TOD: Task-Oriented Dialogue

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CONTENTS

1. TOD

Conversational AI

Conversational AI

Open-domain dialogue system

- ex) Chit-chat
- Training: end-to-end
- Data: large-scale data from social media

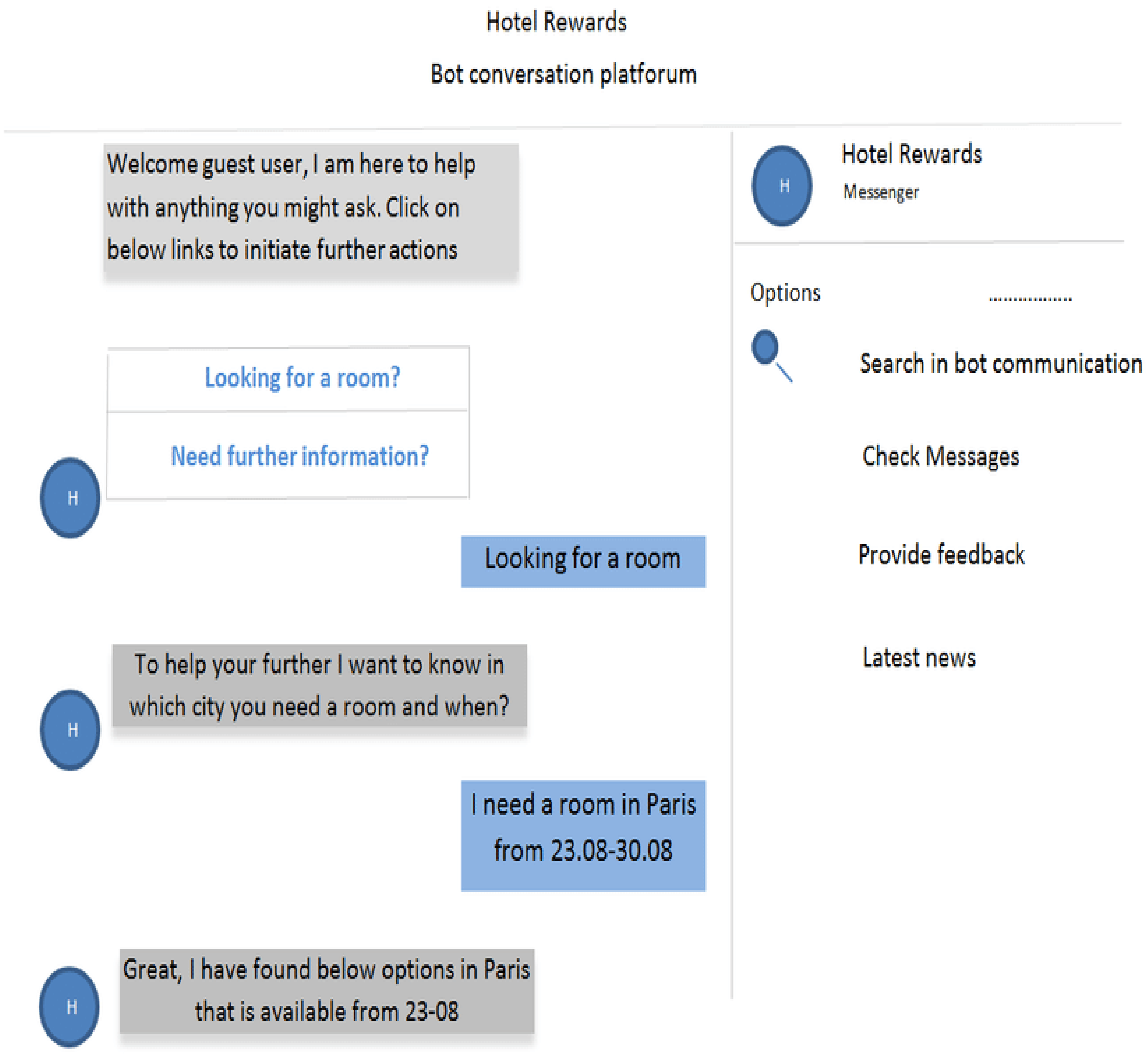
Task-Oriented dialogue system (TOD)

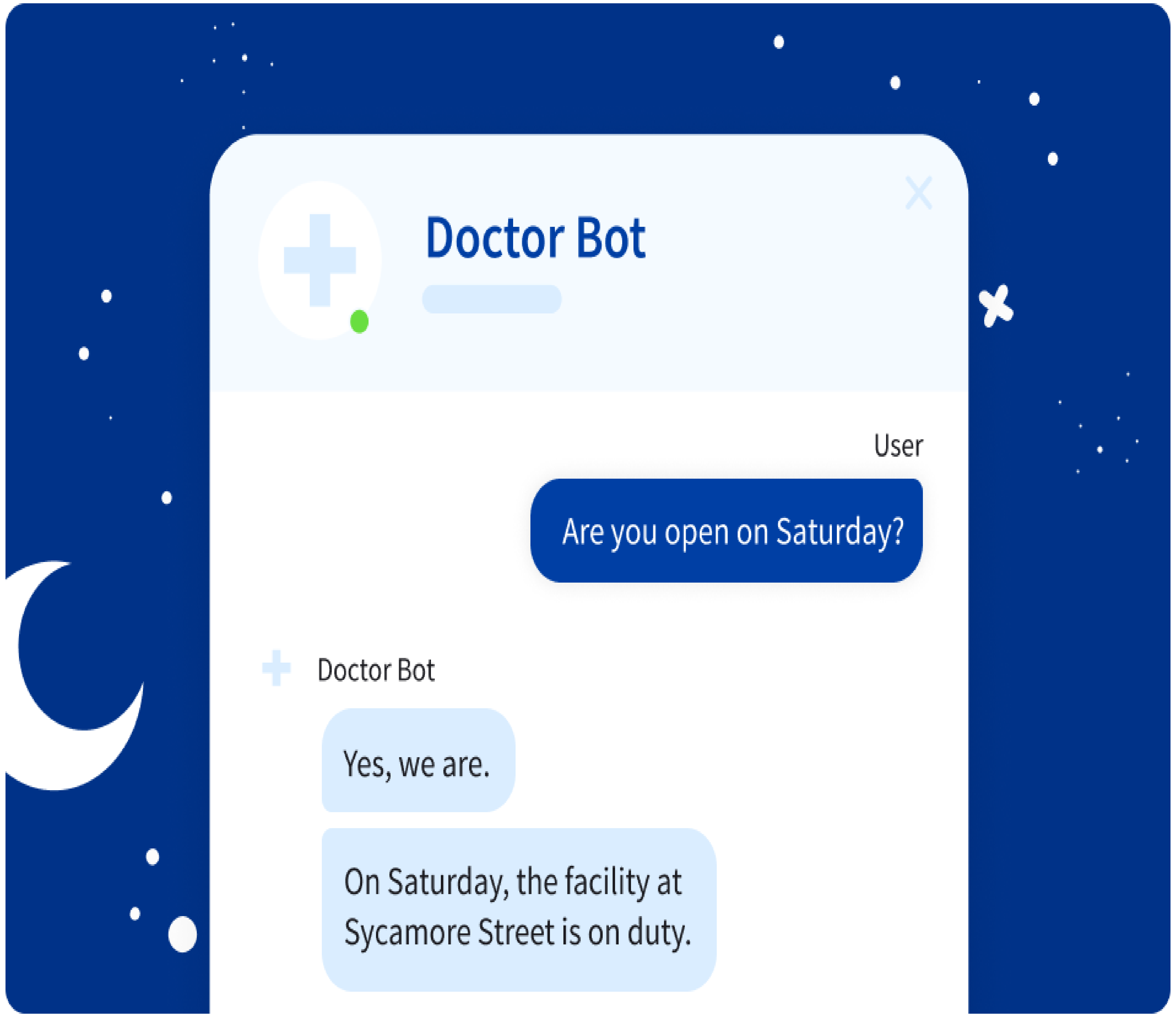
- ex) hotel reservation, medical consultant chatbot
- Goal: To accomplish a goal described by a user

Category	User message (U)	Agent response (R)	External knowledge (K)
Task-oriented	I need to find a nice restaurant in Madrid that serves expensive Thai food	There is a restaurant called *Bangkok City* locating at 9 Red Ave.	Restaurant database
Open-domain	I love the grilled fish so much!	Yeah. it's a famous *Chinese dish*	Commonsense KG

