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Cross-domain Slot Filling with Distinct Slot Entity and Type Prediction

Shudong Liu, Peijie Huang*, Zhanbiao Zhu, Hualin Zhang and Jianying Tan
South China Agricultural University

Reporter: Shudong Liu

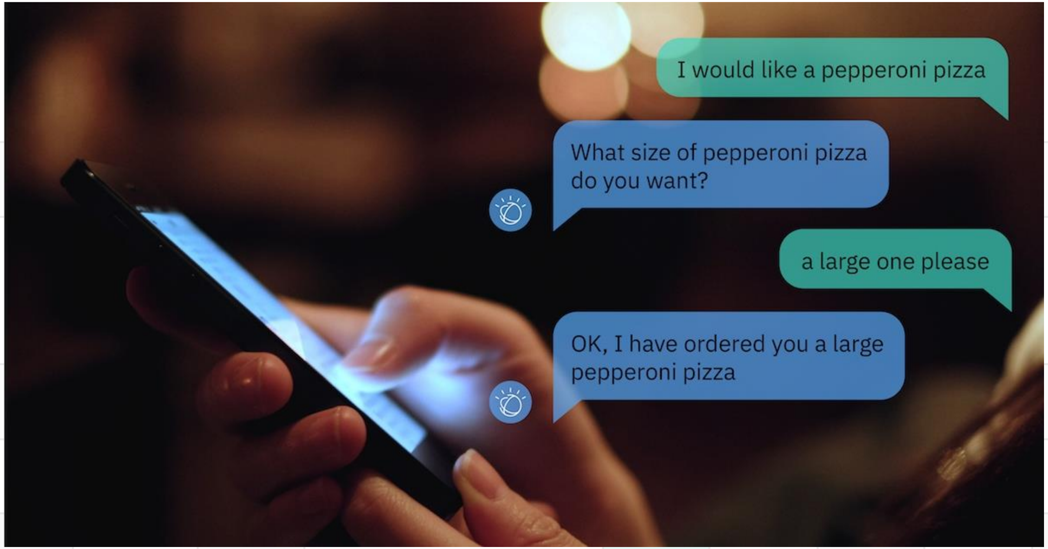
The Report Outline

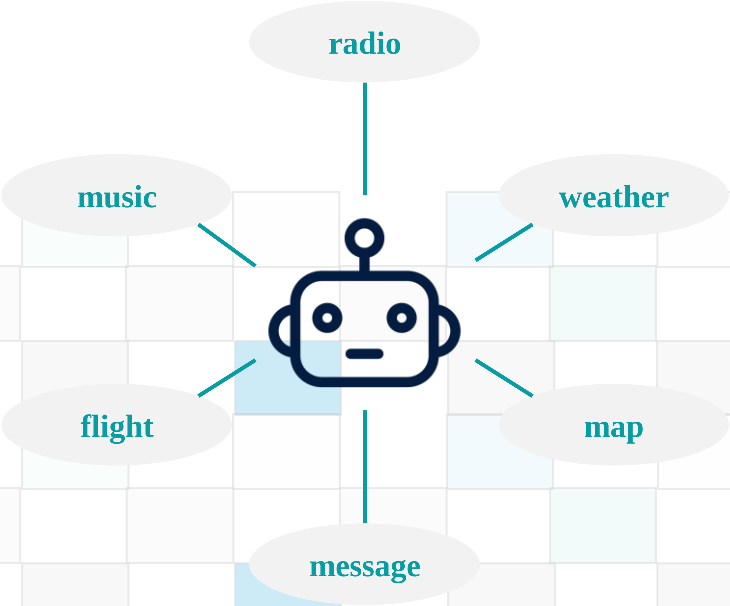
1. **Research Background**
2. Motivations
3. Methods
4. Experiments
5. Conclusion and Prospect

Research Background-Task Background

Task-oriented Dialogue System

- In-car dialog systems
- Shopping guide robot system





Spoken Language Understanding

- **Intent Detection** : sentence classification

- **Slot Filling** : sequence labeling

Sentence	What	is	the	weather	in	Qingdao	this	year
SLOT	O	O	O	O	O	B-city	B-timerange	I-timerange
INTENT	Get Weather							

