

Towards Detecting Intra- and Inter-Sentential Negation Scope and Focus in Dialogue

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Abstract

We present in this paper a study on negation in dialogues. In particular, we analyze the peculiarities of negation in dialogues and propose a new method to detect intra-sentential and inter-sentential negation scope and focus in dialogue context. A key element of the solution is to use dialogue context in the form of previous utterances, which is often needed for proper interpretation of negation in dialogue compared to literary, non-dialogue texts. We have modeled the negation scope and focus detection tasks as a sequence labeling tasks and used Conditional Random Field models to label each token in an utterance as being within the scope/focus of negation or not. The proposed negation scope and focus detection method is evaluated on a newly created corpus (called the DeepTutor Negation corpus; DT-Neg). This dataset was created from actual tutorial dialogue interactions between high school students and a state-of-the-art intelligent tutoring system.

Introduction

According to SIL International (Summer Institute of Linguistics), negation is a morphosyntactic operation in which a lexical item denies or inverts the meaning of another lexical item or construction. A *negator* (or negation cue), is a lexical item that expresses negation. **Morphological negation** occurs when a word is negated by an affix (prefix or suffix) as in **un-happy** or **sense-less** whereas **syntactic negation** means an entire clause is negated explicitly (using a negator) or implicitly, e.g. verbs or nominalizations that negate their complements such as *fail* or *deny*.

In explicitly negated statements, negation is marked using cue words, such as *not*, *no* and *neither ... nor*. A negation cue word or negator can affect the meaning of a part of the sentence in which it appears or part of previous sentence from the discourse context. The part of the sentence

affected by the negation cue is called *negation scope*. The part of the scope that is most prominently negated is called *negation focus* (Huddleston & Pullum, 2002).

An example of negation is shown for the following sentence where we indicate the negation cue (in $\langle \rangle$), the negation scope (in $[]$) and the negation focus (in $\{\}$): *The desk stops moving because [there is] \langle no \rangle [{net force} acting on it].*

Negation is a frequent and complex phenomenon in natural language. Tottie (1991) noted that negation is twice as frequent in spoken sentences (27.6 per 1,000 words) as in written text (12.8 per 1,000 words). Elkin and colleagues (2005) found that 12% of the concepts in 41 health records are negated while Councill and Velikovich (2010) report that 19% of the product review sentences contain negations. In an analysis of student utterances in dialogues collected from the Intelligent Tutoring System (ITS) DeepTutor (Rus, D'Mello, Hu, & Graesser, 2013), it has been found that 9.36% of the student answers contain explicit negation. The relative high frequency of negation and its key role in many applications such as intelligent tutoring, sentiment analysis, and information extraction emphasize the importance of the negation handling problem. In particular, the negation scope and focus can be used in semantic representations of negation, such as the one proposed by Blanco and Moldovan (2011).

Negation may become quite complex when interacting with other linguistic phenomena such as ellipsis and pragmatics, two frequent phenomena in dialogues, as illustrated in the example below. The example shows four different real answers (A1-4) as typed by high-school students during their interaction with the intelligent tutoring system DeepTutor.

Example 1. DeepTutor: *Do these balls (red ball and blue ball) ever have the same speed?*

A1: *They do not have the same speed.*

A2: *No.*

A3: *The balls never have the same speed.*

A4: *The red one goes faster.*

The four student answers are triggered by the same hint in the form of a question from the intelligent tutoring system. Answers A1-A3 contain explicit negations whereas in answer A4 the negation is not explicit. We do not handle such cases, as in answer A4, as our focus is on explicit negation.

While datasets and computational approaches to negation have been recently developed, to the best of our knowledge, there is no previous work that systematically addresses the identification of negation scope and focus in dialogues. Previous work on computational approaches to negation have focused primarily on same-sentence negations, i.e. the scope and focused are in the same sentence where the negation cue word is (Vincze et al., 2008; Morante et al., 2008; Morante & Blanco, 2012; Morante, Schrauwen, & Daelemans, 2011; Thompson et al., 2011). Our approach can detect negation scope and focus even when they reside in another sentence, i.e. the previous dialogue utterance. It should be noted that even when the scope and focus are in the same sentence as the negator, the context (of the dialogue in our case) could be helpful to correctly identify the focus.