1. TOD

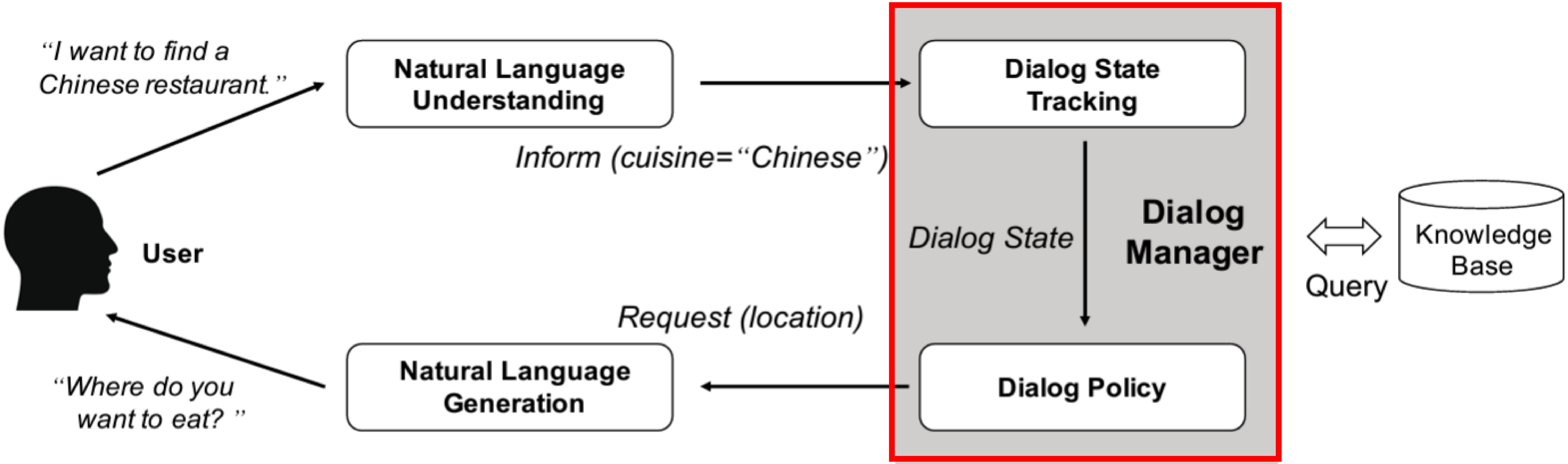
Example of TOD





1. TOD

Traditional 3 Pipelines



1. NLU **module:** extract belief state
2. DM module (Dialogue Manager): decides which actions to take based on those beliefs
   - Dialogue State Tracking (DST), Dialogue Policy
3. NLG **module:** generate responses

➔ Traditionally, each component is trained independently with different supervision

1. TOD

Traditional 3 Pipelines: Example

Knowledge Base

I'm looking for a restaurant at UNIST.

NLU + DST

Dialogue state (=Belief state):
Domain(restaurant), Area(UNIST), Date(07-20-2023),
Intent(Search_Restaurant)

Database Query
SELECT *from RESTAURANT
WHERE area=UNIST

Dialogue Manager

Query Result
value_count = 5

Policy

Decide Action:
INFORM_CHOICE, REQUEST_FOOD,
BYE, CONFIRM, ….

NLG

There are [value_count] restaurants that meet your criteria. What type of food do you want?

1. TOD

MultiWOZ Dialogue Dataset (Multi-Domain Wizard-of-Oz)

Domain	Categorical slots	Non-categorical slots	Intents
Restaurant	pricerange, area, bookday, bookpeople	food, name, booktime, address, phone, postcode, ref	find, book
Attraction	area, type	name, address, entrancefee, openhours, entrancefee, openhours, phone, postcode	find
Hotel	pricerange, parking, internet, stars, area, type, bookpeople, bookday, bookstay	name, address, phone, postcode, ref	find, book
Taxi	-	destination, departure, arriveby, leaveat, phone, type	book
Train	destination, departure, day, bookpeople	arriveby, leaveat, trainid, ref, price, duration	find, book
Bus	day	departure, destination, leaveat	find
Hospital	-	department , address, phone, postcode	find
Police	-	name, address, phone, postcode	find

- 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**.

sample task template (domain: hotel)

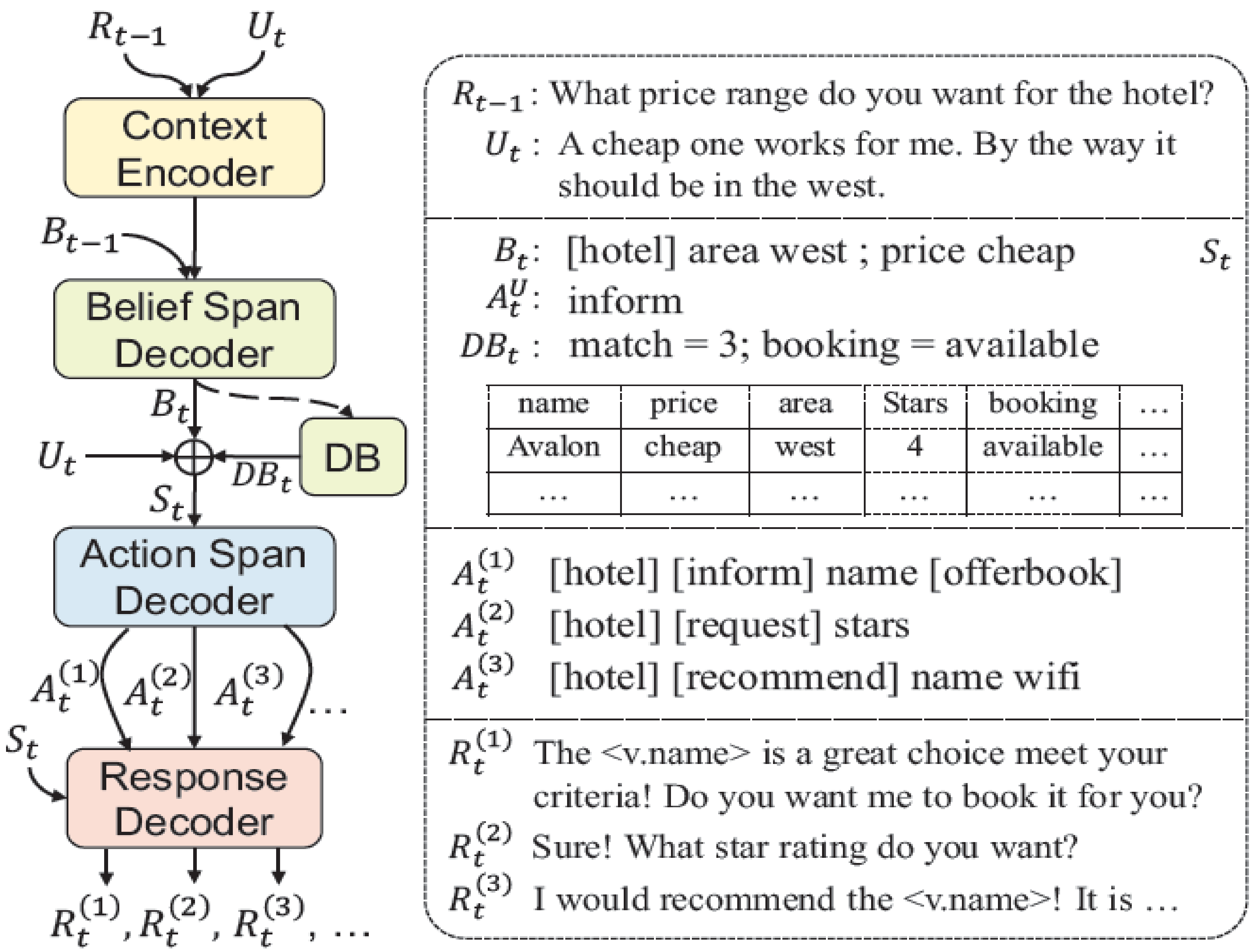
- CamRest and MultiWOZ
- 8 domains
- 14,000 multi-turn dialogues

1. TOD

Towards End-to-End Training

Prior work (1) domain-aware **multi-decoder** model (DAMD) + augmentation

- Single-sequence: Greedy Decoding
- Multiple actions: Beam Search + Diverse Beam Search/Top-K Sampling



$$B_t = \mathrm{seq2seq}(R_{t-1}, U_t, B_{t-1})$$

$$A_t = \mathrm{seq2seq}(U_t, B_t, DB_t)$$

$$R_t = \mathrm{seq2seq}(A_t, U_t, B_t, DB_t)$$

1. TOD

Towards End-to-End Training

Prior work (1) domain-aware multi-decoder model (DAMD) + augmentation
[Evaluation] SoTA combined score for Dialogue Management and Response Generation

<Automatic Evaluation Metrics>

1. **Inform rate**: provides an correct entity
2. **Success rate**: answers all the requested information
3. **BLEU**: fluency
4. **Combined score**: (inform + Success) x 0.5 + BLEU
   = overall quality measure

