# (A short intro to) LLMs-based Recommender Systems

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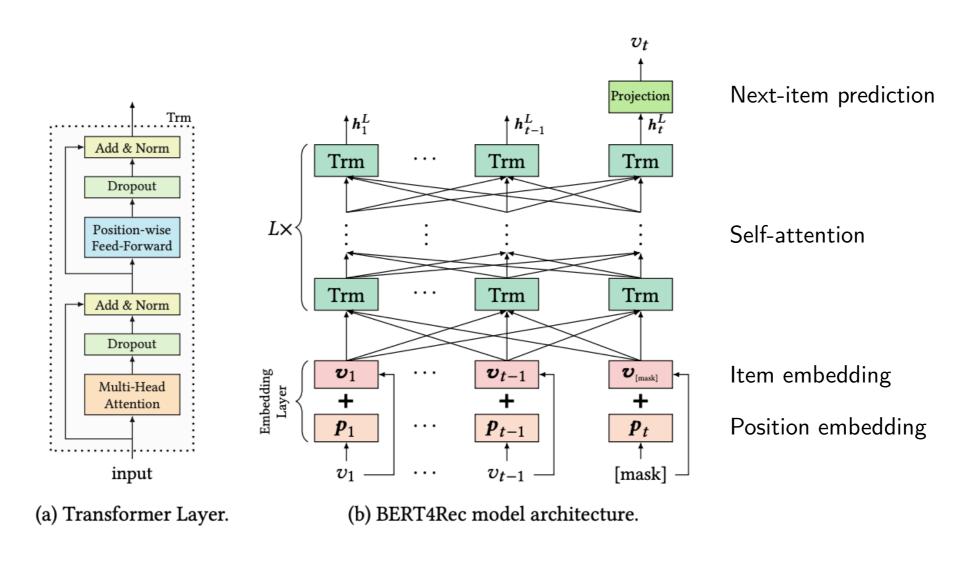
### The emergence of Large Language Models (LLMs)

- LLMs emerging as a powerful tool for NLP
- Remarkable abilities in several areas, e.g.,
  - ► Text completion, summarization, Q&A, translation, among others
- Billions of parameters, trained on a chunk of the internet
- Pretrained models, supports fine-tuning and in-context learning



# Generative Models for RecSys

### BERT4Rec for sequential recommendation



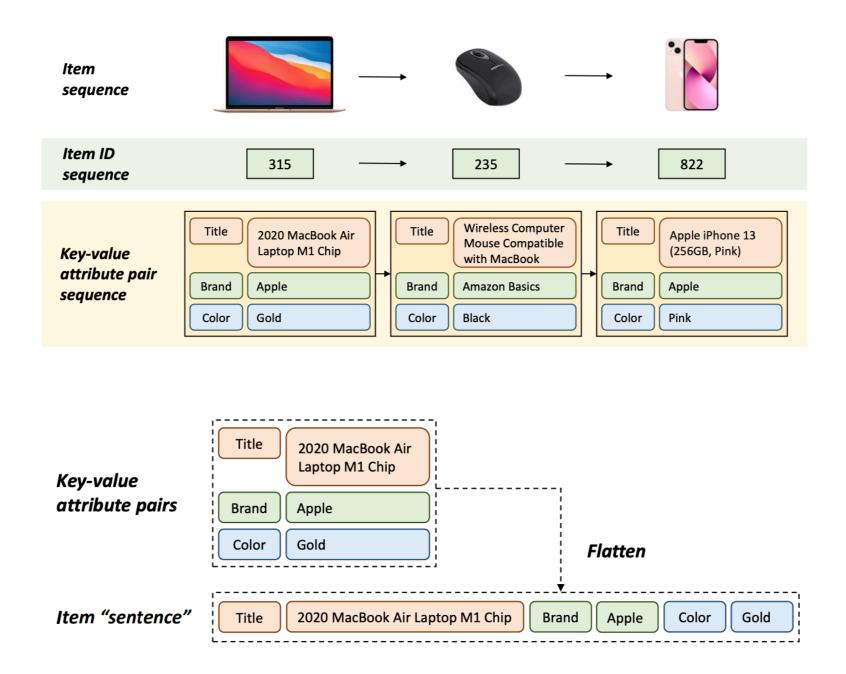
NLP:

