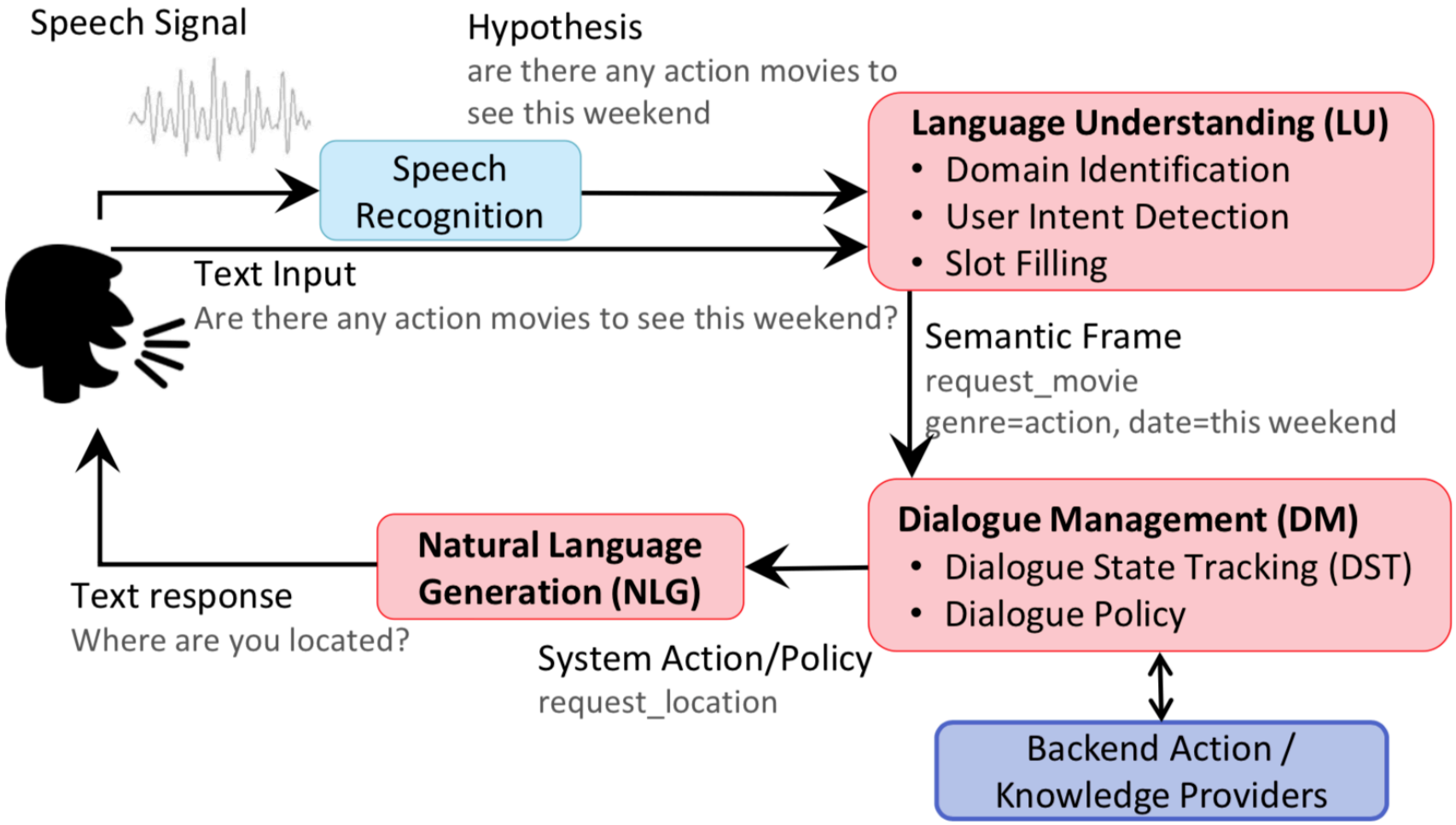
Source-Critical Reinforcement Learning for Transferring Spoken Language Understanding to a New Language

He Bai

Outline

- Background
- Related Works
- Methods
- Experiments
- Conclusions

Background


Speech Signal
Hypothesis
are there any action movies to see this weekend
Speech Recognition
Language Understanding (LU)
• Domain Identification
• User Intent Detection
• Slot Filling
Text Input
Are there any action movies to see this weekend?
Semantic Frame
request_movie
genre=action, date=this weekend
Dialogue Management (DM)
• Dialogue State Tracking (DST)
• Dialogue Policy
Natural Language Generation (NLG)
Text response
Where are you located?
System Action/Policy
request_location
Backend Action / Knowledge Providers

Background

Suppose we have a Chinese SLU model, how can we extend it to handle queries in other language?