Model	Belief State Type	System Action Type	System Action Form	Inform (%)	Success (%)	BLEU	Combined Score
1. Seq2Seq + Attention (Budzianowski et al. 2018)	oracle	-	-	71.3	61.0	**18.9**	85.1
2. Seq2Seq + Copy	oracle	-	-	86.2	**72.0**	15.7	94.8
3. MD-Sequicity	oracle	-	-	**86.6**	71.6	16.8	**95.9**
4. SFN + RL (Mehri et al. 2019)	oracle	generated	one-hot	82.7	72.1	16.3	93.7
5. HDSA (Chen et al. 2019)	oracle	generated	graph	82.9	68.9	**23.6**	99.5
6. DAMD	oracle	generated	span	**89.5**	75.8	18.3	100.9
7. DAMD + multi-action data augmentation	oracle	generated	span	89.2	**77.9**	18.6	**102.2**
8. SFN + RL (Mehri et al. 2019)	oracle	oracle	one-hot	-	-	29.0	106.0
9. HDSA (Chen et al. 2019)	oracle	oracle	graph	87.9	78.0	**30.4**	113.4
10. DAMD + multi-action data augmentation	oracle	oracle	span	**95.4**	**87.2**	27.3	**118.5**
11. SFN + RL (Mehri et al. 2019)	generated	generated	one-hot	73.8	58.6	**16.9**	83.0
12. DAMD + multi-action data augmentation	generated	generated	span	**76.3**	**60.4**	16.6	**85.0**

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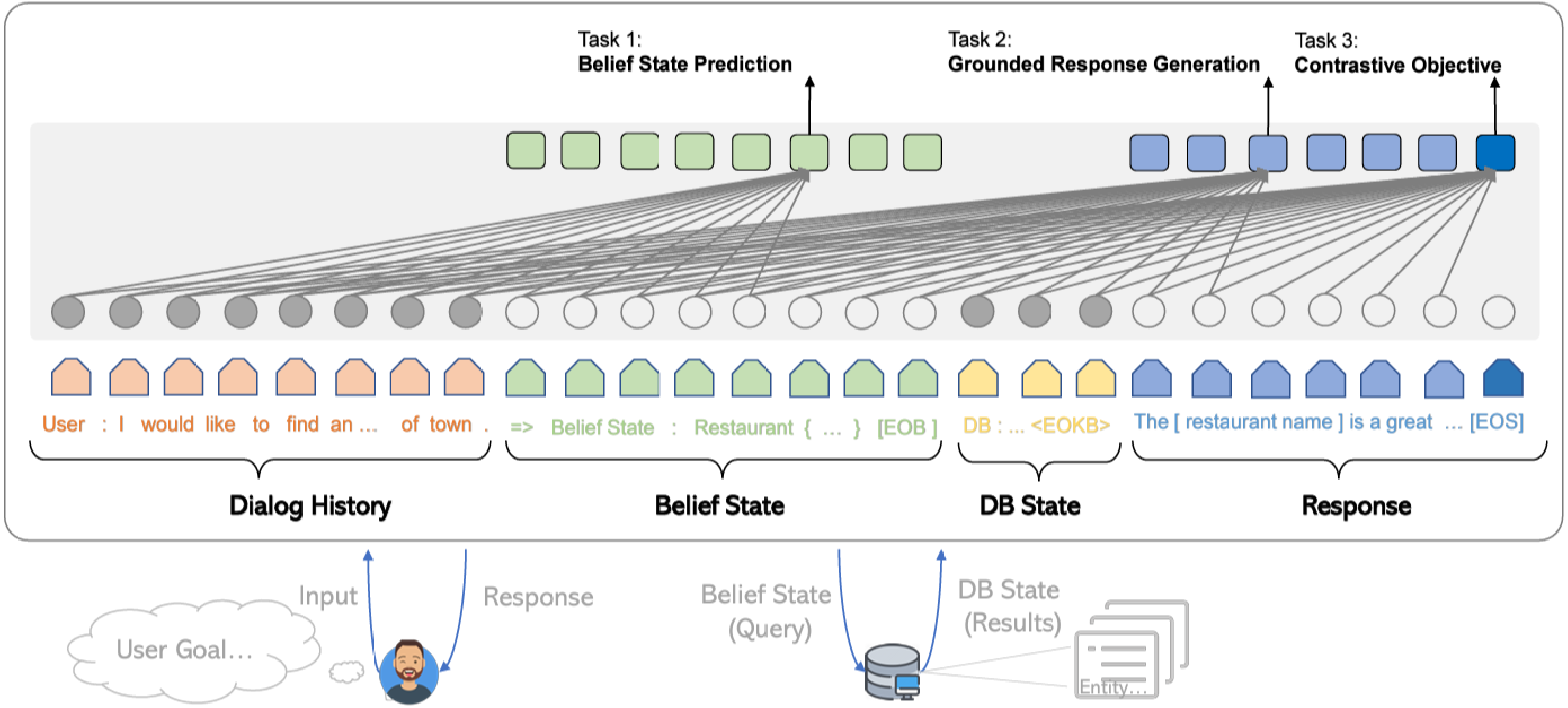
Towards End-to-End Training

Prior work (2) SOLOIST: GPT2-based end-to-end training model

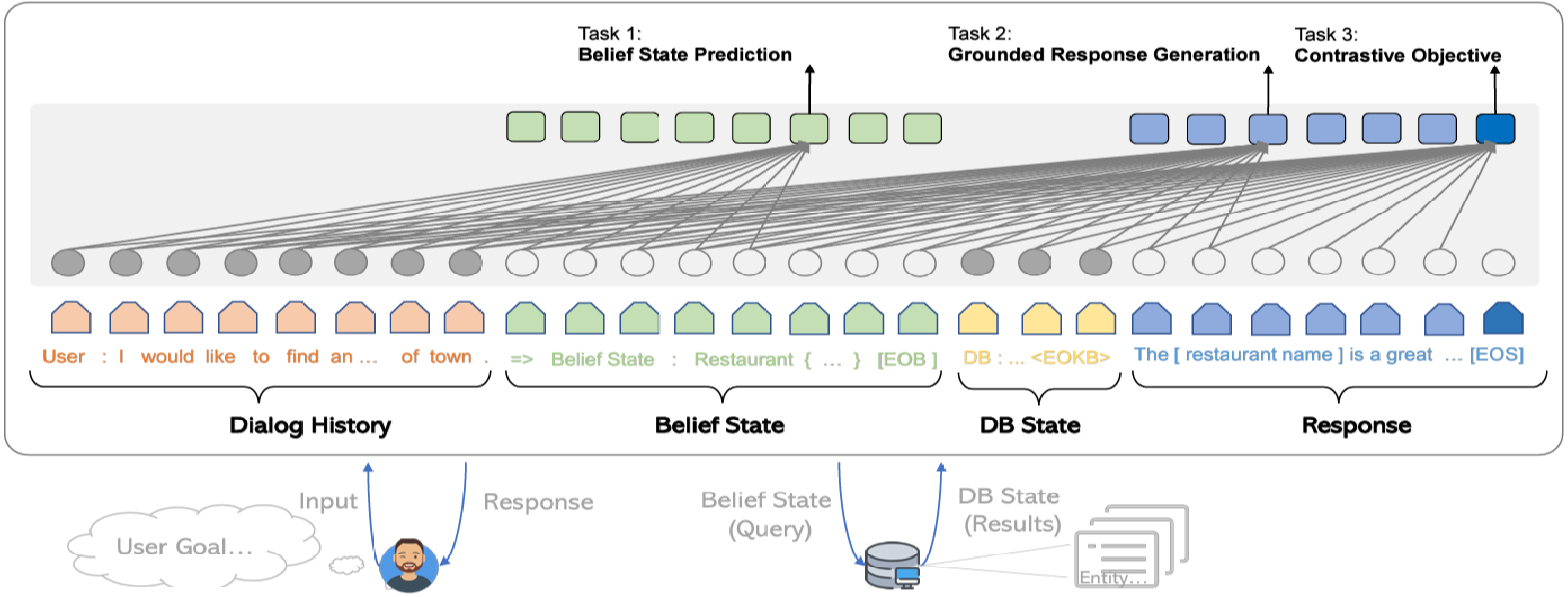


1. TOD

Towards End-to-End Training

$$p(\boldsymbol{x}) = p(\boldsymbol{r}, \boldsymbol{c}, \boldsymbol{b}, \boldsymbol{s}) = \underbrace{p(\boldsymbol{r}|\boldsymbol{c}, \boldsymbol{b}, \boldsymbol{s})}_{\text{Grounded Response Generation}} \; \underbrace{p(\boldsymbol{b}|\boldsymbol{s})}_{\text{Belief Prediction}} \; p(\boldsymbol{s}).$$

