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Don't Let Notes Be Misunderstood: A Negation Detection Method for Assessing Risk of Suicide in Mental Health Records [SUPPLEMENT]

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Supplement

To further understand the performance of the negation resolution algorithms compared to the gold standard annotations, we analyse a few example sentences.

Table 1 presents a few representative cases where our methodology differs from pyContextNLP-N. Sentences 1-4 present positive cases that contain linguistic negation cues and therefore pose a serious challenge for automated negation resolution.

- In sentence 1, which contains the negation cue “no”, our methodology prunes the node together with the complete governing Noun Phrase (“no recent periods of low mood”). In contrast, pyContextNLP-N considers the negation cue within the scope of the target keyword.
- Sentence 2 is a similar example where a negation cue “tricks” pyContextNLP-N. Our method correctly resolves negation, since it marks the phrase “she might commit suicide” as a dominating subordinate clause and ignores the rest of the text.
- Sentence 3 contains the phrase “not what they used to be” which is a pseudo-negation. Our tool fails to identify this whereas pyContextNLP-N is equipped with a corresponding rule and correctly classifies it.
- Both tools erroneously detect negation in sentence 4. The node “due to risk of suicide” (an adjective phrase by CoreNLP) is not considered a special case by either of the tools and negation is propagated to the target keyword.

Sentences 5-8 present negative cases (i.e. cases where negation is present).

- In sentence 5, the negation stopword “deny” is correctly associated with the target keyword in our approach, whereas pyContextNLP-N is – presumably – not equipped with a corresponding rule.
- In sentence 6, the phrase “that she was suicidal” is identified as a dominating subordinate clause and marked as positive in our methodology; pyContextNLP-N considers the whole text and marks it as negative.
- Sentence 7 is another example with opposite outcomes for the two tools. The sentence contains the negation cue “absence” which is not in our dictionary but exists in pyContextNLP-N.
- Finally, sentence 8, which is a case of coreference, is a missed instance for both tools. In future work, we intend to make use of automated coreference resolution, as provided by CoreNLP.

Negation keywords

The keywords used for our proposed negation detection methodology are the following:

no, without, nil, not, n't, never, none, neither, nor, non, deny, reject, refuse, subside, retract.

Table 1: A few examples as annotated by the human annotator (Class), our proposed model and pyContextNLP-N.

No	Sentence	Class	Proposed Model	pyContextNLP-N
1	ZZZZ reported no recent periods of low mood, discussed how in the past she made many suicide attempts	Positive	Positive	Negative
2	No issues other than her indicating that she might commit suicide	Positive	Positive	Negative
3	He said that his suicidal thoughts are not what they used to be	Positive	Negative	Positive
4	The team does not support a return to prison due to risk of suicide	Positive	Negative	Negative
5	He continues to deny any suicidal thoughts and is happy to come to the XXX for medical review tomorrow	Negative	Negative	Positive
6	She did not say that she was suicidal	Negative	Positive	Negative
7	Client reassured us of her safety, and absence of suicidal ideation	Negative	Positive	Negative
8	Directly asked regarding suicidality now and he stated he had no such thoughts at present	Negative	Positive	Positive