$ returns FR if the distributional similarity of the conjuncts is greater than $\theta_3$, and NI otherwise. In R1, $C_3$ returns NI.

($C_4$) **Semantic similarity** measures the similarity between conjunct$_1$ and conjunct$_2$ based on their meanings in WordNet. The intuition is that conjuncts with high semantic similarity can be regarded as one unit, thus favoring FR. $C_4$ returns FR if the semantic similarity is greater than $\theta_4$, and NI otherwise. In R1, $C_4$ returns FR.

($C_5$) **Suffix matching** examines the number of shared trailing characters (suffixes) of conjunct$_1$ and conjunct$_2$. For example, “installation and configuration” share five trailing characters. Suffixes are used to change the meaning (e.g., “-able” in noticeable) or grammatical property (e.g., “-ed” in closed) of a given word [73]. Hence, matching suffixes provides a cue about how words are semantically or syntactically related [33]. The intuition is that conjuncts with the same number of trailing characters are likely to be a single unit, thus favoring FR. $C_5$ returns FR if the conjuncts share trailing characters greater than $\theta_5$, and NI otherwise. In R1, $C_5$ returns NI.

**Heuristics for PAA.** A segment in $S_p$ contains a verb (v) and a following noun (n$_1$), followed by a preposition (p) and another noun (n$_2$). PAA heuristics attempt to interpret a segment as either VA or NA, as explained below. If a heuristic cannot interpret a segment, it returns not interpretable (NI).

($P_1$) **Preposition co-occurrence frequency** compares the frequency of $p$ occurring with $v$ against $p$ occurring with $n_1$. The intuition is that, based on the co-occurrence frequency of $v$ (or $n_1$) and $p$, PP can be regarded as an adverbial modifier leading to VA or a noun attribute leading to NA. For example, in the segment “provide user with a valid option”, the preposition “with” frequently follows the verb “provide”, thus leading to a VA interpretation. Precisely, $P_1$ returns VA if the co-occurrence frequency of $v$ and $p$ is strictly larger than that of $n_1$ and $p$. $P_1$ returns NA if the converse is true. If there is a tie between the frequencies, e.g., when the frequencies are zero due to $v$, $n_1$ or $p$ being absent from the corpus, $P_1$ returns NI. In R2, $P_1$ returns NA.

($P_2$) **Prepositional-phrase (PP) co-occurrence frequency** has a similar definition and intuition to $P_1$, the only difference being that we consider the entire PP (i.e., $p$ and $n_2$) instead of just $p$. For example, consider the segment “provide [...]” used for illustrating $P_1$. $P_2$ would return VA because the PP “with a valid option” has a higher co-occurrence frequency with $v$ (“provide”) than with $n_1$ (“user”). $P_2$’s precise definition is easy to extrapolate from the definition of $P_1$ and is omitted for space. In R2, $P_2$ returns NA.
By sharing a semantic class, we mean that X and Y contain E. Handling Ambiguity returns weighted voting (using the tuned weights of Section IV-D) following two conditions is met: (a) X matches some pattern and definition as C1 - C6 for CA classes in WordNet that group words with similar meanings. For example, WordNet puts “scissors” and “knife” under the same semantic class, namely “tool”. T3 is applied after all the segments in S_c have been already processed by P1 and P2. Specifically, T3 attempts to find an interpretation for the segments that have been deemed as NI by both P1 and P2. For any such segment X, T3 checks whether there is some segment Y in S_p which has been interpreted as VA or NA (by either P1 or P2) and which shares a semantic class with X. By sharing a semantic class, we mean that X and Y contain nouns or verbs that fall under the same WordNet semantic class. If Y has been interpreted as VA (respectively, NA) and X shares a verb class (respectively, a noun class) with Y, then T3 interprets X as VA (respectively, NA).

The intuition is as follows: segments that contain words with similar meanings are likely to have the same interpretation [34]. For instance, a segment X: “offeroperator with a valid option” is interpreted as VA by P3 if there is a segment Y: “provide user with a valid option” already interpreted as VA by P2. This is because the verbs “provide” and “offer” have the same WordNet semantic class: “possession”.

