MPC: Prompted LLMs as Chatbot Modules for Long Open-domain Conversation

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56 citations

KRAFTON

01. **INTRODUCTION**

02. **METHOD**

03. **EXPERIMENTS**

04. **LIMITATIONS**

INTRODUCTION

Long-term memory problem

- Issues
 - Virtual friend (Chatbot) interacts with users by sharing their experiences
 - Long-term memory problems prevents users from maintaining immersion and interest
- Objective
 - Design the model to achieve long-term consistency



INTRODUCTION

Target domain

- Fine-tunes LLMs to align with the target domain
 - Computation cost
 - Lack of datasets
 - There is a risk of losing domain-independent knowledge acquired during pretraining
- Context learning
 - Perform target task without fine-tuning using few-shot example, Chain-of-Thought

INTRODUCTION

Target domain

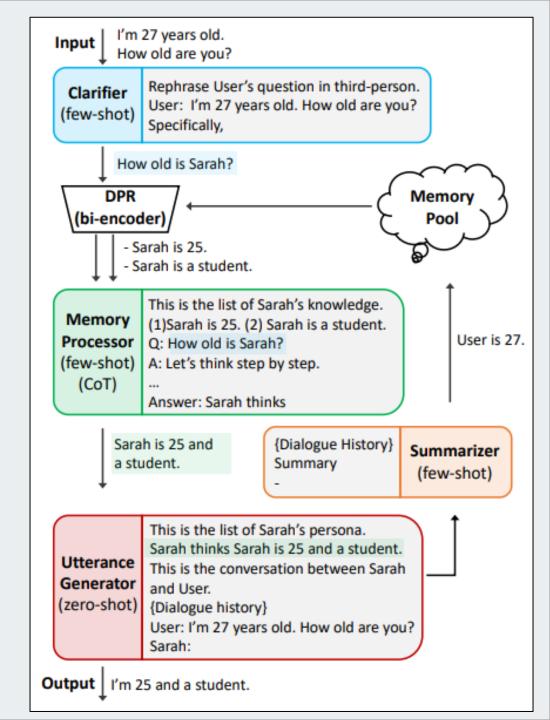
- Fine-tunes LLMs to align with the target domain
 - Computation cost
 - Lack of datasets
 - There is a risk of losing domain-independent knowledge acquired during pretraining
- Context learning
 - Perform target task without fine-tuning using few-shot example, Chain-of-Thought
- MPC (Modular Prompted Chatbot)
 - Introduce new approach for creating high-quality conversational agents
 without fine-tuning (i.e., context learning)

Components

- Clarifier (few-shot)
- DPR
- Memory Processor (few-shot, CoT)
- Utterance Generator (zero-shot)
- Memory Pool

