Paraphrase Identification via Textual Inference

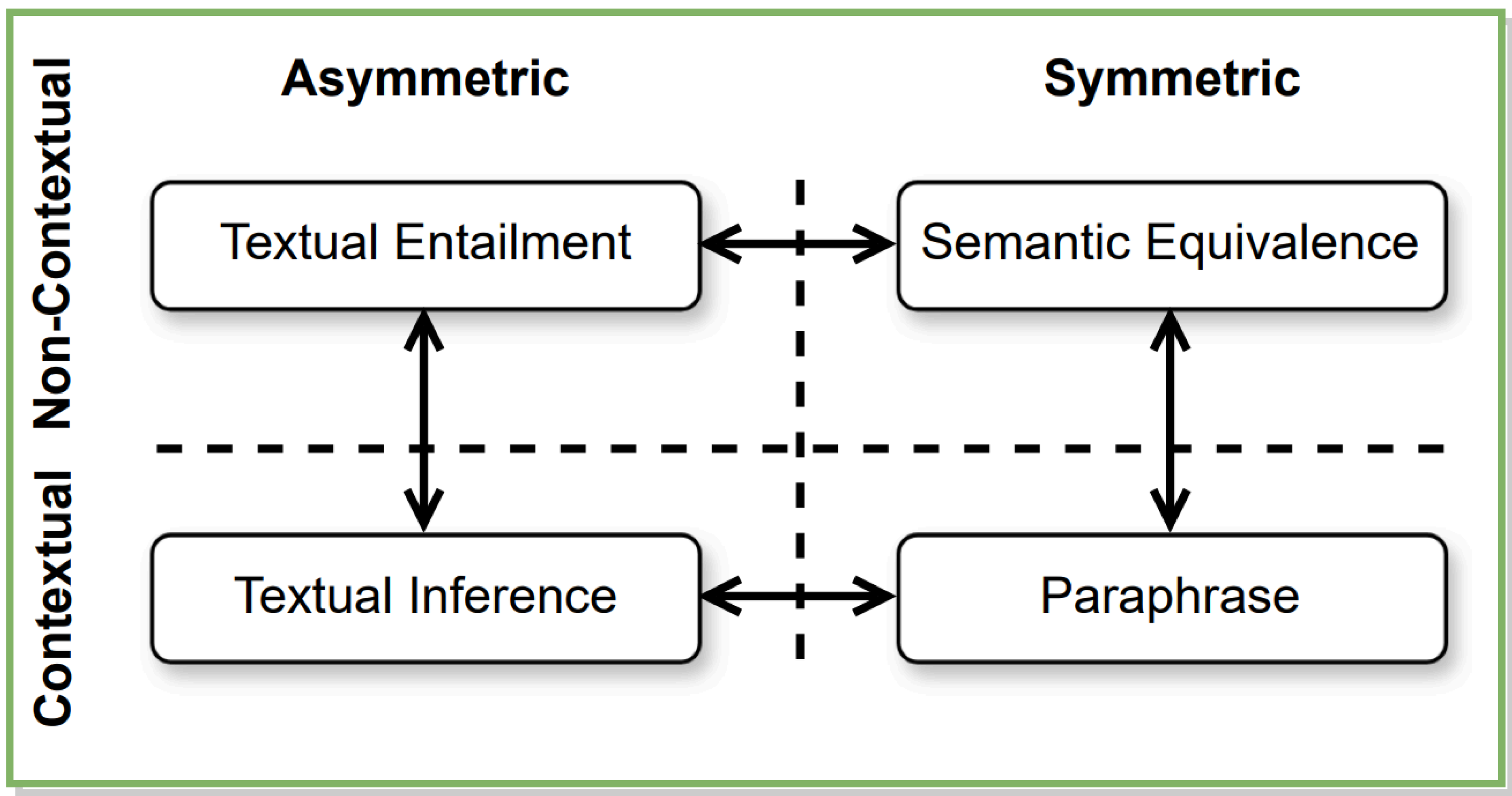
Ning Shi, Bradley Hauer, Jai Riley, Grzegorz Kondrak
{ning.shi,bmhauer,jrbuhr,gkondrak}@ualberta.ca

Introduction

Paraphrase **I**dentification **(PI)** is the task of deciding whether two sentences **convey the same meaning.**
Natural **L**anguage **I**nference **(NLI)** involves three labels that describe the **relationship between two sentences: entailment,** contradiction, and neutral.

It has been hypothesized that **paraphrasing corresponds to bidirectional textual entailment,** but existing empirical methods lack theoretical formalization and resemble traditional PI approaches.

We present the first theoretical formalization implying a practical reduction of PI to NLI, validated by fine-tuning an NLI model for PI.