(P3) Semantic-class enrichment utilizes the semantic classes in WordNet that group words with similar meanings. For example, WordNet puts “scissors” and “knife” under the same semantic class, namely “tool”. T3 is applied after all the segments in S_c have been already processed by P1 and P2. Specifically, T3 attempts to find an interpretation for the segments that have been deemed as NI by both P1 and P2. For any such segment X, T3 checks whether there is some segment Y in S_p which has been interpreted as VA or NA (by either P1 or P2) and which shares a semantic class with X. By sharing a semantic class, we mean that X and Y contain nouns or verbs that fall under the same WordNet semantic class. If Y has been interpreted as VA (respectively, NA) and X shares a verb class (respectively, a noun class) with Y, then T3 interprets X as VA (respectively, NA).

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(P4) Attachment syntactic analysis has the same intuition and definition as C6, except that it applies to a PP-attachment segment. P4 returns VA or NA, as per the parsing results. P4 returns NI if the parser fails. In R2, P2 returns VA.

Combination of Heuristics. To produce a single interpretation for each segment, we combine through voting the results of the heuristics for each ambiguity type (C1 - C6 for CA and P1-P4 for PAA). We consider two voting methods: majority voting and weighted voting [74]. In majority voting, all heuristics contribute equally and the resulting interpretation is based on the majority. In weighted voting, the contribution of each heuristic is weighted differently. The weights are tuned in Section IV-D. In R1, majority voting yields FR, while weighted voting (using the tuned weights of Section IV-D) yields SR. We compare the accuracy of both voting methods in Section IV.

Step 4 partitions S_c and S_p into two subsets each: the first subset contains the interpretable segments (FR or SR for segments in S_c, and VA or NA for segments in S_p); the second subset contains the segments that are not interpretable. These subsets are passed on to step 5 for ambiguity handling.

E. Handling Ambiguity

In this final step, we classify into ambiguous and unambiguous the segments in S_c and S_p. This classification is based on the results of steps 2 and 4 in our approach (see Fig. 3). A segment X is classified as ambiguous if either of the following two conditions is met: (a) X matches some pattern in step 2, or (b) X is deemed as not interpretable (NI) in step 4. Any segment that is not classified as ambiguous would be unambiguous. We say that a requirement is ambiguous if it has some ambiguous segment; otherwise, we say the requirement is unambiguous. Our empirical evaluation, discussed next, is at a segment level (rather than a requirement level), because each requirement may contain multiple segments that are subject to ambiguity analysis.

IV. Evaluation

In this section, we empirically evaluate our approach.

A. Research Questions (RQs)

Our evaluation addresses four research questions:

RQ1. What configuration of our approach yields the most accurate results for ambiguity handling? Our approach can be configured in a number of alternative ways; the alternatives arise from the choices available for the selection of patterns (Section III-B), the use of default versus optimal thresholds for CA heuristics (Section III-D), and the voting method for combining the heuristics (Section III-D). RQ1 identifies the configuration that produces the best overall results.

RQ2. How effective is our approach at detecting unacknowledged ambiguity? As discussed in Section I, unconscious misunderstandings may occur due to unacknowledged ambiguity. Using the best configuration from RQ1, RQ2 assesses the effectiveness of our approach in automatically detecting unacknowledged ambiguity.

RQ3. How accurate are the interpretations provided by our approach? While the exact interpretation of a segment found by our approach (FR or SR for segments in S_c, and VA or NA for segments in S_p) has no bearing on how we tell apart unambiguous cases from ambiguous ones, we want the interpretations to be as correct as possible. A correct interpretation is important both for reducing manual work (in case the analysis choose to set the automatic interpretations), and also for ensuring that any subsequent automated analysis over the requirements, e.g., automated information extraction, will produce high-quality results. RQ3 examines the accuracy of the interpretations provided by our approach.

RQ4. Does our approach run in practical time? RQ4 studies whether the execution time of our approach is practical.

B. Implementation

We have implemented our approach (Fig. 3) in Java. The implementation has \( \approx 8500 \) lines of code excluding comments. The NLP pipeline of step 1 is implemented using DKPro [75]. For implementing step 3, we use the English Wikipedia dump\(^3\) timestamped 01/11/2018. We access the data in this dump using the JWPL library [76]. In step 4, we transform the raw text of Wikipedia articles into an n-grams table using the JWEB1T library [77]; this enables us to compute our interpretation heuristics more efficiently. We use Stanford Parser [78] to obtain the parse trees required by heuristics C5 and P2. For C4, we compute semantic similarity using the Resnik measure [79] as implemented by the WSJ4 library [80]. For implementation availability, please see the footnote on page 2.