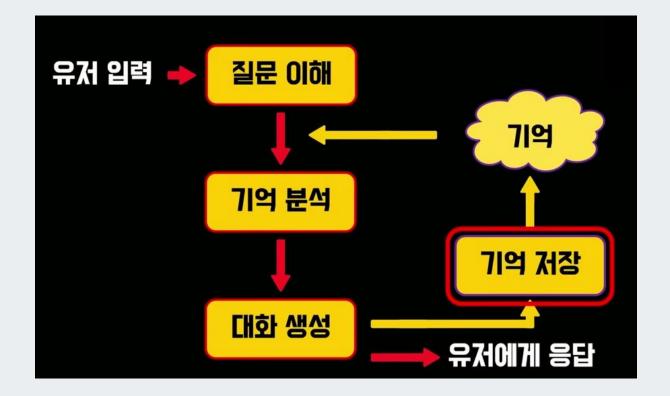
Base LMs

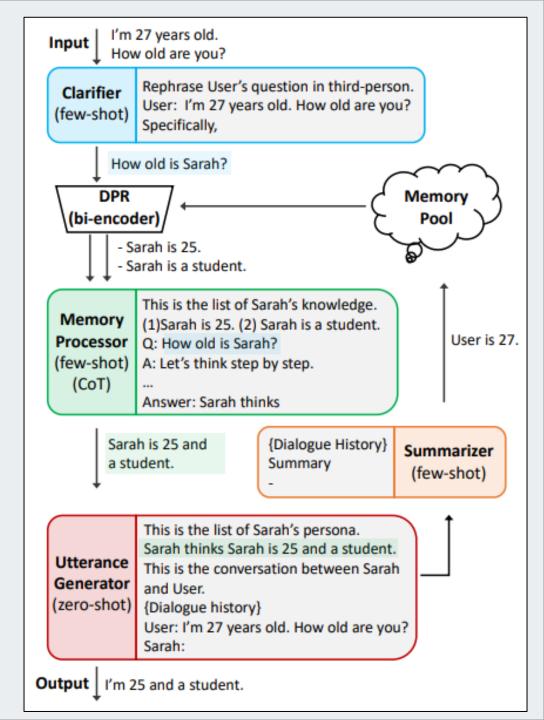
- OpenAI GPT-3 text-davinci-002 (td2)
- Davinci
- OPT 30B, 66B
- GPT-JT-6B
- BLOOM-176B



Overview

 At the start of a conversation, a pre-defined persona is stored in the memory pool





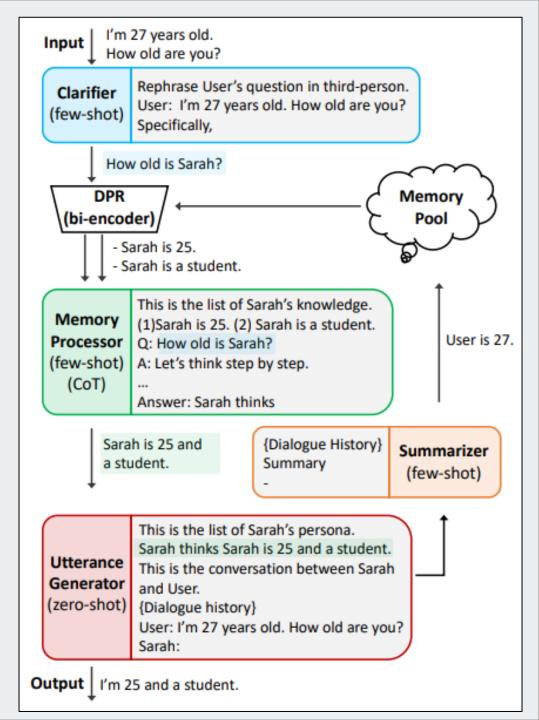
Clarifier (few-shot)

 The clarifier rephrases user messages to resolve any ambiguities and pass it to the DPR model

Do you like working there?

Does Sarah like working at ZYX company?

- DPR model
 - Retrieves relevant memories from the memory pool



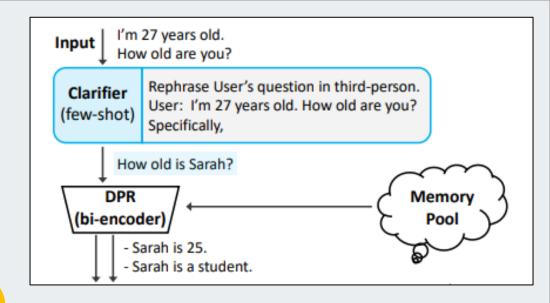
Clarifier (few-shot)

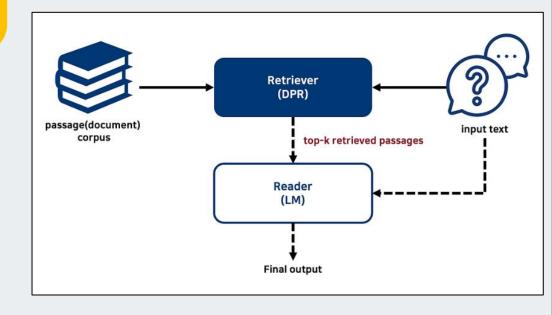
 The clarifier rephrases user messages to resolve any ambiguities and pass it to the DPR model

Do you like working there?

Does Sarah like working at ZYX company?