Research Background-Task Background

Cross-domain Slot Filling

- Recent approaches are expensive and time-consuming due to the difficulties in **collecting high-quality labeled training data with different domains**
- **Cross-domain adaptation** copes with the data scarcity problem in low-resource target domains

Cross-domain Slot Filling

Domain	slots	
	cross-domain shared	domain-specific
AddToPlaylist	artist, playlist, music_item	playlist_owner, entity_name
BookRestaurant	country, state, timeRange, sort, spatial_relation, city	party_size_number, poi, restaurant_type, facility, party_size_description, served_dish, cuisine, restaurant_name
GetWeather	country, state, timeRange, city, spatial_relation	spacurrent_location, condition_description condition_temperature, geographic_poi
PlayMusic	sort, artist, playlist, music_item	year, album, genre, track, service
RateBook	object_type, object_name	object_part_of_series_type, rating_value, object_select, best_rating, rating_unit
SearchCreativeWork	object_type, object_name	-
FindScreeningEvent	timeRange, object_type, spatial_relation	object_location_type, movie_type, movie_name, location_name

Motivations

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Motivations

Challenges

- Unseen slot labels
- Zero-shot learning
- Differences between domains

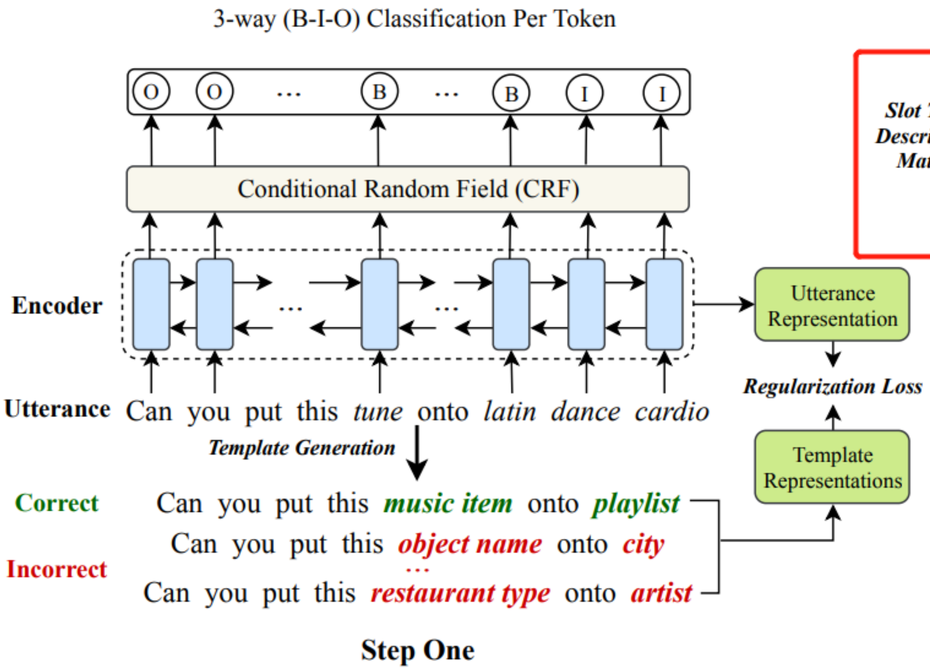
Slot Description

- Label description
- Make labels have semantic information
- Example:

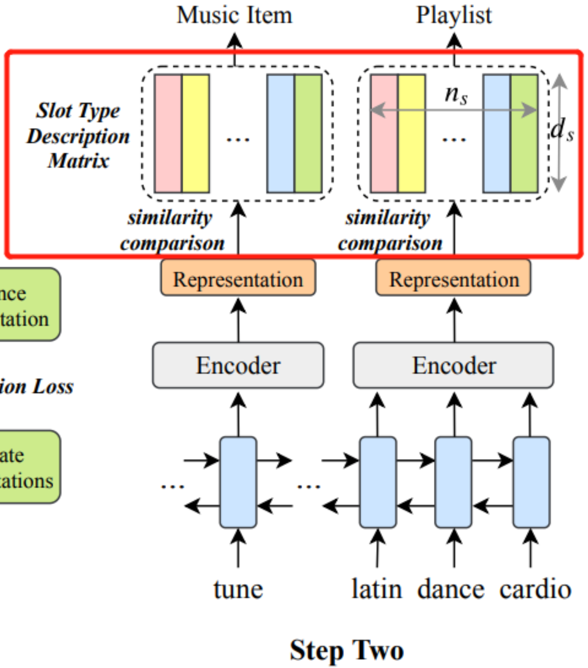
Slot	artist
Simple Description	artist
Complex Description	a person who is engaged in artistic creation or has artistic achievements