C. Data Collection

Our data collection has human experts examine and annotate potential CA and PAA in industrial requirements. We collected

\(^3\)https://dumps.wikimedia.org/backup-index.html
above, provides empirical evidence for this belief. Annotators labeled the segment in question as ambiguous. Prevalent in requirements \([3], [23]\), the analysis, discussed in the paper, unacknowledged ambiguity is believed to be due to (i) interpretations (i.e., unacknowledged ambiguity). As stated earlier, an “agreement” between annotators is observed for segment \(X\), when both of them either find \(X\) ambiguous or interpret \(X\) the same way. Any other situation is a “disagreement”. Using Cohen’s kappa metric (\(\kappa\)) \([81]\), we obtain an inter-rater agreement of 0.37, suggesting “fair agreement”. To examine the sources of disagreement, we further analyze the cases where \(X\) is deemed ambiguous (i.e., acknowledged ambiguity). For these cases, we obtain \(\kappa = 0.78\) (“substantial agreement”), indicating that most disagreements are due to different interpretations (i.e., unacknowledged ambiguity). As stated earlier in the paper, unacknowledged ambiguity is believed to be prevalent in requirements \([3], [23]\). The analysis, discussed above, provides empirical evidence for this belief.

We constructed our ground truth as follows: (i) any segment labeled as ambiguous by at least one annotator is a case of acknowledged ambiguity, (ii) any segment labeled with different interpretations by the annotators is a case of unacknowledged ambiguity, and (iii) any segment labeled with the same interpretation by both annotators is unambiguous. We motivate our definitions of acknowledged and unacknowledged ambiguity by considering what might happen during a manual inspection where a team would typically be involved. If a segment is ambiguous enough for someone (not necessarily everyone) to raise a concern, then this segment is likely to be further discussed by the team (acknowledged). The situation is different for unacknowledged ambiguity. In reality and under time pressure, the analysts are unlikely to spell out their interpretations when they feel there is no ambiguity. Consequently, the disagreement remains hidden (unacknowledged).

Table III provides overall statistics about our data collection, showing for each domain, the number of RDs, the total number of requirements, and the number of requirements and segments in \(S_c\) and \(S_p\). The table further lists the number of ambiguous segments (grouped into acknowledged and unacknowledged) and the number of unambiguous segments. We observe from Table III that out of the total of 2980 segments analyzed by the annotators, 57% are ambiguous and the remaining 43% are unambiguous. In the ambiguous segments, the proportion of segments with unacknowledged ambiguity (1042/1690 \(\approx 62\%\)) is significantly higher than the proportion of segments with acknowledged ambiguity (648/1690 \(\approx 38\%\)). We note that repeated segments constitute a relatively small fraction of the ground truth: \(\approx 9\%\) (137/1506) for CA and \(\approx 8\%\) (116/1474) for PAA. These repetitions are not disproportionately concentrated in one group. More precisely, in the case of CA, 44 repetitions are unambiguous, 48 are acknowledged, and 45 are unacknowledged. For PAA, 39 repetitions are unambiguous, 35 are acknowledged, and 42 are unacknowledged. Since there is no disproportionate concentration of occurrences, repetitions have no major bearing on our findings.

We set aside \(\approx 20\%\) of our ground truth for parameter tuning, as we will discuss in Section IV-D. We refer to this subset of the ground truth as \(T\). The remaining \(\approx 80\%\) of the ground truth is referred to as \(E\). We use \(E\) for answering all the RQs, except RQ4 which is answered over \(T \cup E\). The tuning set, \(T\), consists of six RDs from six domains with a total of 550 requirements and representing 26% and 21% of the coordination and PP-attachment segments, respectively. We selected one RD from each domain; this was done in a way that the selected document would be as close as possible to containing \(\approx 20\%\) of the requirements we had in each domain. We did not select for tuning any documents from the domain of medicine, since we had only one RD from this domain.

