LangCon 2021

Scalable Dialogue System

Naver AI Lab / 김성동

Who Am I?

Language Conference

이름: 김성동
소속: NAVER AI Lab / Language Research
관심 분야
- Language Model
- Robust and Scalable Dialogue Model
- Text Generation

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목차

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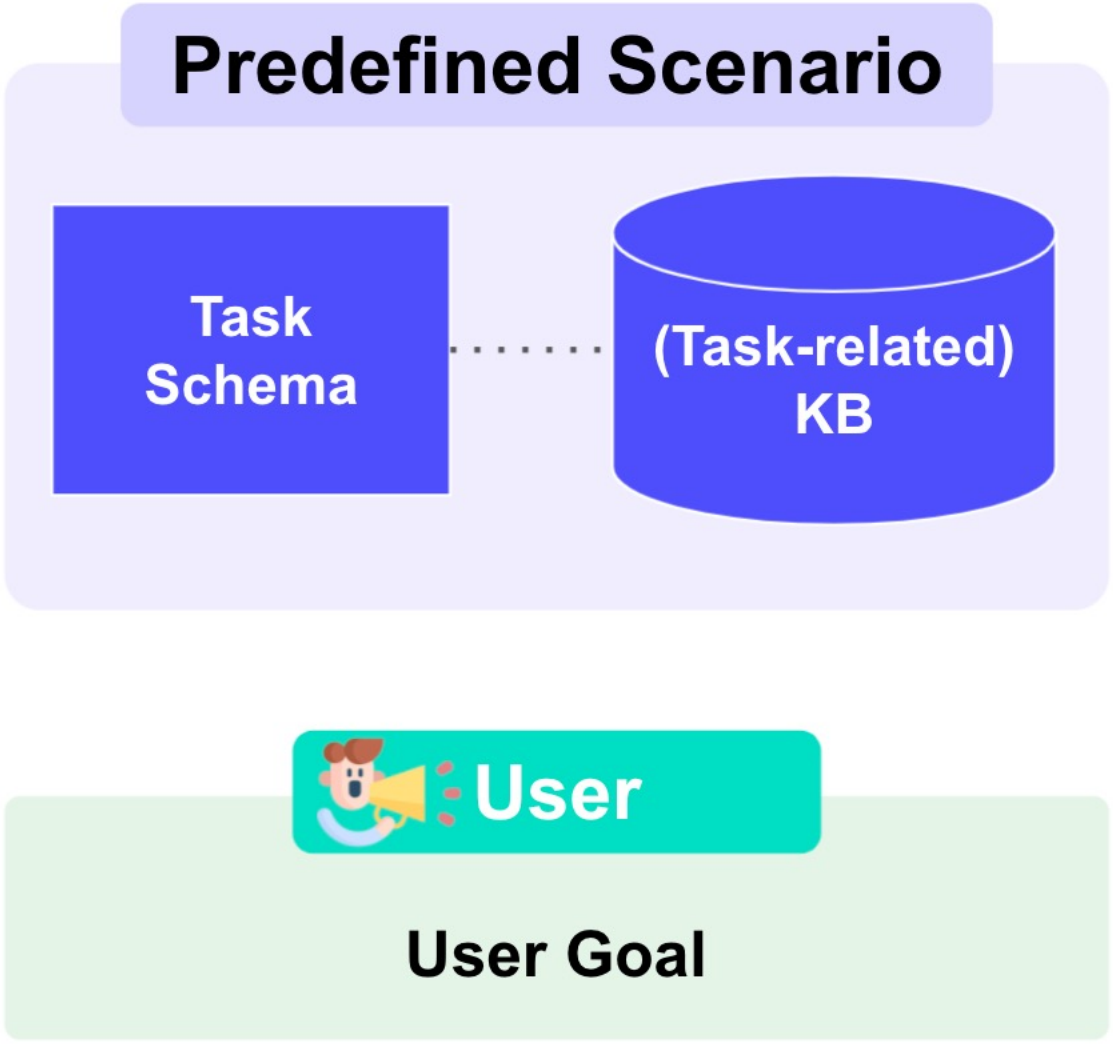
Task-Oriented Dialogue

"Task"-Oriented Dialogue

(Human's) Dialogue Coverage

Predefined Scenario

"Task"-Oriented Dialogue



1. User Goal

유저는 미리 정의된 KB의 특정 Instance 정보를 찾거나, 추가적인 정보를 제공하여 새로운 Instance를 찾고 싶어 한다는 가정

2. KB

시나리오에서 제공하고자 하는 정보를 담은 DB

3. **Task/Domain Schema**

User가 원하는 정보를 찾거나 시나리오에 맞는 정보를 줄 수 있도록 정의 된 메타 정보

"Task"-Oriented Dialogue

User

User Goal
==
Informable Slot
&
Requestable Slot

TOD는 User Goal의 파악 및 연계된 Task의 성공이 목적

User Goal은 크게 2가지 종류의 정보로 구성 된다고 가정

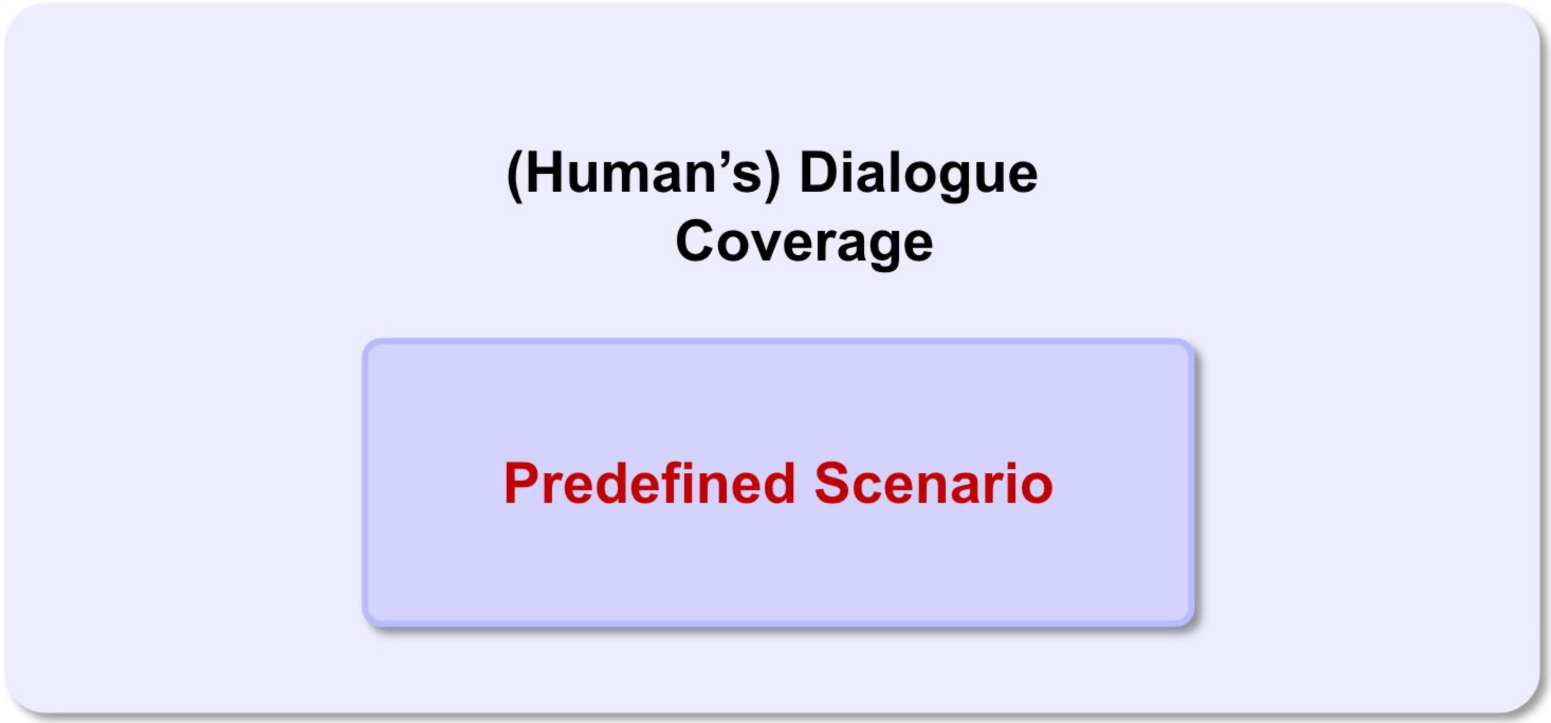
Informable Slot: 특정 KB instance를 찾거나, 새로운 instance를 write하기 위해 User가 System에게 주거나 맥락에 의해 User가 의도할 수 있는 타입의 정보 (**대화에 대한 제약 사항 및 DST의 target**)

Requestable Slot: 특정 KB instance가 선택된 이후, 추가로 정보를 요청할 수 있는 타입의 정보 (System이 User에게 제공)

이러한 정보의 "정의"가 바로 **Task Schema**

Limitations of TOD system

- 매우 좁은 커버리지 / 스킬셋(N intents, M slots)
- 극도로 제한된 대화 주도권 (시스템 사이드)
- 여러가지 가정들..!
- **사전 정의된 시나리오에 대한 높은 의존도**
  - **제한된 확장성 (시나리오 확장의 어려움)**



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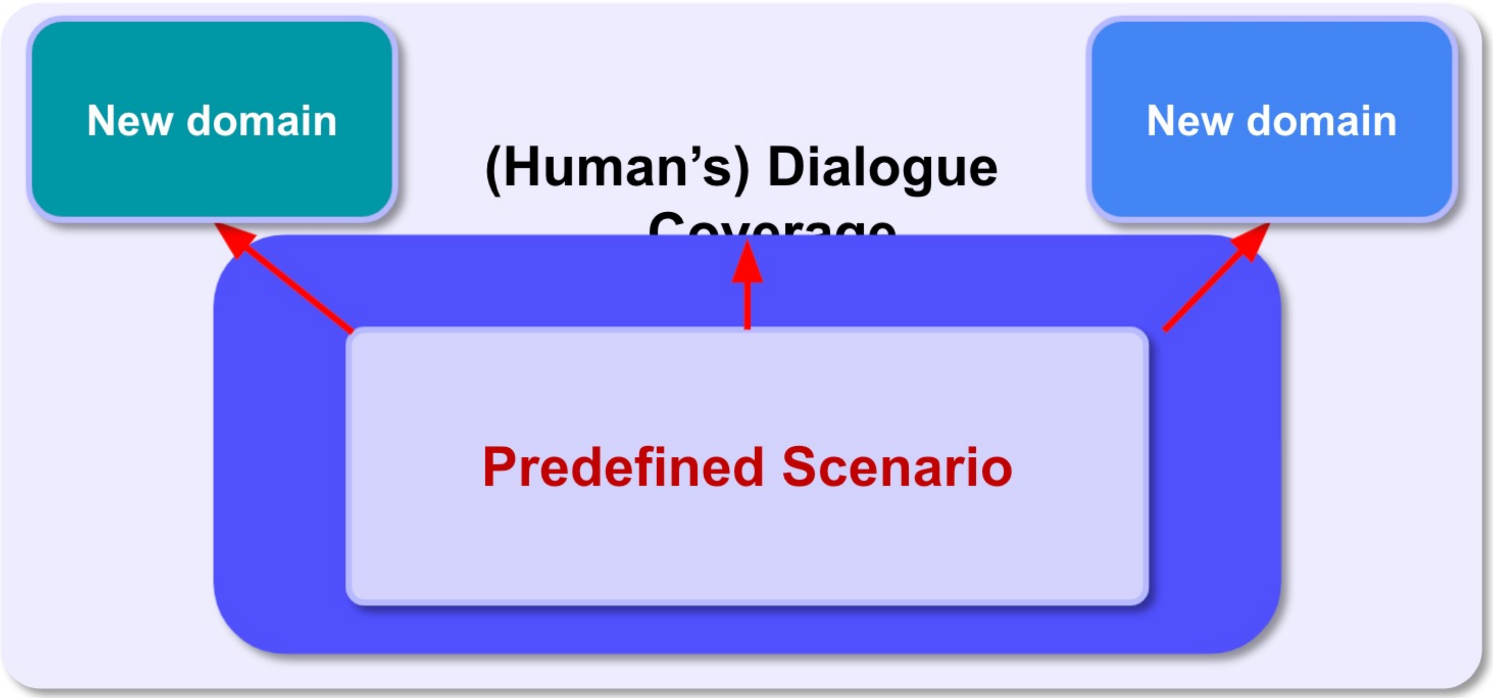
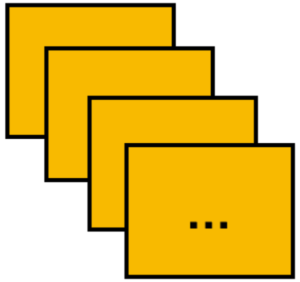
실제 상황에서는 **시나리오의 확장** (새로운 도메인/태스크)이 자주 요구된다!

