Retrieval-Augmented Generation for Immersive Formal Dialogue

Mark Snaith

School of Computing, Engineering & Technology Robert Gordon University, Aberdeen UK **Simon Wells**

School of Computing, Engineering & The Built Environment Edinburgh Napier University UK

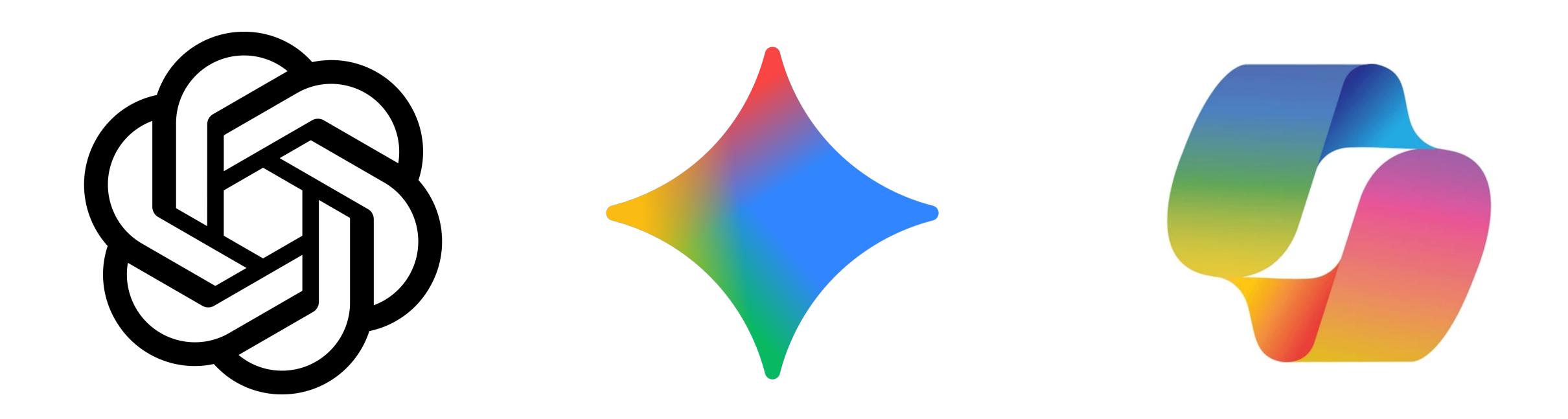




Overview

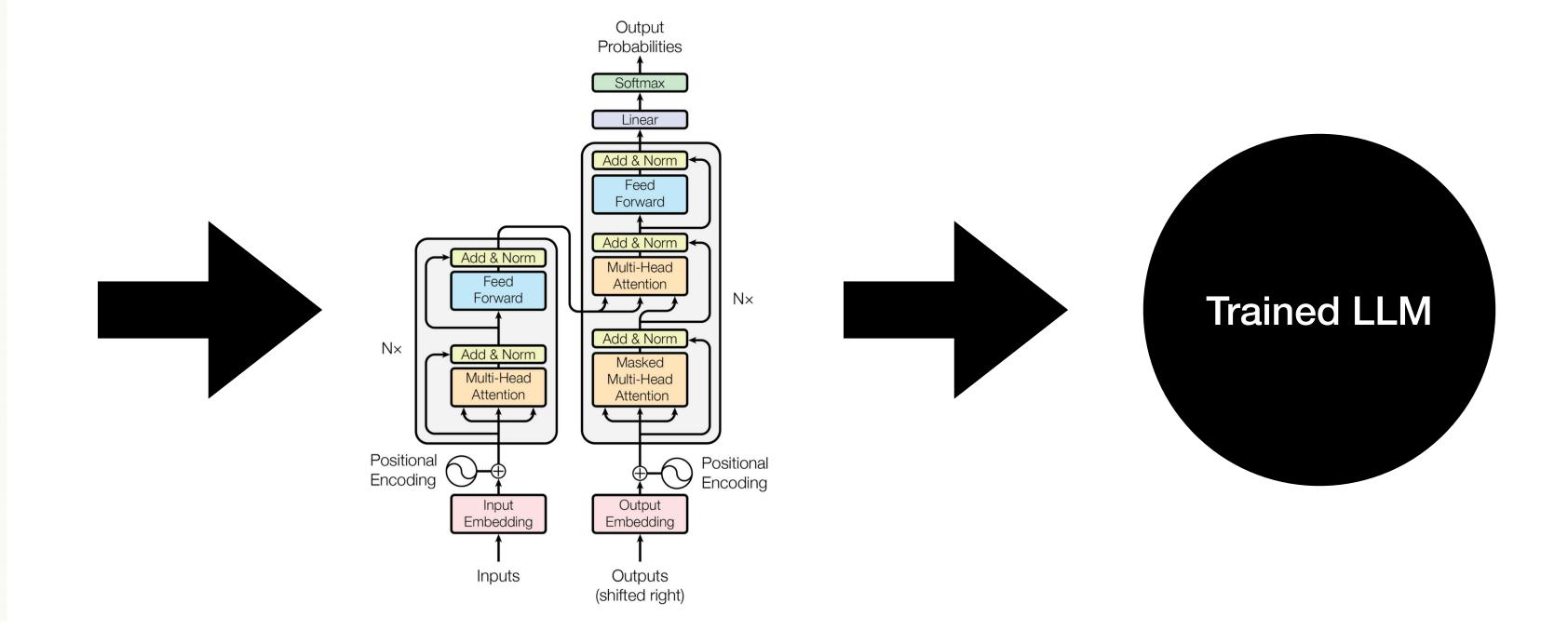
- A brief introduction to LLMs, RAG and Formal Dialogue
- Formal Dialogue vs LLMs vs LLMs + RAG + Formal Dialogue
- RAG-based pipeline