- Token sequence
- Inter-token correlations

RecSys:

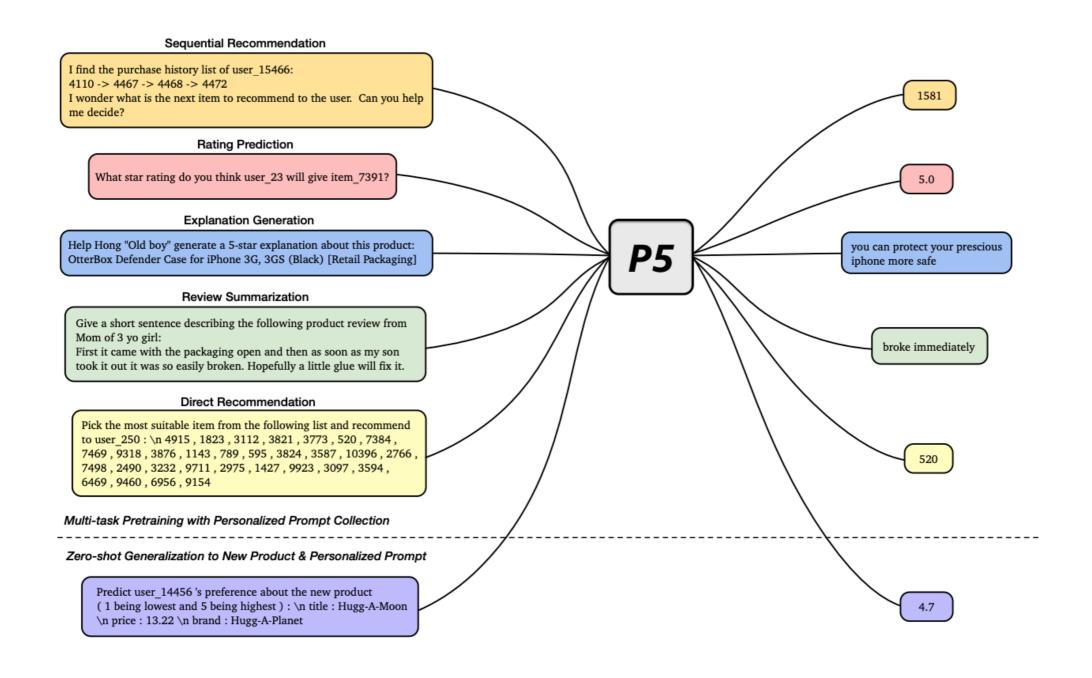
- ▸ ID sequence
- Inter-item correlations

### RecFormer - Text is all you need

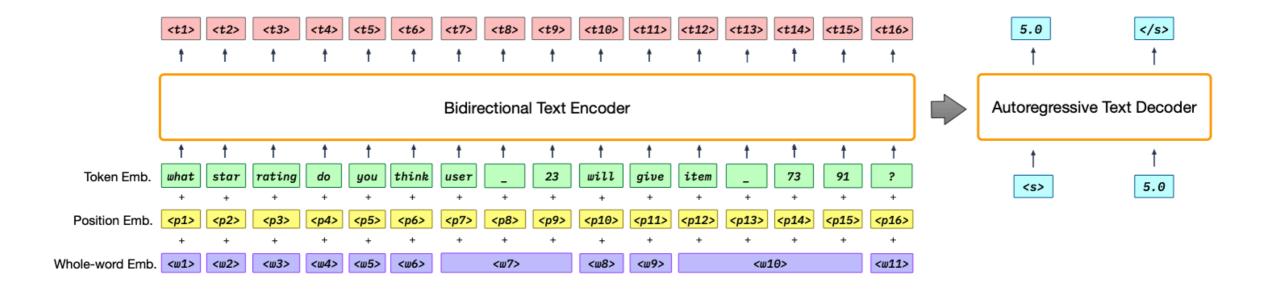


# In-Context Learning/LLMs for RecSys

### Recommendation as language processing



### Recommendation as language processing



### LLMs as a reranker

#### Point-wise

#### You are a movie recommender system now.

{{Demonstration Examples}}

Input: Here is the watching history of a user:  $\{\{User\ History\}\}$ . Based on this history, please predict the user's rating for the following item:  $\{\{Candidate\ item\}\}\$  (1 being lowest and 5 being highest)

