Zero-shot Slot Filling with Slot-Prefix Prompting and Attention Relationship Descriptor

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Abstract

This presentation is to present our recent work of addressing zero-shot slot filling problem [1]. Zero-shot slot filling task aims to build a system that can generalize to unseen slot types without any training data. The key to zero-shot slot-filling is to match the tokens from the utterance with the semantic definition of the slot without training data in the target domain. Our work tackles this problem by devising a scheme to fully leverage pre-trained language models (PLMs). To this end, we propose a new prompting scheme - Slot-Prefix (SP) Prompting that utilizes both learnable tokens and slot names to guide the model to focus on the relevant text spans for a given slot. Figure 1 presents the scheme differences between our work and previous state-of-the-art methods. Furthermore, we use attention values between tokens to form a feature descriptor for each token, which is motivated by the fact that the attention value in a PLM naturally characterizes various relationships, e.g., syntactic or semantic, between tokens. By further consolidating those features with an additional transformer-based aggregation module, we create a simple-but-effective zero-shot slot filling system that can achieve significantly better performance than the previous methods, as demonstrated in Table 1.

References

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Training Setting	SNIPS Zero-Shot							
Model ↓	ATP	BR	GW	PM	RB	SCW	FSE	**Avg F1**
CT (Bapna et al., 2017)	38.82	27.54	46.45	32.86	14.54	39.79	13.83	30.55
RZT (Shah et al., 2019)	42.77	30.68	50.28	33.12	16.43	44.45	12.25	32.85
Coach (Liu et al., 2020)	50.90	34.01	50.47	32.01	22.06	46.65	25.63	37.39
CZSL (He et al., 2020)	53.89	34.06	52.24	34.59	31.53	50.61	30.05	40.99
ZSBT[BERT] (Devlin et al., 2018)	55.78	**49.34**	56.58	28.35	27.09	57.61	20.05	42.18
PCLC (Wang et al., 2021)	59.24	41.36	54.21	34.95	29.31	53.51	27.17	42.82
QASF (Du et al., 2021)	**59.29**	43.13	59.02	33.62	33.34	59.90	22.83	44.45
SPFT (ours)	<u>58.16</u>	<u>44.94</u>	**66.06**	<u>36.53</u>	28.02	<u>67.77</u>	<u>34.54</u>	<u>48.00</u>
SPPT (ours)	55.61	44.39	<u>65.53</u>	**41.19**	<u>33.87</u>	**71.95**	**39.01**	**50.22**

Table 1: Zero-shot Slot Filling F1-scores (%) for seven different target domains on SNIPS dataset. The highest scores are **bolded**. The second highest score is <u>underlined</u>. SPFT refers to our proposed SP prompting based on finetuning, SPPT refers to SP prompting based deep prompt tuning.

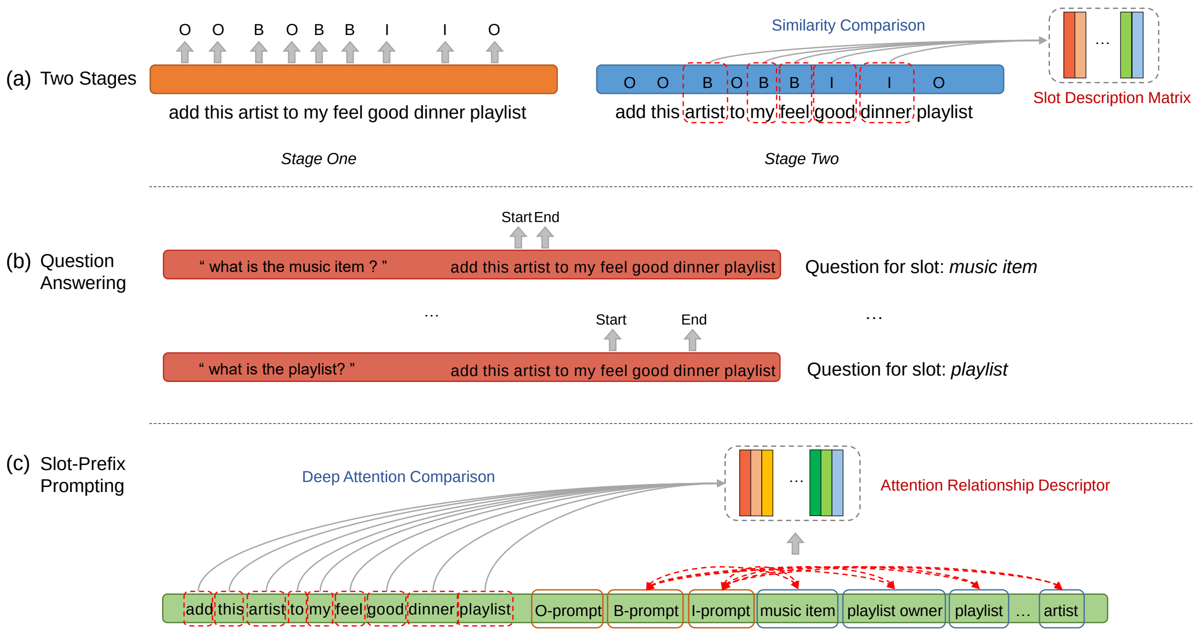

Figure 1: Comparison for zero-shot slot filling systems. (a) Two stage methods conduct BIO classification at first stage. Then, they apply an another encoder to extract features from B and I positions, and use the features to do similarity comparison with slot description representations. (b) Question answering approaches generate a question for each slot type and predict the slot span from start and end position of input utterance in a single stage. (c) Our proposed Slot-Prefix Prompting method reconstructs the input with continuous learnable prompts and slot descriptions, it can use a PLM to perform deep attention comparison and predict all slot types in a single stage.