Large Language Models



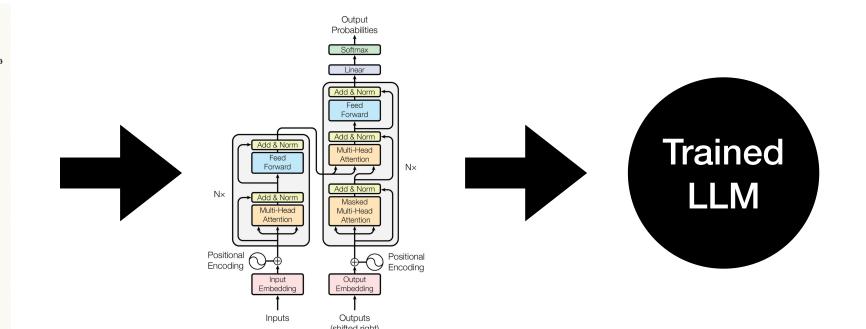
Large Language Models (LLMs)

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Large Language Models (LLMs)

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Prediction and generation of words in context

Natural conversational responses

But...can go off-topic...

Please give me a recipe for cupcakes

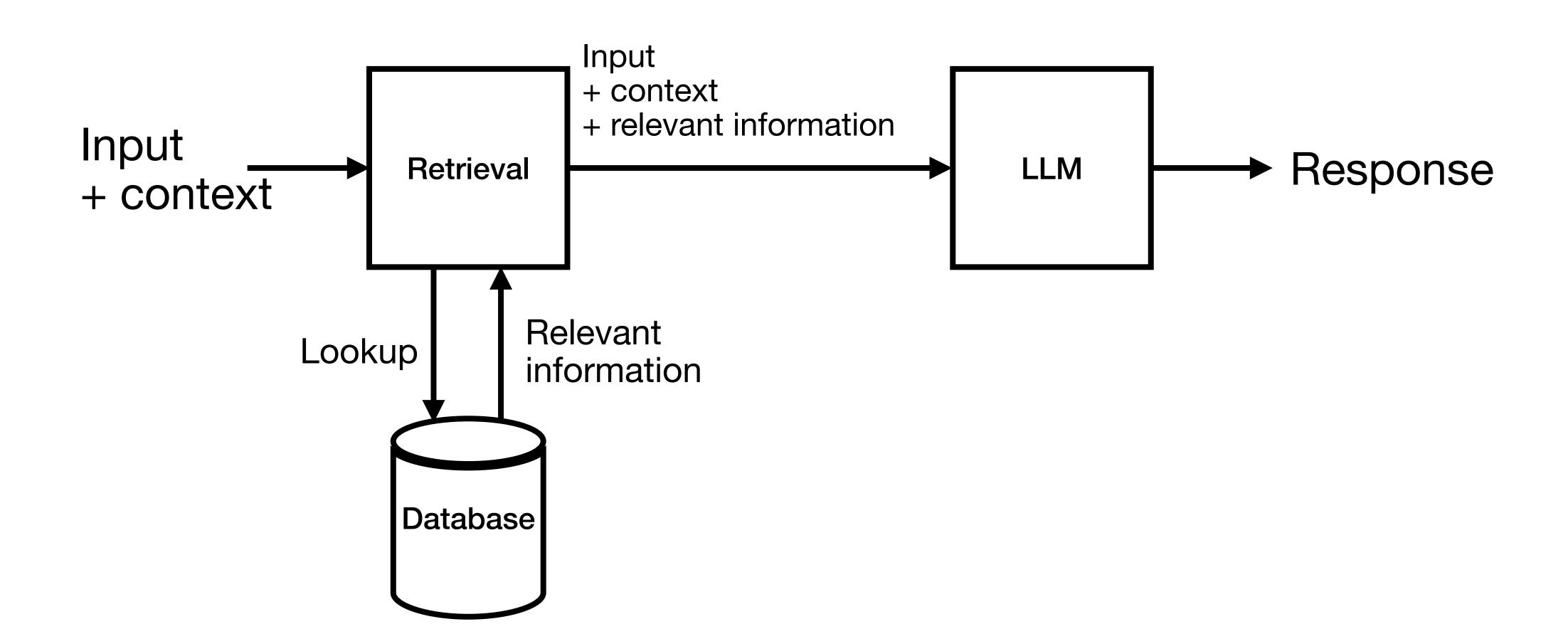
Can also hallucinate - responses not grounded in truth