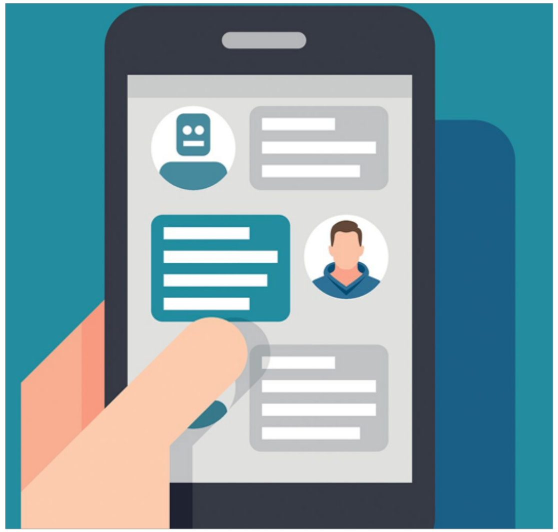


Bottlenecks of building TOD system

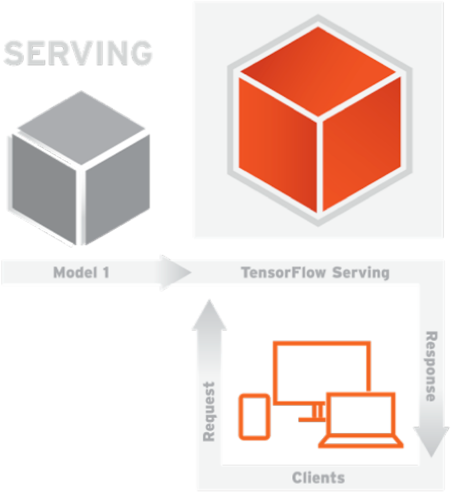
Cold start problem



Dialogue data collection



Build Dialogue System



Serving & Maintain

Bottlenecks of building TOD system

Dialogue data collection **Build Dialogue System** **Serving & Maintain**

Synthetic Dialogue Generation

User Simulation Approaches

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1. 클라우드소싱은 비싸고 시간이 많이 든다

2. 대화의 다양한 분포를 컨트롤하기가 어렵다

3. 다양한 종류의 어노테이션 에러 및 바이어스

=> Start with synthetic data from User Simulator and get feedback from real user quickly

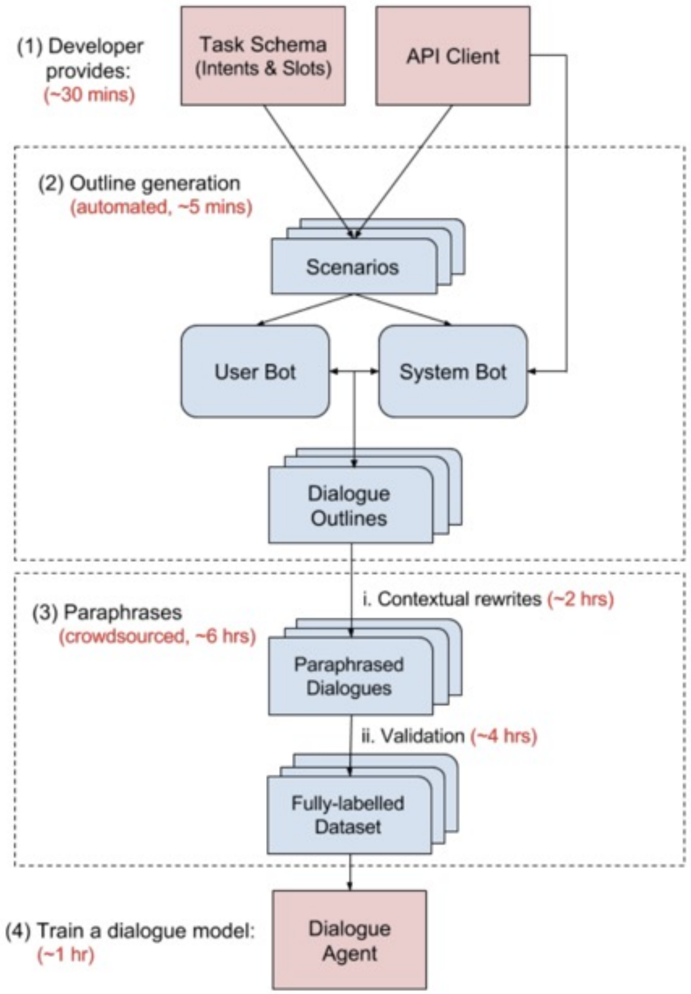
https://www.amazon.science/blog/amazon-unveils-novel-alexa-dialog-modeling-for-natural-cross-skill-conversations

User Simulation Approaches

Language Conference

M2M

1. 시나리오 정의 (Task Schema & KB)
2. **Rule-based Simulation을 통한 Synthetic data 생성**
3. Paraphrasing (Crowdsourcing)
4. Dialogue Agent 학습



Building a Conversational Agent Overnight with Dialogue Self-Play (2018, Shat et al.)

User Simulation Approaches

M2M

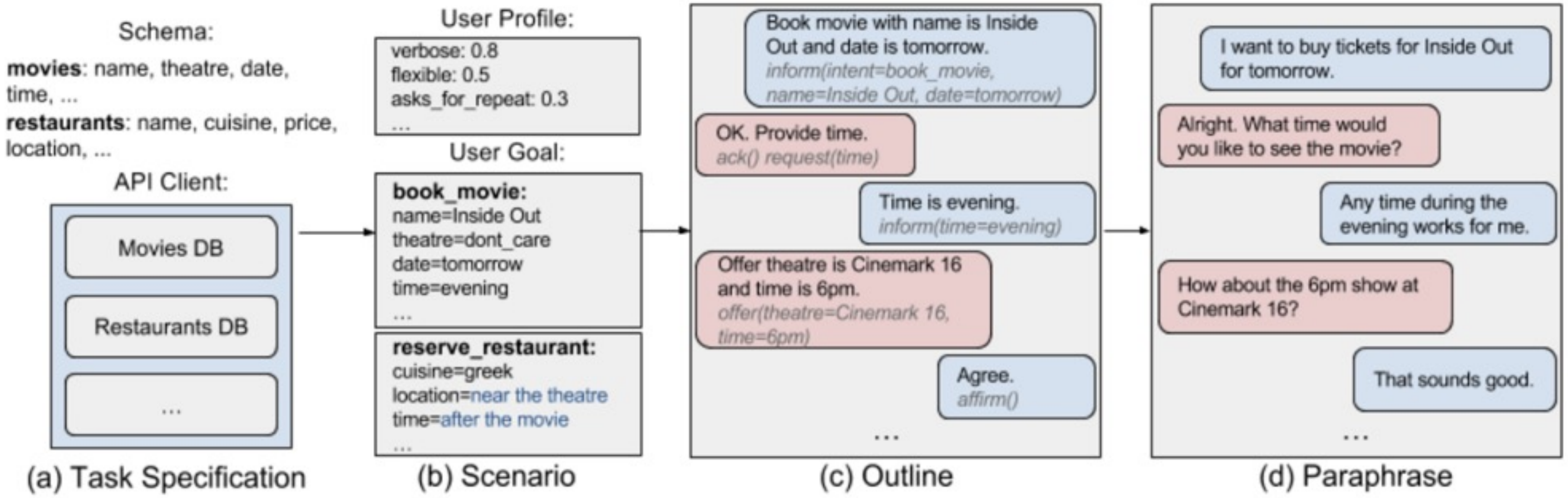


Figure 2: Example of generating an outline and its paraphrase. See text for details.

Building a Conversational Agent Overnight with Dialogue Self-Play (2018, Shat et al.)

Zero-shot Domain Transfer Learning

Leave-one-out setting

Train model on Source Domain/Scenario → Test on (Unseen) Target Domain/Scenario

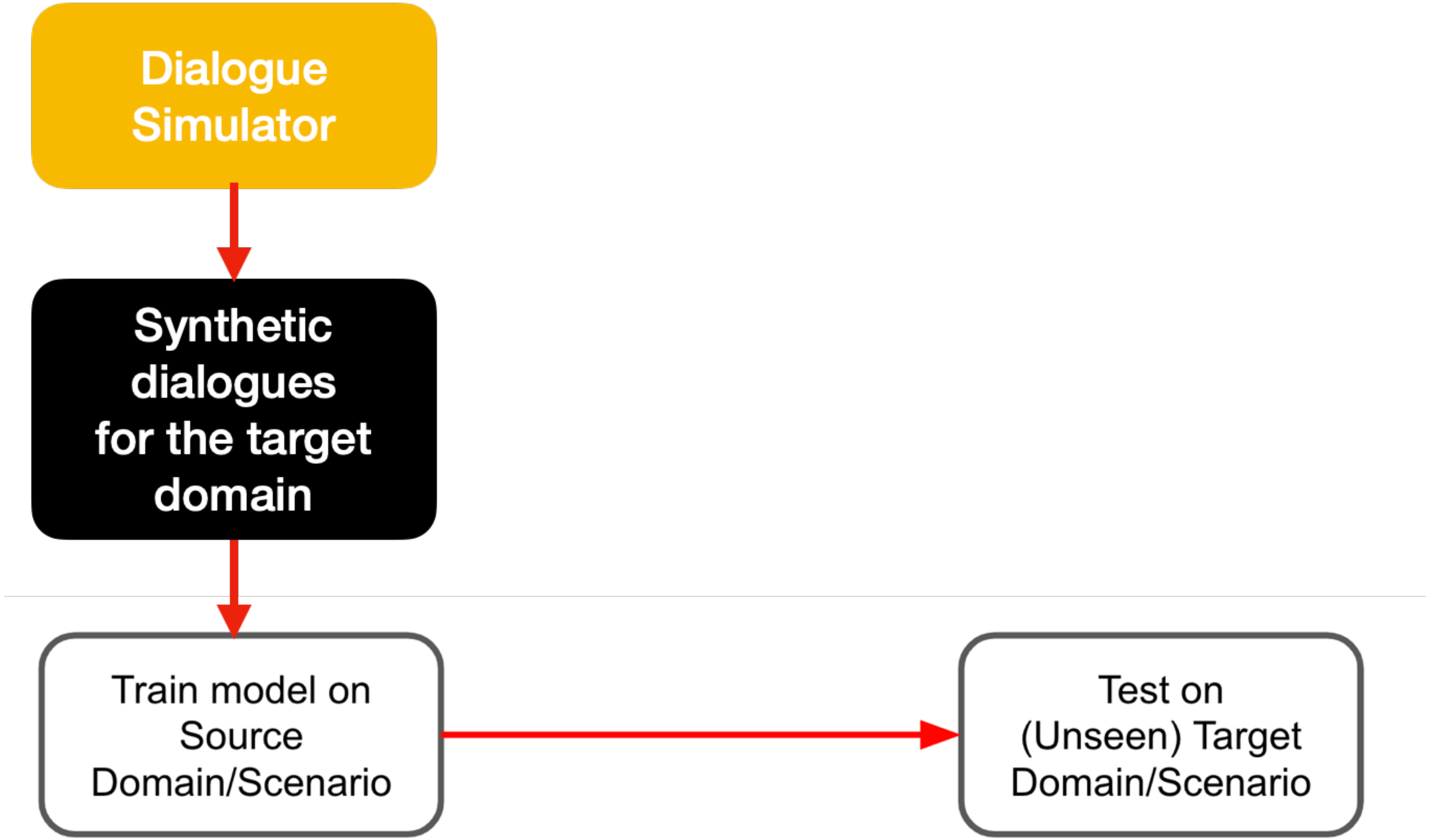
Leave-one-out setting

	Trained Single		Zero-Shot	
	Joint	*Slot*	*Joint*	*Slot*
Hotel	55.52	92.66	13.70	65.32
Train	77.71	95.30	22.37	49.31
Attraction	71.64	88.97	19.87	55.53
Restaurant	65.35	93.28	11.52	53.43
Taxi	76.13	89.53	**60.58**	73.92

