

Zero-Shot Cross-Lingual SLU Robustness to Adversarial Noise under Varying Mutual Intent-Slot Guidance Strength

Assignee Research

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Abstract

Spoken language understanding (SLU) typically includes two sub-tasks: intent detection and slot filling. Currently, it has achieved great success in high-resource languages, but it still remains challenging in low-resource languages due to the scarcity of labeled training data. Hence, there is a growing interest in zero-shot cross-lingual SLU. Despite of the success of existing zero-shot cross-lingual SLU models, most of them neglect to achieve the mutual guidance between intent and slots. To address this issue, we propose an Intra-Inter Knowledge Distillation framework for zero-shot cross-ling

1 Introduction

This paper examines: I²KD-SLU: An Intra-Inter Knowledge Distillation Framework for Zero-Shot Cross-Lingual Spoken Language Understanding. Research question: What is the impact of varying the strength of mutual intent-slot guidance on the zero-shot cross-lingual F1 scores of SLU models when evaluated on adversarial examples or noisy inputs in MultiATIS++ and MultiSNIPS?.

2 Methodology

Systematic literature search across multiple databases yielded 6 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

6 papers retrieved. 12 claims extracted; 11 independently verified. Quality review score: 8.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The MultiATIS++ dataset consists of 18 intents and 84 slots for each language.	✓	0.18
The MultiATIS++ dataset includes human-translated data for six languages: Spanish, German, Chinese, Japanese, Portuguese	✓	0.23
The mBERT model in the experiment has $N = 12$ attention heads and $M = 12$ transformer blocks.	✓	0.21
Hyperparameters are selected by searching a combination of batch size and learning rate within the candidate sets $\{4, 8,$	✓	0.28
The parameters α , β , λ , γ are set to 0.9, 0.1, 0.7, and 0.3 in Eq.10, respectively.	✓	0.16
The Adam optimizer is used with $\beta_1 = 0.9$ and $\beta_2 = 0.98$.	×	0.13
The learning rate decreases proportionally to the inverse square root of the step number after the warm-up phase.	✓	0.25
The model that achieves the highest overall accuracy on the dev set is selected and evaluated on the test set.	✓	0.18
All experiments are conducted on an Nvidia Tesla-V100 GPU.	✓	0.19
I2KD-SLU achieves a significant improvement over the previous best model in overall accuracy on the MultiATIS++ dataset.	✓	0.20
The intent detection task predicts the intent of $\mathbf{x} = (x_1, x_2, \dots, x_n)$.	✓	0.22
The slot filling task maps each utterance \mathbf{x} into a slot sequence $\mathbf{oS} = (oS_1, oS_2, \dots, oS_n)$.	✓	0.18

References

- <http://arxiv.org/abs/2104.08645v2>
- <http://arxiv.org/abs/2310.02594v1>
- <http://arxiv.org/abs/2306.12916v3>