Related Works

- **Test on Source**
  - Translate English query into Chinese and predict with Chinese model
  - The final search engine has to deal with Chinese while the target answer database might be still in English
- **Train on Target**
  - Generate English annotated training data with Chinese SLU data and model, and then an English model can be trained.
  - Allows tuning and adaptation of the models in the target language directly,
  - Avoids an overhead of machine translation during real-time execution.

Related Works

- **Train on Target**
  - Both query and its semantic annotation need to be transferred properly to the target language

    我想给<*contact_name*> 王小明 <*contact_name*>发短信，告诉他 <*content*> 我今晚回家吃饭 <*content*>

    I want to send a text message to <contact_name> Wang Xiaoming <\contact_name> to tell him that <content> I will go home for dinner tonight <\content>

  - Two schemes:
    - Transferring source language annotation indirectly through word alignment
    - Adapting the translation model directly so that it learns how to translate text with slot labels

Related Works

- **Train on Target**
  - Slot Adaptation (Culture Adaptation)

A. 叫辆车去紫禁城

Call a taxi to Forbidden City

Call a taxi to Tower of London

B. 请拨打文彭凤的电话号码

Please call wen peng fung ' s phone number

Please call Bruno Clark' s phone number

Methods

- **1. Naive Translation**
  - Translate plain text with a well-trained general-purpose translator
  - Add back slot labels by alignment

Methods	Source input	Translation result
Naive Translation	我想打个电话给白晓霞	I would like to make a call to telephone number of white sunshine
Token-added Translation	我想打个电话给（a 白晓霞）	I would like to make a call to (a white sunshine) 's telephone number please
Class-based / SCRT	我想打个电话给 $contact_name	I would love to make a call to $contact_name 's number please

Methods

- **1. Naive Translation**
  - Translate plain text with a well-trained general-purpose translator
  - Add back slot labels by alignment

- A.请拨打 <contact_name> 王小明 <contact_name> 的电话号码
- B.请拨打王小明的电话号码
- C.Please call Wang Xiaoming ' s phone number
- D.Please call <contact_name> Wang Xiaoming </ contact_name> ' s phone number

Methods

- **1. Naive Translation**
  - Need no extra parallel data
  - Distant language pair
  - Wrong translations might result in wrong alignments

Methods

- **2. Token-added Translation**
  - special tokens to mark the segmentation boundary for the slot value
  - special tokens to indicate the slot name

Methods	Source input	Translation result
Naive Translation	我想打个电话给白晓霞	I would like to make a call to telephone number of white sunshine
Token-added Translation	我想打个电话给（a 白晓霞）	I would like to make a call to (a white sunshine) 's telephone number please
Class-based / SCRT	我想打个电话给 $contact_name	I would love to make a call to $contact_name 's number please

Methods

- **2. Token-added Translation**
  - Need no extra parallel data
  - No additional word alignment process is required
  - Relies heavily on the NMT general training data where the special tokens are kept in both source and target data

Methods

- **3. Class-based Translation**
  - Class symbol to replace both the slot label and its slot value in the source sentence

Methods	Source input	Translation result
Naive Translation	我想打个电话给白晓霞	I would like to make a call to telephone number of white sunshine
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Methods

- **3. Class-based Translation**
  - Class symbol to replace both the slot label and its slot value in the source sentence

- A.请拨打 <contact_name> 王小明 </contact_name> 的电话号码
- B.请拨打 <contact_name> 的电话号码
- C.Please call <contact_name> ' s phone number
- D.Please call <contact_name> Bruno Clark </contact_name> ’s phone number

Methods

- **3. Class-based Translation**
  - Avoiding a multi-word segment to be translated into several non-consecutive segments and not enclosed by the correct slot-label pairs
  - In-domain SLU parallel data is scarce, slots will be missed or mistranslated without enough parallel data

Methods

Can we take advantage of the existing Chinese SLU corpus to solve the slots missing or mistranslated problem of class-based method ?