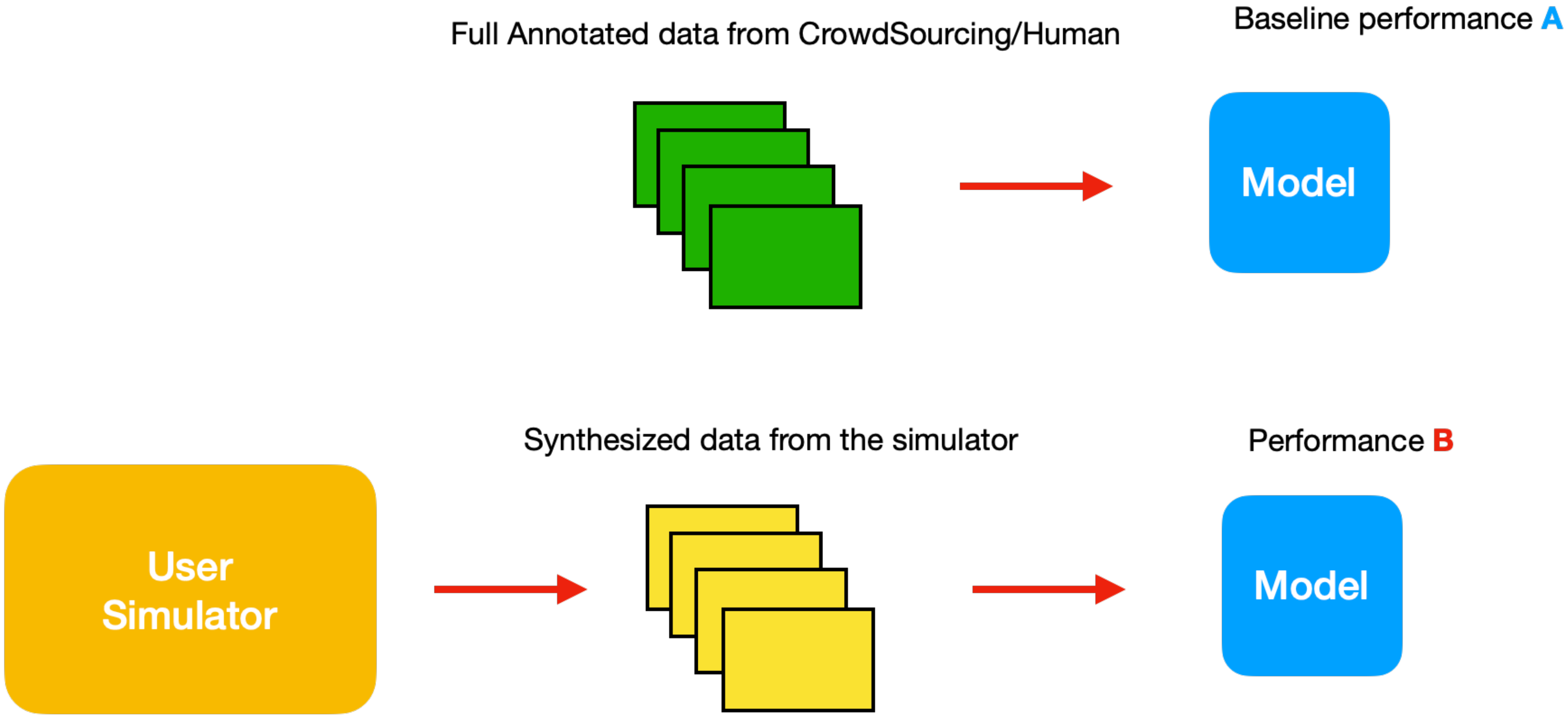
Training on Train, Attraction, Restaurant and Taxi
Evaluate on Hotel

[Transferable Multi-Domain State Generator for Task-Oriented Dialogue Systems (Wu et al., 2019)]

Zero-shot Domain Transfer Learning

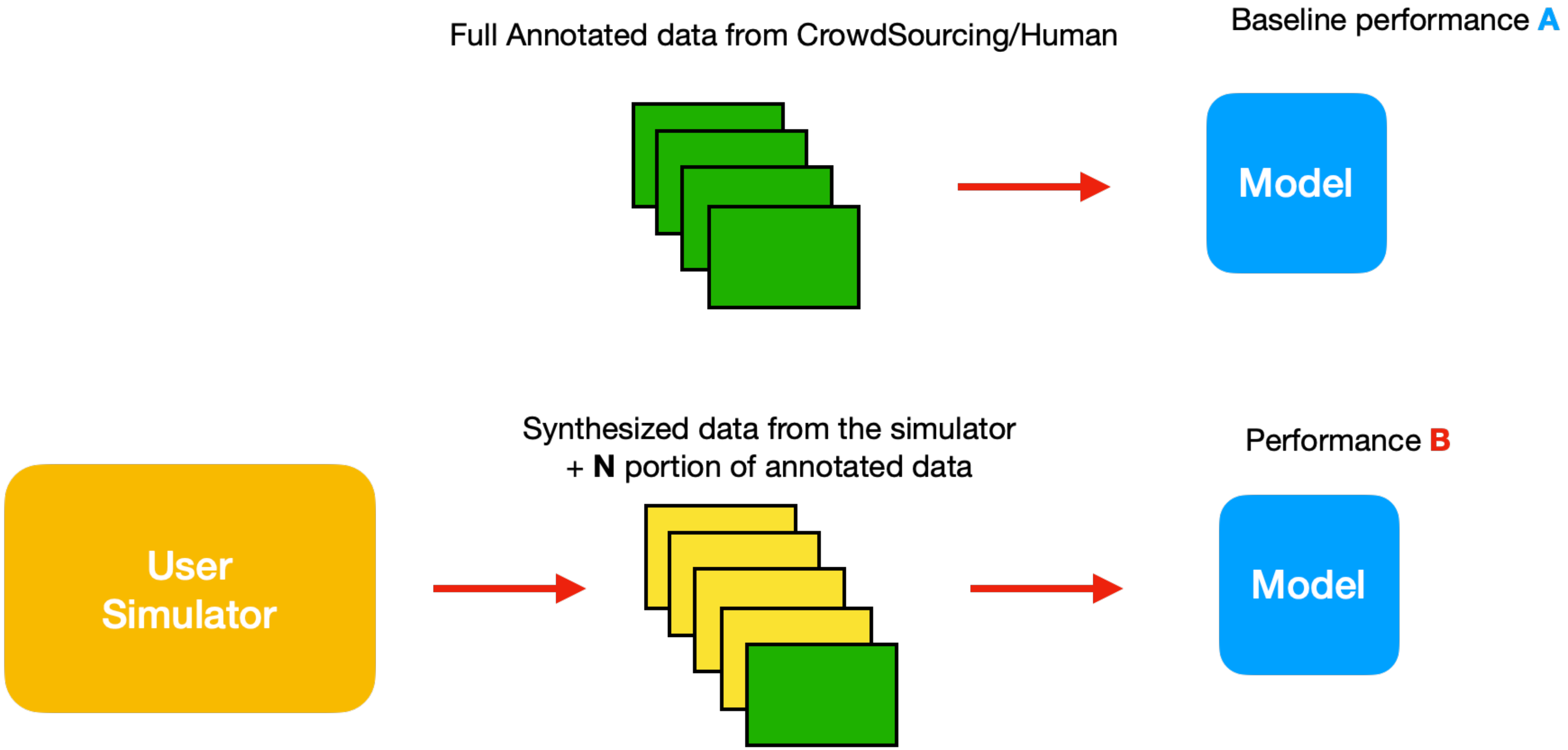


Evaluation of Synthetic Dialogue



Zero-shot coverage: B / A * 100

Evaluation of Synthetic Dialogue



Few-shot coverage: B / A * 100 (N%)

Abstract Transaction Dialogue Model

Agenda-based Simulation보다 복잡한 형태의
Rule-based Simulation

* **Abstract State Transition Matrix 정의**
* **다양한 Template의 활용**

$$
\begin{aligned}
\textsc{SlotQuestion} := \ & \text{"How about" } \textsc{name} \text{ "? It is a " } \textsc{np} \text{ "."} \\
& \text{"<sep> Is it" } \textsc{adj\_slot} \text{ "?":} \\
& \lambda(\mathit{state}, \mathit{name}, \mathit{np}, \mathit{adj\_slot}) \rightarrow \{ \\
& \quad \textbf{if } \mathit{adj\_slot} \in (\mathit{state}.\text{slots} \cup \mathit{np}) \\
& \qquad \textbf{return } \perp \\
& \quad \mathit{state}.\text{abstract} = \textsc{SlotQuestion} \\
& \quad \mathit{state}.\text{slots}[\mathit{adj\_slot}.\text{name}] = \text{"?"} \\
& \quad \textbf{return } \mathit{state} \\
& \}
\end{aligned}
$$

$$
\begin{aligned}
\textsc{np} &:= \textsc{adj\_slot}\ \textsc{np} : \lambda(\mathit{adj\_slot}, \mathit{np}) \rightarrow \mathit{np} \cup \{\mathit{adj\_slot}\} \\
\textsc{np} &:= \textsc{np}\ \textsc{prep\_slot} : \lambda(\mathit{np}, \mathit{prep\_slot}) \rightarrow \mathit{np} \cup \{\mathit{prep\_slot}\} \\
\textsc{np} &:= \text{"restaurant"} : \lambda() \rightarrow \emptyset
\end{aligned}
$$

$$
\begin{aligned}
\textsc{adj\_slot} &:= \textsc{food} \mid \textsc{price} : \lambda(x) \rightarrow x \\
\textsc{prep\_slot} &:= \text{"in the" } \textsc{area} \text{ "of town"} : \lambda(x) \rightarrow x \\
\textsc{name} &:= \text{"Curry Garden"} \mid \ldots : \lambda(x) \rightarrow \text{name} = x \\
\textsc{food} &:= \text{"Italian"} \mid \text{"Indian"} \mid \ldots : \lambda(x) \rightarrow \text{food} = x \\
\textsc{area} &:= \text{"north"} \mid \text{"south"} \mid \ldots : \lambda(x) \rightarrow \text{area} = x \\
\textsc{price} &:= \text{"cheap"} \mid \text{"expensive"} \mid \ldots : \lambda(x) \rightarrow \text{price} = x
\end{aligned}
$$

From Abstract State	Agent Dialogue Act	User Dialogue Act	To Abstract State
Start		Greet	Greeting
		Ask by name	Info request
		Ask with constraints	Search request
Greet	Greet	Ask by name	Info request
		Ask with constraints	Search request
Search request	Ask to refine search	Provide constraints	Search request
	Ask question	Answer question	Search request
	Propose constraint	Accept constraint	Search request
		Add constraints	Search request
	Propose entity	Accept	Complete request
		Add constraints	Search request
		Reject	Search request
		Ask slot question	Slot question
		Ask info question	Info question
	Empty search, offer change	Change constraints	Search request
		Insist	Insist
Info request	Provide info, offer reservation	Accept	Accept
		Provide reservation info	Accept
		Ask info question	Info question
Info question	Answer, offer reservation	Accept	Accept
		Provide reservation info	Accept
		Thanks	Close conversation
Slot question	Answer, offer reservation	Accept	Accept
		Add constraint	Search request
Insist	Repeat empty search	Apologize	Close conversation
		Change constraints	Search request
Complete request	Offer reservation	Accept	Accept
		Thanks	Close conversation
Accept	Ask missing slots	Answer question	Complete transaction
Complete transaction	Execute	Ask transaction info	Transaction info question
		Thanks	Close conversation
	Error	Thanks	Close conversation
Transaction info question	Answer	Thanks	Close conversation
Close conversation	Anything else	Thanks	End

Zero-Shot Transfer Learning with Synthesized Data for Multi-Domain Dialogue State Tracking (2020, Campagna et al.)

