

Research Proposal

Dialogue Retrieval for LLM-based ToD in few-shot setting

2023 SS Natural Language Processing (CSW6035)

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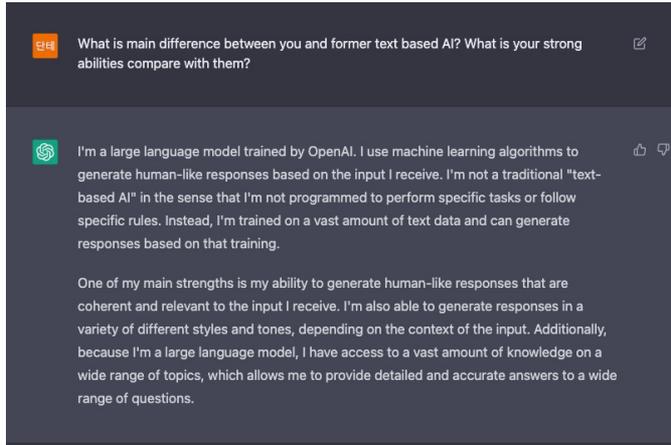
1. Introduction
2. Problem States
3. Suggestion
 - Research Questions
 - Toy Experiments
4. Related Works
5. Experiments (Plan)
6. Future Works

1. Introduction

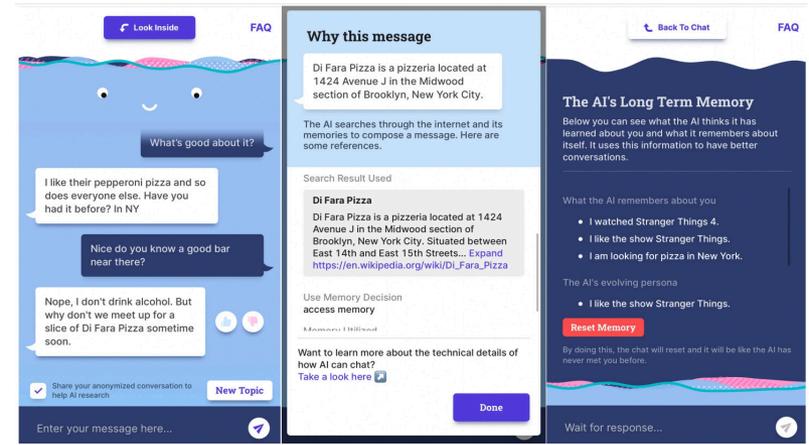
- Chit-Chat vs. Task-oriented Dialogue
- Task-oriented Dialogue System
- Dialogue Representation

Introduction

• Chit-Chat vs. Task-oriented Dialogue



▲ ChatGPT (OpenAI)



▲ BlenderBot3 (Meta)



▲ 에이닷 (SKT)



▲ 이루다 2.0 (SCATTER LAB)

Introduction

• Chit-Chat vs. Task-oriented Dialogue



▲ ChatGPT (OpenAI)



▲ 이루다 2.0 (SCATTER LAB)

Introduction

• Chit-Chat vs. Task-oriented Dialogue

Chit-chat

- No specific Goal
- Focus on
 - generating natural responses
- The more turns the better
- Using variants of generation models



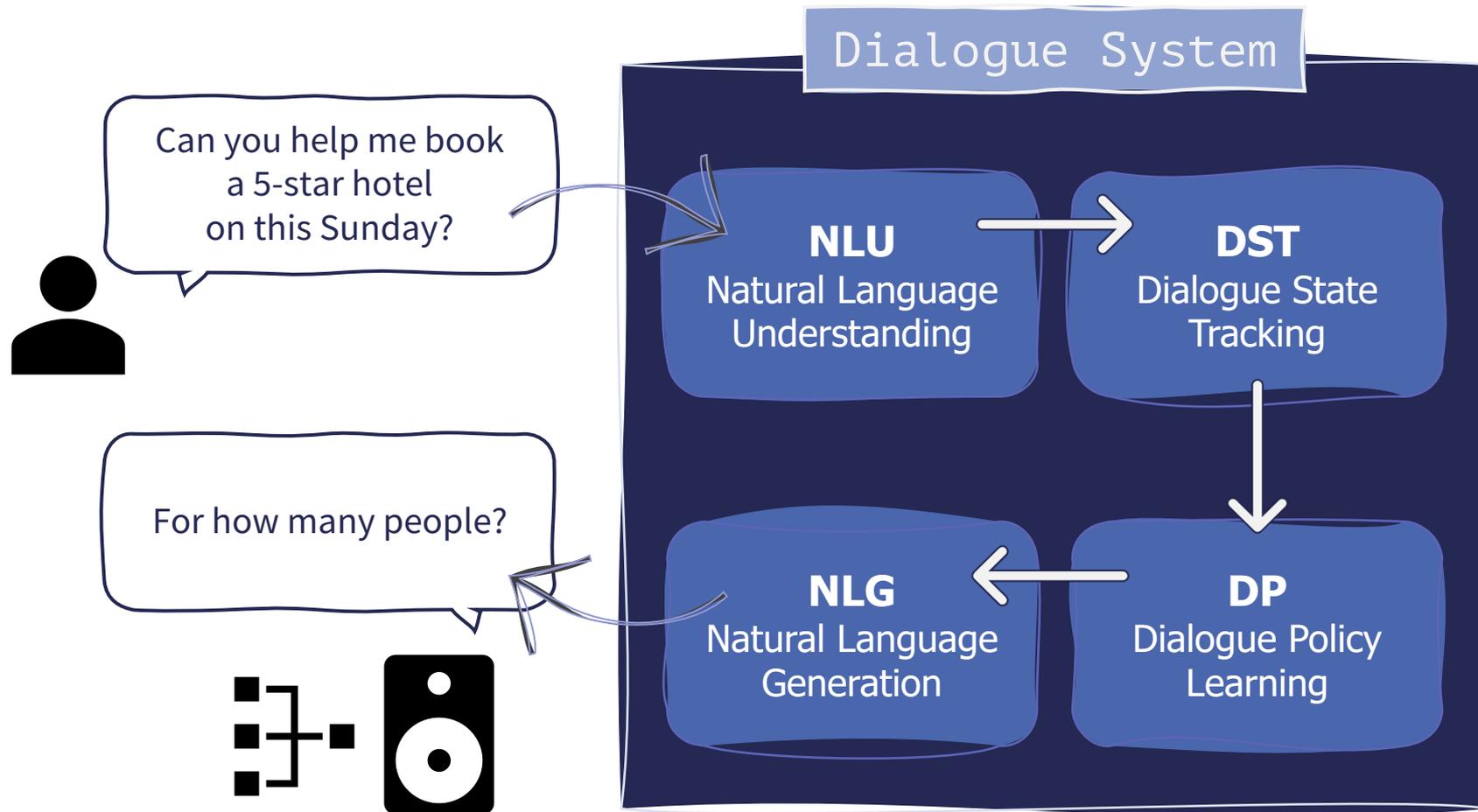
ToD

- Help users achieve their goal
- Focus on
 - tracking states
 - generating next actions
- The less turns the better
- Combination of rules & statistical components



Introduction

- Task-oriented Dialogue System



Prerequisites :: MultiWoZ 2.2

• Data Structure

- Multi-turn dialogue btw USER & AGENT
- Instance
 - Each turn has single utterance, e.g.:

```
['What fun places can I visit in the East?',  
'We have five spots which include boating, museums and entertainment. Any  
preferences that you have?']
```

- Utterance of USER: also annotated w. frames denoting their intent and belief state

```
[{'service': ['attraction'],  
  'slots': [{'copy_from': [],  
             'copy_from_value': [],  
             'exclusive_end': [],  
             'slot': [],  
             'start': [],  
             'value': []}],  
  'state': [{'active_intent': 'find_attraction',  
            'requested_slots': [],  
            'slots_values': {'slots_values_list': [['east'],  
                                                  'slots_values_name': ['attraction-area']}]},  
            {'service': [], 'slots': [], 'state': []}]
```

Prerequisites :: MultiWoZ 2.2

• Data Structure

- Multi-turn dialogue btw USER & AGENT
- Instance
 - Each of the utterances us annotated w/ dialog acts which provide a structured representation of what the USER or AGENT is inquiring or giving information about.