Prior work (2) SOLOIST: GPT2-based end-to-end training model



$$\mathcal{L}_{\text{B}} = \log p(\boldsymbol{b}|\boldsymbol{s}) = \sum_{t=1}^{T_b} \log p_{\boldsymbol{\theta}}(b_t|b_{<t}, \boldsymbol{s})$$

$$\mathcal{L}_{\text{R}} = \log p(\boldsymbol{r}|\boldsymbol{c}, \boldsymbol{b}, \boldsymbol{s}) = \sum_{t=1}^{T_r} \log p_{\boldsymbol{\theta}}(r_t|r_{<t}, \boldsymbol{c}, \boldsymbol{b}, \boldsymbol{s})$$

$$\mathcal{L}_{\text{C}} = y \log(p_{\boldsymbol{\theta}}(\boldsymbol{x})) + (1-y)\log(1 - p_{\boldsymbol{\theta}}(\boldsymbol{x}'))$$

1. TOD

Towards End-to-End Training

Prior work (2) SOLOIST: GPT2-based end-to-end training model

[Evaluation] New SoTA,

But didn't show end-to-end performance w/o pretraining on other dialogue datasets

Model	Inform ↑	Success ↑	BLEU ↑	Combined ↑
Full objective	85.50	72.90	16.54	95.74
- belief	81.50	69.30	16.82	92.22
- belief & response	82.50	67.30	16.28	91.18

$$\mathcal{L}_{\boldsymbol{\theta}}(\mathcal{D}) = \sum_{n=1}^{|\mathcal{D}|}(\mathcal{L}_{\mathrm{B}}(\boldsymbol{x}_n)+\mathcal{L}_{\mathrm{R}}(\boldsymbol{x}_n)+\mathcal{L}_{\mathrm{C}}(\boldsymbol{x}_n))$$

Model	Attraction			Train			Hotel			Restaurant		
	Inform ↑	Success ↑	BLEU ↑	Inform ↑	Success ↑	BLEU ↑	Inform ↑	Success ↑	BLEU ↑	Inform ↑	Success ↑	BLEU ↑
DAMD (Zhang et al., 2019a)	70.00	15.00	6.90	75.00	39.50	6.20	62.50	20.50	7.60	68.00	19.50	10.50
SOLOIST w/o pre-training	65.66	46.97	5.85	59.00	44.00	7.07	62.50	40.00	7.70	75.50	44.50	11.00
SOLOIST	86.00	65.00	12.90	80.81	64.65	9.96	74.50	43.50	8.12	81.00	55.50	12.80
SOLOIST$_{\mathrm{L}}$	**86.00**	**68.00**	**14.60**	**81.31**	**74.24**	**11.90**	**75.00**	**51.50**	**10.09**	**84.00**	**62.50**	**13.17**

Table 7: End-to-end evaluation on MultiWOZ in a few-shot learning setting.

SimpleTOD:
End-to-End Baseline Model

- uses a single, casual (unidirectional) LM
- trained on all sub-tasks
- in an end-to-end single sequence prediction
- first model to achieve SoTA performance for DST, action decisions, and response generation

A Simple Language Model for Task-Oriented Dialogue

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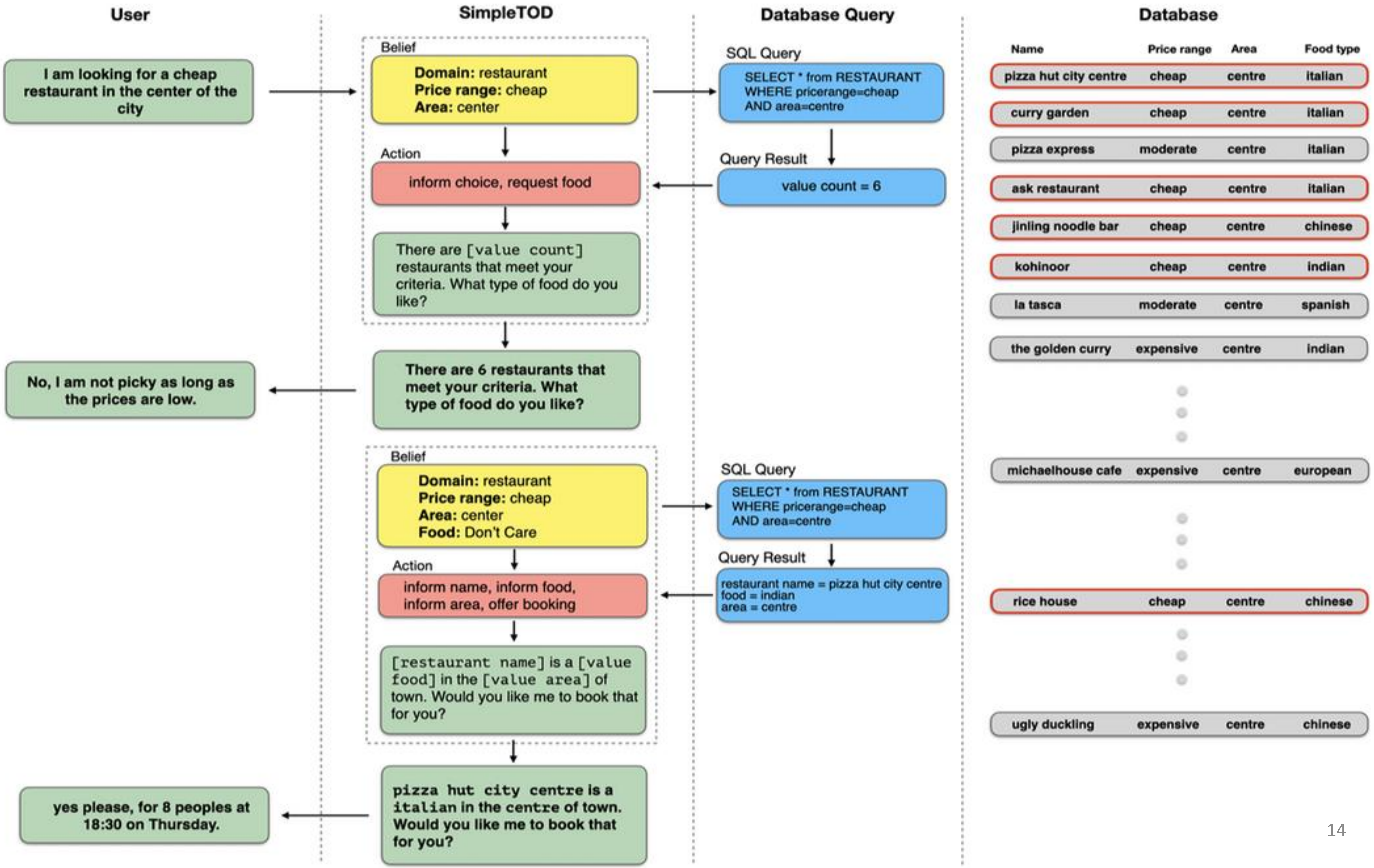
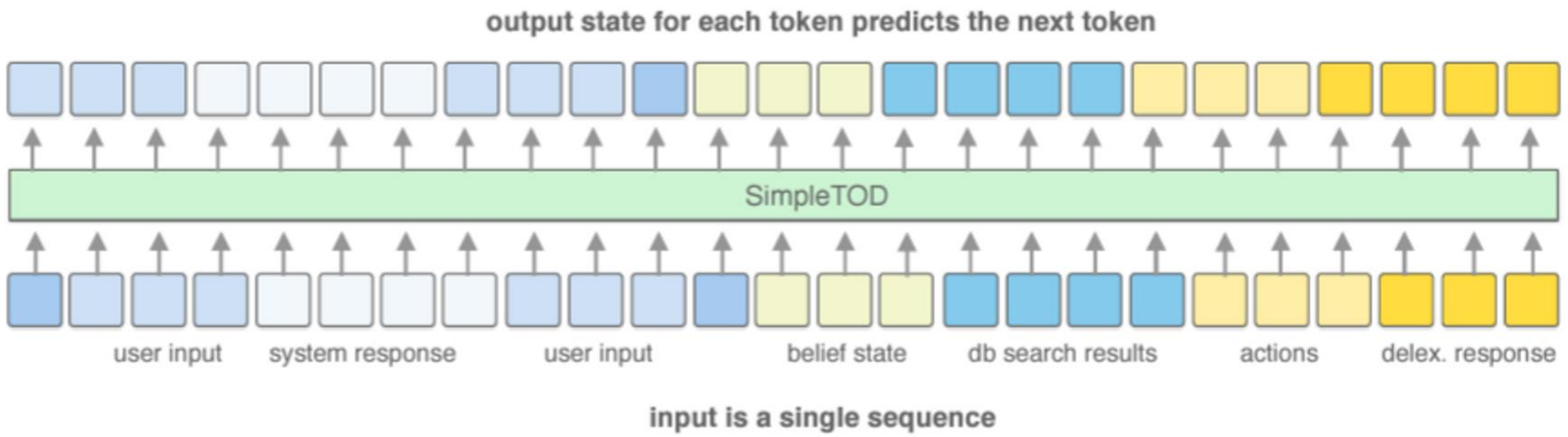