D. Parameter Tuning

Tuning involves two groups of parameters: parameters for generating a domain-specific corpus (Section III-C) and parameters associated with the heuristics (Section III-D). Both groups of parameters are tuned with the goal of maximizing the overall accuracy of the interpretation heuristics. Note that tuning is performed exclusively over \(T\) (see Section IV-C).

Parameters for Corpus Generation. Generating a domain-specific corpus requires tuning the maximum number of keywords (\(K\)) to select from an input RD and the maximum number of articles (\(\alpha\)) in a given category in Wikipedia. For each RD in \(T\), we generate a domain-specific corpus. To tune

| Domain | RDs | Acknowledged | Acknowledged | Unacknowledged | Unacknowledged | Total |
|--------|-----|--------------|--------------|----------------|----------------|-------|
| Sp     | 1510 | 284 | 284 | 701 | 189 | 1420 | 142 | 5156 |
| Sc     | 353 | 44 | 238 | 272 | 19 | 333 | 69 | 1328 |

| Sc     | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |

| Total  | 388 | 64 | 266 | 312 | 20 | 360 | 81 | 1474 |
|--------|-----|--------------|--------------|----------------|----------------|-------|
| Acknowledged | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |
| Unacknowledged | 171 | 15 | 19 | 109 | 19 | 154 | 0 | 487 |
| Unambiguous | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |

| Total  | 388 | 64 | 266 | 312 | 20 | 360 | 81 | 1474 |
|--------|-----|--------------|--------------|----------------|----------------|-------|
| Acknowledged | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |
| Unacknowledged | 171 | 15 | 19 | 109 | 19 | 154 | 0 | 487 |
| Unambiguous | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |

| Total  | 388 | 64 | 266 | 312 | 20 | 360 | 81 | 1474 |
|--------|-----|--------------|--------------|----------------|----------------|-------|
| Acknowledged | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |
| Unacknowledged | 171 | 15 | 19 | 109 | 19 | 154 | 0 | 487 |
| Unambiguous | 133 | 28 | 233 | 106 | 20 | 128 | 2 | 649 |
K, we experiment with five values at regular intervals between 50–250. Values of K outside this range are undesirable as they result in a corpus that is either too small (for K < 50) or too large (for K > 250). A suitably large corpus is necessary for accurately estimating the co-occurrence frequencies of words in a specific domain [70]. Building and using a corpus that is too large would be time-consuming and, more importantly, would defeat the goal of being domain-specific. Using a corpus that is too small would simply be ineffective. For tuning α, we experiment with values in the range of 50–1000 in intervals of 50. Larger categories (i.e., α > 1000) are too generic, and smaller ones (with α < 50) are already covered by α > 50, as α is the upper bound for the number of articles in a category. For optimizing K and α, we use grid search [82]. The resulting optimal values are K = 100 and α = 250.

**Parameters for Heuristics.** Applying the interpretation heuristics requires tuning four thresholds θ1, θ2, θ3, and θ4. To tune θ4, we use random search [82] to optimize the thresholds because the search space is too large for grid search. The resulting optimal thresholds are θ1 = 0.01, θ3 = 0.12, θ4 = 3.45, and θ5 = 3.

For determining the weights of the heuristics, we first apply each heuristic individually on T. The weight of a given heuristic is determined by its success in providing interpretations for unambiguous segments. In our experiments, the weights of heuristics in descending order for CA are 0.038 for C5, 0.019 for C2, 0.012 for C1, 0.005 for C4, 0.005 for C6, and 0.003 for C3, and the weights for PAA are 0.08 for P1, 0.05 for P2, and 0.03 for P4. P3 is not a standalone heuristic and is thus not weighted. These weights reflect the contribution of the heuristics, in weighted voting, to produce a final interpretation for a segment.

**E. Evaluation Procedure**

We answer our RQs through the following experiments.

**EXPL.** This experiment answers RQ1. We determine the optimal configuration for ambiguity handling by comparing the output of our approach against E. For evaluating the configurations, we define a true positive (TP) as a detected ambiguous segment, a true negative (TN) as an unambiguous segment, a false positive (FP) as a misclassified unambiguous segment, and a false negative (FN) as a misclassified ambiguous segment. We compute Precision (P) as \( \frac{TP}{TP + FP} \), Recall (R) as \( \frac{TP}{TP + FN} \), and F1-score as \( \frac{2PR}{P + R} \).