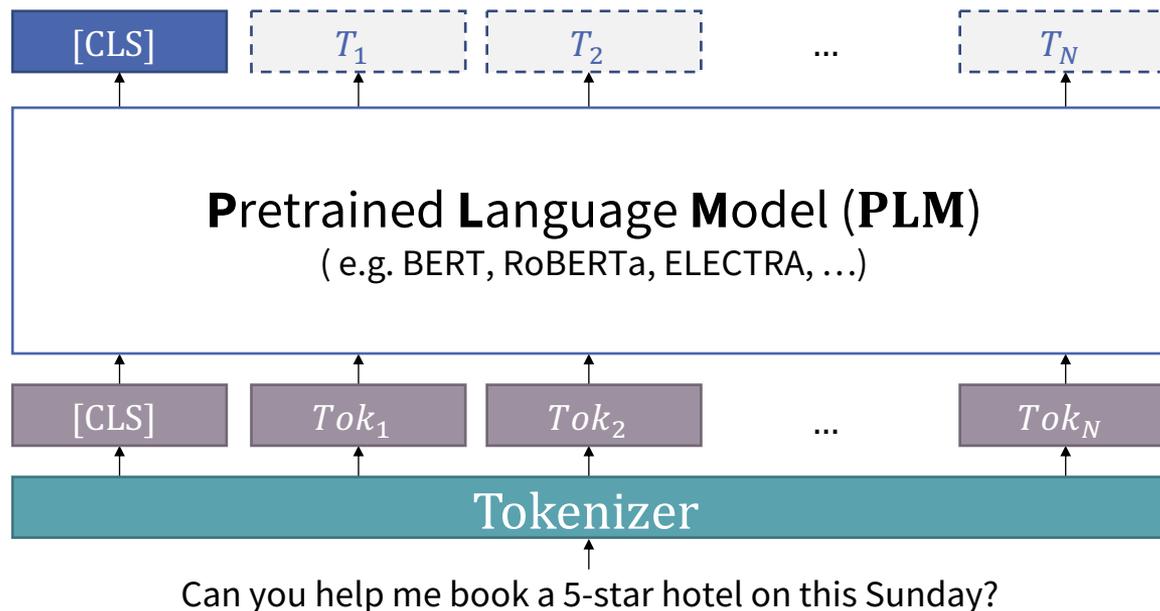
```
[{'dialog_act': {'act_slots': [{'slot_name': ['east'],  
  'slot_value': ['area']}]},  
  'act_type': ['Attraction-Inform']},  
  'span_info': {'act_slot_name': ['area'],  
  'act_slot_value': ['east'],  
  'act_type': ['Attraction-Inform'],  
  'span_end': [39],  
  'span_start': [35]}}],  
  {'dialog_act': {'act_slots': [{'slot_name': ['none'], 'slot_value': ['none']},  
  {'slot_name': ['boating', 'museums', 'entertainment', 'five'],  
  'slot_value': ['type', 'type', 'type', 'choice']}]},  
  'act_type': ['Attraction-Select', 'Attraction-Inform']},  
  'span_info': {'act_slot_name': ['type', 'type', 'type', 'choice'],  
  'act_slot_value': ['boating', 'museums', 'entertainment', 'five'],  
  'act_type': ['Attraction-Inform',  
  'Attraction-Inform',  
  'Attraction-Inform'],  
  'span_end': [40, 49, 67, 12],  
  'span_start': [33, 42, 54, 8]}}]
```

Introduction

• Sentence Representation

- Context Vector is considered a collective representation of the typed sentence.
- Use the mean/max of all of BERT's output vectors.

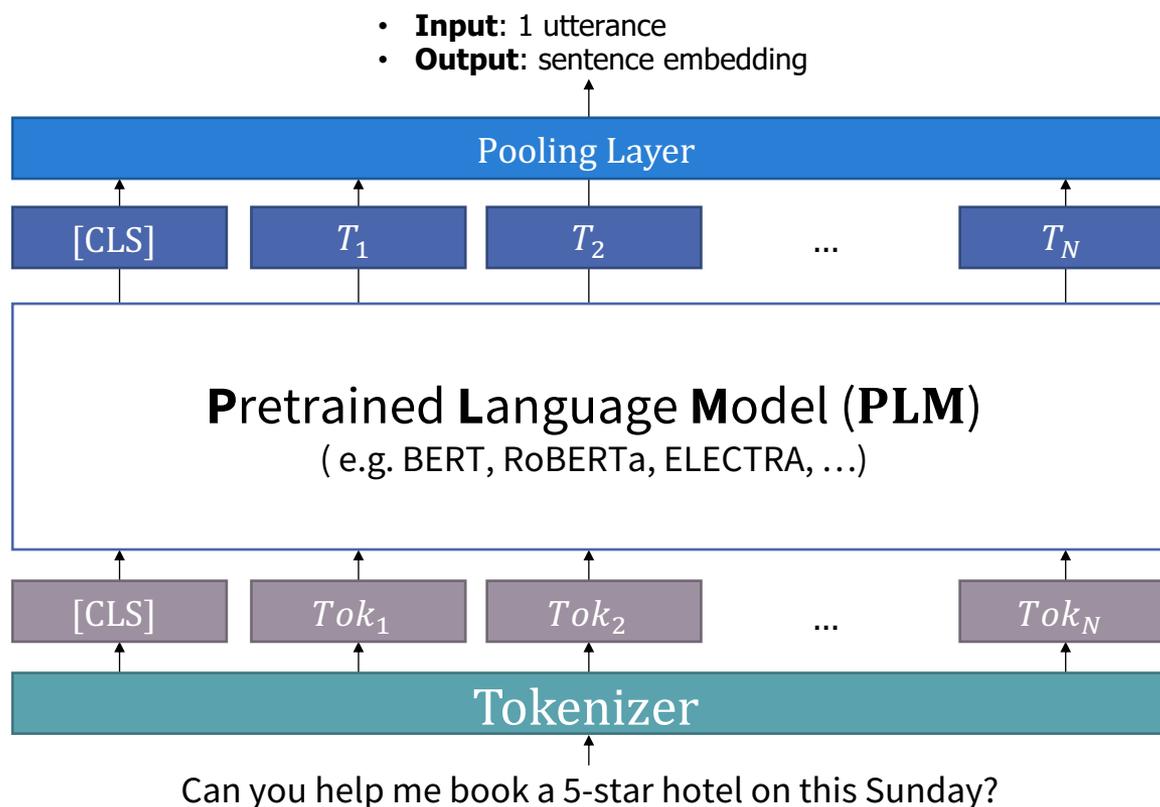
- **Input:** 1 utterance
- **Output:** sentence embedding



Introduction

• Sentence Representation

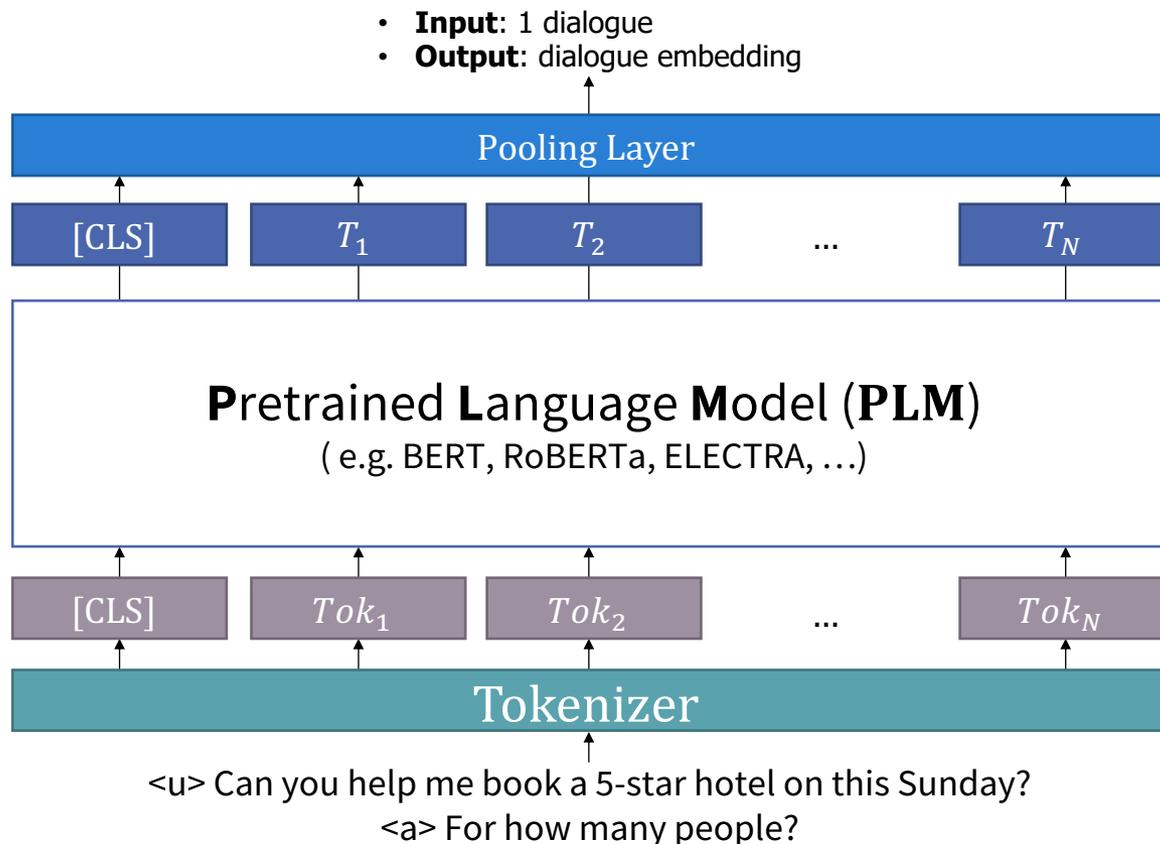
- Context Vector is considered a collective representation of the typed sentence.
- Use the mean/max of all of BERT's output vectors.