User
SimpleTOD
Database Query
Database
I am looking for a cheap restaurant in the center of the city
Belief
Domain: restaurant
Price range: cheap
Area: center
SQL Query
SELECT * from RESTAURANT WHERE pricerange=cheap AND area=centre
Action
inform choice, request food
Query Result
value count = 6
There are [value count] restaurants that meet your criteria. What type of food do you like?
There are 6 restaurants that meet your criteria. What type of food do you like?
No, I am not picky as long as the prices are low.
Belief
Domain: restaurant
Price range: cheap
Area: center
Food: Don't Care
SQL Query
SELECT * from RESTAURANT WHERE pricerange=cheap AND area=centre
Action
inform name, inform food, inform area, offer booking
Query Result
restaurant name = pizza hut city centre
food = indian
area = centre
[restaurant name] is a [value food] in the [value area] of town. Would you like me to book that for you?
pizza hut city centre is a italian in the centre of town. Would you like me to book that for you?
yes please, for 8 peoples at 18:30 on Thursday.
Name
Price range
Area
Food type
pizza hut city centre cheap centre italian
curry garden cheap centre italian
pizza express moderate centre italian
ask restaurant cheap centre italian
jinling noodle bar cheap centre chinese
kohinoor cheap centre indian
la tasca moderate centre spanish
the golden curry expensive centre indian
michaelhouse cafe expensive centre european
rice house cheap centre chinese
ugly duckling expensive centre chinese

2. <SimpleTOD> Review

Training

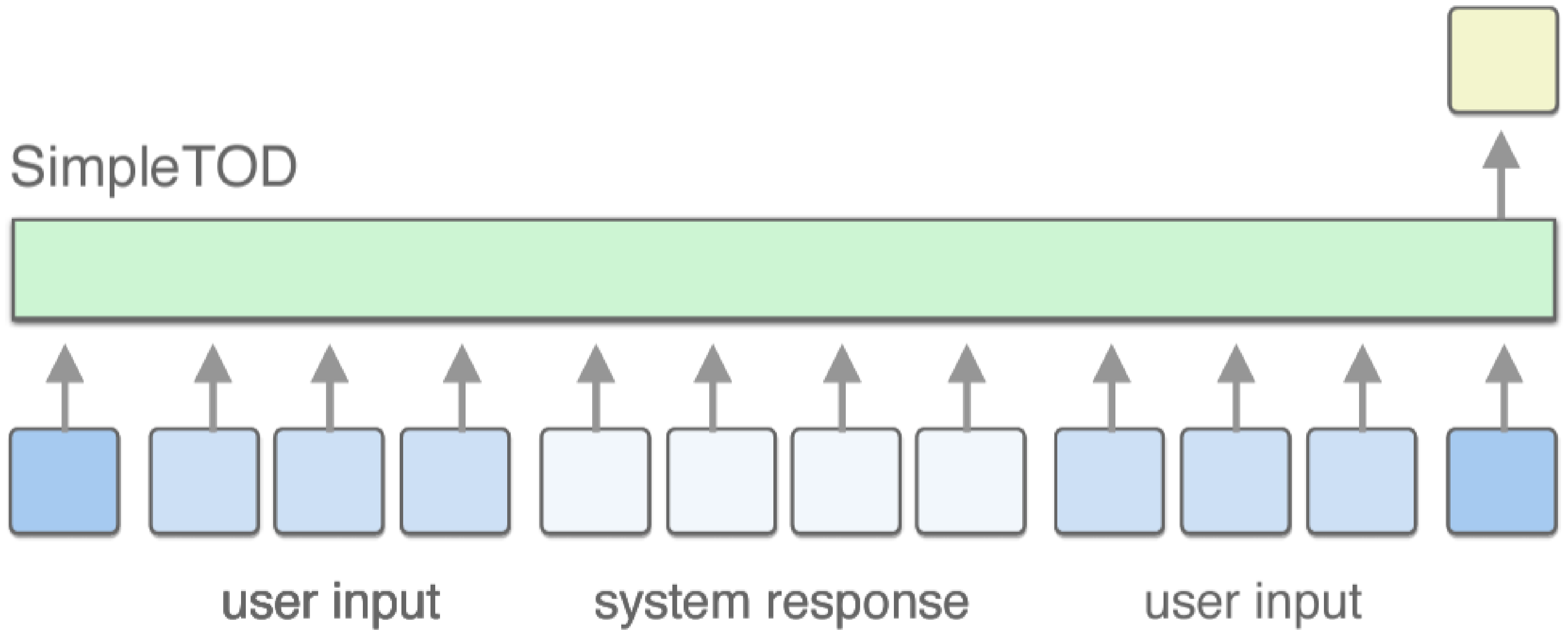


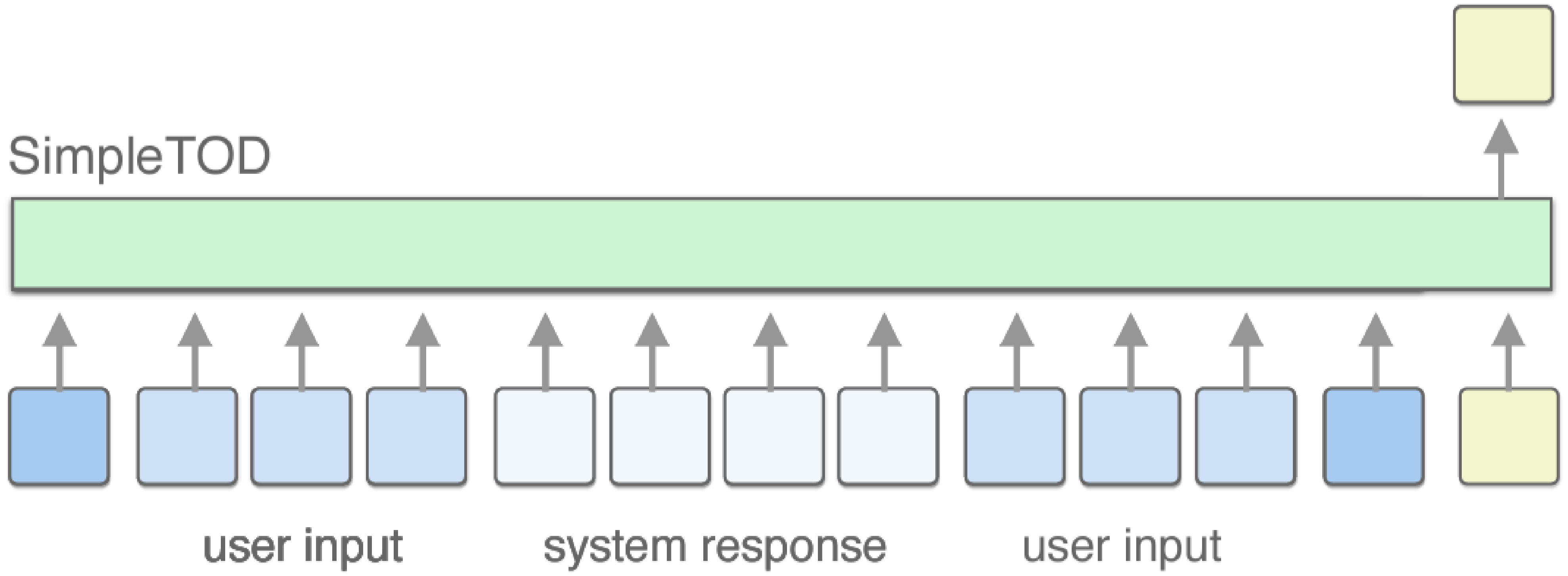
- t : $turn$
- U_t : $user\ input$
- $C_t = [U_0, S_0, \ldots, U_t]$: $context$
- $B_t = SimpleTOD(C_t)$: $belief\ state$
- D_t : $the\ aggregated\ database\ results\ as\ input$
- $A_t = SimpleTOD([C_t, B_t, D_t])$: $action$
- $S_t = SimpleTOD([C_t, B_t, D_t, A_t])$: $delexicalized\ response$