Retrieval-Augmented Generation (RAG)

Grounds an LLM's output by retrieving relevant information from external sources before generating a response

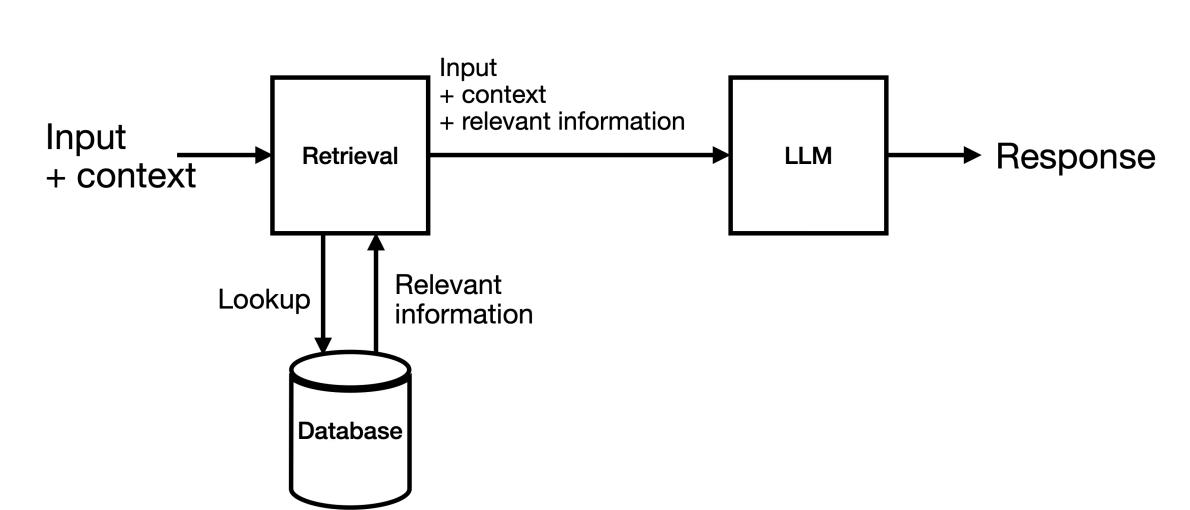
Retrieval-Augmented Generation (RAG)

Grounds an LLM's output by retrieving relevant information from external sources before generating a response



Retrieval-Augmented Generation (RAG)

Grounds an LLM's output by retrieving relevant information from external sources before generating a response



Common use-cases:

- Customer support: LLM retrieves specific company policies etc. to provide bespoke answer
- Summarisation: provide documents and ask LLM to generate a summary

Formal Dialogue

Model conversations as structured, rule-governed exchanges aimed at specific goals (e.g. persuasion, inquiry, negotiation)