Introduction

• Dialogue Representation

- Context Vector is considered a collective representation of the typed sentence.
- Use the mean/max of all of BERT's output vectors.



2. Problem States

- Limitations of Instruction-tuned LLMs
- LLM-based ToD

Problem States

• Limitation of Instruction-tuned LLMs

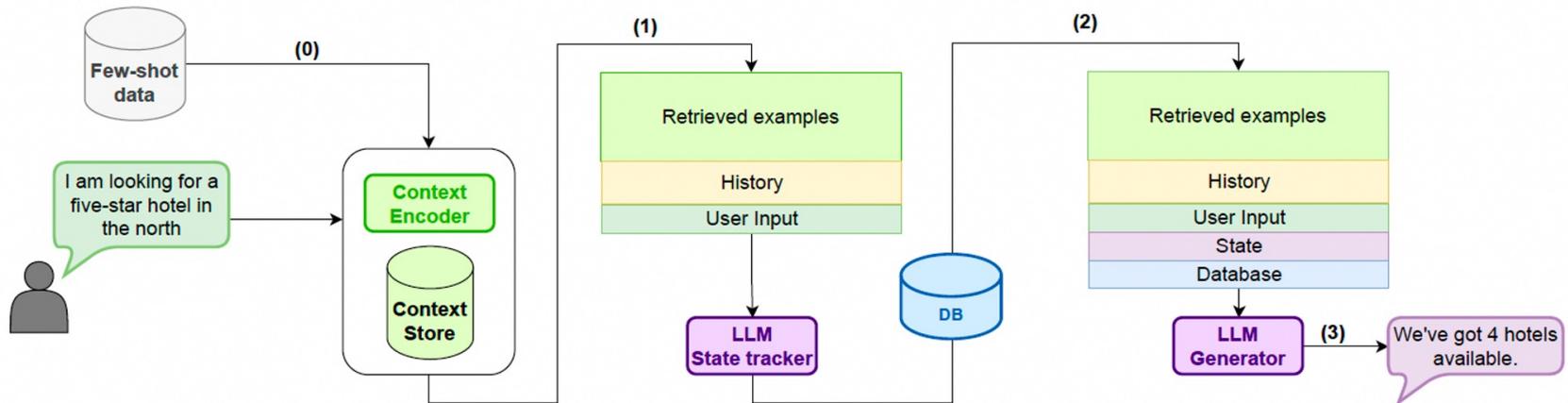
 Vojtech Hudecek and Ondrej Dusek. “Are LLMs All You Need for Task-Oriented Dialogue?”
arXiv: 2304.06556v1 (2023) #TOD #Prompt #DST #Retrieval

model	few shot	oracle BS	Schema Guided Dialogues				MultiWOZ 2.2			
			BLEU	JGA	Slot-F1	Success	BLEU	JGA	Slot-F1	Success
supervised SotA	✗	✗	29.90	0.30	0.60	–	19.90	0.58	–	0.80
<i>Alpaca-LoRA-7B-zs-gbs</i>	✗	✗	2.66	0.06	0.05	0.08	1.47	0.11	0.11	0.05
<i>Tk-Instruct-11B-zs-gbs</i>	✗	✗	4.01	0.04	0.02	0.07	2.27	0.03	0.02	0.12
<i>GPT-NeoXT-20B-zs-gbs</i>	✗	✗	0.29	0.03	0.01	0.07	0.23	0.05	0.06	0.06
<i>OPT-IML-30B-zs-gbs</i>	✗	✗	1.85	0.04	0.01	0.07	0.44	0.08	0.16	0.03
<i>ChatGPT-zs-gbs</i>	✗	✗	–	–	–	–	2.99	0.24	0.37	0.15
<i>Alpaca-LoRA-7B-zs-obs</i>	✗	✓	2.68	–	–	0.23	1.64	–	–	0.09
<i>Tk-Instruct-11B-zs-obs</i>	✗	✓	4.95	–	–	0.24	2.62	–	–	0.24
<i>GPT-NeoXT-20B-zs-obs</i>	✗	✓	0.61	–	–	0.22	0.26	–	–	0.05
<i>OPT-IML-30B-zs-obs</i>	✗	✓	1.90	–	–	0.23	0.29	–	–	0.06
<i>ChatGPT-zs-obs</i>	✗	✓	–	–	–	–	3.58	–	–	0.34
<i>Alpaca-LoRA-7B-fs-gbs</i>	✓	✗	4.92	0.04	0.02	0.08	3.83	0.08	0.07	0.08
<i>Tk-Instruct-11B-fs-gbs</i>	✓	✗	8.17	0.04	0.02	0.07	6.24	0.05	0.04	0.05
<i>GPT-NeoXT-20B-fs-gbs</i>	✓	✗	2.83	0.07	0.07	0.08	2.59	0.11	0.18	0.08
<i>OPT-IML-30B-fs-gbs</i>	✓	✗	0.82	0.06	0.06	0.07	3.90	0.06	0.11	0.05
<i>ChatGPT-fs-gbs</i>	✓	✗	–	–	–	–	7.17	0.21	0.36	0.20
<i>Alpaca-LoRA-7B-fs-obs</i>	✓	✓	5.09	–	–	0.23	4.52	–	–	0.30
<i>Tk-Instruct-11B-fs-obs</i>	✓	✓	8.87	–	–	0.24	7.38	–	–	0.36
<i>GPT-NeoXT-20B-fs-obs</i>	✓	✓	3.06	–	–	0.23	2.83	–	–	0.23
<i>OPT-IML-30B-fs-obs</i>	✓	✓	0.56	–	–	0.22	4.16	–	–	0.24
<i>ChatGPT-fs-obs</i>	✓	✓	–	–	–	–	8.06	–	–	0.58

Problem States

• LLM-based ToD

📄 Vojtech Hudecek and Ondrej Dusek. “Are LLMs All You Need for Task-Oriented Dialogue?”
arXiv: 2304.06556v1 (2023) #ToD #Prompt #DST #Retrieval



(0) Encode dialogues for using few-shot examples

(1) Retrieve the relevant examples w/user query & construct initial prompt

(2) Track dialogue state by calling the instruction-tuned LLM

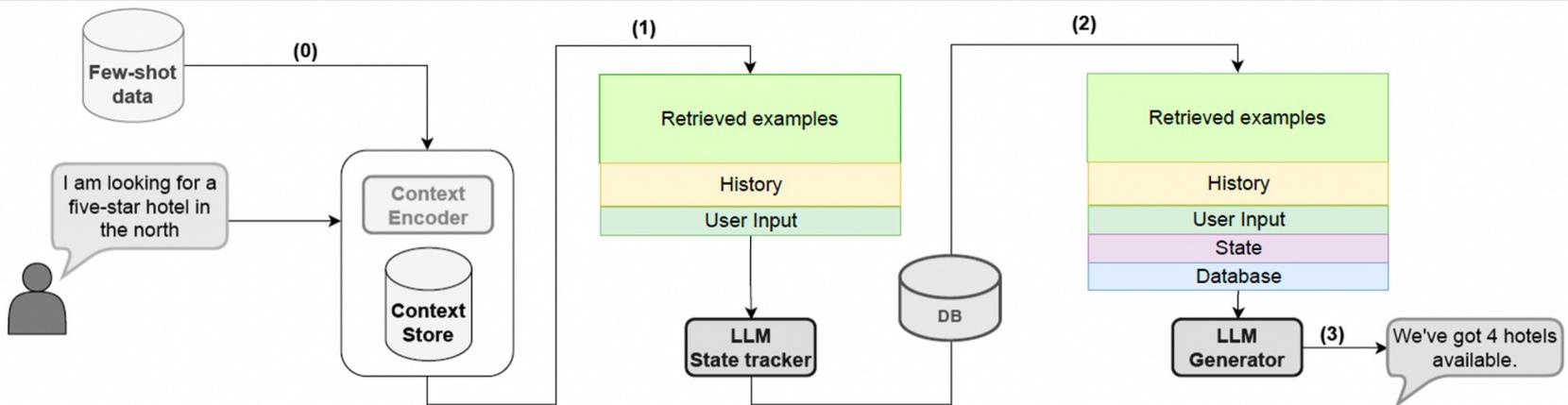
→ DB query results + DST + current dialogue context + user query