Related Works

- One-stage Model



- Two-stage Model



Motivations

Related Works

- One-stage Model: conducts slot filling(3-classification) individually for each slot type based on slot descriptions
- Two-stage Model: use the shared representation to identify whether the tokens are slot entities or not (3-classification), and then predict their specific slot types based on slot descriptions
- Our pipeline Model: Use distinct representation for two sub-tasks

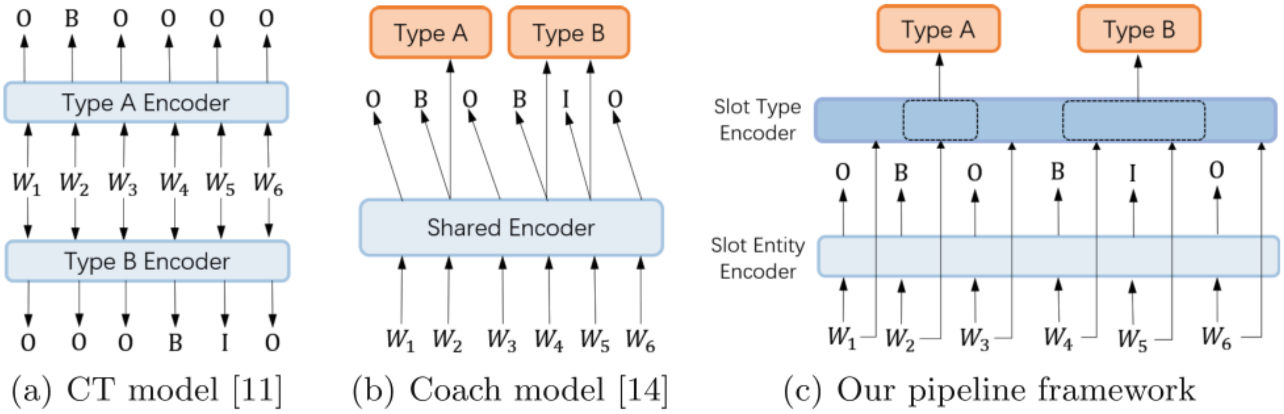


Fig. 1. Cross-domain slot filling frameworks.

Motivations

Remaining challenges

- The information captured in cross-domain learning in slot entity identification and slot type alignment is different. The slot entity identification is to detect the entity boundary while the slot type alignment is to predict slot labels by contexts. The performance of these two-stage models drops in both tasks since affecting each other.
- Such approaches treat each source domain corpus equally. However, in cross-domain learning, different source domains have different contributions to the target domain, and some of them may even cause negative transfer problems.
- For example, given target domain "GetWeather", the model can get more improvements from "BookRestaurant" domain because of the location-related shared slots, but fewer improvements from the "PlayMusic" domain with no related shared slots at all.