- DPR model (2020, Facebook AI)
 - Retrieves relevant memories from the memory pool





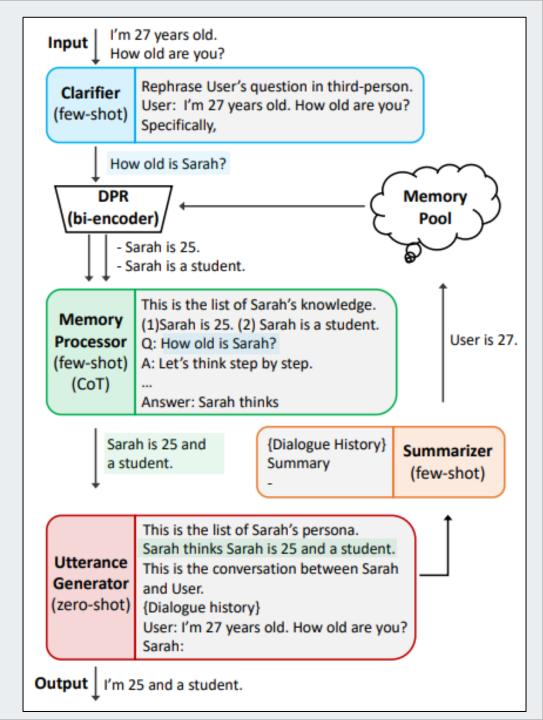
Clarifier (few-shot)

 The clarifier rephrases user messages to resolve any ambiguities and pass it to the DPR model

Rephrase User's question in third-person.

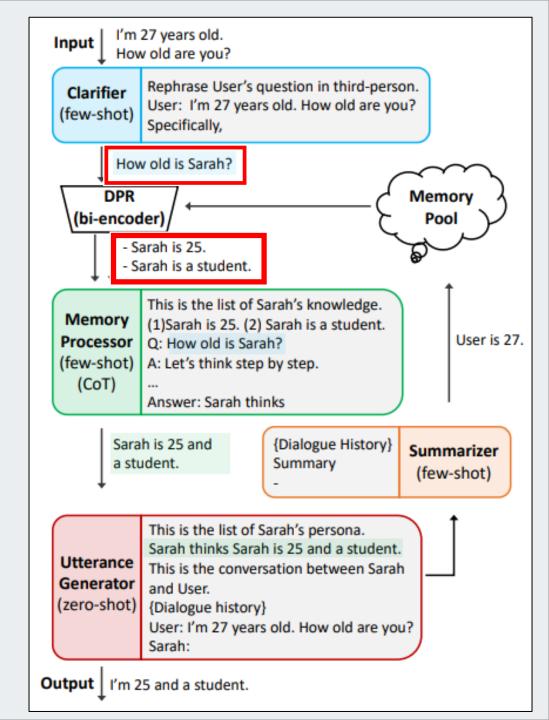
Sarah: I've been working at the coffee shop for about six months.

User: I see. what did you do before that?
Specifically, What did Sarah do before working at a coffee shop for six months?#



Memory Processor (few-shot, CoT)

- Utilize output of clarifier and DPR
- Find the most relevant information given the dialogue



Memory Processor (few-shot, CoT)

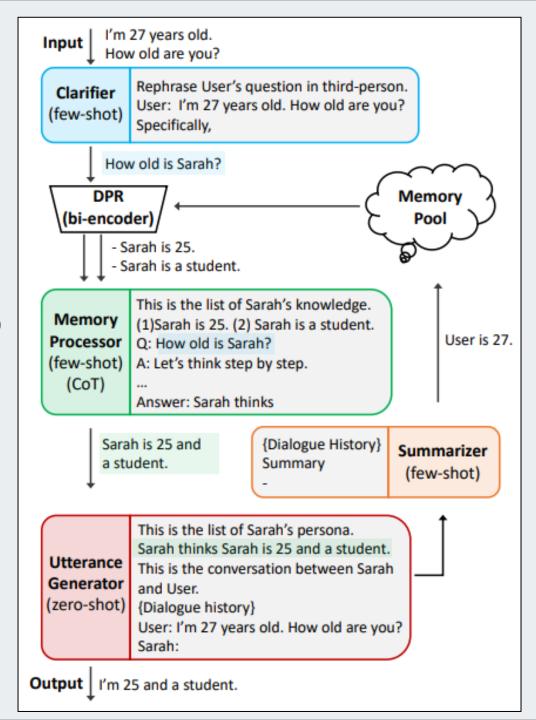
- # This is the list of Ashley's knowledge.
- (1) Ashley likes history documentaries.
- (2) Ashley does not like Korean food.
- (3) Ashley is a teacher at a local middle school.
- (4) User likes biology and especially anatomy.
- (5) Ashley likes French cuisine.
- Q: What is Ashley's favorite dish?
- A: Let's think step by step.