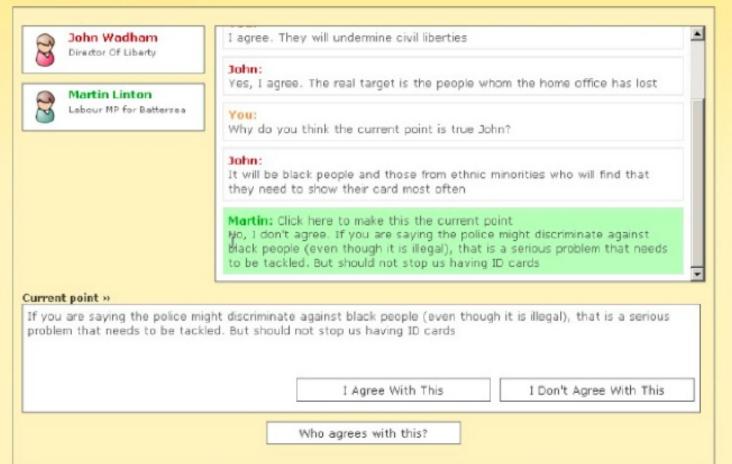
Formal Dialogue

Model conversations as structured, rule-governed exchanges aimed at specific goals (e.g. persuasion, inquiry, negotiation)