Dataset Adaptation

We posit that the task of **PI can be reduced to NLI (PI2NLI),** specifically the detection of the TI relation by training an NLI system on PI data.
To do this, we **convert each positive PI instance into two distinct positive NLI** instances (NLI label is entailment), one in each direction, indicating **mutual TI between two paraphrases.**

Positive Paraphrase Instance → **Positive NLI Instance**, **Positive NLI Instance** → **Mutual Entailment**

A **negative PI instance** is transformed into **a negative NLI instance** (NLI label randomly selected as either contradiction or neutral) in **one randomly selected direction.**

Negative Paraphrase Instance → **Negative NLI Instance** → **Contradiction /Neutral**

Methodology

We **solve Paraphrase Indentification (PI) by reducing the problem to Textual Inference (TI)** and solving via a fine-tuning procedure that allows an NLI model to be fine-tuned for PI instances. To do this we make the following formalizations:

S**emantic **E**quivalence,* ***SEQ(S_1, S_2) := *"the sentences, S_1 and S_2, convey the same meaning"*

P**araphrase **R**elation,* ***PR(C, S_1, S_2) := *"the sentences, S_1 and S_2, convey the same meaning in the given context, C"*

For example:

S_1 = We must work hard to win this election.

S_2 = The Democrats must work hard to win this election.

Reduction from SEQ to PR:

$$SEQ(S_1, S_2) \Leftrightarrow \forall C : PR(C, S_1, S_2)$$

T**extual **E**ntailment,* ***TE(S_1, S_2) := *"the sentence, S_2, can be inferred from the sentence, S_1"*

Reduction from SEQ to TE:

$$SEQ(S_1, S_2) \Leftrightarrow TE(S_1, S_2) \wedge TE(S_2, S_1)$$

T**extual **I**nference,* ***TI(C, S_1, S_2) := *"the sentence, S_2, can be inferred from the sentence, S_1, given the context, C"*

Reduction from TE to TI:

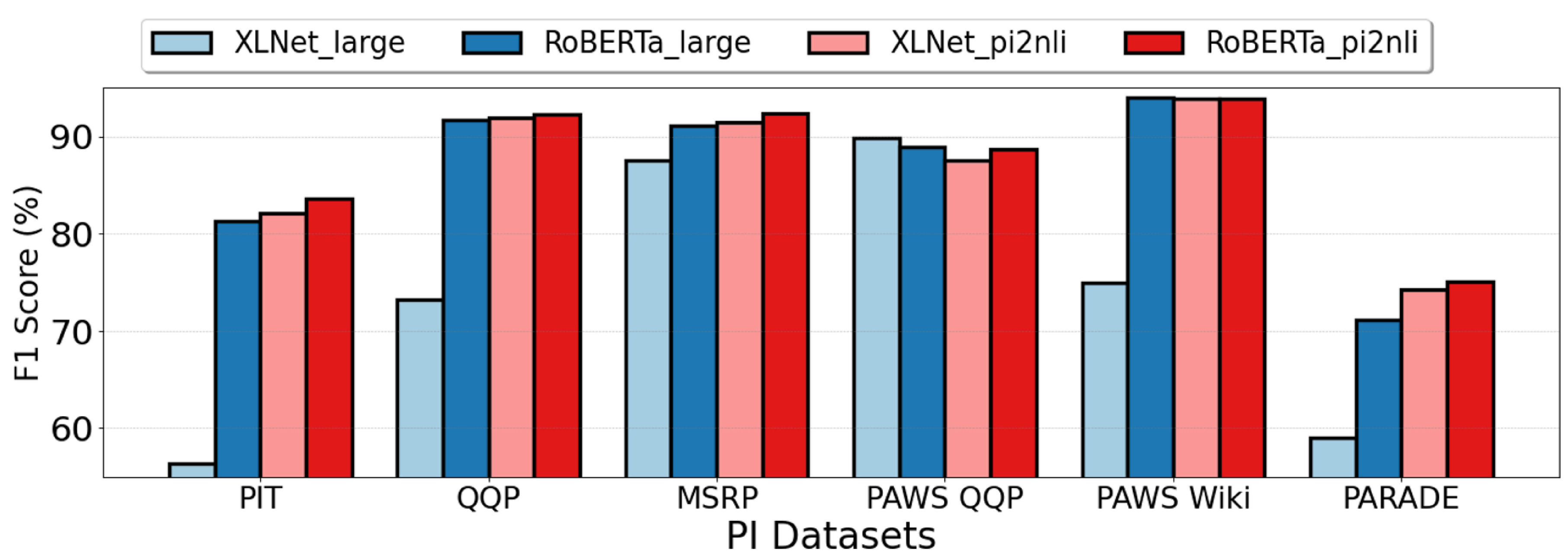
$$TE(S_1, S_2) \Leftrightarrow \forall C : TI(C, S_1, S_2)$$