We address here negation in dialogues and handle both scope and focus detection. To this end, we collected and annotated a corpus from real dialogues between the computer tutor DeepTutor and high-school students. The corpus is called the DT-Neg corpus¹ – DeepTutor Negation corpus - and consists of 1,088 instances. The corpus was manually annotated with negation cue words, negation scope, and negation focus. We then developed a method to detect negation scope and focus based on Conditional Random Fields (CRF). We report results for focus detection with and without use of dialogue contextual features.

Negation in Dialogue

We argue that the scope and focus of negation in dialogue utterances is best determined in context. In this view, we adhere to the principle that the focus of negation is determined by coherence constraints in a discourse (Rooth, 1996; Roberts, 1996; Anand & Martel, 2012). That is, the scope and focus identification processes are informed by dialogue coherence constraints in the sense that, for instance, a word is preferred as a focus over another if it leads to better dialogue coherence. In our case, we use clues from previous dialogue utterances to help us disambiguate the scope and focus of a negation instance.

In Example 1, student answer A1 contains an explicit form of negation. The student answer is ambiguous in the sense that the focus switches from *ever* to *have*, given that *ever* is not mentioned by the student. That is, in one interpretation the student answer is understood as indicating

that the two balls do not have the same speed (*ever*, i.e. *ever* is assumed to be implied by the student answer given the context of the tutor question). In another interpretation, the student answer A1 may be understood as indicating that the two balls do not have the same speed at some moment but may have the same speed at some other moment, which is the correct answer, by the way.

Answer A2 is a short answer. Such short answers are a typical case of ellipsis which is quite frequent in dialogue contexts, i.e. when words are elided from the student answer albeit implied by the context. Indeed, these types of negations in the presence of ellipsis can only be interpreted by considering the previous dialogue context which in this case is the tutor’s previous question. Answer A3 is the cleanest form of negation because it is easiest to interpret as the student answer is self-contained and well-formed. A4 is an interesting answer in the sense that it does not contain an explicit negation. However, in the context of the previous question from the tutor this student answer is an indirect answer to the question. That is, in order to obtain the direct answer to the tutor question, answer A4 should be interpreted as “Because of the fact that *the red one goes faster* the two balls do not have the same speed.”, where we underlined the implied direct answer to the tutor question. This implied direct answer contains a negation. When analyzing negation in dialogues, the dialogue context will influence subtly the negation scope and focus. Consider the dialogue snapshot below.

- *Does the coin land in his hand?*

- *No.*

Because the focus of the question is asking where the coin will land, the focus of the negation in the student answer is the location, i.e. *hand*. That is, the student is saying that the coin will land somewhere else (*not in his hand*).

Let’s now consider the following dialogue snapshot:

- *Can you articulate the relevant principle?*

- *No.*

In this example, the computer tutor is specifically asking the student to articulate (not to apply) the relevant principle. Therefore, the focus is the verb *articulate*. One can also argue that the focus is the verb *can*. However, the clear intention of the “*Can you articulate ...*” utterance from the intelligent tutoring system is an invitation to the student to articulate the principle, that is, the tutor’s intention is actually “*Please articulate the relevant principle.*” Since the invitation to articulate the principle maximizes the dialogue coherence, we choose *articulate* as the focus.

Related Work

Negation has been studied in the field of philosophy, psychology, linguistics, and computational linguistics starting with Aristotle (Wedin, 1990). Horn (1989) describes negation from philosophical and psychological perspectives,

¹ The dataset is freely available at <http://language.memphis.edu/>

including constructs, usage, and cognitive processing of negation.

While logical negation has a very crisp definition (Horn, 1989; Rosenberg, 2013), negation in natural language statements is more nuanced and subtle. Tottie (1991) presents a comprehensive taxonomy of clausal English negations – denials, rejections, imperatives, questions, supports, and repetitions. Huddleston and Pullum (2002) have categorized the expression of negation into two types – verbal or nonverbal, and analytic or syntactic – in their book *The Cambridge Grammar of the English Language*. Miestamo (2006) distinguishes between standard negation and negation in imperatives, existential, and non-verbal clause.

Negation handling approaches were initially developed in the medical domain for the purpose of processing and indexing clinical reports and discharge summaries. Mutalik et al. (2001) developed Neg-finder in order to recognize negated patterns in medical texts. Chapman et al. (2001) created a simple regular expression algorithm called Neg-Ex that can detect phrases indicating negation and identify medical terms falling within the negative scope. Morante et al. (2008) proposed a method of learning the scope of negation in biomedical text. Many other research works in negation handling focused on the medical domain (Rokach, Romano, & Maimon, 2008; Gindl, Kaiser, & Miksch, 2008; MacNamee, Kelleher, & Delany, 2008). Vincze et al. (2008) annotated negation cues and their scopes in the BioScope corpus. The corpus consists of medical free texts, biological full papers and abstracts.