Abstract Transaction Dialogue Model

	Attraction	Hotel	Restaurant	Taxi	Train
# user slots	3	10	7	4	6
# agent slots	5	4	4	2	2
# slot values	167	143	374	766	350
# real dialogues	3,469	4,196	4,836	1,919	3,903
# in-domain turns	10,549	18,330	18,801	5,962	16,081
# in-domain tokens	312,569	572,955	547,605	179,874	451,521
# domain subject templates	3	5	4	2	4
# slot name templates	15	17	21	18	16
# slot value templates	7	30	30	37	42
# information utterance templates	1	14	13	13	27
# synthesized dialogues	6,636	13,300	9,901	6,771	14,092
# synthesized turns	30,274	62,950	46,062	35,745	60,236
# synthesized tokens	548,822	1,311,789	965,219	864,204	1,405,201
transfer domain	Restaurant	Restaurant	Hotel	Train	Taxi
overlapping slots	2	6	6	4	4

Zero-Shot Transfer Learning with Synthesized Data for Multi-Domain Dialogue State Tracking (2020, Campagna et al.)

Abstract Transaction Dialogue Model

About 7~80% zero-shot coverage when using pre-trained LM on DST task

Model	Training	Attraction Joint	Attraction Slot	Hotel Joint	Hotel Slot	Restaurant Joint	Restaurant Slot	Taxi Joint	Taxi Slot	Train Joint	Train Slot
TRADE	Full dataset	67.3	87.6	50.5	91.4	61.8	92.7	72.7	88.9	74.0	94.0
	Zero-shot	22.8	50.0	19.5	62.6	16.4	51.5	59.2	72.0	22.9	48.0
	Zero-shot (Wu)	20.5	55.5	13.7	65.6	13.4	54.5	60.2	73.5	21.0	48.9
	Zero-shot (DM)	**34.9**	**62.2**	**28.3**	**74.5**	**35.9**	**75.6**	**65.0**	**79.9**	**37.4**	**74.5**
	Ratio of DM over full (%)	51.9	71.0	56.0	81.5	58.1	81.6	89.4	89.9	50.5	79.3
SUMBT	Full dataset	71.1	89.1	51.8	92.2	64.2	93.1	68.2	86.0	77.0	95.0
	Zero-shot	22.6	51.5	19.8	63.3	16.5	52.1	59.5	74.9	22.5	49.2
	Zero-shot (DM)	**52.8**	**78.9**	**36.3**	**83.7**	**45.3**	**82.8**	**62.6**	**79.4**	**46.7**	**84.2**
	Ratio of DM over full (%)	74.3	88.6	70.1	90.8	70.6	88.9	91.8	92.3	60.6	88.6

Zero-Shot Transfer Learning with Synthesized Data for Multi-Domain Dialogue State Tracking (2020, Campagna et al.)

NeuralWOZ: Learning to Collect Task-Oriented Dialogue via Model-based Simulation

Sungdong Kim, Misuk Chang, Sang-Woo Lee
@ACL-IJCNLP 2021

LangCon 2021

Motivation

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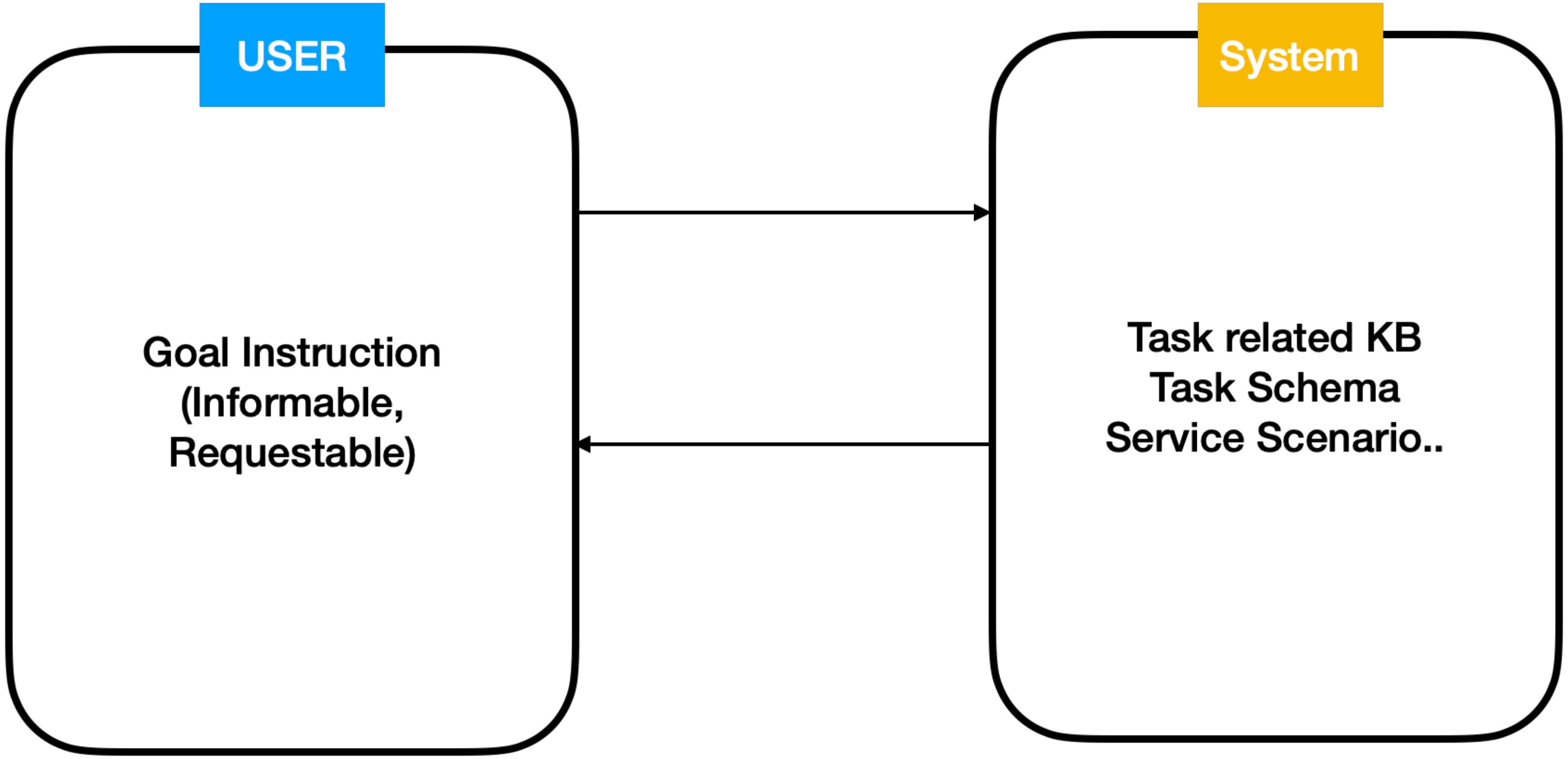
Task-Oriented Dialogue as information exchange game



Motivation: Wizard-of-Oz

USER

- You are traveling to Cambridge and looking forward to try local restaurants.
- You are looking for a **place to stay**. The hotel should be in the type of **hotel** and should be in the **centre**.
- The hotel should **include free wifi** and should have **a star of 4**.
- Once you find the **hotel** you want to book it for **3 people** and **5 nights** starting from **monday**.
- Make sure you get the **reference number**.
- You are also looking for a **restaurant**. The restaurant should serve **australasian** food and should be in the **moderate** price range.
- The restaurant should be **in the same area as the hotel**.
- If there is no such restaurant, how about one that serves **british** food.
- Once you find the **restaurant** you want to book a table for **the same group of people** at **18:30** on **the same day**.
- Make sure you get the **reference number**

System


```
[{'address': 'regent street',
  'area': 'centre',
  'internet': 'yes',
  'parking': 'yes',
  'id': '30',
  'location': [52.19942, 0.12722],
  'name': 'university arms hotel',
  'phone': '01223351241',
  'postcode': 'cb21ad',
  'price': {'double': '124', 'famil
  'pricerange': 'expensive',
  'stars': '4',
  'takesbookings': 'yes',
  'type': 'hotel'}]
```


MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling (2018, Budzianowski et al.)

Overview

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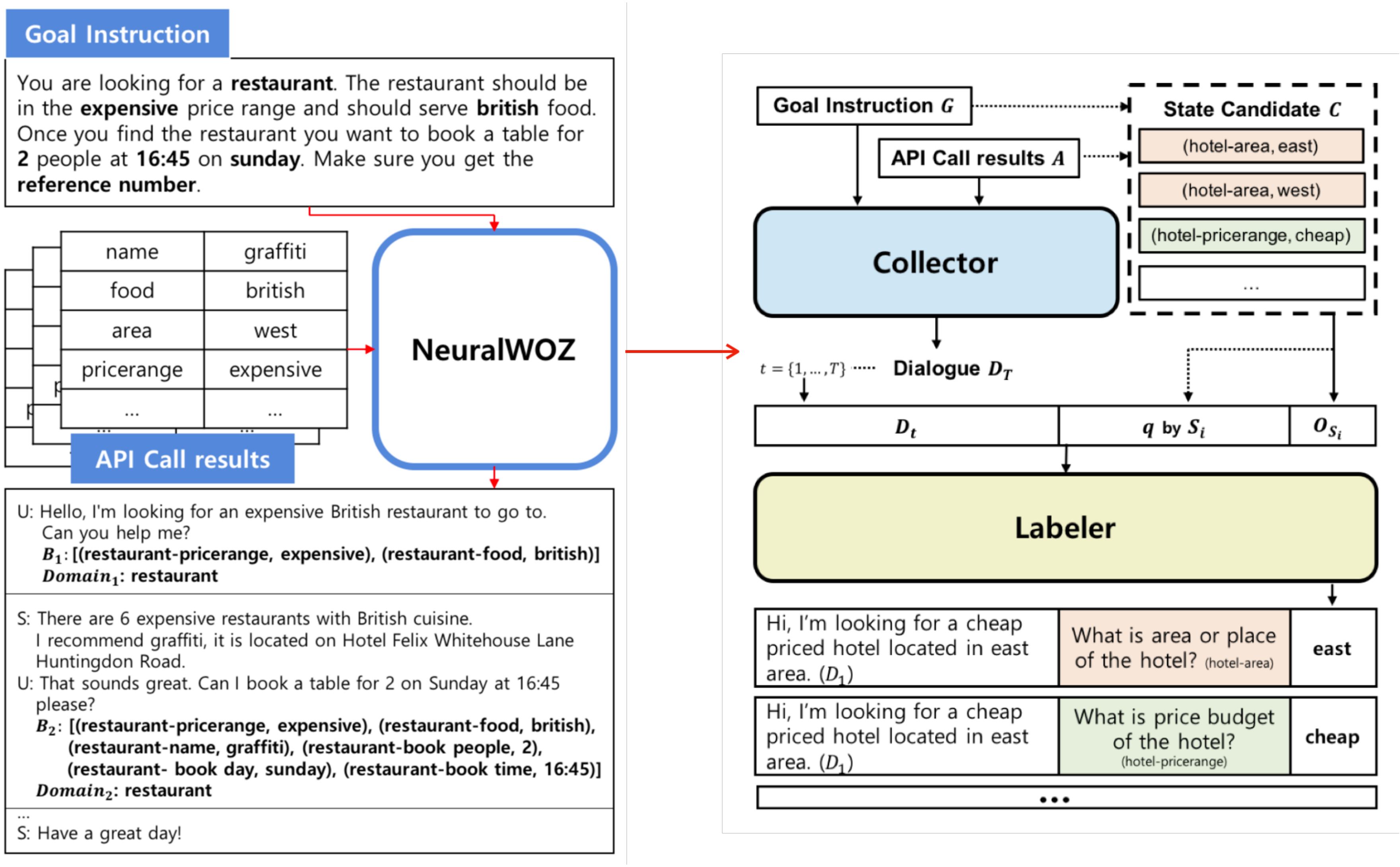