(3) Generate final response

Problem States

• Improve LLM-based ToD

 Vojtech Hudecek and Ondrej Dusek. “Are LLMs All You Need for Task-Oriented Dialogue?”
arXiv: 2304.06556v1 (2023) #ToD #Prompt #DST #Retrieval



1. Prompt Engineering

- More specific instruction
- Set a role of the model

2. Adapt better DST approach

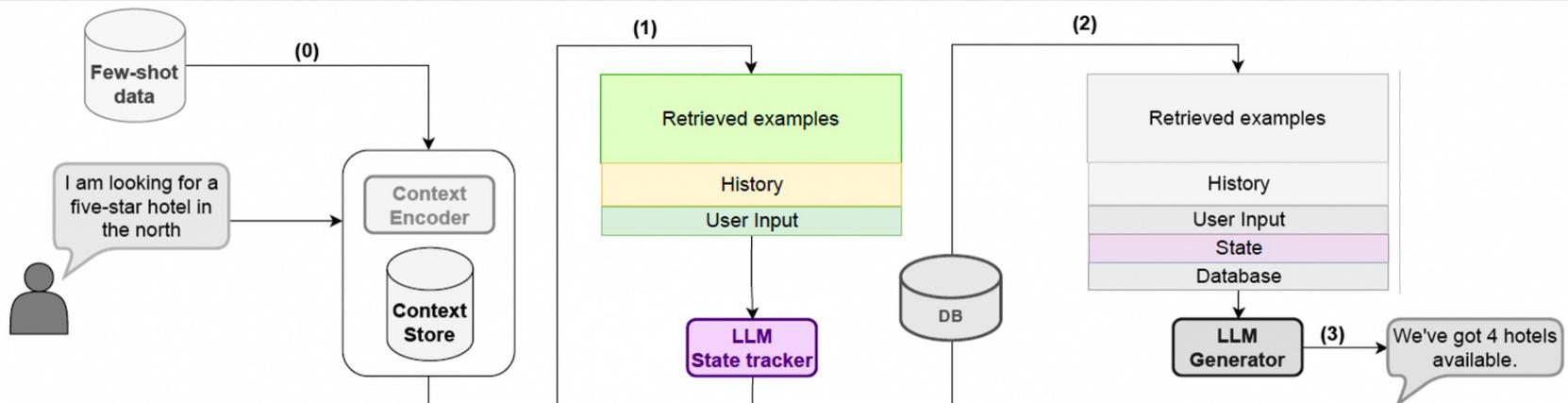
- Retrieve better examples for Few-shot DST
- Make LLMs to interpret the structured manner
- Use FFT SOTA DST model

Prompt	Definition: Capture values from a conversation about hotels in JSON. Values that should be captured are: - "price": the price of the hotel ... [history] Customer: "I want a cheap place to stay." Output:
Output:	{ "price": "cheap" }

Problem States

• Improve LLM-based ToD

📄 Vojtech Hudecek and Ondrej Dusek. “Are LLMs All You Need for Task-Oriented Dialogue?”
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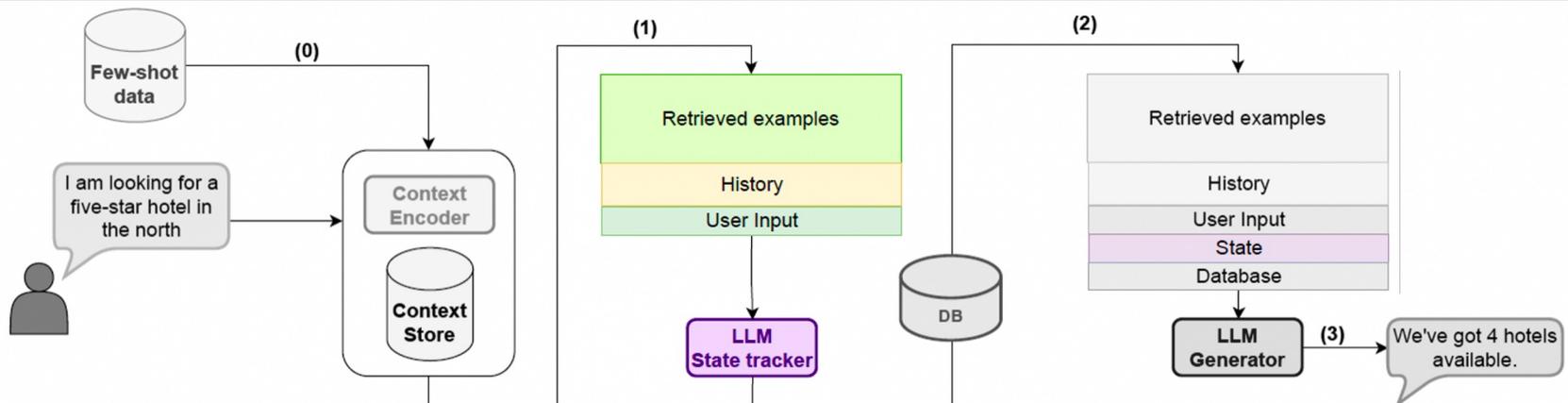
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Problem States

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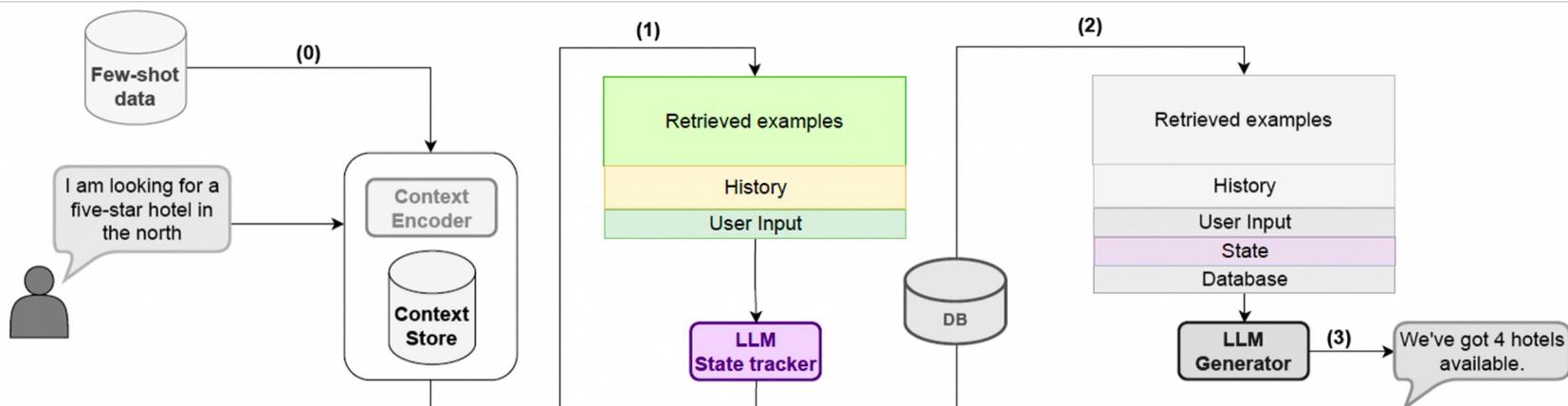
3. Suggestions

- RQ1) Does using good examples improve few-shot DST performance?
- RQ2) What is a good dialogue example?
- RQ3) Can we expect better performance using relevant dialog examples in other tasks?

Suggestions

RQ1) Does using good examples improve few-shot DST performance?