- 我想听专辑<album>的<song>
- I want to listen to <album> of <artist>

Methods

- **Slot keeping ratio(SKR)**

For each (Chinese) sentence c_i , its SKR is defined as the number of slots in the translated (English) sentence, e_i, divided by the number of slots in c_i:

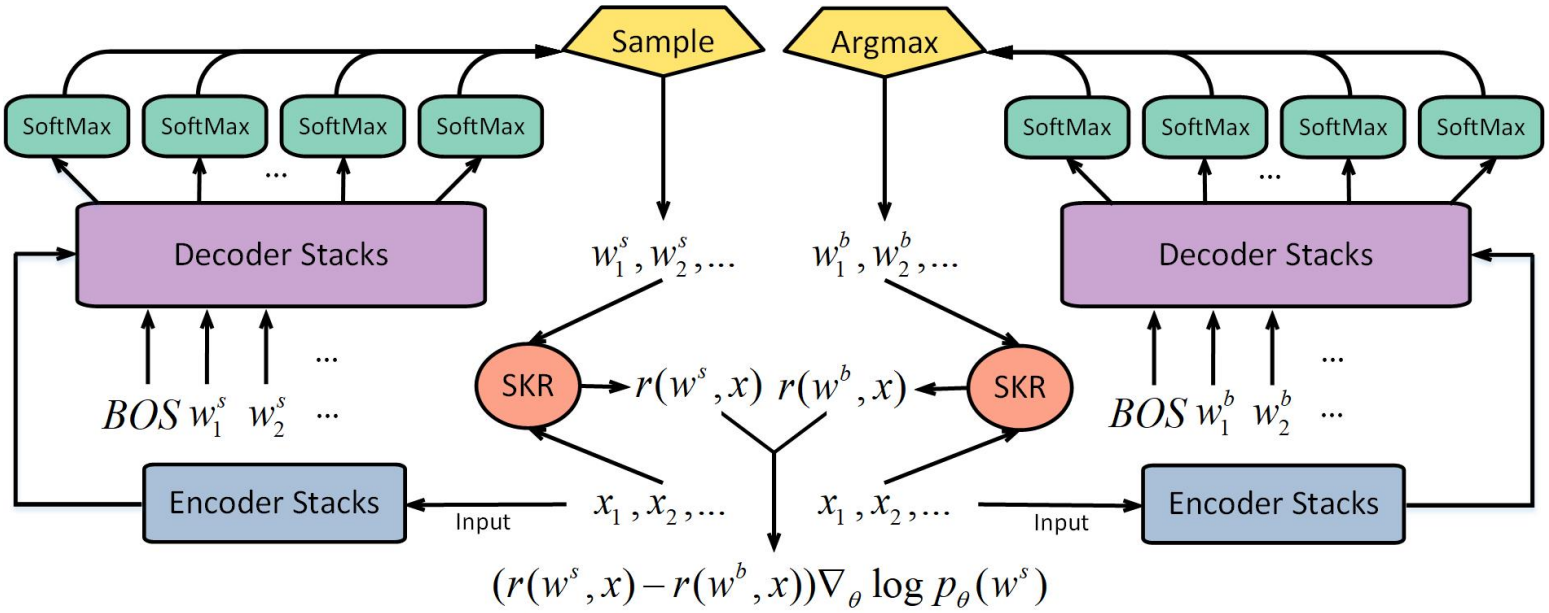
$$\mathrm{SKR}(c_i, e_i) = \frac{\sum_s \min(g(c_i, s), g(e_i, s))}{\sum_s g(c_i, s)} \times 100\%$$

The function $g(c_i, s)$ is used to count the occurrences of slot s in sentence c_i.