Negation was also studied in the context of sentiment analysis. Councill et al. (2010) focused on explicit negation and created a product review corpus annotated with negation cue and scope. Others have studied content negators such as “hampered”, “denied”, etc. (Moilanen and Pulman, 2007; Choi and Cardie, 2008). Since identification of negation in review texts can help opinion mining tasks, Konstantinova et al. (2012) annotated the SFU Review Corpus.

In 2011, Morante, Schrauwen, and Daelemans published a more comprehensive set of guidelines for the annotation of negation cues and their scope. In fact, one of the shared tasks in the *SEM 2012 conference was dedicated to negation scope and focus detection (Morante & Blanco, 2012). Blanco and Moldovan (2011) annotated negation focus on text extracted from the PropBank corpus and the resulting dataset was used in the shared task (Morante & Blanco, 2012). Many of the participating teams adopted machine learning techniques for cue, scope, and focus detection. Some others used rule based systems as well. Although some of the evaluated approaches showed good performance on that dataset, it is not clear whether those systems perform well in general as they were evaluated only with narrative, non-dialogue texts.

Zou, Zhu, and Zhou (2014) showed the importance of discourse context for negation focus detection but their

work was limited to focus detection when the focus and negator are in the same sentence. In this paper, we approach the tasks of scope and focus detection for intra- and inter-sentential negation in dialogue.

Data

We created the DT-Neg dataset by extracting student answers containing explicit negation cues from logged tutorial interactions between high-school students and the DeepTutor tutoring system. During the interactions, students solved conceptual physics problems, as opposed to quantitative problems, and the interactions were in the form of pure natural language texts (i.e., no mathematical expressions and special symbols were involved). Each problem contained multiple questions. In 27,785 student responses, we found 2,603 (9.36%) student responses that contained at least one explicit negation cue word, such as *no* and *not*. We have not considered affixal negations, such as *un* in *un-identified*.

We tokenized the dialogue utterances using Stanford CoreNLP Toolkit (Manning et al., 2014). As we focused on explicit negation, we identified student answers containing negation cue words based on a list of cue words which we compiled from different research reports (Morante, Schrauwen, & Daelemans, 2011; Vincze et al., 2008) as well as our own data. If a student response contained multiple negations, they were treated as separate instances in our corpus. We then annotated each such candidate negation instance for negation cue, scope, and focus.

Annotation procedure. During annotation, annotators were asked to validate the automatically detected negation cue words and identify the corresponding negation scope and focus. It should be noted that we only targeted student responses for negation handling and not all the dialogue utterances, because the system/tutor utterances are system generated and therefore their interpretation is known.

The annotation was conducted by a group of 5 people comprised of graduate students and researchers who were first trained before being asked to annotate the data. They had access to an annotation manual during actual annotation for reference. The guidelines have been inspired from the one prepared by Morante, Schrauwen, and Daelemans (2011) for non-dialogue texts. We have developed our guidelines to best fit the context of our work, i.e. dialogues.

Annotators were instructed to use contextual information to best disambiguate the scope and focus. For this, annotators were shown the student response containing the negation as well as the previous system turn (tutor question). The Example 2 and Example 3 below illustrate annotations where in one case the negation scope and focus are in the same sentence as the negation cue word (Example 2) whereas in the other (Example 3) the negation scope and

focus are located in the dialogue context, i.e. the previous dialogues utterance generated by the tutor. The cue, scope, and focus are marked by $\langle \rangle$, $[\]$, and $\{ \}$, respectively.

Example 2: Question: Do these balls (red ball and blue ball) ever have the same speed?

A: $[They\ do]\ \langle not \rangle\ [have\ the\ \{same\}\ speed]$.

Example 3: Question: Do [these balls (red ball and blue ball)] ever [have the {same} speed]?

A: $\langle No \rangle$.