 Vojtech Hudecek and Ondrej Dusek. “Are LLMs All You Need for Task-Oriented Dialogue?”
arXiv: 2304.06556v1 (2023) #TOD #Prompt #DST #Retrieval



1. Select Dialogues to reproduce the experiment from LLM-based ToD paper
2. Complete the few-shot prompt given a proper or random dialogue example
3. Compare the performance of few-shot DST
4. Evaluate the benchmarks on ToD or multi-turn Dialogue and verify robustness and performance improvements (may take into OOD issues)

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

1. Select Dialogues to reproduce the experiment from [LLM-based TOD paper](#)

 [Vojtech Hudecek and Ondrej Dusek. Are LLMs All You Need for Task-Oriented Dialogue? arXiv: 2304.06556v1 \(2023\) #TOD #Prompt #DST #Retrieval](#)

- Experiment details are not publicly available.
- Sample of zero-shot prompt

Task Def.

Domain Info.

Dialogue History

Query

```
Definition: Capture values from conversation about hotels in JSON.
Values that should be captured are:
- "price": the price of the hotel
- "area": area where the hotel is located
- "internet": if the hotel has wifi internet. Capture yes/no
- "parking": if the hotel has free parking. Capture yes/no
Customer: "I want a cheap place to stay."
Assistant: "Sure, what part of town do you prefer?"
Output: I need it to be in the city centre
```

> It said it had trouble updating the entire BST, so it only generate the slots to update. (The example prompt didn't show that)

- Output / Updated State

```
{"area": "center"}
```

```
hotel {"price": "cheap", "area": "center"}
```

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

1. Select Dialogues to reproduce the experiment from [LLM-based TOD paper](#)

1) Select Dialogue to test: MultiWOZ 2.2 test.json; MUL0484.json

Customer: "Hello, I am looking for a restaurant in Cambridge. I believe it is called Golden Wok."
Assistant: "It is located at 191 Histon Road Chesterton"
Customer: "Can you book me a table for 11:00 on Friday?"
Assistant: "Yes I can! Table for 1?"
Customer: "Actually, for 4, please."
Assistant: "Okay, your booking was successful! The reference number is MUFCMYFF . The table will be reserved for 15 minutes."

Restaurant

Customer: "Great, can you also get me information or architecture in the area"
Assistant: "Sure. There are several churches and an old schools attraction, all in the centre area. Do you have a preference?"
Customer: "What do you recommend?"
Assistant: "old schools is lovely, they are on trinity lane and free admission"

Attraction

Customer: "Can I get the postcode for that? I also need to book a taxi to the Golden Wok."
Assistant: "The postcode is cb21tt. Are you looking for a taxi from Old Schools to the Golden Wok?"
Customer: "Yes I do. I'd like to make sure I arrive at the restaurant by the booked time. Can you check?"
Assistant: "What time do you want to leave?"
Customer: "Actually all you have to do is set the taxi so it arrives by the arrived time. Am I better off booking it myself?"
Assistant: "I have booked you a taxi for Friday to arrive at Old Schools at 10:45. Is there anything else I may help you with?"
Customer: "I need the contact number and car type also."
Assistant: "it is a Lexus white in colour and contact number is 07381884388"
Customer: "Thanks for the service, good day."
Assistant: "You're welcome! Have a great day!"

Taxi

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

1. Select Dialogues to reproduce the experiment from [LLM-based TOD paper](#)

- 1) Select Dialogue to test: MultiWOZ 2.2 test.json; MUL0484.json
- 2) Select Dialogue to use as a proper example: same all domains, same slot to update

Customer: "What is the address for Holy Trinity Church?"

Assistant: "The address for holy trinity church is market street postcode cb23nz and the phone number is 01223355397."

Attraction

Customer: "thank you. i wish to get entrance fee"

Assistant: "Holy trinity church is free. May I help you with anything else today?"

Customer: "Yes, I am looking for an Indian restaurant in the east."

Assistant: "The four choices range from moderate to expensive in their price range. Do you have a preference?"

Customer: "How about an expensive one. What are my choices in that range?"

Assistant: "Pipasha Restaurant and Sitar Tandoori are the 2 expensive Indian restaurants in the area. Do you want the information on those?"

Restaurant

Customer: "i want o book for 7 people at 18:00 on monday"

Assistant: "I booked you for pipasha restaurant. The table will be reserved for 15 minutes. Reference number is : 3W8KKL0J . Can i help you with anything else?"

Customer: "Yes, one more thing. I will need a taxi from Holy Trinity Church to pipasha restaurant."

Assistant: "Sure! And what time do you prefer?"

Customer: "I need to arrive by the booked time at the restaurant."

Assistant: "For how many people?"

Customer: "There will be 7 people travelling."

Taxi

Assistant: "A grey volvo will pick you up at Holy Trinity Church for your arrival at Pipasha by 18:00. Should you need to contact the driver, the number is: "07746897279"

Customer: "Thank you. That is all I need."

Assistant: "Thank you for using the Cambridge towneinfo centre. Goodbye"

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

1. Select Dialogues to reproduce the experiment from [LLM-based TOD paper](#)

- 1) Select Dialogue to test: MultiWOZ 2.2 test.json; MUL0484.json
- 2) Select Dialogue to use as a proper example: same all domains, same slot to update
- 3) Select Dialogue to use as a random example: same some domains, not same slot

Customer: "Hello. I'm going out for an expensive dinner and need to find a restaurant. I'd like somewhere in the north, and I'm willing to pay quite a bit of money."

Assistant: "I'd be happy to help you with that. I have 5 expensive restaurants in the north. Did you have a type of cuisine in mind?"

... Skip the middle ...

Restaurant

Customer: "How about at 16:45?"

Assistant: "Booking was successful. The table will be reserved for 15 minutes. The reference number is: "0PK0TW8F"

Customer: "I'm also looking for a place to stay that offers both internet and free parking."

Assistant: "There are 29 places in Cambridge which offer both, any other preferences?"

Customer: "Hmm, yes. Someplace expensive."

Assistant: "I can recommend the University Arms hotel in the centre of the city."

Hotel

... Skip the middle ...

Assistant: "Alright! I was able to book your room for 1 night at the University Arms Hotel for 3 people. Your reference number is F13028XH . Can I help with anything else?"

Customer: "I'm going to need a taxi as well from the hotel to the restaurant that arrives at 16:45. Could I get the contact number and car type for that?"

Assistant: "Sure! The contact number is 07648846859 and the car is a black audi. Is there anything else you need help with?"

Taxi

Customer: "No, you have been most helpful. Have a nice day."

Assistant: "Thanks, have a nice day as well."

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

2. Complete the few-shot prompt given a **proper** or random dialogue example

Definition: Capture values from conversation about restaurant and taxi in JSON.

Task Def.

Values that should be captured are (some may not need to be captured):

- "r-name": the name of the restaurant
- "r-bookpeople": number of people booked in the restaurant
- "r-bookday": the day of the week that the restaurant is booked
- "r-booktime": the time that the restaurant is booked. Format is 00:00.
- "t-departure": where the taxi will depart from
- "t-destination": where the taxi will arrive
- "t-arriveby": the time that the taxi is arrived at the destination

example conversation:

Example 1

Customer: "Yes, one more thing. I will need a taxi from Holy Trinity Church to pipasha restaurant."
Assistant: "Sure! And what time do you prefer?"

correct answer:

```
{"t-departure": "holy trinity church"}, {"t-destination": "pipasha restaurant"}
```

example conversation:

Example 2

Customer: "I want to depart the restaurant at 05:00 to go to the attraction"
Assistant: "A yellow Tesla will pick you up, and the contact number is 07267272725.
Can I help with anything else today?"

wrong answer:

```
{"h-internet": "yes"}, {"t-destination": "05:00"}
```

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

2. Complete the few-shot prompt given a proper or **random** dialogue example

Definition: Capture values from conversation about restaurant and taxi in JSON.

Task Def.

Values that should be captured are (some may not need to be captured):

- "r-name": the name of the restaurant
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- "r-booktime": the time that the restaurant is booked. Format is 00:00.
- "t-departure": where the taxi will depart from
- "t-destination": where the taxi will arrive
- "t-arriveby": the time that the taxi is arrived at the destination

example conversation:

Example 1

Customer: "Hmm, yes. Someplace expensive."

Assistant: "I can recommend the University Arms hotel in the centre of the city."

correct answer:

```
{"h-pricerange": "expensive"}
```

example conversation:

Example 2

Customer: "That is all. Thank you for your help."