Methods

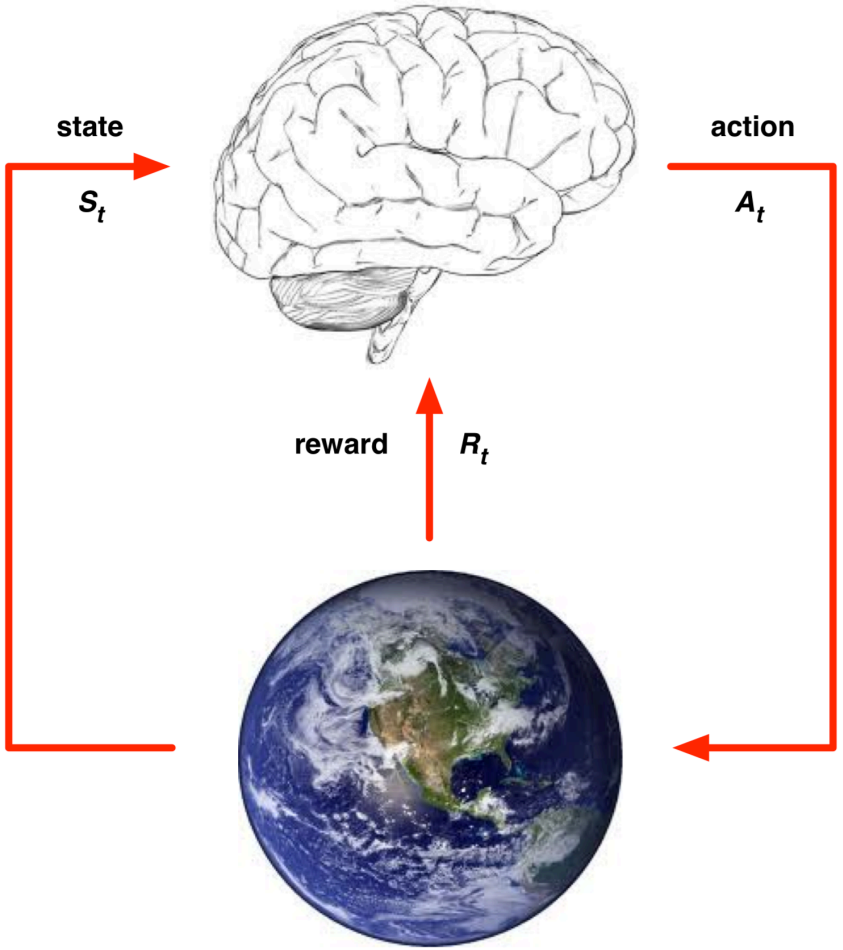
- **4. Source-Critical Reinforcement Translation**

$$\mathrm{SKR}(c_i, e_i) = \frac{\sum_s \min(g(c_i, s), g(e_i, s))}{\sum_s g(c_i, s)} \times 100\%$$



Methods

- **4. Source-Critical Reinforcement Translation**
  - agent: NMT model
  - policy: parameters of neural network
  - external environment: words
  - action: the prediction of the next word
  - reward: SKR



Methods

- **4. Source-Critical Reinforcement Translation**

$$
\begin{aligned}
L(\theta) &= -\sum_{w_1^g,\ldots,w_T^g} p_\theta(w_1^g, \ldots, w_T^g | x)\, r(w_1^g, \ldots, w_T^g, x) \\
&= -\mathbb{E}_{w^g \sim p(\theta)} r(w^g, x)
\end{aligned}
$$

$$
\nabla_\theta L(\theta) = -\mathbb{E}_{w^g \sim p(\theta)} r(w^g, x) \nabla_\theta \log p_\theta(w^g)
$$

$$
\begin{aligned}
\nabla_\theta L(\theta) &= -\mathbb{E}_{w^s \sim p(\theta)} (r(w^s, x) - b) \nabla_\theta \log p_\theta(w^s) \\
&\approx -(r(w^s, x) - b) \nabla_\theta \log p_\theta(w^s)
\end{aligned}
$$

Methods

- **4. Source-Critical Reinforcement Translation**

  Our SCRT only optimizes the SKR score with monolingual data and the SKR criterion itself does not impose constraints on translation quality.