The annotators’ agreement for a scope location judgment, i.e. the same sentence or in the previous dialogue, was very high at 94.33%. When the annotators agreed on the location of scope and focus, we measured the agreement for scope and focus, respectively. The average token (sentence) level agreement was 89.43% (66.60%) and 94.20% (66.95%) for scope and focus, respectively. The main disagreement among annotations was on how to use the contextual information. The disagreements were discussed among the annotators and fixed. The role of the discussion was to both reach an agreement and improve consistency of future annotations. In total, we have annotated 1,088 valid instances (an instance is a pair of tutor question and student answer). We randomly divided the data into training and test set in 70-30%. General characteristics of the DT-Neg corpus are offered in Table 1. Different forms of the same cue, such as *n’t* or *not* or *NOT* were considered identical while counting unique cues. We can observe that 42% of the instances in DT-Neg dataset have scope and focus in context (i.e., they are inter-sentential negations). The further details about the dataset and the annotation process can be found in Banjade and Rus (2016).

Parameter	Training	Test
# instances (total)	761	327
#instances with scope/focus in context	328	130
#unique cues	10	9

Table 1: DT-Neg dataset summary

System Description

We have modeled negation scope and focus detection as a sequence labeling task in which each word in the negated sentence is either labeled as in-scope/focus or out-of-scope/focus. We used MALLET SimpleTagger (McCallum & Andrew, 2005) which is a Java implementation of Conditional Random Fields (CRFs). CRF is a discriminative method for sequence labeling. It has been successfully applied in a number of sequence labeling tasks such as POS-tagging, and Chunking. It defines conditional probability distributions $P(Y|X)$ of label sequences Y given input sequences X . In our case, Y is a set of binary decisions about

a token in the sentence where the negation scope/focus lies and X is the input sequence represented as a set of features. CRFs models may account for the full context of a set of observations such as the labels of tokens before and after the current token in the sentence. For instance, if a given token in a phrase is labeled as within the negation scope, the probability of other tokens in the same phrase being in the negation scope will be high. Therefore, CRF is a best choice to label scope/focus when expert-labeled data are available to train the model.

Features. Each token in the student answer where the negation is present has a set of features which includes positional, lexical, syntactic, and semantic information. The following features were used for CRFs modeling and labeling purposes.

1. **Cue** – the negation cue itself (multiple words in the cue, such as *neither nor*, were merged together).
2. **Before cue** – whether the current token appears before the cue (first cue word if the cue has multiple words).
3. **Distance from the cue**– how far the current token is from the cue. Word next to the cue word has distance of 1.
4. **POS tag** – Part-of-speech tag of the token.
5. **Conjunction in between** – whether there is a conjunction (coordinating or subordinating) in between the token and the negation cue.
6. **Punctuation** – whether the token is punctuation.
7. **Student Answer type (1/0)** – short versus full sentence; this features suggest whether to look in the student answer for the scope and focus or in the previous utterance.
8. **Dep1** - whether there is a direct syntactic dependency between the current token and the cue word.
9. **Semantic role** - semantic role of the token.
10. **First word of question** – wh-word or first word of previous tutor utterance.
11. **Head word of question** – the lemma of the head word of the question obtained from the dependency parsing.
12. **Found in Question** – whether the word (stop-words are ignored) in its lemmatized form is found in question.

We will refer to these features by their numeric ids. Also, we categorize these features into the following groups: basic features (1-3), syntactic-semantic roles features (4-9), and contextual features (10-12). We used Stanford CoreNLP Toolkit (Manning et al., 2014) to extract POS tags, dependency information, and head words. Semantic roles were generated using SENNA tool (Collobert et al., 2011).

Negation Scope and focus detection. The training examples consist of tokens, associated features, and scope labels (using IOB2 format where the B- prefix before an in-scope/focus tag indicates that the tag is the beginning of the scope, and an I- prefix before a tag indicates that the

tag is inside a scope/focus and O indicates that a token is outside of the scope/focus). Scope labels were removed from the test examples as the goal is to discover the labels automatically. As discussed earlier, the focus of negation may depend on the context even if it is in the same sentence where the negation cue word is (intra-sentential negation) or not (inter-sentential negation). The type of the previous question from the intelligent tutoring system (or another conversational partner in the general case of a dialogue system), the head word of the previous tutor question, and information about whether the word in the student answer is found in previous utterances are used as contextual clues in our model.

To measure the performance of the proposed models, we adopted the token label scoring used in *SEM 2012 Shared task (Morante & Blanco, 2012). We ignored punctuations when computing token label performance. A training-testing methodology was followed in which we first cross-validated the models using training data and then evaluated their performance on separate, previously unseen testing data. The default settings of CRF in MALLET (version 2.0.7) tool were used during model development.