We consider eight alternative configurations for our approach, denoted as V4–V8. These configurations are induced by three binary decisions. The first decision is whether to use the collected or the enhanced patterns in step 2 of our approach (see Table I). The second decision is whether in step 4 we should use for the thresholds the default or the optimal values (from Section IV-D). And, the third decision is whether the method for combining the heuristics is majority or weighted voting (see Section III-D). To analyze the impact of using domain-specific corpora, we compare our approach against baselines, denoted as B2–B6, with similar configurations but using a generic corpus: the British National Corpus [83].

To run EXPI, we first need to generate seven corpora, one for each application domain in our ground truth (see Table III). Six of these corpora are reused from Section IV-D. The last one – for the domain of medicine – is generated based on the single RD we have in our dataset for this domain. Except for the domain of medicine, EXPI provides an implicit assessment of how reusable a domain-specific corpus is, being generated from one RD and reused for other RDs from the same domain.

**EXPII.** This experiment answers RQ2. Given the optimal configuration of our approach from EXPI, EXPII assesses how well our approach can detect unacknowledged ambiguity in different domains. In EXPII, we compute Recall (R) similar to EXPI, but limiting the evaluation to only the segments with unacknowledged ambiguity in E. The corpora used in EXPII are the same as those in EXPI.

**EXPIII.** This experiment answers RQ3. We evaluate the interpretation provided by our approach for the segments classified as unambiguous (FR or SR for segments in S3, and VA or NA for segments in S4). Specifically, EXPIII compares the interpretations produced by our approach against the interpretations of unambiguous segments in E, reporting the ratio of the correctly interpreted segments (i.e., Accuracy).

The corpora used in EXPIII are the same as those in EXPI and EXPLII. We further compare our approach against Stanford Parser [78] – one of the commonly used tools for interpreting syntactic ambiguity [84].

**EXIV.** This experiment answers RQ4 by running the best configuration from RQ1 over T ∪ E. The experiment is done on a laptop with a 2.3 GHz CPU and 16GB of memory.

**F. Answers to the RQs**

**RQ1.** Table IV shows the results of EXPI (on E). To determine the optimal configuration of our approach, we investigate among all configurations the factors that cause the most variation in accuracy. We do so by performing regression tree analysis (tree not shown) [85]. The most influential factor for both CA and PAA, as per regression tree analysis, is the choice of domain-specific versus generic corpus. The configurations that use a domain-specific corpus, V4–V8, have an average gain in accuracy of ≈6% over the configurations that use a generic corpus, V1–V3. This observation clearly highlights the importance of domain knowledge in ambiguity handling.

Among V4–V8, using enhanced patterns has a considerable impact on detecting CA. Compared to the configurations with collected patterns (V4–V8), the configurations with enhanced patterns (V5–V6) lead to an average gain of ≈6% in accuracy...
TABLE IV
RESULTS OF AMBIGUITY HANDLING (RQ1).

| Domain | CA | PAA |
|--------|----|-----|
|        | Patterns | Thresholds | Voting | A (%) | P (%) | R (%) | A (%) | P (%) | R (%) |
|        | V₁      | collected | default | majority | 70.8 | 76.9 | 66.6 | 78.4 | 77.8 | 84.0 |
|        | V₂      | collected | default | weighted | 71.6 | 78.0 | 66.9 | 78.0 | 78.5 | 84.0 |
|        | V₃      | collected | optimal | majority | 74.5 | 81.1 | 69.5 | 82.0 | 81.5 | 86.4 |
|        | V₄      | collected | optimal | weighted | 75.3 | 82.2 | 69.9 | 82.5 | 82.2 | 86.4 |
|        | V₅      | enhanced | default | majority | 76.7 | 75.6 | 84.6 | 78.6 | 76.3 | 87.7 |
|        | V₆      | enhanced | default | weighted | 77.5 | 76.4 | 84.9 | 79.1 | 76.9 | 87.7 |
|        | V₇      | enhanced | optimal | majority | 81.3 | 79.8 | 87.9 | 82.7 | 80.3 | 90.1 |
|        | V₈      | enhanced | optimal | weighted | 81.3 | 79.8 | 87.9 | 82.7 | 80.3 | 90.1 |