Goal Instruction

Goal Instruction

You are looking for a **restaurant**. The restaurant should be in the **expensive** price range and should serve **british** food. Once you find the restaurant you want to book a table for **2** people at **16:45** on **sunday**. Make sure you get the **reference number**.

Goal Instruction ***G***

Slot	Value
restaurant-price range	expensive
restaurant-food	british
restaurant-book people	2
restaurant-book time	16:45
restaurant-book day	sunday

C^G

대화 D에서의 유저 행동을 제약/가이드하기 위한 자연어 텍스트

제약 사항은 informable 및 requestable slot으로 구성되어 있음

이 중 명시적으로 드러난 Informable slots을 C^G

$$C^G = \{(S_i^G, V_i^G) \mid 1 \leq i \leq |C^G|, S_i^G \in informable\}$$

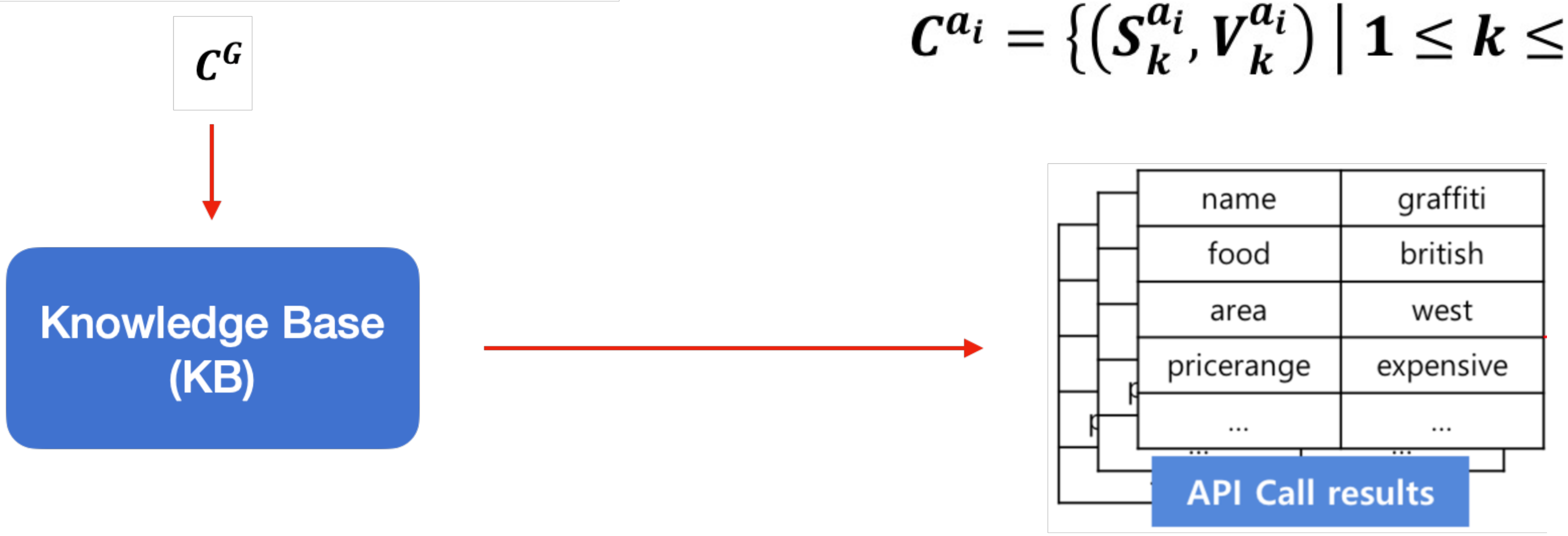
API Call results

Slot	Value
restaurant-price range	expensive
restaurant-food	british
restaurant-book people	2
restaurant-book time	16:45
restaurant-book day	sunday

이전에 정의한 **C^G**를 이용하여 **KB**에 관련된 쿼리 결과 **A**를 미리 얻어낼 수 있고,

각 인스턴스인 **C^{a_i}**는 해당 도메인에 연관된 informable/requestable slot으로 구성되어 있음

$$C^{a_i} = \{(S_k^{a_i}, V_k^{a_i}) \mid 1 \leq k \leq |C^{a_i}|\}$$



A

API Call results

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API Call results *A*

name	graffiti
food	british
area	west
pricerange	expensive
…	…

C^{a_1}

name	the cambridge chop house
food	british
area	centre
pricerange	expensive
…	…

C^{a_2}

이 중 다시 informable slot들을 모아서 그 집합을 **C^A**로 정의

$$C^A = \{(S_i^A, V_i^A) \mid 1 \le i \le |C^A|, S_i^A \in informable\}$$

State Candidate

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Slot	Value
restaurant-price range	expensive
restaurant-food	british
restaurant-book people	2
restaurant-book time	16:45
restaurant-book day	sunday

C^G

Slot	Value
restaurant-price range	expensive
restaurant-food	british
restaurant-book people	2
restaurant-book time	16:45
restaurant-book day	sunday
restaurant-name	graffiti
restaurant-area	west
restaurant-name	the cambridge chop house
restaurant-area	centre

C

Slot	Value
restaurant-name	graffiti
restaurant-food	british
restaurant-area	west
restaurant-pricerange	expensive
restaurant-name	the cambridge chop house
restaurant-area	centre

C^A

두 종류의 집합 **C^G와 C^A의 합집합을 State Candidate C**로 정의

이는 대화 D에서 등장할 수 있는 모든 Dialogue State의 slot, value pairs의 전체 집합으로 볼 수 있음
=> Labeler가 Labeling을 효율적으로 할 수 있도록 meta 정보로 제공

State Candidate

Language Conference

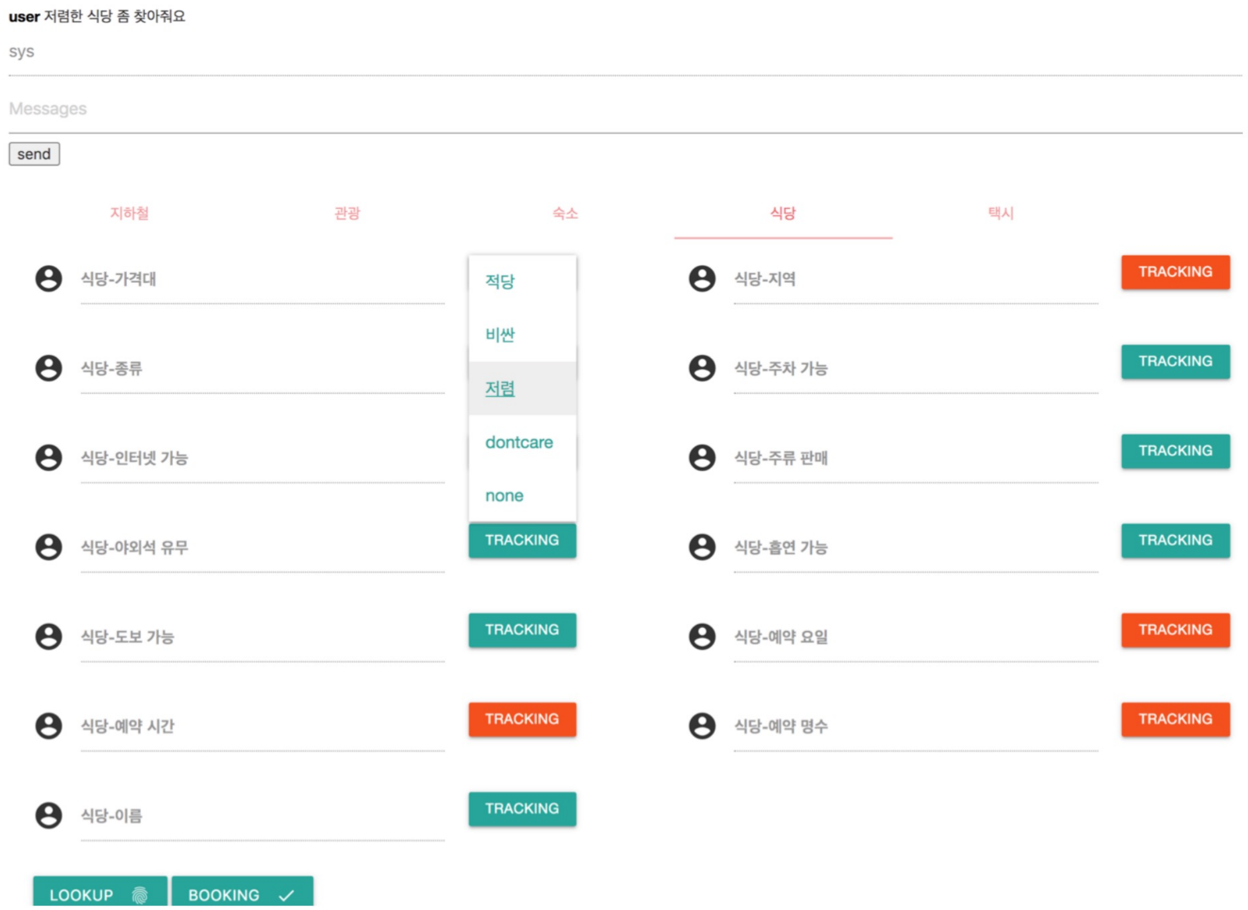
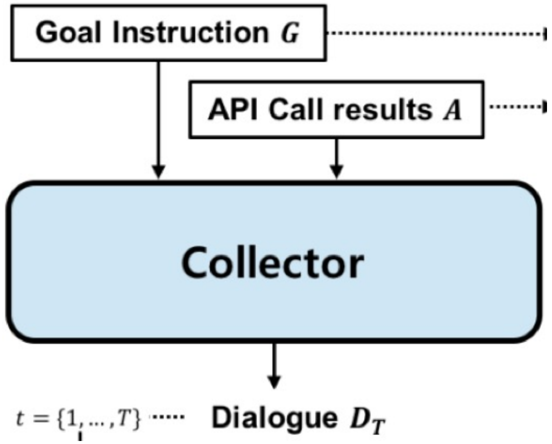


Figure 7: Graphical web interface for system side worker.

이 State Candidate의 아이디어는 KLUE benchmark의 WoS 구축에도 사용되었음…!!