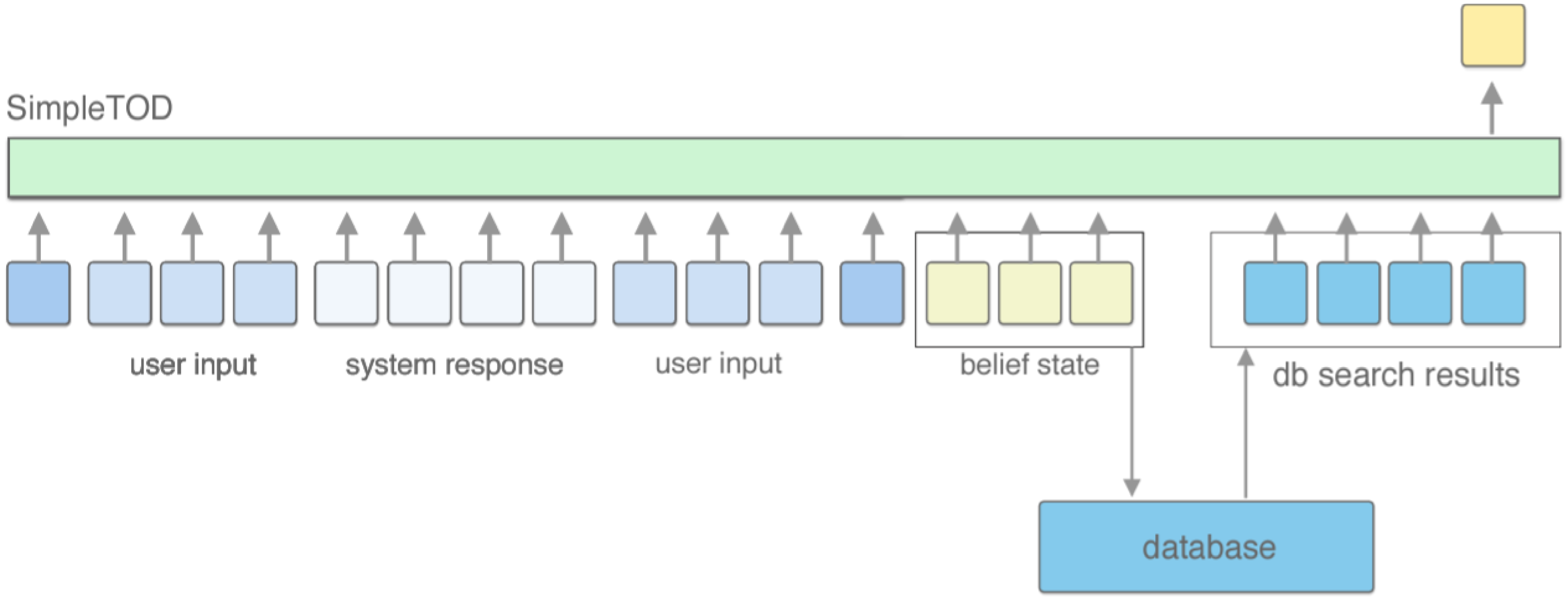
$$x^t = [C_t; B_t; D_t; A_t; S_t]$$

2. <SimpleTOD> Review

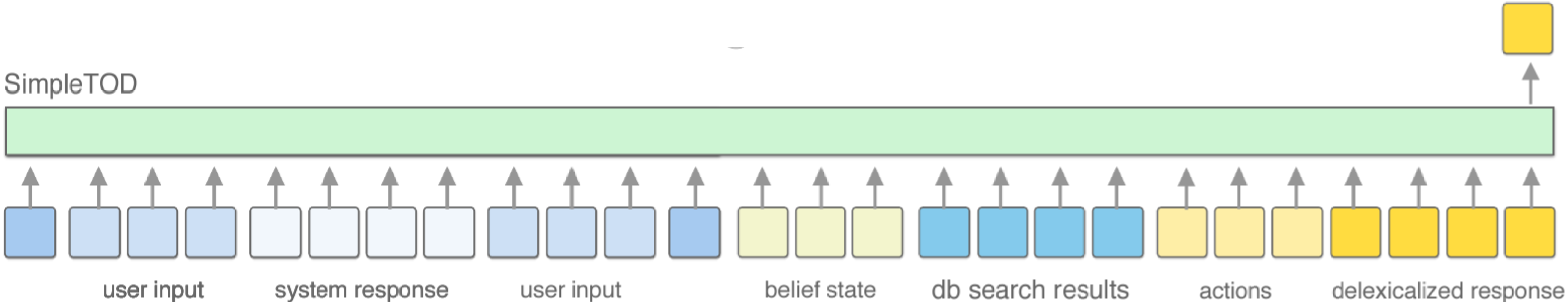
Causal Language Modeling







$$p(x) = \prod_{i=1}^{n} p(x_i | x_{<i}) \qquad \mathcal{L}(D) = -\sum_{t=1}^{|D|} \sum_{i=1}^{n_t} \log p_\theta(x_i^t | x_{<i}^t)$$



2. <SimpleTOD> Review

Evaluation

Model	Decoder	Context Encoder	Extra Supervision	Joint Accuracy
TRADE*	Generative + Classifier	Bidirectional	-	45.6
DSTQA**	Classifier	Bidirectional	knowledge graph	51.17
DST-Picklist*	Classifier	Bidirectional	-	53.3
SST*	Generative	Bidirectional	schema graph	55.23
TripPy†	Classifier	Bidirectional	action decision	55.3
SimpleTOD^o	Generative	Unidirectional	-	55.72
SimpleTOD*	Generative	Unidirectional	-	**55.76**
SimpleTOD$^+$	Generative	Unidirectional	-	57.47

Table 1: Evaluation of Dialogue State Tracking (DST) on MultiWOZ 2.1 using joint accuracy metric. * uses test label cleaning proposed by Wu et al. [53] and recommended by MultiWOZ authors. † uses label normalization and equivalent matching proposed in Heck et al. [19]. ** uses the cleaning of * models plus additional accounting for label variants. $^+$ performs cleaning of Type 2 and partial cleaning of Type 4 noisy annotations as outlined in Section 5, which is currently non-standard and so left unbolded. ^{o} no label-cleaning.

Model	Belief State	DB Search	Action	Inform	Success	BLEU	Combined
DAMD+augmentation	generated	oracle	generated	76.3	60.4	16.6	85
SimpleTOD (ours)	generated	oracle	generated	78.1	63.4	16.91	87.66
SimpleTOD (ours)	generated	dynamic	generated	81.4	69.7	16.11	91.66
SimpleTOD (ours)	generated	-	generated	**84.4**	**70.1**	15.01	**92.26**

2. <SimpleTOD> Review

Wrap-up

Previous Models

- All previous models propose a bidirectional encoder

  → to learn better representation of context

- beam search, diverse beam search, top-k sampling

  = costly decoding strategy

- test label cleaning

SimpleTOD

- Causal Language Modeling (unidirectional)

  = NOT bidirectional

- Simple Greedy Decoding

  = NOT costly

- w/o any cleaning or normalization

  = simply on the raw, original annotations

3. Recent Advancements

SPACE: Unified Pre-trained Conversation Model for TOD

Unified Dialog Model Pre-training for Task-Oriented Dialog Understanding and Generation

