

Paraphrase Identification via Textual Inference

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Natural Language Inference

Natural Language Inference (NLI) involves three labels that describe the relationship between two sentences.

Entailment, Contradiction, Neutral

For example:

S_1 : "This man is surfing."

S_2 : "A man is on water."

Surfing: an aquatic activity or website browsing?



Paraphrase Identification

Paraphrase Identification (PI) is the task of deciding whether two sentences convey the same meaning.

Hypothesis:

Paraphrasing corresponds to **bidirectional textual entailment**.

Prior work:

- A blend of modules complicates the analysis
- Bias to traditional PI methods
- Lacks any theoretical formalization

Our Contributions

We present the **first theoretical formalization** implying a **practical reduction of PI to NLI** (PI2NLI), validated by fine-tuning an NLI model for PI.

- A theoretical task reduction showing how PI can be reduced to NLI.
- Extensive evaluation across zero-shot and fine-tuning.
- We found fine-tuned NLI models can **outperform** dedicated PI models on PI datasets.

A **P-to-Q** reduction solves an instance of a problem **P** by combining the solutions of one or more instances of **Q**.

Sentence-level Relations

Contextual Non-Contextual

Asymmetric

Symmetric

Textual Entailment

Semantic Equivalence

Textual Inference

Paraphrase

Equivalence and Paraphrasing

Semantic Equivalence relation, $\text{SEQ}(S_1, S_2)$:=
“the sentences S_1 and S_2 convey the same meaning”

Paraphrase Relation, $\text{PR}(C, S_1, S_2)$:= “the sentences S_1 and S_2 convey the same meaning
given the context C ”

The relationship in between:

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

Example:

S_1 : “We must work hard to win this election.”

S_2 : “The Democrats must work hard to win this election.”

Entailment and Inference

Textual Entailment, $TE(S_1, S_2) :=$

“the sentence S_2 can be inferred from the sentence S_1 ”

Textual Inference, $TI(C, S_1, S_2) :=$ “the sentence S_2 can be inferred from the sentence S_1 given the context C ”

The relationship in between:

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

Example:

S_1 : “This man is surfing.”

S_2 : “A man is on water.”

Proposition

Given context C , sentences S_1 and S_2 are paraphrases if and only if they can be mutually inferred from each other.

Formally:

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

Context:

- Context includes common sense and world knowledge.
- In practice, context is embedded in the data distribution.

Data Adaptation

Positive PI instances:

We convert each positive PI instance into two distinct NLI positive instances, one in each direction.

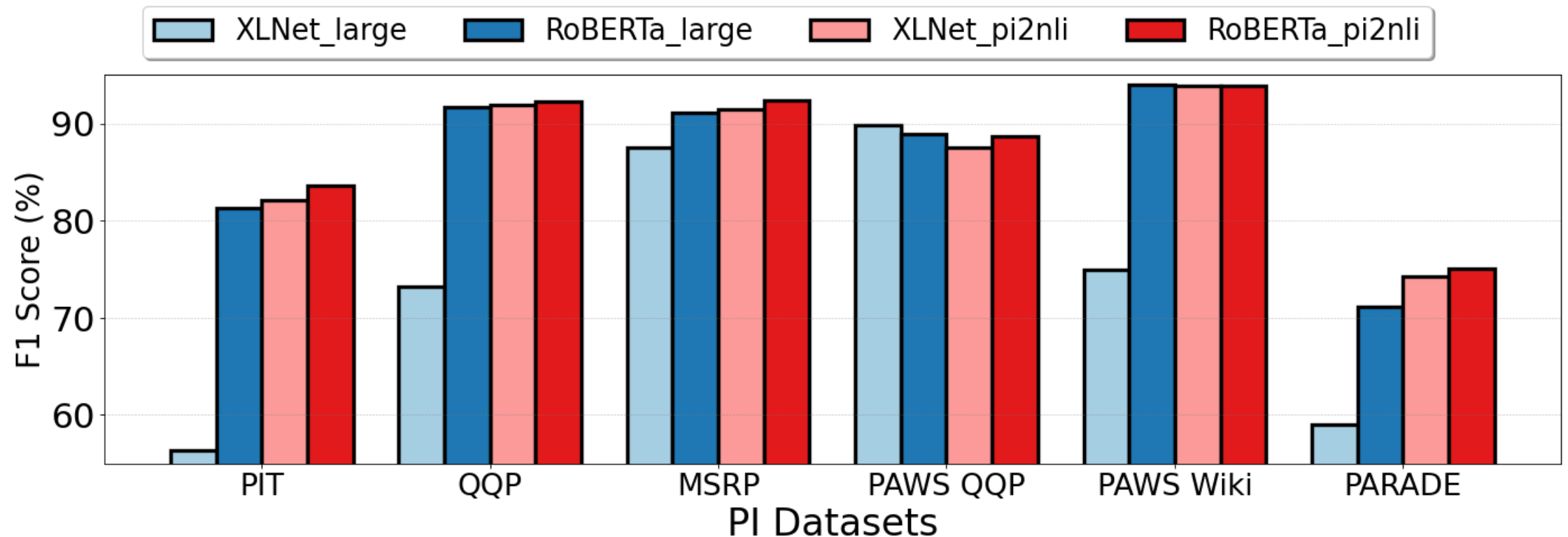
$PI(S_1, S_2, \text{True}) \rightarrow NLI(S_1, S_2, \text{Entailment})$ **AND** $NLI(S_2, S_1, \text{Entailment})$