  We initialize the SCRT model with parameters from the adapted class-based model and gradually increase the number of SCRT training steps.

Experiments

- **Experimental Setup**
  - **Data**
    - 3 domain: Communication, Music, Navigation
    - 3K Chinese annotated data to be transferred
    - 1.5K English annotated data as test set
    - 40k other domain data from Weiyuyi
    - 9M Zh-En parallel sentences without any annotations

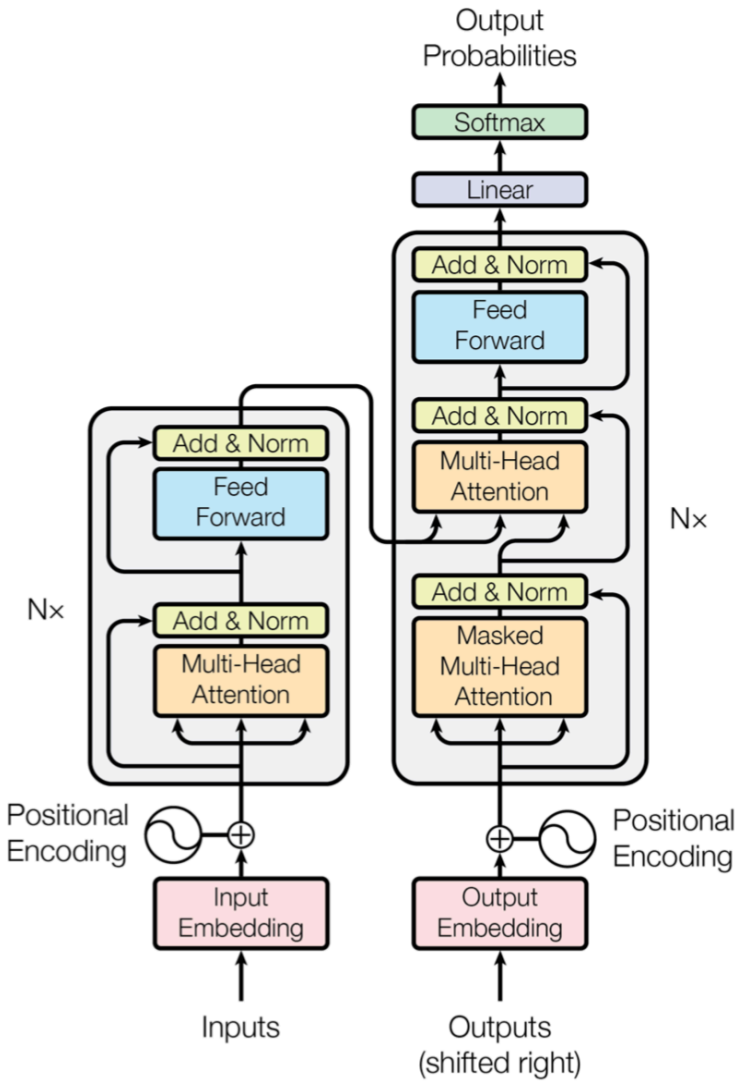
Experiments

- **Experimental Setup**
  - **Gazetteers for slot adaptation**

    We collect thousands of English names, artists, songs and albums to build a database for both slot adaptation and class symbol replacement.

Experiments

- **Experimental Setup**
  - **Model**
    - domain classify: SVM
    - slot filling: CRF
    - NMT: Transformer



Experiments

- **Results**
  - **Without parallel adaptation corpus**

Trans.	**Slot A.**	SKR	Slot_F1	Dom_Acc
Naive	No	57.13%	45.39	45.87%
Naive	Yes	57.13%	69.78	78.93%
TA	No	60.82%	24.87	55.07%
TA	Yes	60.82%	34.14	81.4%

Experiments

- **Results**
  - **With the additional 1200 parallel SLU sentences**

Trans.	Slot A.	SKR	Slot_F1	Dom_Acc
Naive	No	57.50%	56.79	68.73%
Naive	Yes	57.50%	70.79	81.4%
TA	No	**98.55%**	90.20	66.86%
TA	Yes	**98.55%**	91.91	82.87%
Class-based	Yes	97.03%	93.04	82.12%
+SCRT	Yes	98.08%	**97.19**	**84.2%**