Accuracy (A), Precision (P) and Recall (R) in percentage (%)

TABLE V
UNACKNOWLEDGED AMBIGUITY DETECTION USING V₈ (RQ2).

| Domain | Sp | PAA |
|--------|----|-----|
|        | TP | FN  | TP | FN |
|        | 145 | 15 | 78 | 19 | 46 | 0 | 268 |
|        | 84.7 | 86.6 | 89.4 | 87.5 | 100 | 88.4 | - | 87.3 |
|        | R (%) | 84.7 | 86.6 | 89.4 | 87.5 | 100 | 88.4 | - | 87.3 |
|        | TP | 83 | 15 | 120 | 17 | 4 | 141 | 32 | 412 |
|        | 92.3 | 88.2 | 91.6 | 94.4 | 90.0 | 90.1 | 88.8 | 91.8 |

RQ2. The results of SPECI, obtained from running V₈ (the best configuration from RQ1) on E are shown in Table V. Overall, our approach detects unacknowledged ambiguity with an average recall of 87.3% for CA and 91.8% for PAA.

Our error analysis (Section IV-G) examines missed cases of unacknowledged ambiguity in the entire dataset (T ∪ E). Over the entire dataset, V₈ detects unacknowledged ambiguity with an average recall of 87.8% for CA and 92.6% for PAA.

RQ3. The interpretations provided by V₈ for the segments in Sₑ and Sₚ (when restricted to E) have an average accuracy of 85.2% and 84.4%, respectively. The accuracy of the approach on the entire dataset is marginally higher (by an average of ≈1%). We examine interpretations errors in Section IV-G.

Applying the Stanford Parser to Sₑ and Sₚ (when restricted to E) yields interpretations with an average accuracy of 65.7% and 72.6%, respectively. In an RE context and in comparison to the Stanford Parser, the integration of domain knowledge increases the interpretation accuracy of coordination and PP-attachment structures by an average of ≈16%.

RQ4. Executing steps 1 and 2 of our approach (Fig. 3) takes ≈0.2 milliseconds per requirement. Step 3 is performed only when a suitable corpus is absent, i.e., when no corpus has been generated before for the domain of a given RD, or when the domain of the RD is difficult to ascertain. Across the seven corpora we generated for answering RQ1-3, the average execution time was ≈58 minutes (standard deviation: ≈21 minutes). To be able to generate corpora, there is a one-time overhead of ≈3 hours; this is to set up a query engine over Wikipedia (see step 3.2 in Section III-C). Once set up, this query engine does not have to be rebuilt, unless one wants to switch to a different edition of Wikipedia. With a corpus at hand, execution time is dominated by the computation of the frequencies required by the heuristics of step 4. This on average takes ≈6.8 seconds for a requirement in Sc and ≈1.5 seconds for one in Sₚ. Processing the requirements in Sₑ takes longer because there are more corpus-based heuristics for CA than PAA. Non-corpus-based heuristics take negligible time.

Excluding corpus generation, the largest document in our dataset took ≈51 minutes to process. This document had 492 requirements with 392 coordination and 245 PP-attachment segments. Such an execution time is practical for offline (e.g., overnight) processing. With regard to using our approach interactively, we observe that, at any point in time, an analyst likely works on only a small part of a large document. For interactive use, ambiguity handling can be localized to the document fraction (e.g., page) that the analyst is reviewing.

G. Error Analysis

In this section, we analyze the root causes of the errors made by our approach (V₈) on the entire dataset (T ∪ E).

Errors in RQ1 and RQ2. Out of 1690 segments (Table III), our approach missed 192 ambiguous segments, of which 100 are unacknowledged. These errors can be explained as follows.

1) Coverage of patterns: 169 segments do not match any pattern in Table I. For example, the segment “register the
microservice in the operations server” matches no PAA pattern. One can avoid such errors by expanding the pattern set. However, our experiments indicate that doing so comes at the cost of a large number of FPs and is thus not worthwhile.