Negative PI instances:

We generate a negative NLI instance (randomly selected as either contradiction or neutral) in one randomly selected direction.

$PI(S_1, S_2, \text{False}) \rightarrow$ $NLI(S_1, S_2, \text{Contradiction})$ **OR** $NLI(S_2, S_1, \text{Contradiction})$
 $NLI(S_1, S_2, \text{Neutral})$ **OR** $NLI(S_2, S_1, \text{Neutral})$

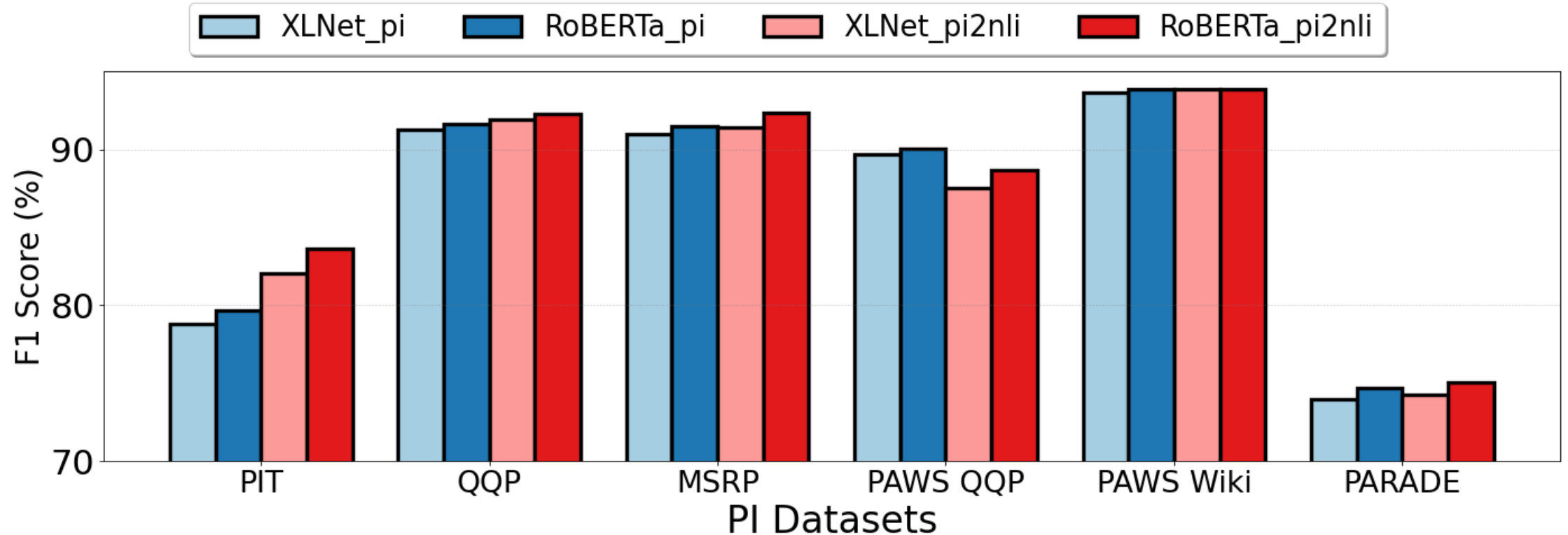
Results



XLNet_large (Yang et al., 2019); RoBERTa_large (Liu et al., 2019)

PAWS QQP and PAWS Wiki include **adversarial** example created by word scrambling and back-translation.