=> 각 Slot마다 Dropdown options 을 제공하여 작업자들의 annotation error를 방지하고 작업 속도 증대

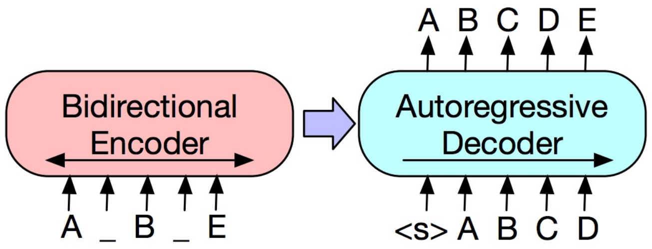
Collector



Goal Instruction과 API Call Results를 인풋으로 받아 Dialogue를 생성하는 Seq2Seq model

* BART 모델을 초기 파라미터로 사용

$$p(D_T|G, A) = \prod_{i=1}^{N} p(w_i|w_{<i}, G, A)$$



$$D_T = (r_1, u_1, ..., r_T, u_T)$$

[BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension]

Collector

API Call results ***A***

<domain> hotel
<slot> address-151 hills road
<slot> area-south
<slot> internet-yes
<slot> parking-yes
<slot> id-11
<slot> name-bridge guest house
<slot> phone-01223247942
<slot> postcode-cb28rj
<slot> pricerange-moderate
<slot> stars-3
<slot> takesbookings-yes
<slot> type-guesthouse
<slot> reference-85BGKWO4

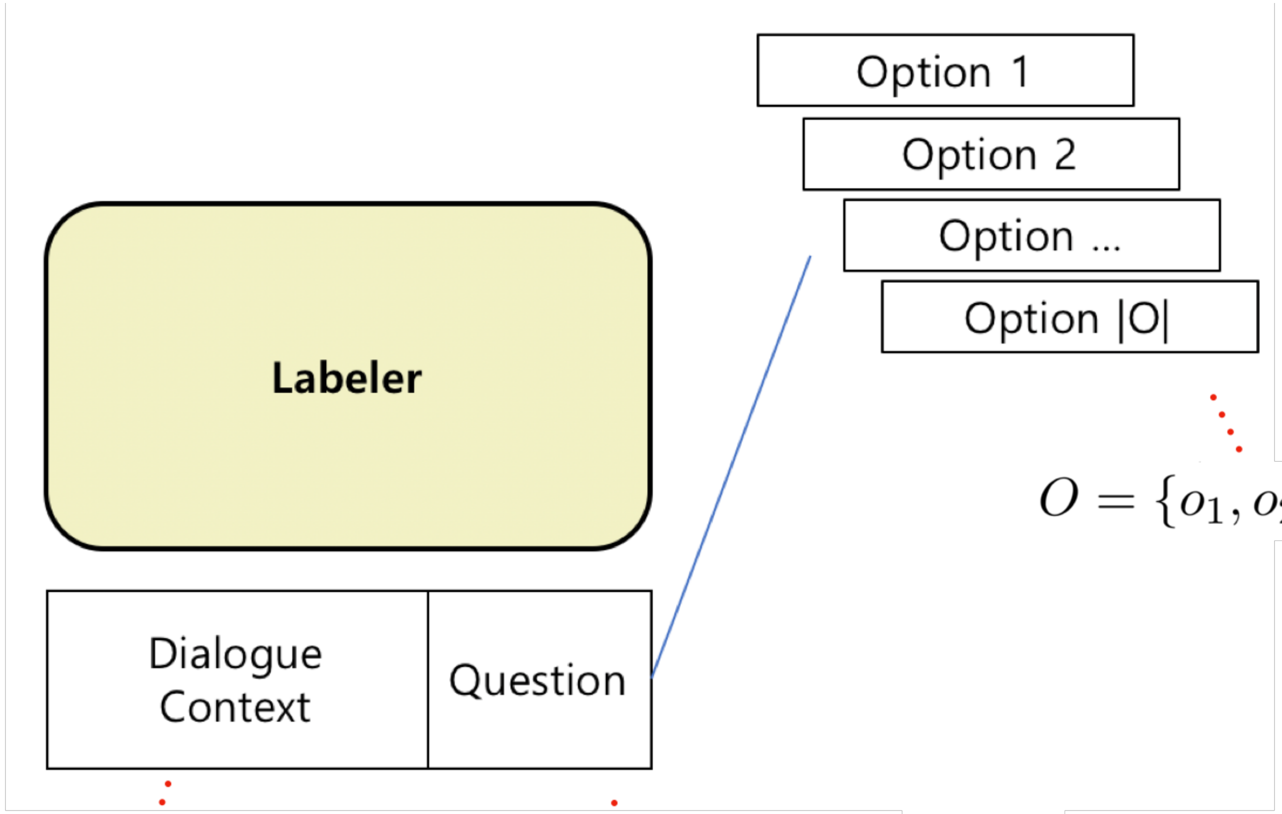
Goal Instruction ***G***

<s> You are looking for a place to stay.
The hotel should be in the **moderate** price range and should be in the type of **guesthouse.**
The hotel should have **a star of 3.**
Once you find the hotel you want to book it for **4 people** and **2 nights** starting from **saturday.**
If the booking fails how about **1 nights.**
Make sure you get the **reference number** </s>

Collector

U: I need a **guesthouse** in the **moderate** price range.
S: There are several options available.
Would you like to try the **Bridge Guest House** in the **South** area?
U: What's the star rating please?
S: It is a **3 Star** hotel.
U: I need a room for **4** people on **Saturday**.
S: How many days will you be staying?
U: I'll stay **2** days from Saturday night.
S: I'm sorry, but it is not possible there to accommodate you for that length of stay. Would you like me to try a different length of stay?
U: Oh good, how about **1** night?
S: You are booked for 1 night at bridge guest house.
Your reference number to **85BGKWO4**. Can I help further?
U: No thanks that's everything. Bye.

Labeler



$$O = \{o_1, o_2, ..., o_{|O|}\}$$

$$\tilde{o} \in O$$

$$D_t = (r_1, u_1, ..., r_t, u_t)$$

$$q$$

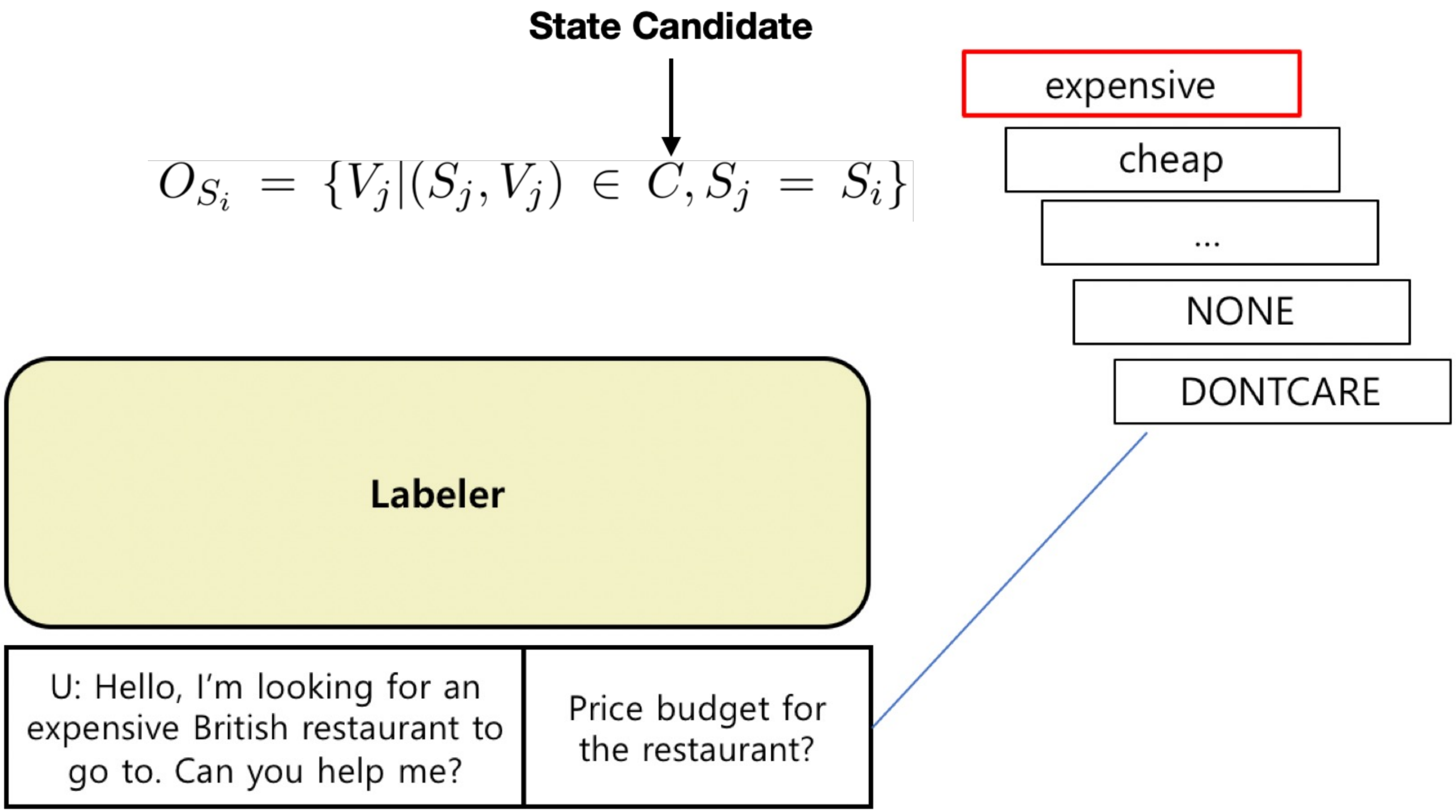
Annotation이란 행위를 **Multiple Choice Problem**으로 수행하는 모델