Methods

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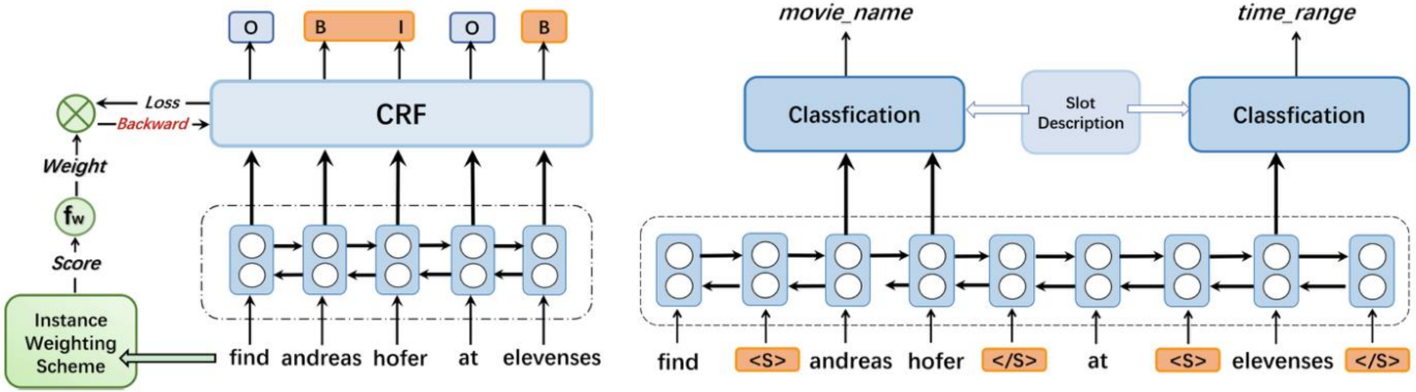
Methods

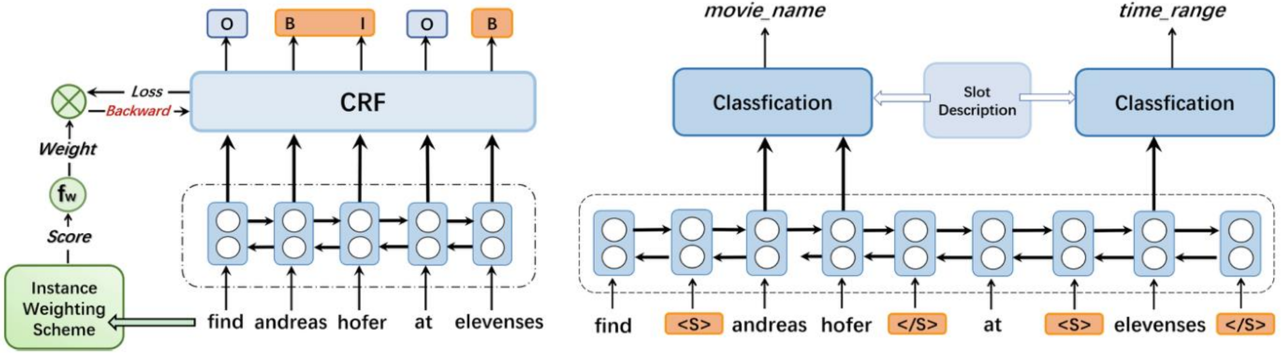
Methods



(a) Slot entity model (b) Slot type model

- Proposing a pipeline approach for cross-domain slot filling with distinct contextual representations for slot entities and slot types.
- Introducing a simple yet effective instance weighting scheme for better capturing slot entities and alleviating the negative transfer problem.
- Experiments in the zero-shot/few-shot settings on SNIPS and SMP-ECDT datasets show that our approach outperforms the state-of-the-art models. Ablation study and quantitative analysis also prove the effectiveness of the proposed model.

Methods



(a) Slot entity model

(b) Slot type model

Boundary markers → $$\widehat{W} = \ldots \langle S \rangle, w_{START(i)}, \cdots, w_{END(i)}, \langle /S \rangle \ldots$$

Domain similarity score → $$score(sd, td) = \frac{|Slot_{shared}|}{|Slot_{sd}|} \cdot \frac{|Slot_{shared}|}{|Slot_{td}|}$$

Weights for learning rate → $$weight(sd, td) = f_w(score) = \alpha + \beta \cdot score(sd, td)$$

Weighted learning rate → $$LR(sd, td) = \epsilon \cdot weight(sd, td)$$

Experiments

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Experiments

- **SNIPS Dataset:** Public spoken language understanding dataset that contains 39 slot types across 7 domains
- **SMP-ECDT Dataset:** Public benchmark corpus os SMP-ECDT provided by iFLYTEK Coporation

Datasets

Table 2. Detailed statistics of SMP-ECDT dataset.