Output: {{Answer}}

#### Pair-wise

#### You are a movie recommender system now.

{{Demonstration Examples}}

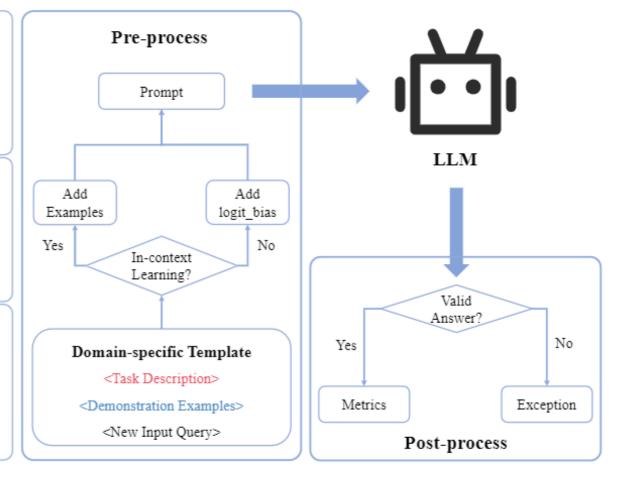
Input: Here is the watching history of a user: {{User History}}. Based on this history, would this user prefer {{Candidate Item 1}} and {{Candidate Item 2}}? Answer Choices: (A) {{Candidate Item 1}}(B) {{Candidate Item 2}} Output: {{Answer}}

#### List-wise

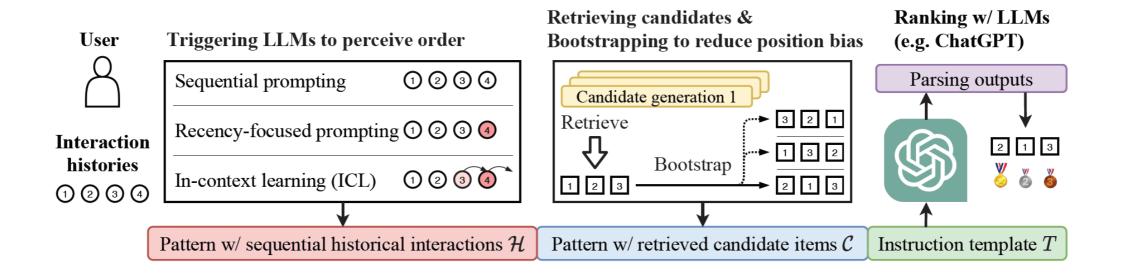
#### You are a movie recommender system now.

{{Demonstration Examples}}

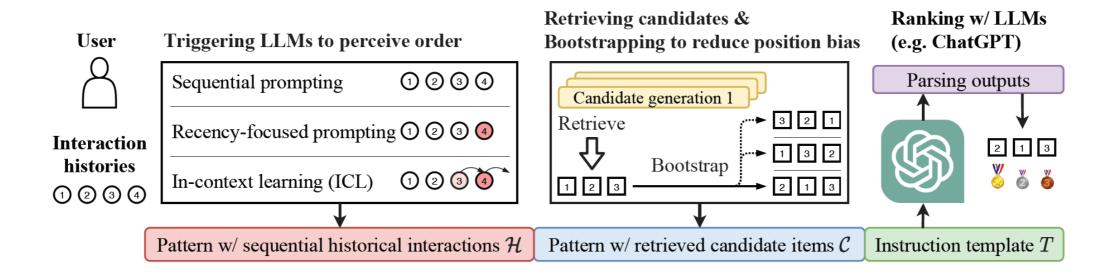
Input: Here is the watching history of a user: {{User History}}. Based on this history, please rank the following candidate movies: (A) {{Candidate Item 1}} (B) {{Candidate Item 2}} (C) {{Candidate Item 3}} (D) {{Candidate Item 4}} (E) {{Candidate Item 5}} ......
Output: The answer index is {{Answer}}}