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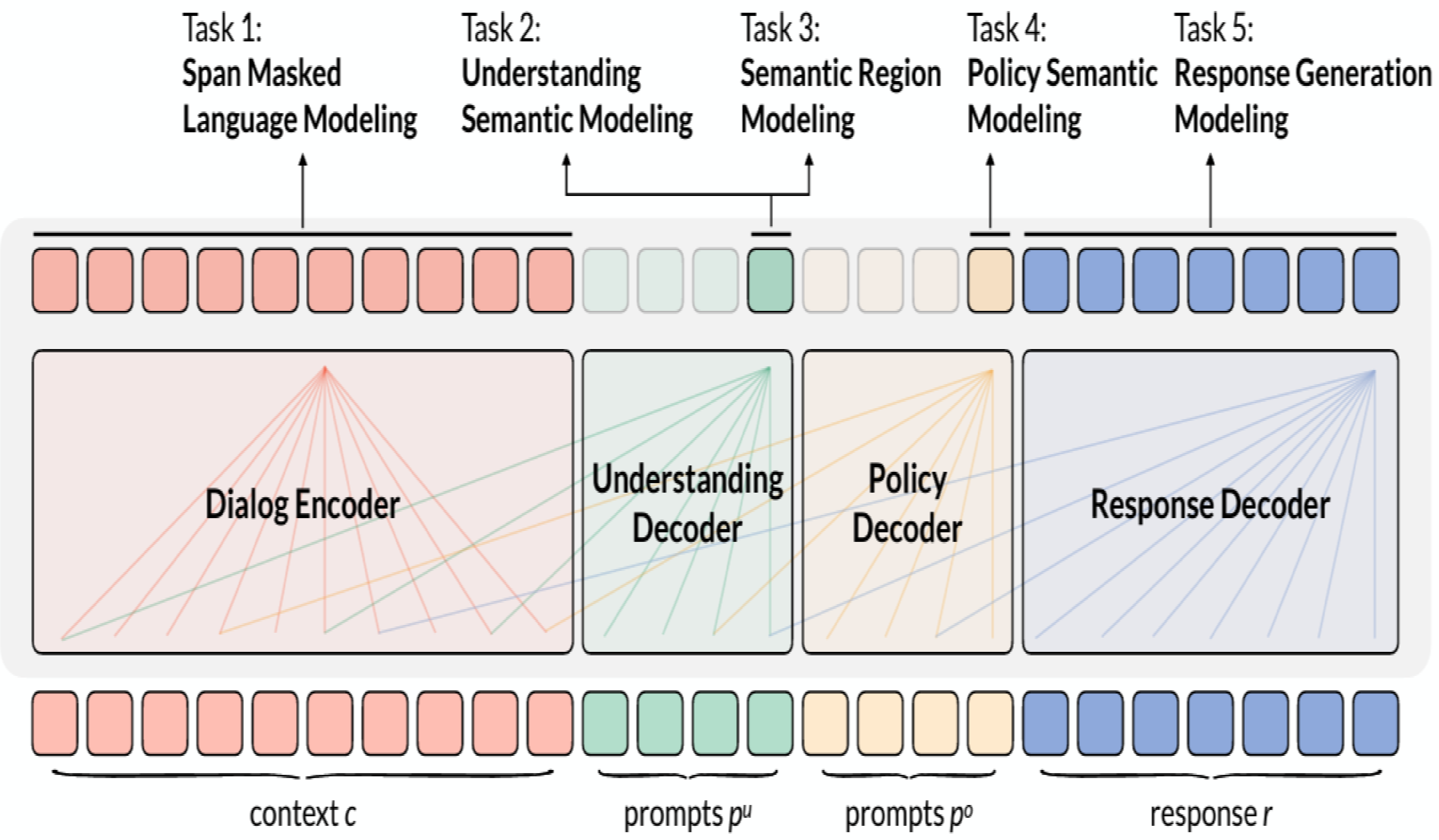
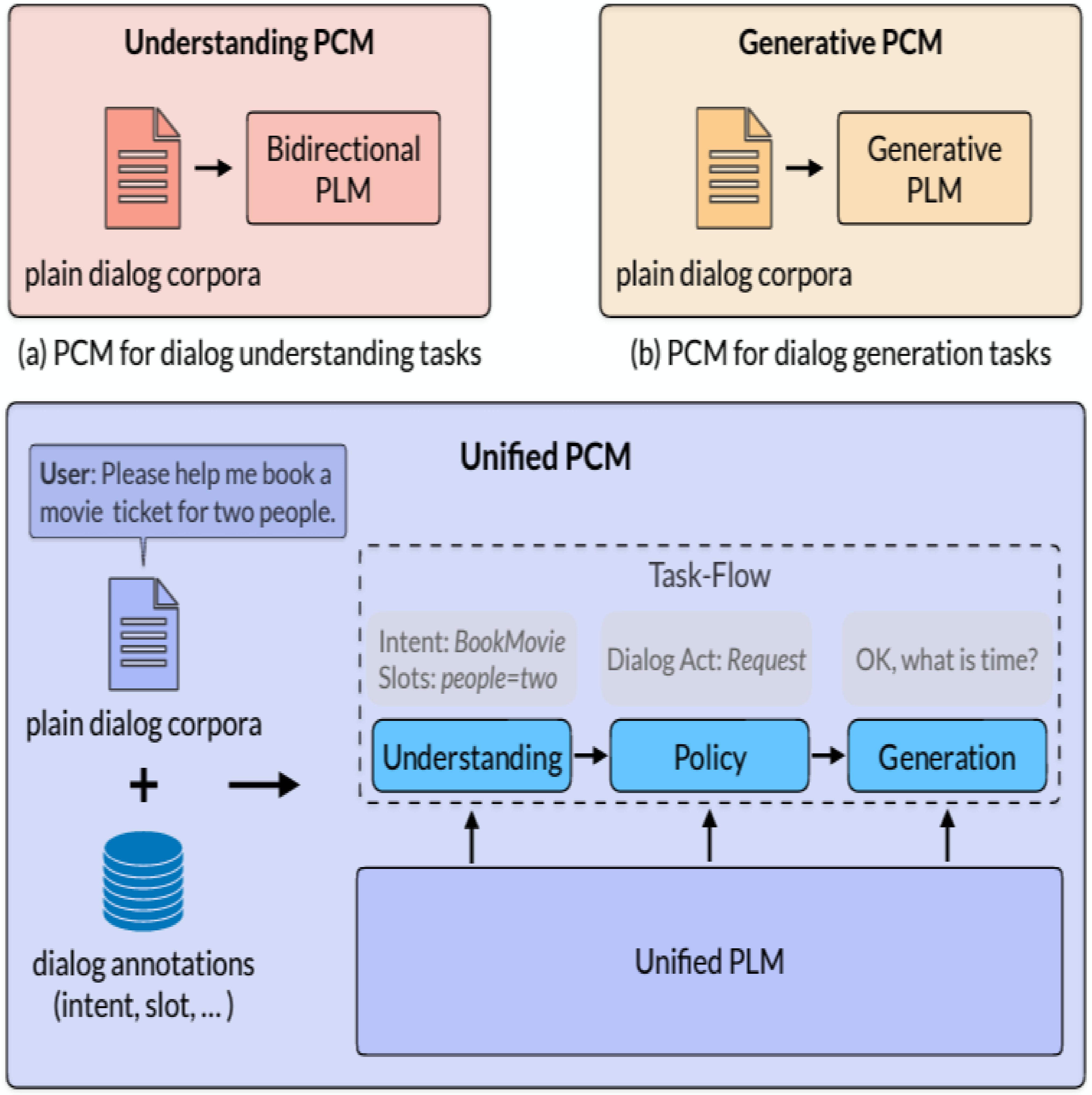
Baselines for Specific Tasks. For intent prediction, we compare SPACE with four state-of-the-art baselines: **ConvBERT** [63], **Example+Observer** [62], **USE+ConveRT** [8], and **ConvFit** [91]. For the dialog state tracking task, we compare with **DS-DST** [112], **Seq2Seq-DU** [24], **PLATO-XL** [4] and **AG-DST** [89]. For the end-to-end dialog modeling task, we have different baselines on different datasets for comparison. For MultiWOZ2.0 and MultiWOZ2.1, we compare with **SimpleTOD** [37], **DoTS** [39], **UBAR** [104], and **MT-TOD** [49]. For CamRest676 and In-Car, we compare with **SEDST** [40], **TSCP** [50], **FSDM** [86] and **LABES** [115].

3. Recent Advancements

SPACE: Unified Dialog Model Pre-training for TOD





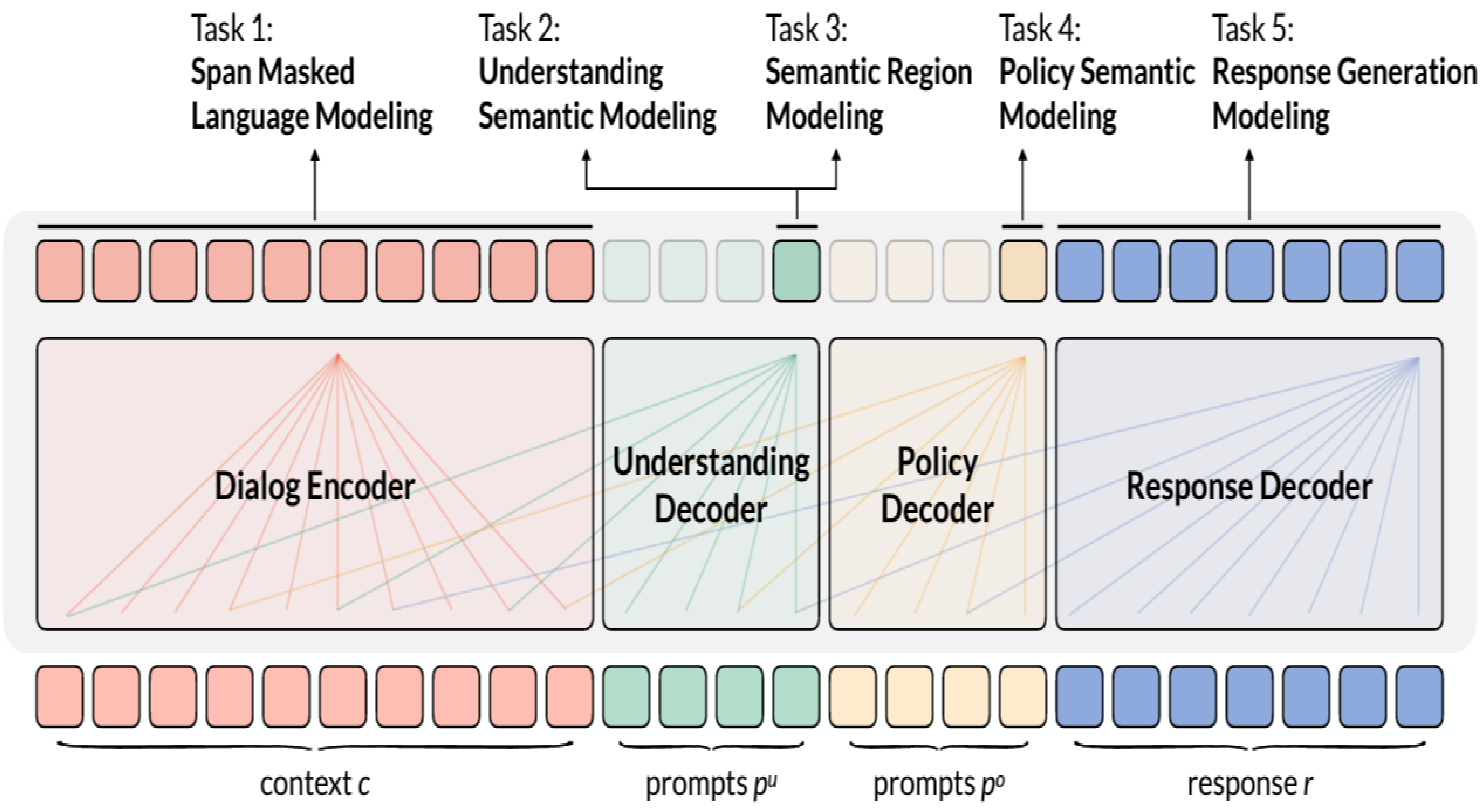
(c) Unified PCM for both dialog understanding and generation tasks