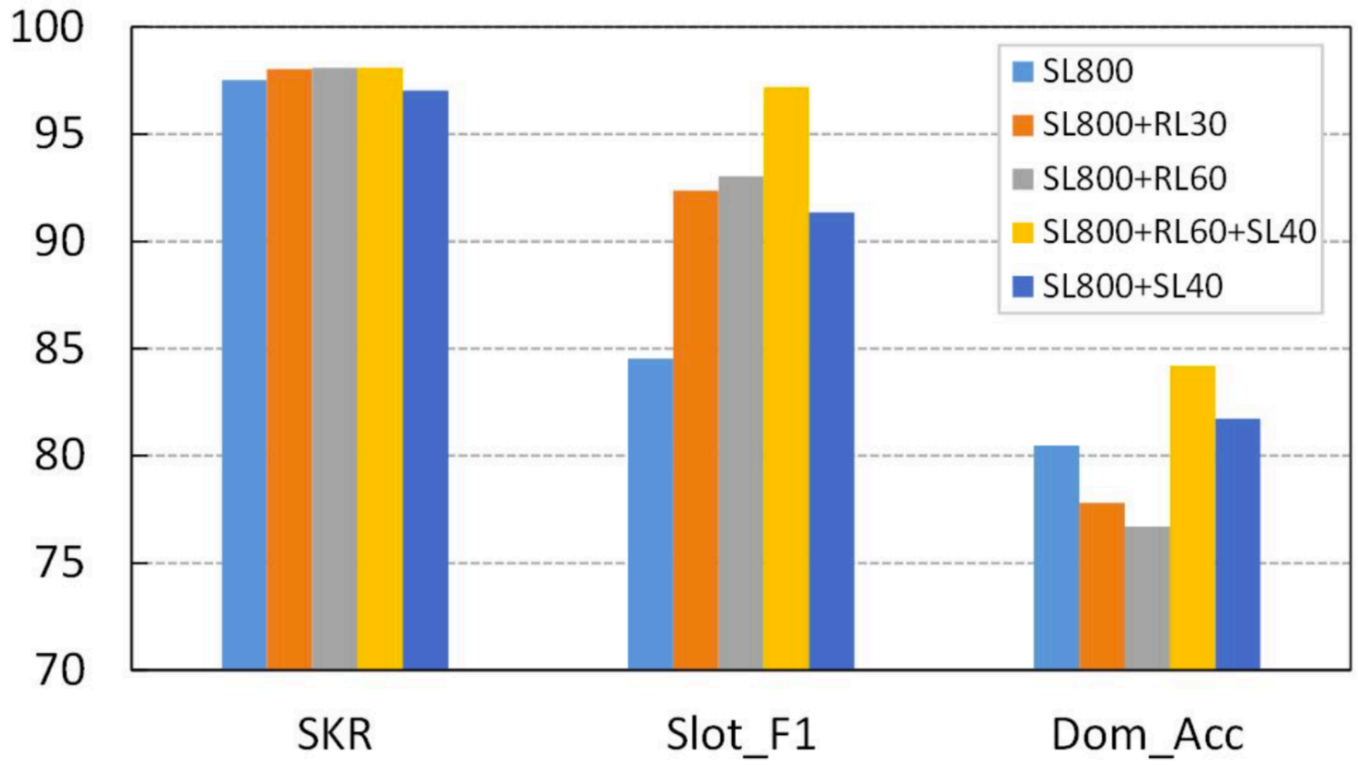
Experiments

- **Results**
  - **With the additional 90 parallel SLU sentences**

Trans.	Slot A.	SKR	Slot_F1	Dom_Acc
Naive	No	57.2%	50.15	76.73%
Naive	Yes	57.2%	70.13	**81.93%**
TA	No	88.22%	84.96	59.8%
TA	Yes	88.22%	85.21	78.53%
Class-based	Yes	85.07%	83.94	76.8%
+SCRT	Yes	**88.6%**	**91.07**	81.46%