2) **NLP errors**: 23 segments are missed due to mistakes by the NLP pipeline (Fig. 4). For example, “support” in the segment “[can] support doctors in the ICU” is erroneously tagged as a noun; this results in the segment not to match any of our patterns. Such NLP mistakes are hard to avoid [86].

**Errors in RQ3.** We found two causes for interpretation errors.

1) **Interpretation errors by the heuristics**: 74 segments fall under this class of errors, having to do with situations where the combination of heuristics provide a wrong interpretation or return not interpretable (NI) where there is indeed an interpretation. For example, for the segment “pulse width and duration” the resulting interpretation is 3R, although it should be FR. One can try to address individual interpretation errors by adjusting the weights of the heuristics. However, doing so will have a negative overall impact by causing other errors.

2) **Document-specific abbreviations**: 58 segments are misinterpreted due to abbreviations. An abbreviation that is specific to a document can mislead frequency computations if the abbreviation has a homonym or is not found in the corpus at all. For example, “MOC” in “MOC operator and component” stands for “MOnitoring and Control” in one of our RDs from the satellite domain. This abbreviation, however, matches “Mars Orbiter Camera” in the corpus that we generate for this domain. Such mismatches can be reduced through abbreviation disambiguation [87]. We leave this for future work.

**H. Discussion about Usefulness**

As shown by Table III, ambiguity was acknowledged by the annotators in only 38% of the cases. The remaining 62% were unacknowledged. In practice, even if the analysts perform a manual review, under time pressure and outside an evaluation setting, they will likely only examine what at least one analyst finds to be ambiguous and thus miss out on the cases where they unconsciously disagree about the interpretation.

We believe that the main benefit of our automated approach is in bringing ≈90% of the cases of unacknowledged ambiguity to the attention of the analysts (see RQ2). This is achieved while maintaining a high overall precision (≈80%), meaning that the analysts will spend a small fraction of their manual effort over false positives. While user studies remain essential for establishing usefulness, our good accuracy results suggest that our approach has the potential to be helpful in practice.

**V. VALIDITY CONSIDERATIONS**

**Internal Validity.** Bias is a potential threat to the internal validity of our evaluation. To mitigate this threat, the authors had no involvement in the annotation activities. Instead, two third-party annotators, who had no knowledge of our technical approach, independently annotated the dataset. Further, we made a strict separation between the data used for defining patterns and tuning, and the data used for assessing effectiveness.

**Construct Validity.** An individual requirement can potentially have multiple instances of CA or PAA. To ensure that this possibility is properly reflected in our metrics, we defined accuracy, precision and recall at the level of segments rather than whole requirements.

**External Validity.** Our evaluation builds on 20 industrial requirements documents, covering seven different domains. The promising results obtained across these domains provide a measure of confidence about the generalizability of our approach. This confidence is further strengthened by the fact that our approach can adapt itself to new domains via the (automatic) generation of domain-specific corpora. Due to this characteristic, we are optimistic that our approach will be able to achieve comparable results in other domains. That said, future case studies would help further improve external validity.

**VI. CONCLUSION**

In this paper, we proposed an automated approach for improving the handling of coordination ambiguity (CA) and prepositional-phrase attachment ambiguity (PAA). The main novelty of our approach is in automatically extracting domain-specific corpora from Wikipedia and utilizing them for increasing the accuracy of CA and PAA handling in requirements documents. We conducted a large-scale evaluation of our approach using more than 5000 industrial requirements from seven different application domains. Our results indicate that our approach can detect CA and PAA with an average precision of ≈80% and an average recall of ≈89%. The results further indicate that employing domain-specific corpora has a substantial positive impact on the accuracy of CA and PAA handling. Specifically, over our dataset, we observed a ≈33% improvement in accuracy when compared against baselines that use generic corpora. While our work is motivated by improving the quality of systems and software requirements, our technical solution is also novel from an NLP standpoint. Our solution thus has the potential to be useful over other types of textual documents within and beyond software engineering.

In future work, we would like to integrate our ambiguity handling approach with automated techniques for extracting structured information from requirements specifications. The motivation for doing so is to increase the quality of information extraction by more accurately interpreting coordination and prepositional-phrase structures. Another direction we would like to explore in the future is to use deep learning to complement or as an alternative to our current approach.

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