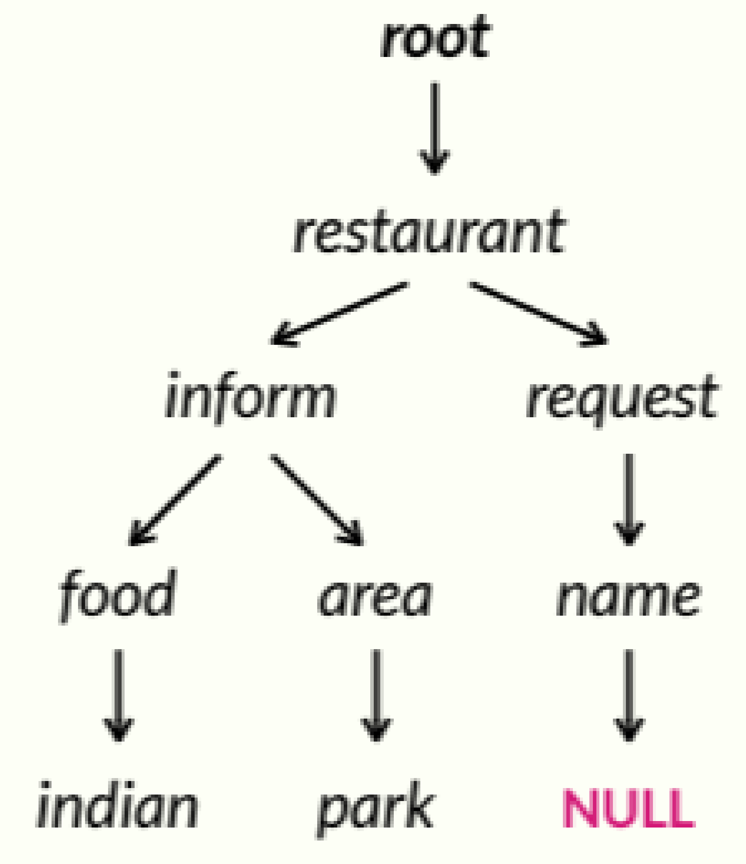
3. Recent Advancements

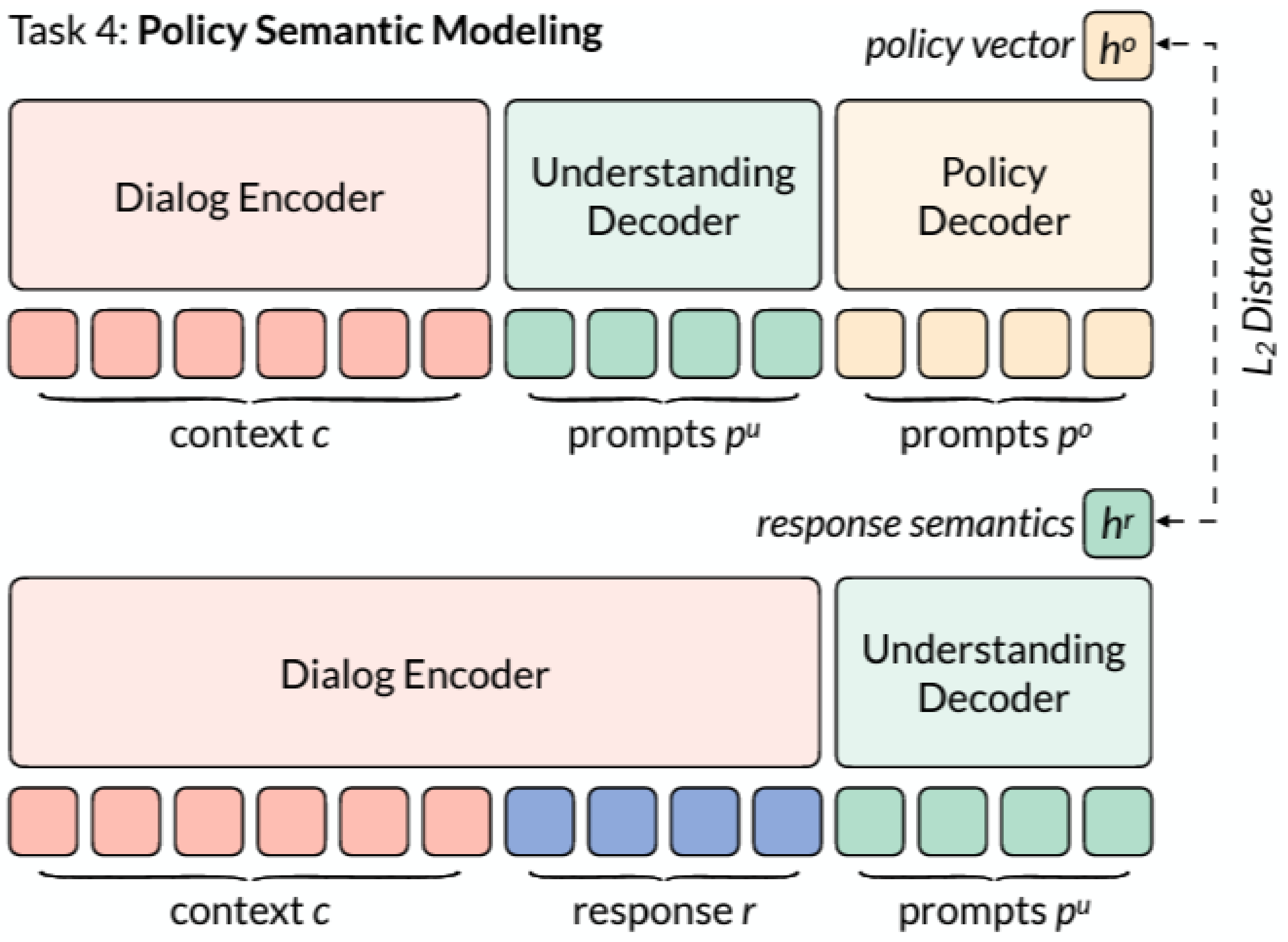
SPACE: Unified Pre-trained Conversation Model for TOD

I want an indian restaurant in park, could you offer me the name ?

restaurant-inform(food=indian, area=park); restaurant-request(name=?)







3. Recent Advancements

SPACE: Unified Dialog Model Pre-training for TOD

Table 4: Comparison results on dialog understanding tasks.

Model	MultiWOZ2.2
DS-DST	51.7
Seq2Seq-DU	54.40
PLATO-XL	57.16
AG-DST	57.26
SPACE	**57.50**

Table 5: Comparison results on four E2E dialog task

Model	MultiWOZ2.0				MultiWOZ2.1			
	Inform	Success	BLEU	Comb	Inform	Success	BLEU	Comb
SimpleTOD	84.40	70.10	15.01	92.26	85.00	70.50	15.23	92.98
DoTS	86.59	74.14	15.06	95.43	86.65	74.18	15.90	96.31
UBAR	**95.40**	80.70	17.00	105.05	**95.70**	81.80	16.50	105.25
MTTOD	90.99	82.58	**20.25**	107.04	90.99	82.08	19.68	106.22
SPACE	95.30	**88.00**	19.30	**110.95**	95.60	**86.10**	**19.91**	**110.76**

References

1. TOD

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2. SimpleTOD Review

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2. Budzianowski, Paweł, et al. "Multiwoz--a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling." arXiv preprint arXiv:1810.00278 (2018).

3. Recent Advancements

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THANK YOU