Assistant: "Thank you for using Cambridge TownInfo centre!
Have a good day!"

wrong answer:

```
{"h-internet": "yes"}, {"t-destination": "05:00"}
```

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

2. Complete the few-shot prompt given a proper or random dialogue example

Definition:

Task Def.

example conversation:
correct answer:

Example 1

example conversation:
wrong answer:

Example 2

the conversation:

History

Customer: "Hello, I am looking for a restaurant in Cambridge. I believe it is called Golden Wok."
Assistant: "It is located at 191 Histon Road Chesterton"
Customer: "Can you book me a table for 11:00 on Friday?"
Assistant: "Yes I can! Table for 1?"
Customer: "Actually, for 4, please."
Assistant: "Okay, your booking was successful! The reference number is MUFCMYFF . The table will be reserved for 15 minutes."
Customer: "Great, can you also get me information or architecture in the area"
Assistant: "Sure. There are several churches and an old schools attraction, all in the centre area. Do you have a preference?"
Customer: "What do you recommend?"
Assistant: "old schools is lovely, they are on trinity lane and free admission"

Output: "Can I get the post code for that? I also need to book a taxi to the Golden Wok."

Query

Suggestions :: Toy Experiments

RQ1) Does using good examples improve few-shot DST performance?

3. Compare the performance of few-shot DST

- LLM: ChatGPT (gpt-3.5-turbo)
 - Model applied to ChatGPT currently in service
 - Equal in completeness to the davinci model, but more efficient in terms of price (1/10 of the davinci)
 - Optimized for conversation and text generation
 - Cannot be fine-tuned

Dialogue History

... Skip the previous ...

Assistant: "old schools is lovely, they are on trinity lane and free admission"

Output: "Can I get the post code for that? I also need to book a **taxi to the Golden Wok.**"

Proper

```
{ "r-name": "Golden Wok", "r-bookpeople": 4, "r-bookday": "Friday", "r-booktime": "11:00", "t-destination": "Golden Wok" }
```

Random

```
{ "r-name": "Golden Wok", "r-bookpeople": 4, "r-bookday": "Friday", "r-booktime": "11:00", "t-destination": "191 Histon Road Chesterton" }
```

Suggestions

RQ2) What is a good dialogue example?

• Initial Opinion

1. Query/passage design

- 1 or 2 last utterances: (Customer +) Assistant
- Entire dialogue embedding vs. turn embedding vs. hybrid

2. Using Label Semantics

- Last utterances + BST
- All dialogue + BST

3. Similarity Score

1) Vanilla similarity

$$\text{sim}(q, p) = E_Q(q)^T E_P(p)$$

2) Utterance-wise similarity

$$\text{sim}(q, p) = \lambda \text{sim}(\text{utt}_{q(n-1)}, \text{utt}_{p(i)}) + (1 - \lambda) \text{sim}(\text{utt}_{q(n)}, \text{utt}_{p(j)})$$

3) Weighted similarity

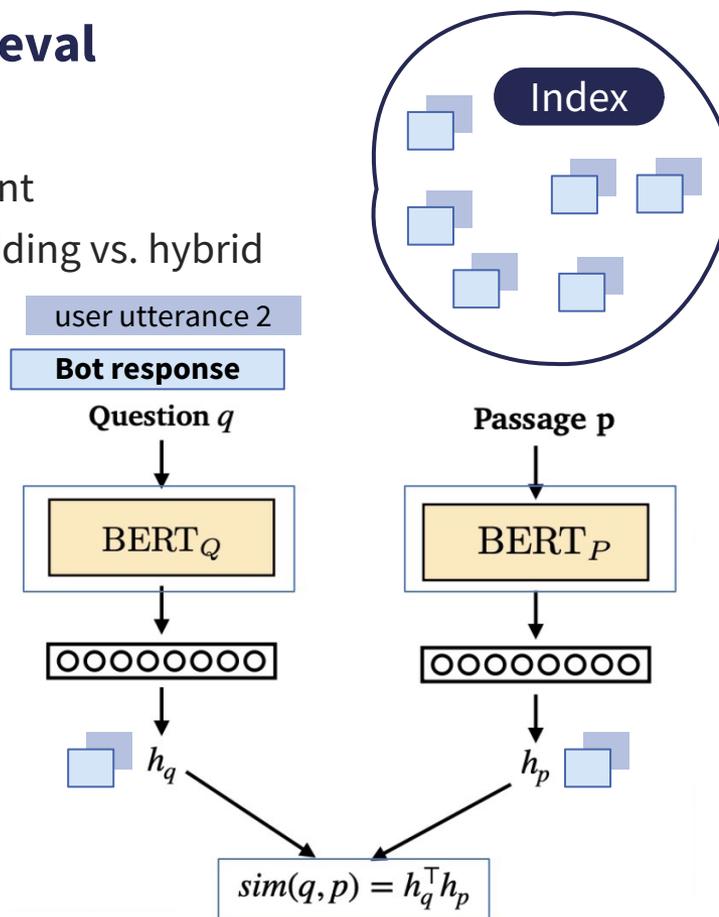
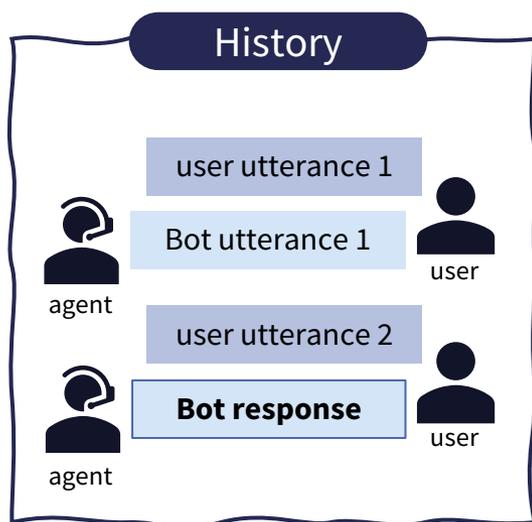
Suggestions

RQ2) What is a good dialogue example?

• Initial Opinion: Dialogue-specific Retrieval

1. Query/passage design

- 1 or 2 last utterances: (Customer +) Assistant
- Entire dialogue embedding vs. turn embedding vs. hybrid



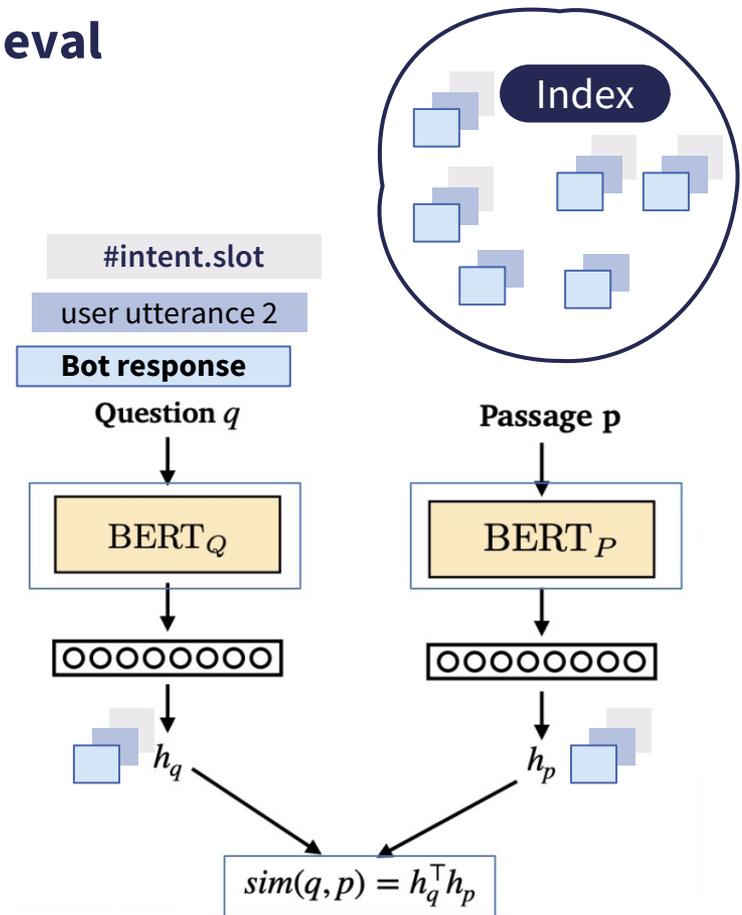
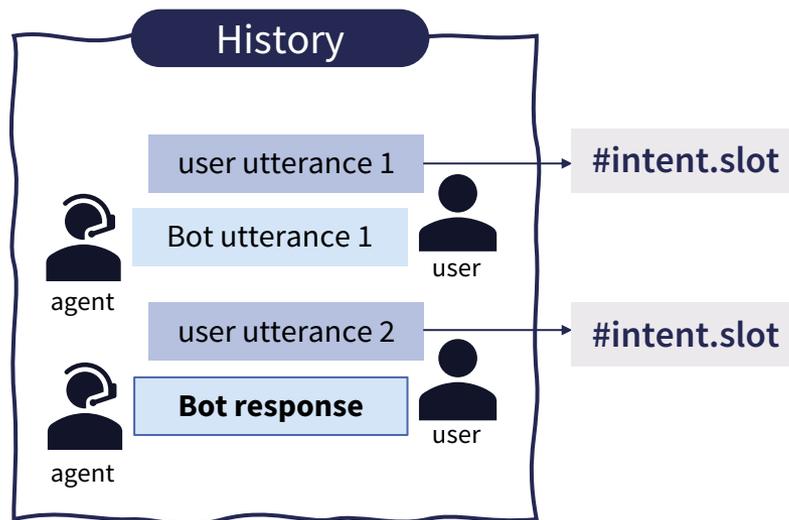
Suggestions

RQ2) What is a good dialogue example?