Domain	Slots	
	Cross-domain shared	Domain-specific
cookbook	keyword	dishName, utensil, ingredient
epg	datetime_time, datetime_date, category, name, code, area	tvchannel
map	startLoc_poi, endLoc_poi, startLoc_city, endLoc_city, endLoc_province, endLoc_area, location_city, location_province, type, startLoc_area	location_area, location_poi
message	name, content, category, teleOperator	receiver, headNum
poetry	keyword, author, name	queryField, dynasty
train	startDate_date, category, startLoc_city, endLoc_city, startLoc_area, endLoc_area, startLoc_province, endLoc_province, startLoc_poi, startDate_time	–
video	name, category, timeDescr, area, popularity, artist	tag, scoreDescr

Main Results

- There are Average-F1 improvements in 2 datasets on zero-shot/few-shot setting compared with all the baselines.

Table 4. Slot F1-scores on SMP-ECDT for different target domains under zero/few-shot learning settings. * indicates the significant improvement over all baselines ($p < 0.05$)

Training Setting	Zero-shot					Few-shot on 5 samples				
Domain↓ Model→	CT	Coach	CZSL	PCD	PCD-Iw	CT	Coach	CZSL	PCD	PCD-Iw
cookbook	1.35	16.95	15.00	16.54	**22.27***	3.47	38.07	43.18	**48.62***	42.31
epg	9.50	18.84	20.54	**25.41***	24.59	13.95	31.37	29.54	39.92	**39.93***
map	16.75	22.15	23.42	22.95	**26.66***	18.39	**35.71**	32.02	28.33	28.40
message	11.19	29.87	25.23	26.59	**29.89***	30.86	33.87	34.86	31.79	**36.63***
poetry	19.03	43.19	43.66	43.41	**43.81**	21.96	50.48	53.67	45.74	**65.52***
train	84.58	**85.71**	85.09	83.96	84.05	84.95	85.16	85.14	**86.65***	86.31
video	19.41	26.39	32.13	**36.68***	32.53	22.14	30.56	30.82	34.42	**35.07***
Average F1	23.21	34.73	35.01	36.50	**37.69***	26.94	43.60	43.92	45.07	**47.73***

Results on Slot Entity Identification

- **Significant improvement especially with instance weighting scheme**

Table 6. BIO F1-scores on SMP-ECDT for different target domains under zero/few-shot learning settings.

Training setting	Zero-shot				Few-shot on 5 samples			
Domain↓ Model→	Coach	CZSL	PCD	PCD-Iw	Coach	CZSL	PCD	PCD-Iw
cookbook	65.84	70.50	73.24	**74.35**	71.74	71.11	**74.71**	74.31
epg	29.72	34.89	41.46	**42.70**	38.61	35.28	49.19	**49.28**
map	53.15	57.00	55.95	**57.32**	56.21	52.63	54.50	**56.25**
message	38.35	33.50	36.17	**44.58**	39.16	40.73	42.06	**46.47**
poetry	51.15	**53.08**	51.41	52.05	53.50	54.68	52.69	**74.86**
train	**92.13**	89.70	91.04	89.20	91.26	89.65	93.00	**93.57**
video	32.39	41.58	42.23	**42.51**	35.12	36.79	40.91	**44.15**
Average F1	51.82	54.32	55.93	**57.52**	55.09	54.41	58.15	**62.70**

Results on Seen and Unseen Slots

- **Improvement on both seen and unseen slots**

Table 7. Average F1-scores on SNIPS and SMP-ECDT for seen and unseen slots across all target domains.

Dataset	SNIPS				SMP-ECDT			
Setting	0 sample		50 samples		0 sample		5 samples	
	unseen	seen	unseen	seen	unseen	seen	unseen	seen
CT	27.10	44.18	62.05	69.64	11.85	30.95	18.29	34.64
Coach	34.09	51.93	76.49	80.16	18.98	44.15	31.45	44.78
CZSL	34.57	52.69	77.15	80.09	17.05	46.74	32.74	43.41
CZSL-Adv	36.35	55.43	78.48	79.36	–	–	–	–
PCD	35.79	55.63	78.84	80.75	20.73	48.70	29.84	46.29
PCD-Iw	**36.98**	**56.96**	**80.61**	**81.66**	**21.12**	**49.08**	**39.76**	**49.17**

Conclusions

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Conclusions

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Thank You !

E-mail: sudan@foxmail.com (Shudong Liu)
pjhuang@scau.edu.cn (Peijie Huang)
Wechat: sudanl1999