* RoBERTa 모델을 초기 파라미터로 사용

Select **answer** from the answer options

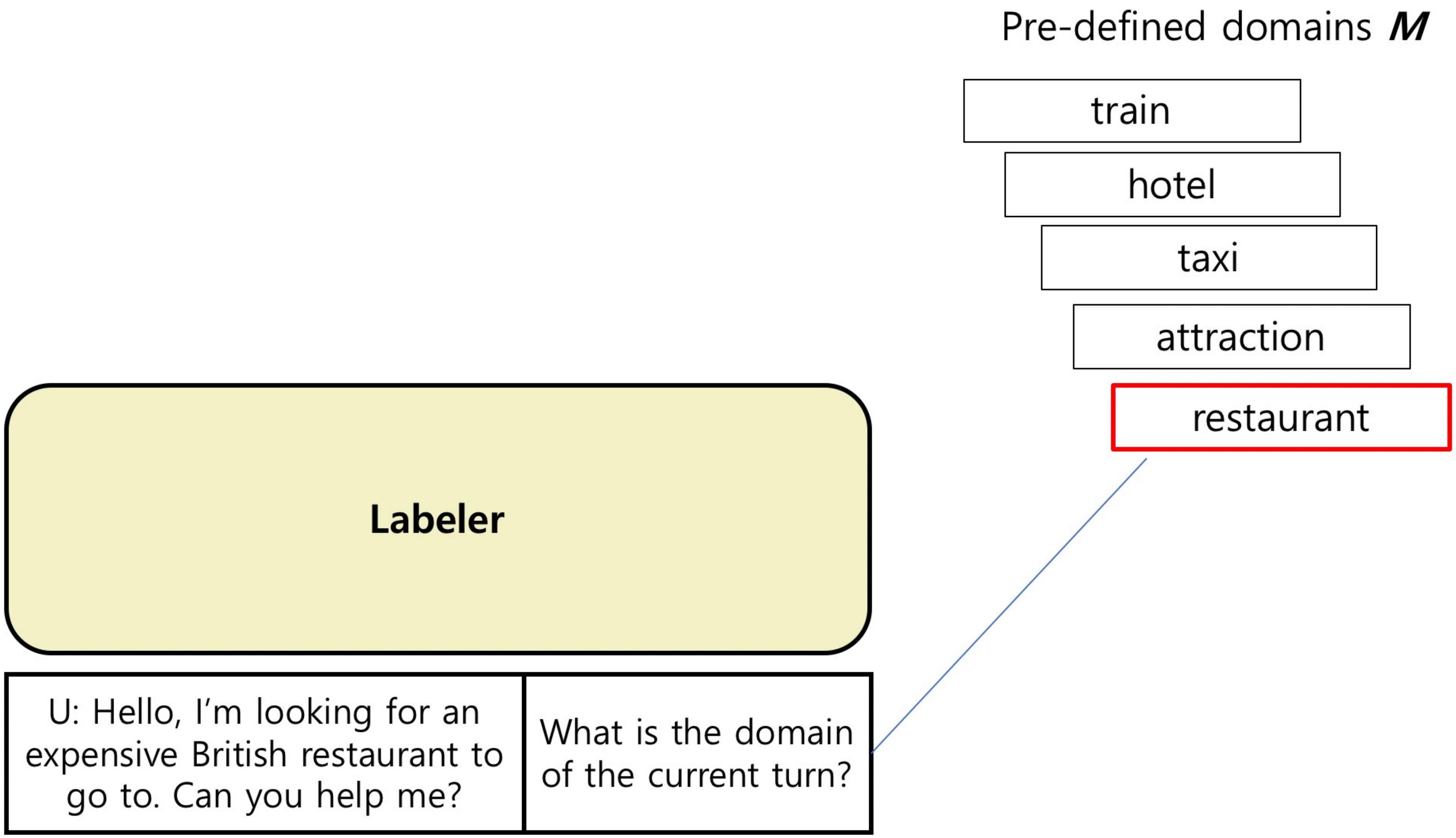
Labeler

Labeling Dialogue State



Labeler

Labeling an Active domain



Dataset

Domain	Slots	# of Dialogues Train	# of Dialogues Valid	# of Dialogues Test	# of Turns Train	# of Turns Valid	# of Turns Test
Attraction	area, name, type	2,717	401	395	8,073	1,220	1,256
Hotel	price range, type, parking, book stay, book day, book people, area, stars, internet, name	3,381	416	394	14,793	1,781	1,756
Restaurant	food, price range, area, name, book time, book day, book people	3,813	438	437	15,367	1,708	1,726
Taxi	leave at, destination, departure, arrive by	1,654	207	195	4,618	690	654
Train	destination, day, departure, arrive by, book people, leave at	3,103	484	494	12,133	1,972	1,976

MultiWOZ - A Large-Scale Multi-Domain Wizard-of-Oz Dataset for Task-Oriented Dialogue Modelling (2018, Budzianowski et al.)

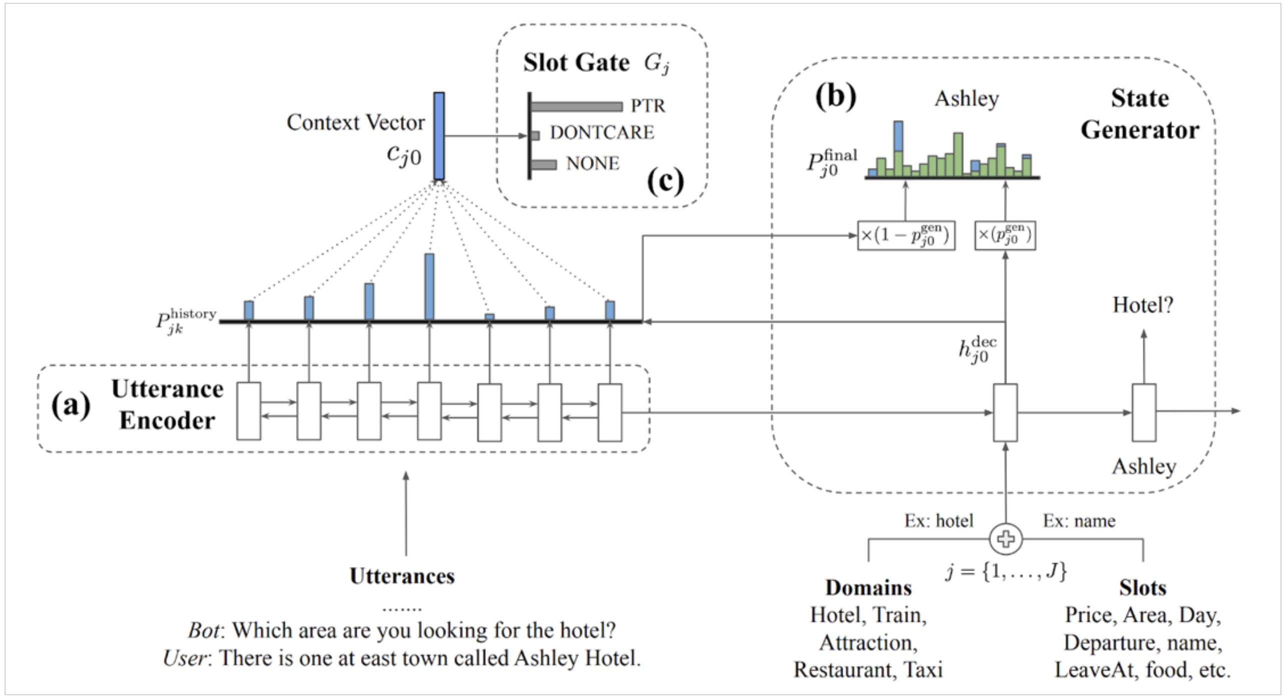
Synthetic Dialogue Generation

	Attraction	Hotel	Restaurant	Taxi	Train	Full
# goal template	411	428	455	215	482	1,000
# synthesized dialogues	5,000	5,000	5,000	5,000	5,000	1,000
# synthesized turns	38,655	38,112	37,230	45,542	37,863	35,053
# synthesized tokens	947,791	950,272	918,065	1,098,917	873,671	856,581

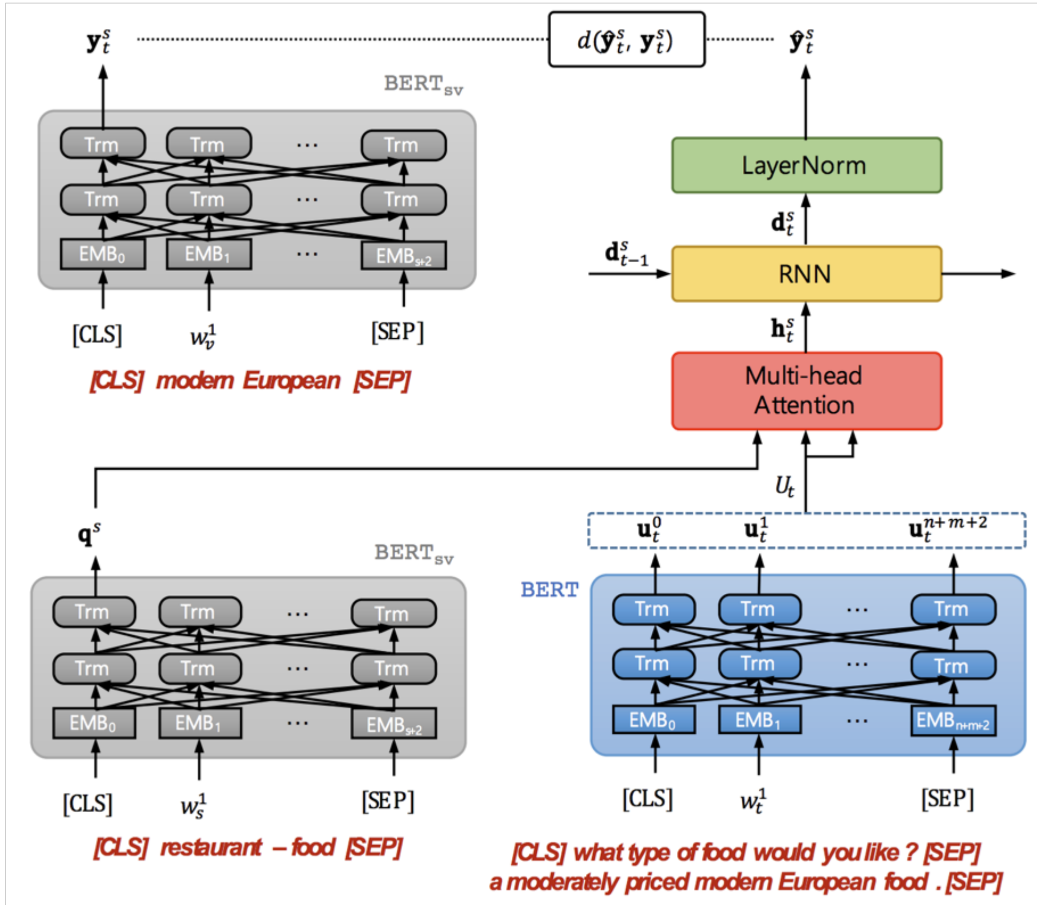
Table 7: Statistics of the synthesized data used in NeuralWOZ using for zero-shot and full augmentation experiments.

Baseline DST models

TRADE



SUMBT



Transferable Multi-Domain State Generator for Task-Oriented Dialogue Systems (Wu et al., 2019)

SUMBT: Slot-Utterance Matching for Universal and Scalable Belief Tracking(Lee et al. 2019)

Zero-shot Domain Transfer

Language Conference

Zeroshot Coverage

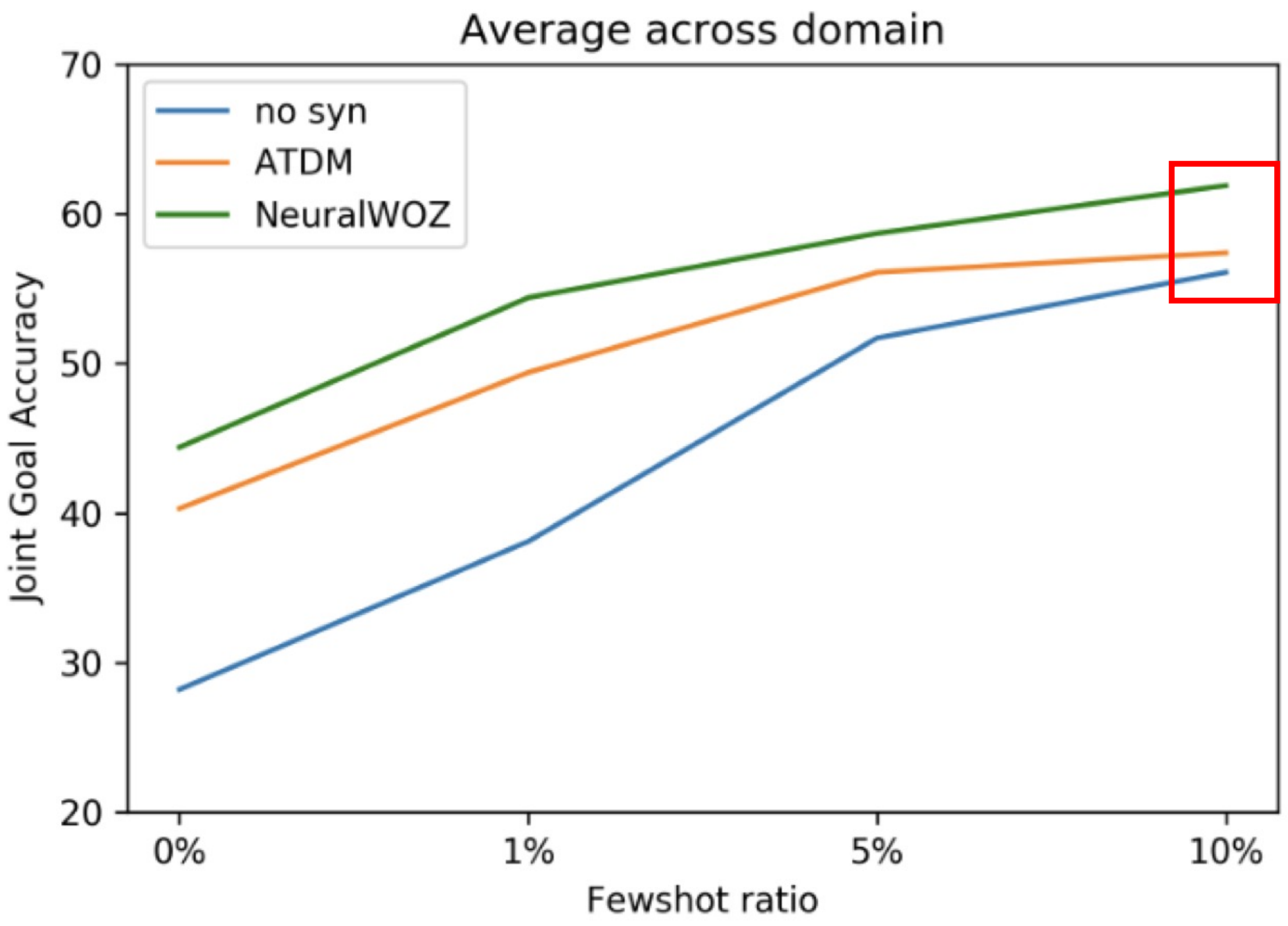
- TRADE: 61.2(ATDM) => **66.9 (NeuralWOZ)**
- SUMBT: 73.5 (ATDM) => **79.2 (NeuralWOZ)**