• Initial Opinion: Dialogue-specific Retrieval

2. Using Label Semantics

- Last utterances + BST
- All dialogue + BST



Suggestions

RQ2) What is a good dialogue example?

• Initial Opinion: Dialogue-specific Retrieval

3. Similarity Score

1) Vanilla similarity

$$\text{sim}(q, p) = E_Q(q)^T E_P(p)$$

* $q: \{utt_{q(n-1)} [\text{SEP}] utt_{q(n)} [\text{SEP}] \dots\}$

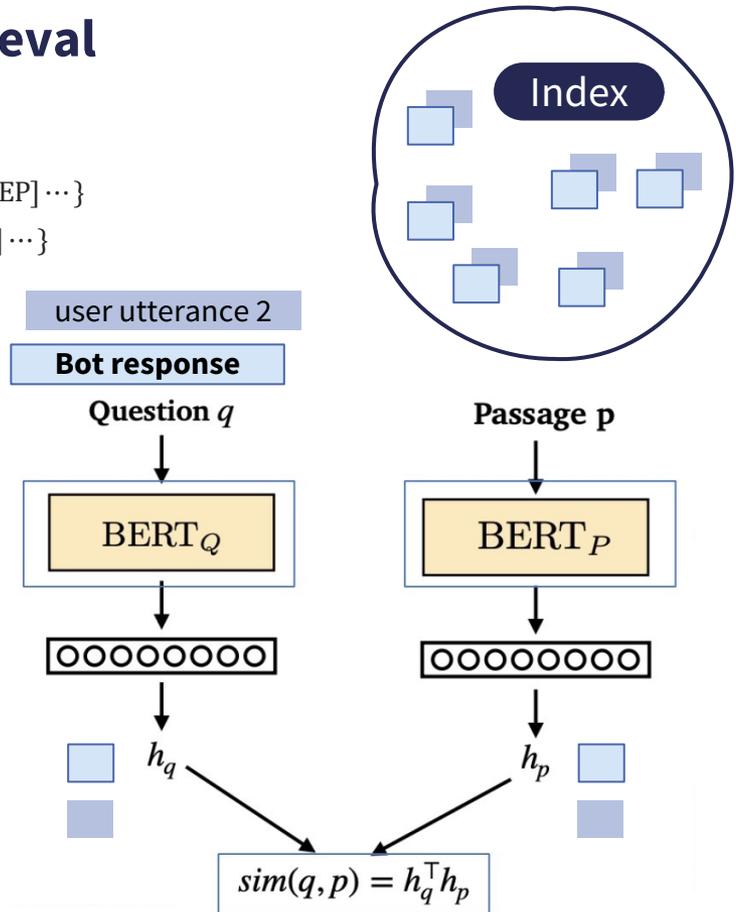
* $p: \{utt_{p(i)} [\text{SEP}] utt_{p(j)} [\text{SEP}] \dots\}$

2) Utterance-wise similarity

$$\begin{aligned} \text{sim}(q, p) &= \lambda \text{sim}(utt_{q(n-1)}, utt_{p(i)}) \\ &\quad + (1 - \lambda) \text{sim}(utt_{q(n)}, utt_{p(j)}) \\ &= \lambda E_Q(utt_{q(n-1)})^T E_P(utt_{p(i)}) \\ &\quad + (1 - \lambda) E_Q(utt_{q(n)})^T E_P(utt_{p(j)}) \end{aligned}$$

3) Weighted similarity

- Domain
- Intent / slot (value)
- Speaker



Suggestions

RQ3) Can we expect better performance using relevant dialog examples in other tasks?

- **Various Tasks**

- Dialogue Response Selection
- DST
 - Intent Detection
 - Dialogue Acts Detection
 - Slot-Filling

- **Various Domain**

- Chit-chat
- Knowledge-grounded Dialogue (FAQ)

4. Related Works

- BERT-FP
- DialogueCSE
- Dialog-BERT (이루다), ToD-BERT

Related Works

📄 Han, Hong, et al. "Fine-grained Post-training for Improving Retrieval-based Dialogue Systems." NAACL-HLT 2021, 1549-1558 (2021). * NAACL 2021, LG AI Research, SGU, SKKU