### Addressing position bias



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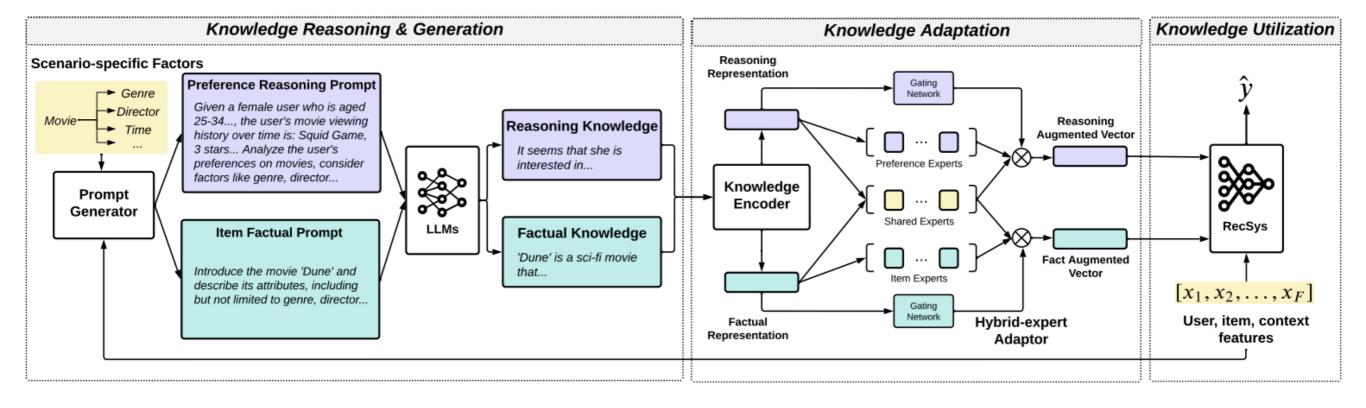
#### Triggering LLMs to perceive order

- Sequential prompting: Historical interactions in their natural order
- Recency-focused prompting: "Note that my most recently watched movie is [...]"
- In-context learning: "If I've watched the following movies in the past in order: [...] then you should recommend [...] to me and now that I've watched [...], then:"