Results

Scope detection (SD). Results (Precision, Recall, and F-measure) for scope detection are summarized in Table 2. In Run 1 (SDR1), we used just the basic features. In Run 2 (SDR2) syntactic and semantic role features were used. Runs SDR3 and SDR4 combine basic and syntactic-semantic role features with and without the contextual features. Run SDR5 uses basic features and contextual features. The baseline results were generated by labeling all tokens as they were in the negation scope.

System/features	Prec	Rec	F1
Baseline	57.87	1.00	73.31
SDR1/1-3	76.97	95.89	85.40
SDR2/4-9	80.83	81.56	81.19
SDR3/1-9	90.80	95.31	93.00
SDR4/1-12	92.97	95.74	94.34
SDR5/1-3, 10-12	83.64	92.92	88.04

Table 2: Scope detection results.

As can be seen from the table, all of our systems performed significantly better than the baseline system. The combination of basic and syntactic-semantic features produced an F1 score of 93.00 and adding contextual features improved the results. The modest improvement when adding contextual features on top of the basic and syntactic-semantic role features could be due to the fact that we used a limited number of contextual features or it might be the case that the performance of the SDR3 model is already very good

and significant improvement is difficult to obtain without an extremely rich model that would include many more contextual features or that the features have limited power. It could also mean that for scope detection syntax and semantic roles features play a more important role than our limited set of contextual features. To find a more precise answer to this latter hypothesis we analyzed the performance of a model (SDR5 in Table 2) that excluded the syntactic and semantic roles features. By comparing the performance of SDR1, SDR5, and SDR4 we can notice that adding the contextual features to the basic features model (SDR1) leads to an almost 3% improvement in the F1 measure. The further addition of the syntactic and semantic roles features to the SDR5 model that includes the basic and contextual features leads to a more than 6% improvement.

Focus detection (FD). The results for focus detection are summarized in Table 3. In this case, we used the same set of features (i.e., features 1-12). In addition, for focus detection we rely on scope labels obtained with the best performing scope detection model (i.e. SDR4 in Table 2) as we assume that the focus is within the scope. The baseline model was developed by treating all the in-scope tokens predicted by the best system (SDR4) as they were also in the focus.

System/features	Prec	Rec	F1
Baseline	17.04	98.03	29.03
FDR1/1-9, S	77.06	75.54	76.29
FDR2/1-12, S	80.82	81.00	80.91
FDR1-Intra	76.60	81.52	78.98
FDR2-Intra	83.88	81.52	82.68
FDR1-Inter	80.00	51.67	62.80
FDR2-Inter	77.41	80.38	78.87

Table 3: Focus detection results (S – scope used).

Compared to the scope detection, the results suggest that focus detection is more challenging and it requires more context to best disambiguate it (we can see that by comparing FDR2 and FDR1 results). In another experiment, we extracted from the DT-Neg corpus only instances in which the scope and focus were in the same sentence as the negation cue word, i.e. similar to how previous data sets treated negation. This allowed us to gauge the importance of context for same-sentence focus detection. Rows with the mark Intra denote this Answers-only focus subset, which includes 197 instances from the test set. By comparing results of FDR1-Intra and FDR2-Intra, we can see that context can improve results and therefore is important for focus detection. Furthermore, we tested the role of contextual features on the remaining instances (i.e., instances where the negation focus itself lies in the context). These results are presented in the FDR1-Inter and FDR2-Inter

rows. In this case also, contextual information improved the results.

Discussion and Conclusion

The proposed method for negation scope and focus detection in dialogue performed very well. Specifically, the results show that the contextual information in intra- and inter-sentential negation focus detection is important. This can be very useful towards improving natural language understanding in conversational (i.e., dialogue based) systems. However, there are still issues that must be addressed. For instance, some of student responses were not well formed which introduce errors in our feature extraction step.

Moreover, as the MITRE Corporation noted in their recent report, there are still some issues with respect to negation annotation and evaluation (Stephen et al., 2013) that need to be addressed by future research. For example, previously existing datasets assumed negation scope is within the same sentence with the negation cue word (or at least annotated so) which does not generalize across all kind of data. We addressed this issue in our work presented here. Also, there may be inconsistencies in annotations proposed by various teams. For example, some negation corpora include cues within the scope whereas others don't. We do not include cue in the scope.

In order to foster research in this area, we intend to make our annotated dataset and annotation proposal freely available.

In the future, we want to work with datasets from different sources and work on the interpretation of negated texts in dialogue contexts which is an important task once negation scope and focus have been identified. For example, we plan to handle negation in automatic answer grading systems in conversational tutoring system.

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