• BERT-FP

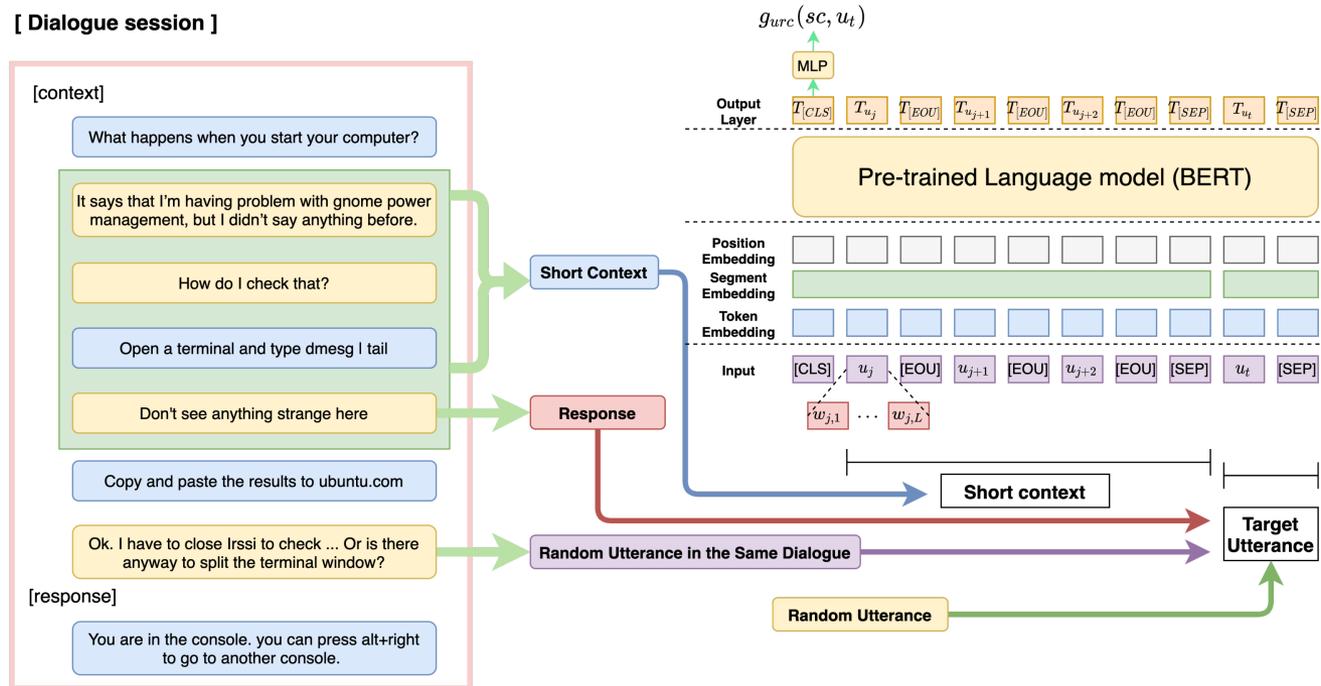


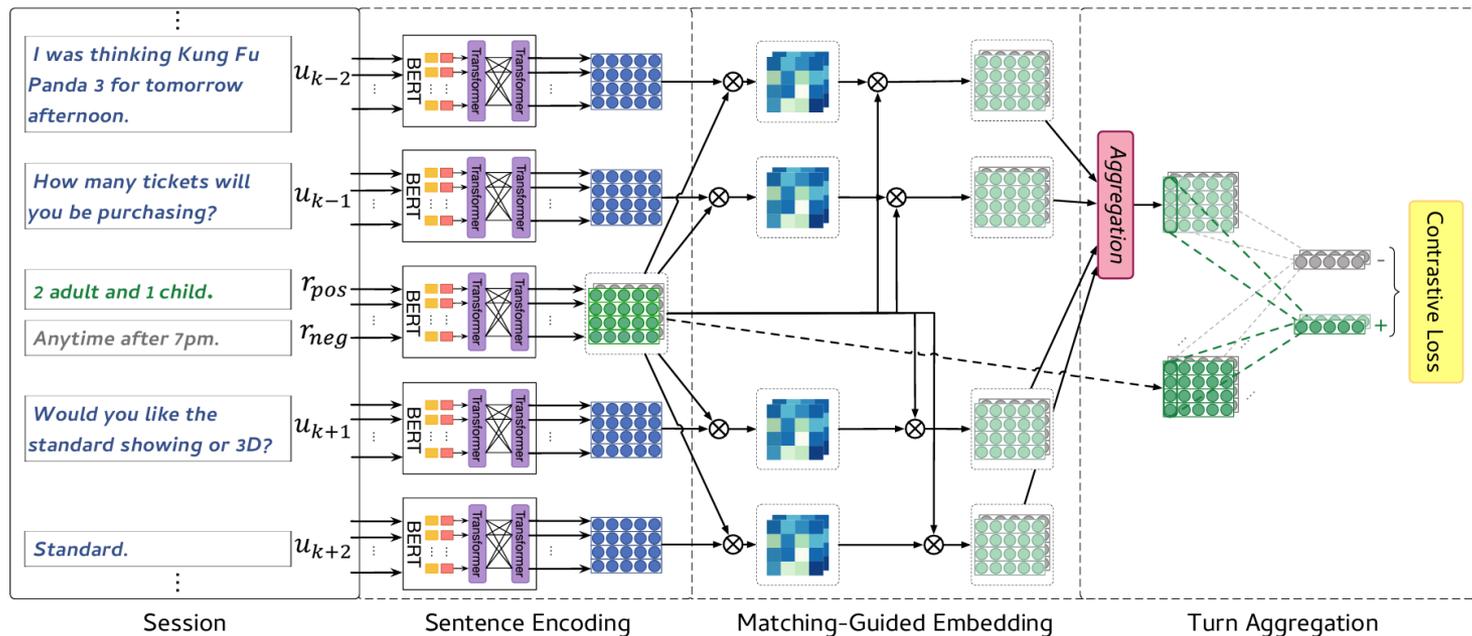
Figure 1: Architecture of fine-grained post-training. The short context length k is three.

Related Works

📄 Liu, Che, et al. (Alibaba Group) "DialogueCSE: Dialogue-based contrastive learning of sentence embeddings." EMNLP 2021.

• DialogueCSE

- DialogueCSE's positive pair
 - Context-free Embedding: Response Embedding (Independent of context)
 - Context-aware Embedding: Context + Response Embedding



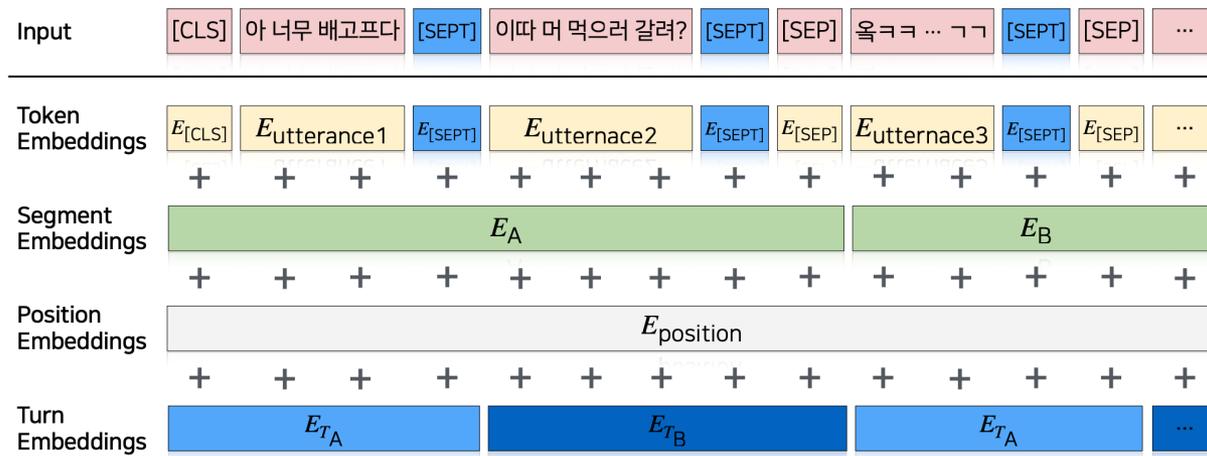
Related Works

SCATTERLABS, Dialog-BERT: 100억 건의 메신저 대화로 일상대화 인공지능 서비스하기, DEVIEW 2019.

Wu, Hoi, et al. (Salesforce) "ToD-BERT: Pre-trained Natural Language Understanding for Task-Oriented Dialogue" EMNLP 2020.

• Dialog-BERT

- Pre-training strategies: Turn-separate Token & Turn embedding
- Fine-tuning strategies



5. Experiments

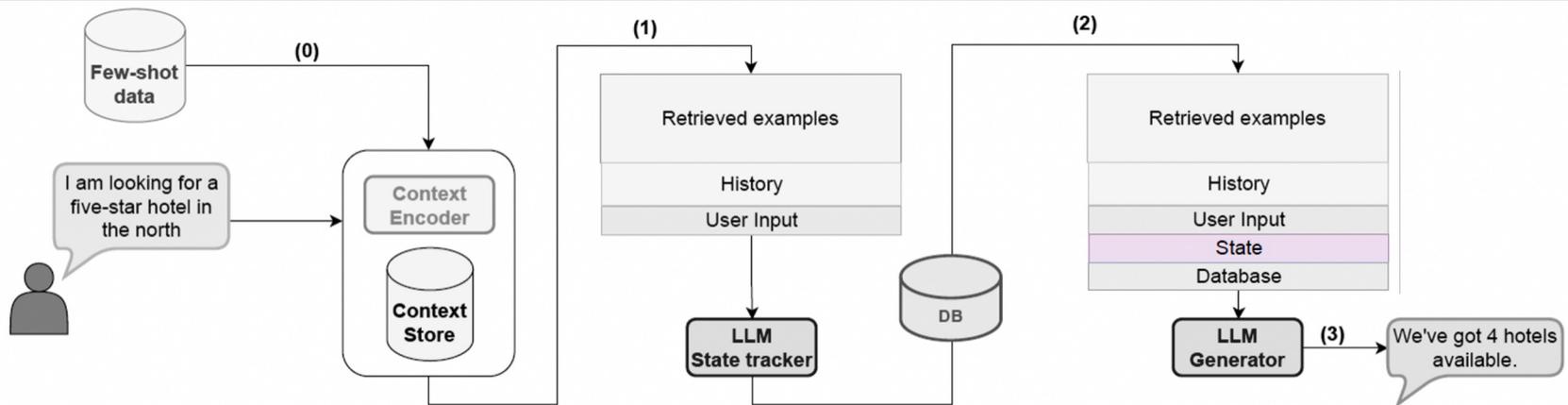
- Backbone: BERT, T5, ToD-BERT, ...
- Datasets: MultiWOZ, SGD, ...

6. Future Works

Future Works

• Improve LLM-based ToD

 Vojtech Hudecek and Ondrej Dusek. “Are LLMs All You Need for Task-Oriented Dialogue?”
arXiv: 2304.06556v1 (2023) #ToD #Prompt #DST #Retrieval



1. Prompt Engineering

- More specific instruction
- Set a role of the model

2. Adapt better DST approach

- Retrieve better examples for Few-shot DST
- **Make LLMs to interpret the structured manner**
- Use FFT SOTA DST model

Prompt	Definition: Capture values from a conversation about hotels in JSON. Values that should be captured are: - "price": the price of the hotel ... [history] Customer: "I want a cheap place to stay." Output:
Output:	{ "price": "cheap" }

Conclusion

- Instruction-tuned LLMs are poor at ToD,
because they have poor DST performance.
- To improve performance,
we need to feed it appropriate examples.
- Suggest a Dialogue Retriever to find
the proper dialog context for in-context learning

Dialogue Retrieval
for LLM-based ToD in few-shot setting

Research Proposal

{ End Page }

Thank you :D

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