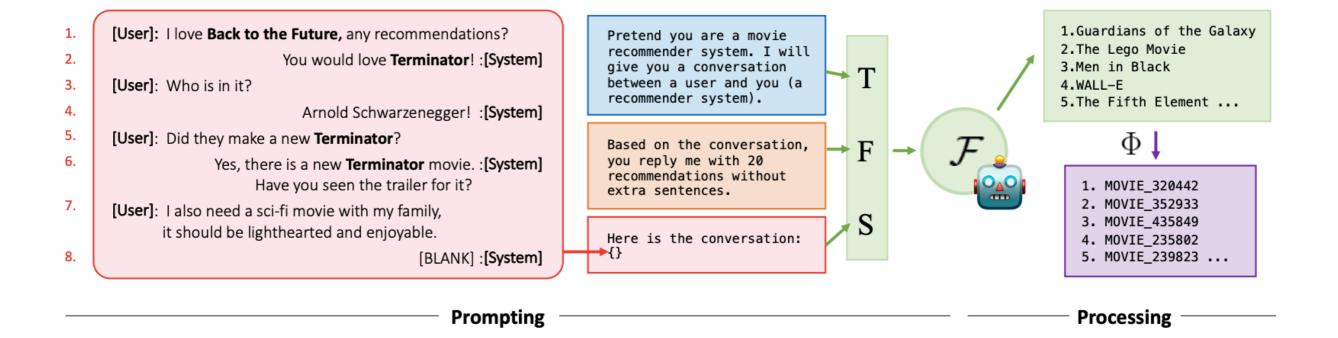
#### Bootstrapping candidates

Randomly shuffle candidates, use each sample to query the LLM, combine outputs

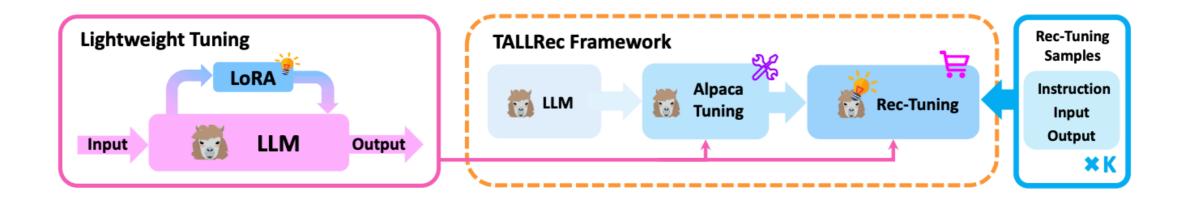
### Knowledge augmentation from LLMs



### LLMs as zero-shot conversational RS



### Tuning LLMs for recommendation

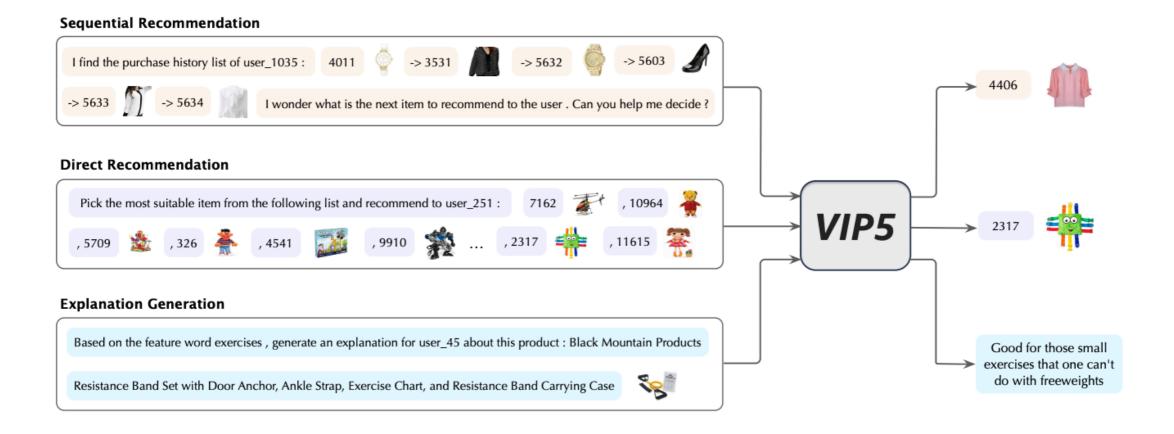


Transforms the recommendation data as instructions used to tune the LLM via an instruction tuning process, e.g.,

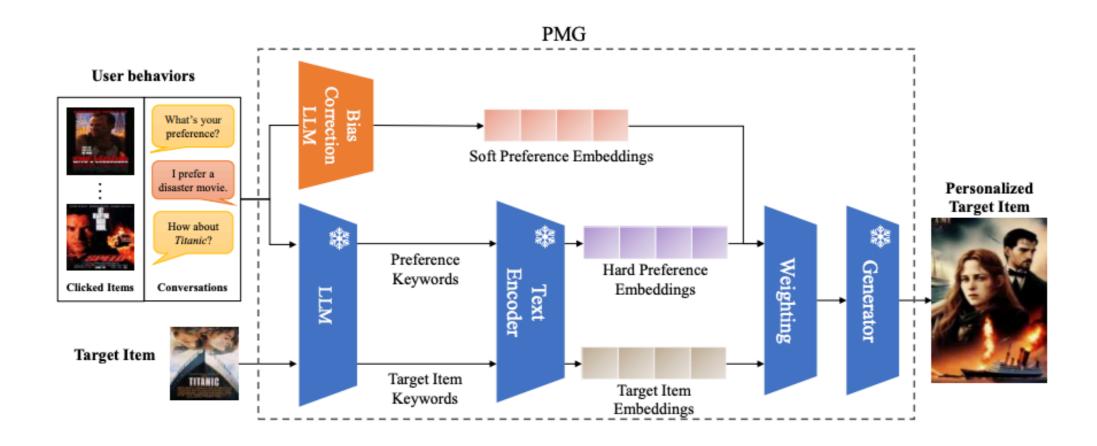
Instruction Input	
Task Instruction:	Given the user's historical interactions, please determine whether the user will enjoy the target new movie by answering "Yes" or "No".
Task Input:	User's liked items: GodFather. User's disliked items: Star Wars. Target new movie: Iron Man
	Instruction Output
Task Output:	No.

# Multimodal RecSys

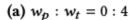
### Multimodal foundation models for recommendation



### Personalized multimodal generation with LLMs









**(b)**  $w_p : w_t = 1 : 3$ 



(c)  $w_p: w_t = 2:2$ 



(d)  $w_p: w_t = 3:1$ 



(e)  $w_p : w_t = 4 : 0$ 

## Conclusion