(1) History documentaries are not related to Ashley's favorite dish. (2) Ashley's favorite dish would not be Korean because she does not like Korean food. (3) Ashley being a teacher does not tell us anything about her favorite dish. (4) This fact is about User, not Ashley. (5) Ashley's favorite dish may be French since she likes French cuisine. Therefore, (2) and (5) can help answer the question.

Answer: Ashley thinks Ashley likes French cuisine but does not like Korean food.

Utterance Generator (zero-shot)

- Generate final response of the chatbot
- ✓ Persona (option)
- ✓ Condensed memory (output of memory processor)
- ✓ Recent dialogue history
- ✓ Generation instruction
 - E.g., "Give a friendly response to the user"



Utterance Generator (zero-shot)

The following are persona facts about Sarah.

Sarah is 40 years old.

Sarah currently lives in small town in Georgia.

Sarah reads twenty books a year.

Sarah is a stunt double as Sarah's second job.

Sarah only eats kosher.

Sarah was poor growing up.

Sarah was raised in a single parent household.

Sarah has two dogs.

✓ Persona (option) + Condensed memory

Sarah is polite, fun, and engaging. The following is a conversation between Sarah and Person1.

Person1: We at least had a playground in tow and my grandparents lived in right in front of it, so we went to both places a good bit.

Sarah: Maybe it was difficult to find things to do in your town, but it sounds like you had a lot of family support, which is really important. It's good that you had a place to go where you felt safe and loved.

Person1: You ended up growing up poor too.
Sarah: Yes, I did. I think it's made me a lot more sympathetic to other people's experiences. ✓ Recent dialogue history

Give a friendly sensible response that is interesting and polite to Person1. End with a question.

Sarah:

✓ Generation instruction

Dialogue Summarizer (few-shot)

 Record specific details of the conversation using few-shot #Dialogue

User: Tell me about yourself

Sally: I'm 26 years old and graduated from

a college in Wisconsin.

User: Were you a leader when you were in college?

Sally: Yes. I was the head TA for a computer science course at our university.

User: Were you involved in any club activities at your university?

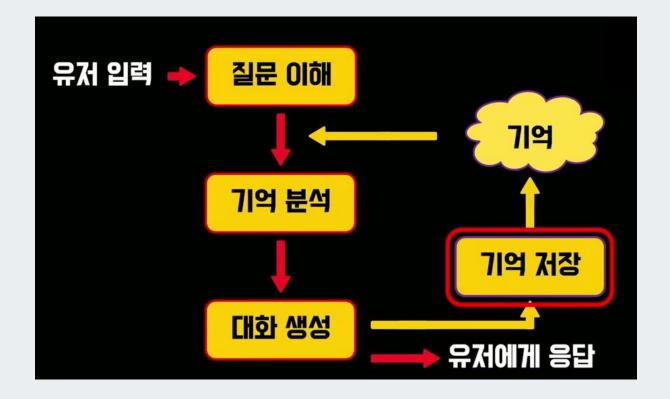
Sally: Yes. I was a member of the basketball Society. I like playing basketball.