Model	Training	Hotel	Restaurant	Attraction	Train	Taxi	Average
TRADE	Full dataset	50.5 / 91.4	61.8 / 92.7	67.3 / 87.6	74.0 / 94.0	72.7 / 88.9	65.3 / 89.8
	Zero-shot (*Wu*)	13.7 / 65.6	13.4 / 54.5	20.5 / 55.5	21.0 / 48.9	60.2 / 73.5	25.8 / 59.6
	Zero-shot (*Campagna*)	19.5 / 62.6	16.4 / 51.5	22.8 / 50.0	22.9 / 48.0	59.2 / 72.0	28.2 / 56.8
	Zero-shot + ATDM	**28.3** / 74.5	35.9 / 75.6	34.9 / 62.2	37.4 / 74.5	65.0 / 79.9	40.3 / 73.3
	Zero-shot + NeuralWOZ	26.5 / **75.1**	**42.0 / 84.2**	**39.8 / 65.7**	**48.1 / 83.9**	**65.4 / 79.9**	**44.4 / 77.8**
	Zero-shot Coverage	52.5 / 82.2	68.0 / 90.8	59.1 / 75.0	65.0 / 89.3	90.0 / 89.9	66.9 / 85.4
SUMBT	Full dataset	51.8 / 92.2	64.2 / 93.1	71.1 / 89.1	77.0 / 95.0	68.2 / 86.0	66.5 / 91.1
	Zero-shot	19.8 / 63.3	16.5 / 52.1	22.6 / 51.5	22.5 / 49.2	59.5 / 74.9	28.2 / 58.2
	Zero-shot + ATDM	**36.3 / 83.7**	45.3 / 82.8	52.8 / 78.9	46.7 / 84.2	62.6 / 79.4	48.7 / 81.8
	Zero-shot + NeuralWOZ	31.3 / 81.7	**48.9 / 88.4**	**53.0 / 79.0**	**66.9 / 92.4**	**66.7 / 83.9**	**53.4 / 85.1**
	Zero-shot Coverage	60.4 / 88.6	76.2 / 95.0	74.5 / 88.7	86.9 / 97.3	97.8 / 97.6	79.2 / 93.4

Table 1: Experimental results of zero-shot domain transfer on the test set of MultiWOZ 2.1. Joint goal accuracy / slot accuracy are reported. The *Wu* indicates original zero-shot scheme of the TRADE suggested by Wu et al. (2019) and reproduced by Campagna et al. (2020). The *Campagna* indicates a revised version of the original by Campagna et al. (2020). The + indicates the synthesized dialogue is used together for the training.

Few-shot Domain Transfer

Language Conference



X축: 실제 (사람이 annotation한) 데이터의 비율 (전체 Training data 중)
Y축: 5개 도메인의 성능(JGA)의 평균 점수

Qualitative Examples

You are looking for a **movie**. The movie should **comedy** genre and the theater should be located in **Gangnam**. Once you find the movie you want to book it for **2** people. Make sure you get the **reference number** and **seat number**. You also check the theater has **snack bar**.

name	Funny family
genre	comedy
city	Gangnam
snack bar	yes
...	...

U: I am looking for a movie in the **Comedy** category.
S: There are 5 options. What part of town would you like?
U: I would like it to be located in **Gangnam**.
S: The only movie I have available is the **Funny Family**. Would you like to book a seat?
U: Yes. Can you book that for **2** people and give me the reference number and seat number?
S: Your booking was successful. The reference number is **SQSX2**. The seat number is **I12, I13**. Can I help you with anything else today?
U: Can you confirm that they have a snack bar?
S: Yes, they do **have a snack Bar**.
U: Thank you. I also need the start time for the movie.
S: It is 18:30. Is there anything else I can help you today?

Figure 5: Unseen domain dialogue generation from NeuralWOZ. The movie domain is an example. It has very different domain schema from the domains in MultiWOZ dataset.

You are looking for a **korean** restaurant. The restaurant should be in the **east** and should be in the **expensive** price range. Once you find the restaurant you want to book a table for **2** people at **12:00** on **saturday**. Make sure you get the **reference number** and **address** of there.

name	spicy club
area	east
pricerange	expensive
food	korean
address	seoul st 30-2

U: I'm looking for an **expensive korean** restaurant on the **east** side.
S: There is one expensive **Korean** restaurant in the **east**, it is the **Spice Club**. Would you like to book a table?
U: Yes, please. Can you make a reservation for **2** at **12:00** on **Saturday**?
S: You are all set, the reference number is **NAIJ84**. Is there anything else I can help you with today?
U: Can I get the address please?
S: The address is **Seoul St 30-2**. Is that all?
U: That's all I need. Thanks!
S: You're welcome. Have a great day!

Seen domain (Restaurant) with unseen KB instance

Seen domain (Restaurant) but different schema / scenario (navigation in-car)

You are driving car. You are looking for **chinese** restaurant. You should find **quickest** way to get there. The way to go to the restaurant should have **moderate** traffic. If you find the restaurant, Make sure you get the **address** and **distance** to get there.

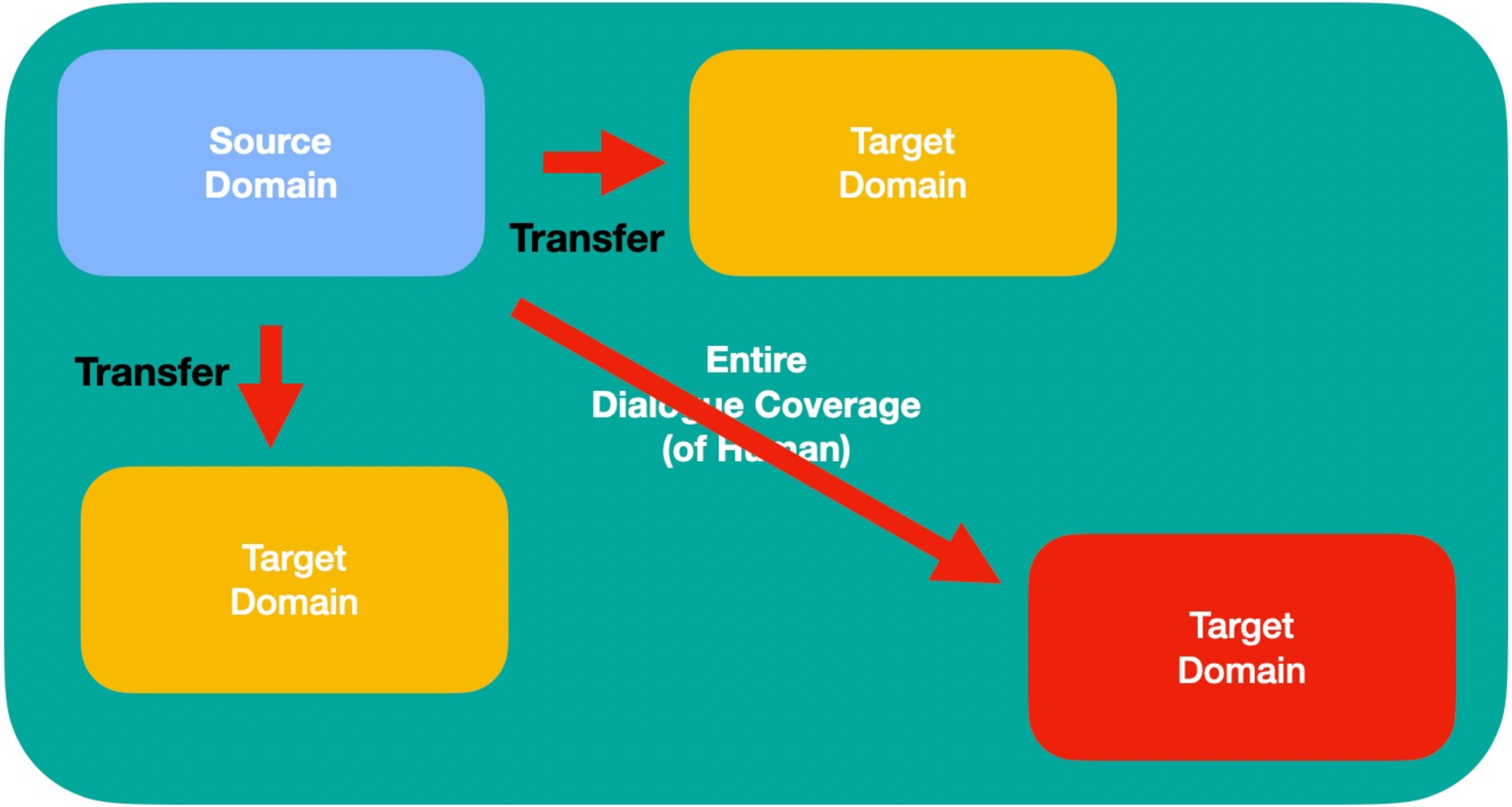
name	P.F. Changs
type	chinese restaurant
traffic_info	moderate
address	669 El Camino Real
distance	5 miles

U: I am looking for a **chinese** restaurant
S: Certainly! There are several. Did you have a price range or location you were looking for?
U: Not really.
S: There are five Chinese restaurants in town. Is there a particular area you are interested in?
U: It doesn't matter, I just need the **address** and the **shortest route** to get there.
S: **P F. Changs** is located at **669 el camino real** and is **closest** to your location.
U: What is the travel time?
S: The travel time would be **5 miles**.
U: I need the location to have **moderate** traffic.
S: The address is for P.F. Chang's at 669 El Camino Real and it has **moderate** traffic. Is there anything else I can help you with today?
U: No, that's it. Thanks!
S: You're welcome! Have a great day!

Figure 7: Qualitative examples of synthesized dialogues from NeuralWOZ in restaurant.

Future Direction

Meta-Domain Transfer: Source Domain과 Target Domain 사이의 분포 차이가 클 때 더욱 Challenging한 transfer 필요



Q & A

발표 들어주셔서 감사합니다 ☺

Paper: https://arxiv.org/abs/2105.14454
Source code: https://github.com/naver-ai/neuralwoz
Contact: sungdong.kim@navercorp.com