Ablation



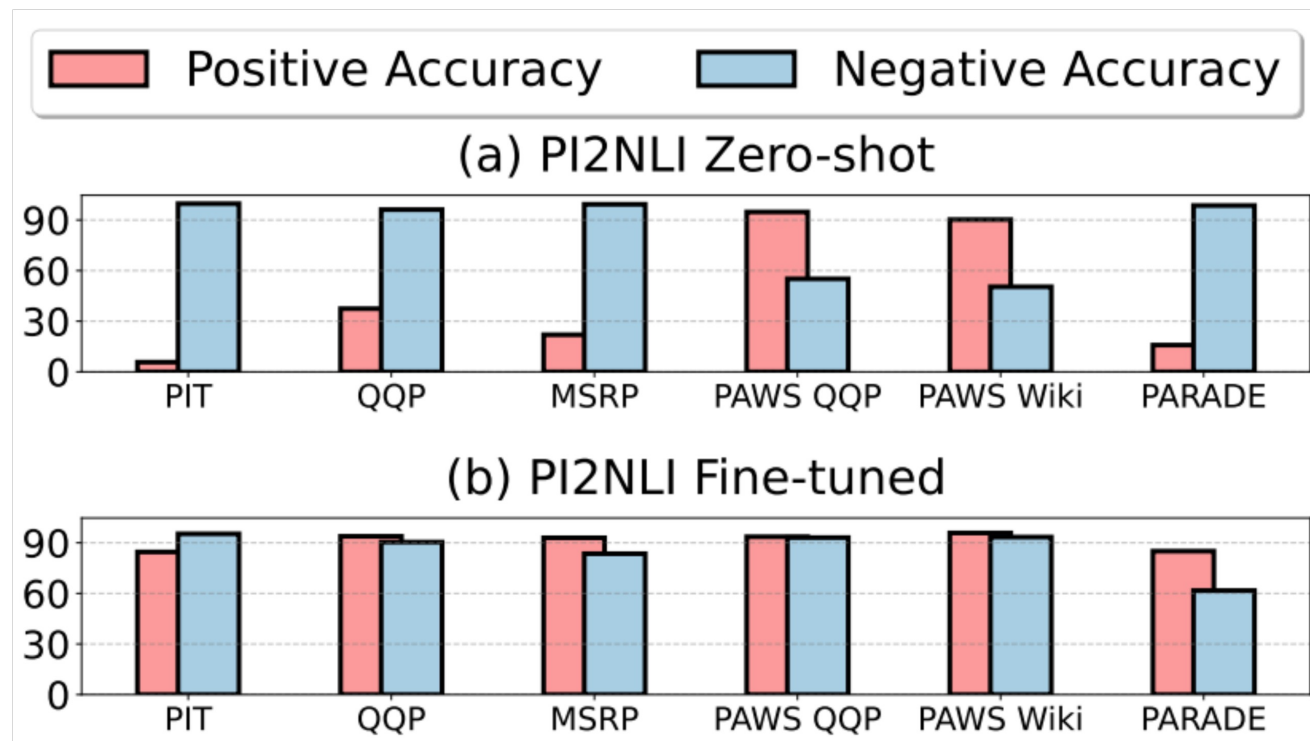
XLNet_pi, RoBERTa_pi (Nie et al., 2020)

The **same** language models with classification heads initialized from **scratch**.

Analysis - Context

A paraphrase identified in one dataset might **NOT** necessarily be considered a valid paraphrase in the other.

We view this **adjustment** as the process of how models learn the **context** inherent in each PI dataset.



Conclusion

We have presented PI2NLI, the first attempt to reduce PI to NLI.

- PI can be reduced to NLI **theoretically** and **empirically**.
- Fine-tuned NLI models can **outperform** PI models on PI datasets.
- Applying PI2NLI in a zero-shot setting show the **limitations** in the current PI datasets.

Future:

- Using NLI to refine PI data?
- Using PI models to solve NLI?
- Using one single model to solve both PI and NLI?