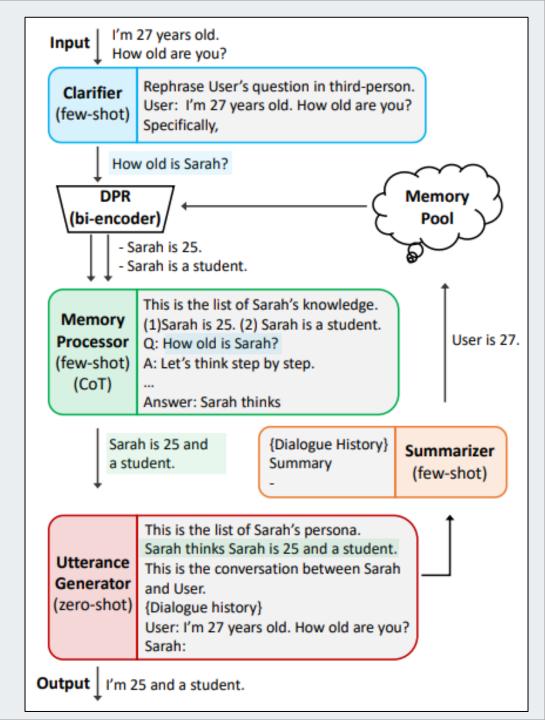
#Summary

- Sally is 26 years old and graduated college in Wisconsin.
- Sally was the head TA for a computer science course.
- Sally played basketball in college.#

Overview

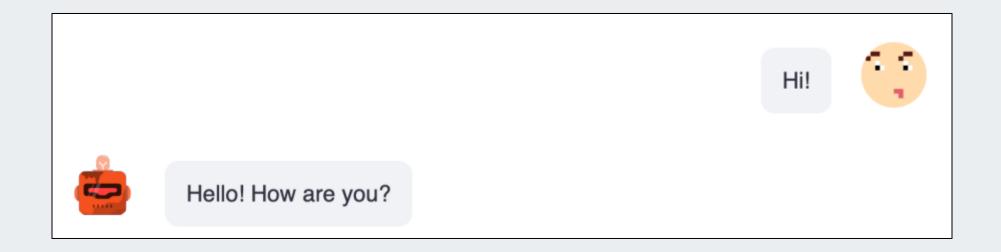
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Settings

- Evaluate chatbot's performance by assessing core skills necessary for long-term conversation
- Collect 20 turns from each evaluator; 500 turns in total from two subgroups
 - Amazon Mechanical Turk and university students



Models

- 1. Fine-tuned chatbot
- 2. Vanilla: an utterance generator
- 3. MPC
- 4. MPC + full persona

Base LMs

- OpenAI GPT-3 text-davinci-002 (td2)
- Davinci
- OPT 30B, 66B
- GPT-JT-6B
- BLOOM-176B

Evaluation

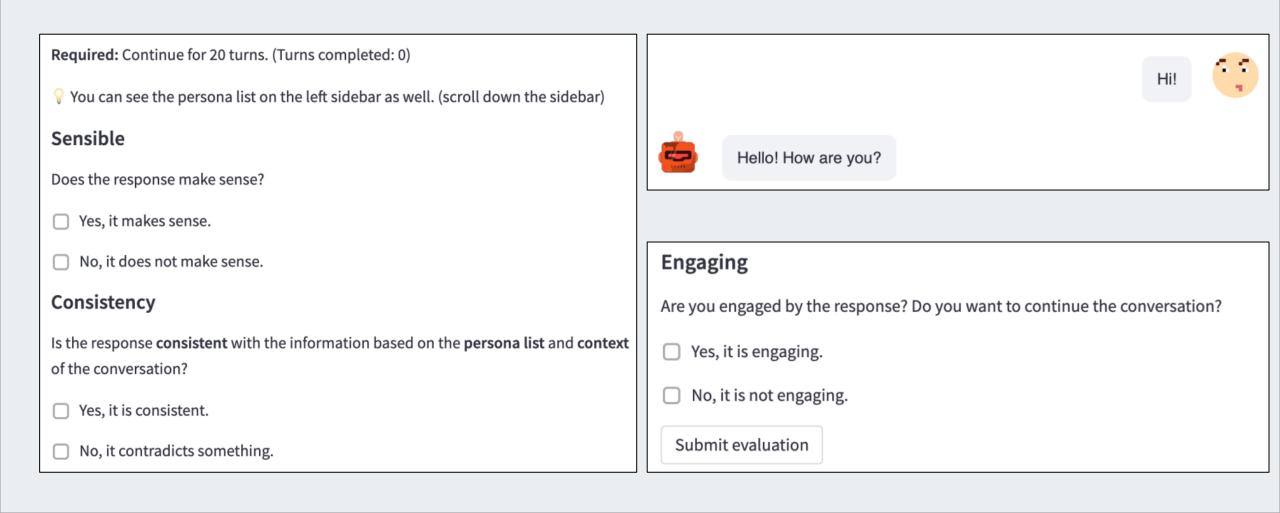
- Single model evaluation
- Pairwise models evaluation