Final Reduction from PR to TI (PI2NLI):

$$PR(C, S_1, S_2) \Leftrightarrow TI(C, S_1, S_2) \wedge TI(C, S_2, S_1)$$

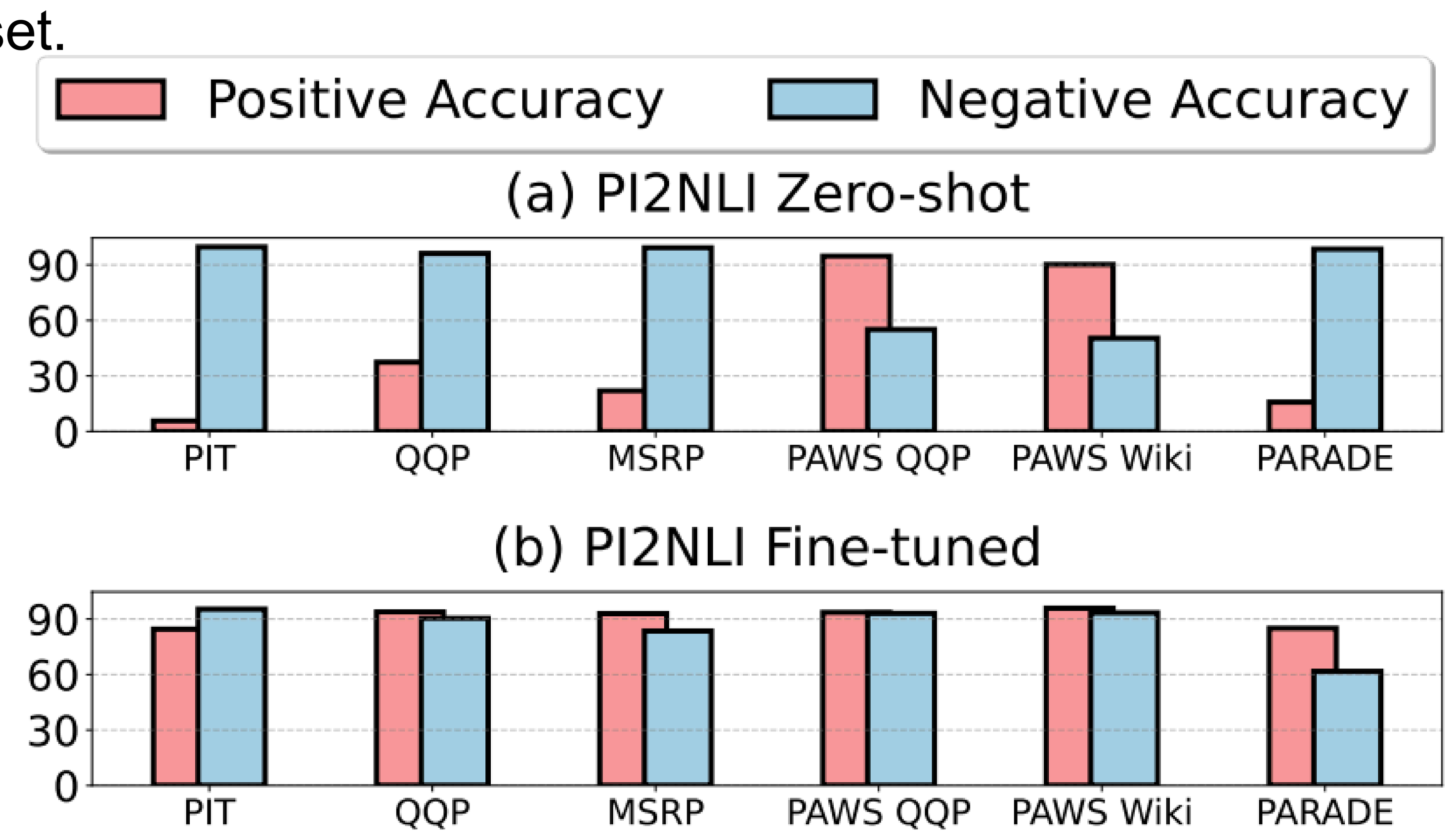
Results

Our PI2NLI reduction yields consistently high F1 scores, outperforming the reported results obtained by prior work on all non-PAWS datasets.



Effect of Fine-Tuning

In order to perform better in the PI task, NLI models can correct their decision boundaries after fine-tuning. We view this adjustment as the **process of how models learn the context** inherent in each PI dataset.



Conclusion

- We **formalize the relationship between** four semantic tasks: **SEQ, PR, TE, and TI.**
- Introduce a **novel method for solving PI using an NLI system,** including the adaptation of PI datasets for fine-tuning NLI models.
- Though our method has limitations, we **achieve SOTA results on 4 PI datasets,** uncovering areas for greater improvement.

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