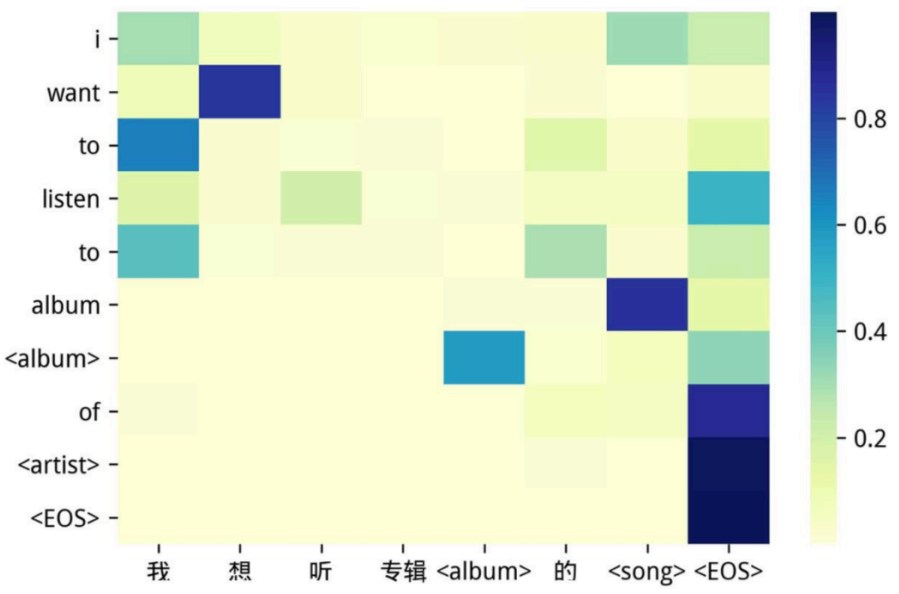
Experiments

- **Analysis**

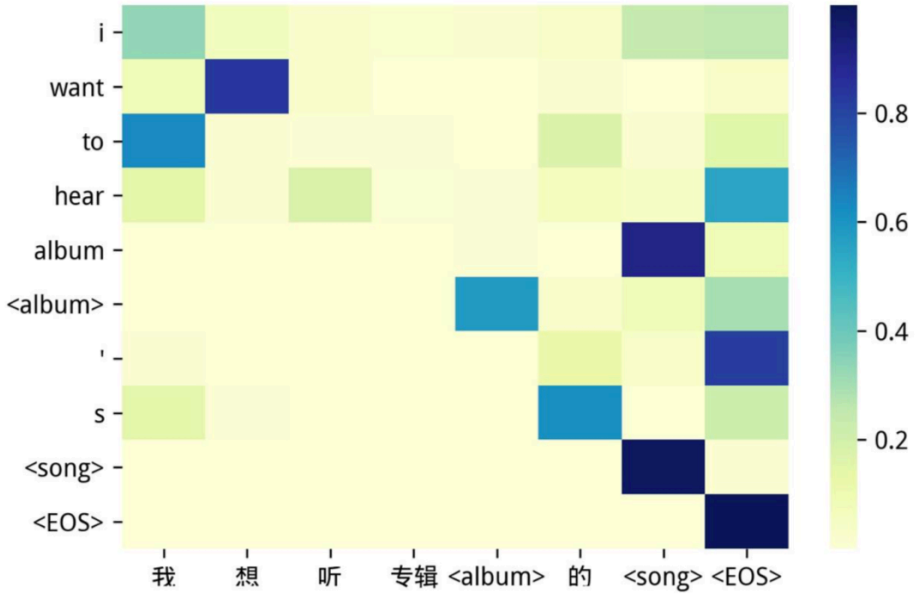


Experiments

- **Analysis**



(a) Class-based



(b) SCRT

Conclusions

- Our work is motivated by the practical demand in language transferring for SLU systems: the lack of large annotated in-domain parallel data, and the requirement of high-quality SLU corpus in the target language.

- We proposed a reinforcement learning approach with a source-critical mechanism to do further adaptation using monolingual data exclusively.

- Comparing with naive translation, the proposed method could improve domain classification accuracy by relatively 22%, and the slot filling F1 score by more than 71%.

Thanks!