Persona of Sarah

- Sarah is 24 years old.
- Sarah currently lives in Canada.
- Sarah is a swim coach at Sarah's local pool.
- Sarah is studying to be a computer programmer.
- Sarah is also a graduate student.
- Sarah is now looking for a new job.
- Sarah's mother is very traditional while
 Sarah prefers to be more free spirited.
- Sarah's family and Sarah are from India.

Single model evaluation

• Sensible, consistency, and Engagingness (합리성, 일관성, 몰입도)



Pairwise models evaluation

 Sensible, interestingness, persona consistency, preference (합리성, 흥미, 페르소나 일관성, 선호도)



Sensible Which response makes more sense? A makes more sense. Tie: both are similarly sensible. B makes more sense.

Single model evaluation

 Pre-trained LLM is better than the fine-tuned BB3-30B

Model	Sens.	Cons.	Eng.	SCE-p	Rating
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Fine-tuned					
BB3-30B	71.3	77.8	73.7	54.3	2.9
BB3-175B	85.9	(88.7)	84.8	73.1	3.8
Full persona					
td2	94.0	94.7	84.3	79.7	4.1
davinci	91.8	89.2	78.8	70.8	3.8
MPC					
td2	93.6	87.8	85.5	75.0	4.2
davinci	80.2	72.0	69.1	53.3	3.1
OPT-66B	90.5	84.8	88.1	73.9	4.1
OPT-30B	86.1	79.1	80.7	63.4	3.6
GPT-JT	91.1	83.2	65.3	53.5	3.1
BLOOM	65.2	65.5	61.4	40.5	2.8
MPC+Full					
td2	94.4	92.2	92.8	83.0	4.2
OPT-30B	85.6	87.2	89.0	72.6	3.7

Pairwise models evaluation

- 상대적 성능을 평가: Sensibleness 45.0 / 32.0 / 23.0 은 MPC가 45%의 비율로 더 낫다는 평가
- p < 0.01: 관찰된 차이가 유의미하며, 차이가 통계적으로 강하게 유의미하다
- p < 0.05: 관찰된 차이가 유의미하다
- $p \ge 0.05$: 관찰된 차이가 우연일 가능성이 높다

MPC	Tie	BB3-30B	
Sensibleness	45.0	32.0	23.0
Consistency	31.3	34.1	34.6
Interestingness	40.9	21.0	38.1
Preference	50.0	9.7	40.3

Table 1: Pairwise evaluation of MPC_{OPT-30B} vs. BB3-30B (Dark highlight: p < 0.01, Light highlight: p < 0.05; We run one-sample t-test dividing ties equally into each side and setting $\mu > 0.5$.)

Modular vs Non-modular

M	PC_{td2}	Tie	td2 (no persona)
Sensibleness	40.6	46.1	13.3
Consistency	57.2	28.9	13.9
Interestingness	47.2	31.1	21.7
Preference	67.2	10.6	22.2

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Effect of size

- When other variables are held the same,
 model size is positively correlated with evaluations
- OPT-66B > OPT-30B

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Effect of size

- Model size is not only factor
- One of the largest models, BLOOM, scores the lowest in experiments

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LIMITATIONS

Long-term English conversation

Optimally choose the LM for each module