- Rules for structure, turn-taking, locutions, commitment, termination etc.
- Participants advance valid moves speech act + content
- Used in human-agent and agent-agent communication
- Can seem rigid and lack expressiveness in human-agent applications

```
• • •
                                                                                              dgdl.g4 — Edited
grammar dgdl;
   'game' '(' 'id' ':' gameID ')' '{' composition (rules)* (interaction)+ '}' EOF;
gameID : identifier;
composition: roleList? participants player+ store* turntaking? backtrack? extURI*;
roleList :
   'roles' '(' role (',' role)* ')';
role : (LISTENER | SPEAKER | identifier);
participants :
   'participants' '(' 'min' ':' minplayers ',' 'max' ':' maxplayers ')';
   'player' '(' 'id' ':' playerID (',' playerRoleList)? (',' 'min' ':' <u>minplayers</u>)? (',' 'max' ':' <u>maxplayers</u>)? ')';
playerID : identifier;
playerRoleList :
   'roles' ':' '{' role (',' role)* '}';
   'store' '(' 'id' ':' storeID ',' 'owner' ':' storeOwner ',' 'structure' ':' storeStructure ',' 'visibility' ':' storeVisibility (',' storeContent)? ')';
storeID : identifier;
storeOwner :
   (identifier | '{' identifier (',' identifier)+ '}');
storeStructure :
   (SET | QUEUE | STACK);
storeVisibility:
   (PUBLIC | PRIVATE);
storeContent :
   '{' (contentVar | STRINGLITERAL) (',' (contentVar| STRINGLITERAL))* '}';
   'turntaking' '(' turntakingtype ')';
turntakingtype : ('strict' | 'liberal');
backtrack :
   'backtracking' '(' onoff ')';
<u>onoff</u> : ('on' | 'off');
   'extURI' '(' 'id' ':' extUriID ',' 'uri' ':' uri ')';
uri : STRINGLITERAL;
extUriID : identifier;
minplayers : number;
maxplayers : (number | 'undefined');
   'rule' '(' 'id' ':' ruleID ',' 'scope' ':' scopeType ')' ruleBody;
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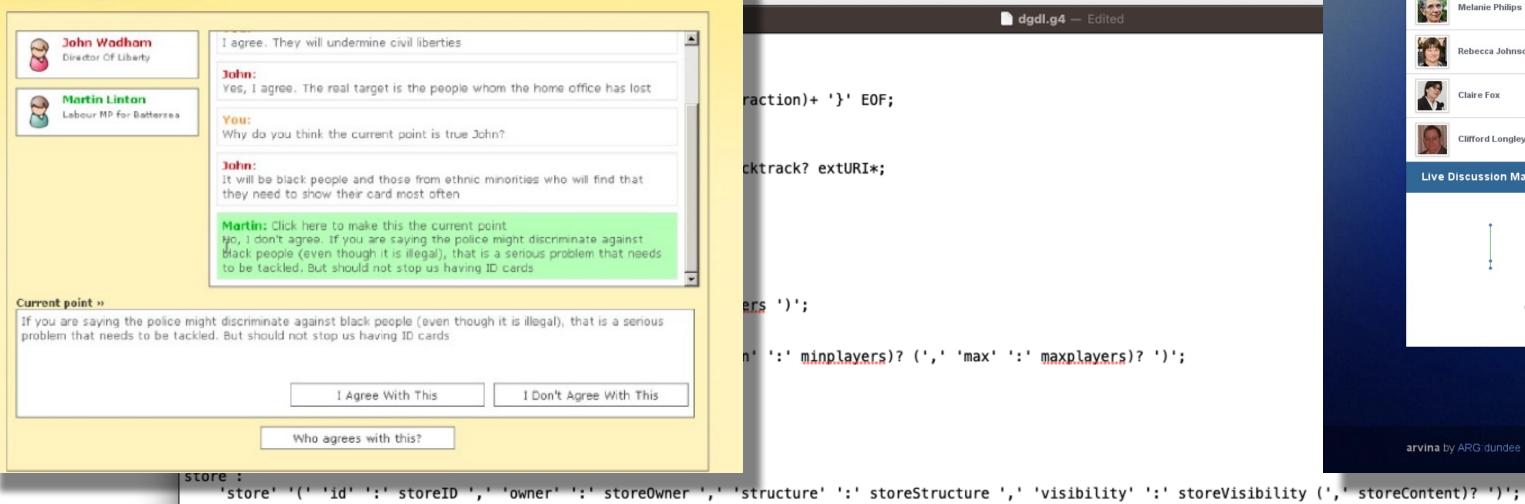


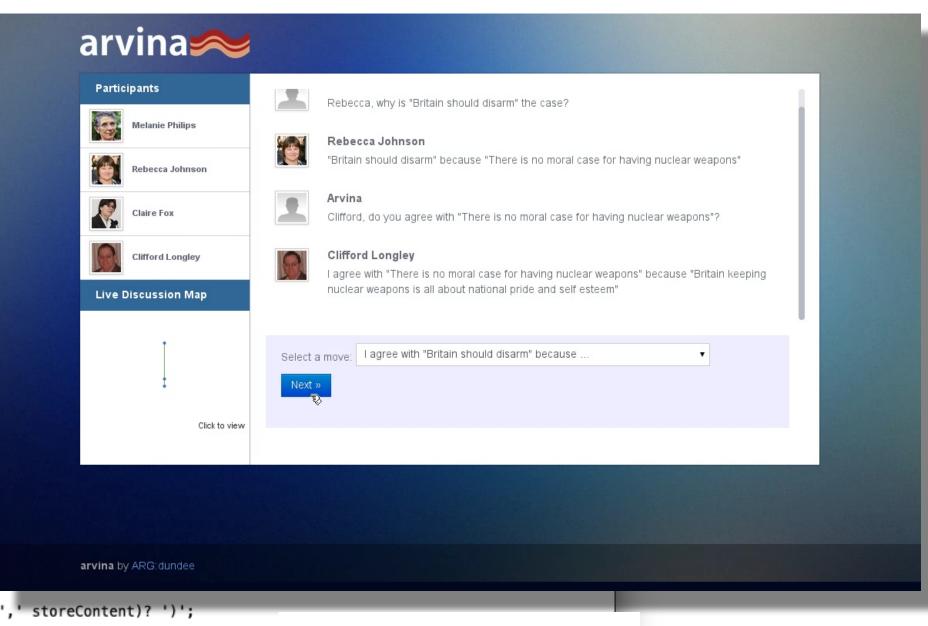
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dgdl.g4 — Edited
                                                              raction)+ '}' EOF;
                                                              cktrack? extURI*;
                                                                 ':' minplayers)? (',' 'max' ':' maxplayers)? ')';
'store' '(' 'id' ':' storeID ',' 'owner' ':' storeOwner ',' 'structure' ':' storeStructure ',' 'visibility' ':' storeVisibility (',' storeContent)? ')';
```

Wells & Reed (2008)

```
(identifier | '{' identifier (', 'identifier)+ '}');
storeStructure :
   (SET | QUEUE | STACK);
storeVisibility:
   (PUBLIC | PRIVATE);
storeContent :
    '{' (contentVar | STRINGLITERAL) (',' (contentVar| STRINGLITERAL))* '}';
turntaking :
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extUriID : identifier;
minplayers : number;
maxplayers : (number | 'undefined');
   'rule' '(' 'id' ':' ruleID ',' 'scope' ':' scopeType ')' ruleBody;
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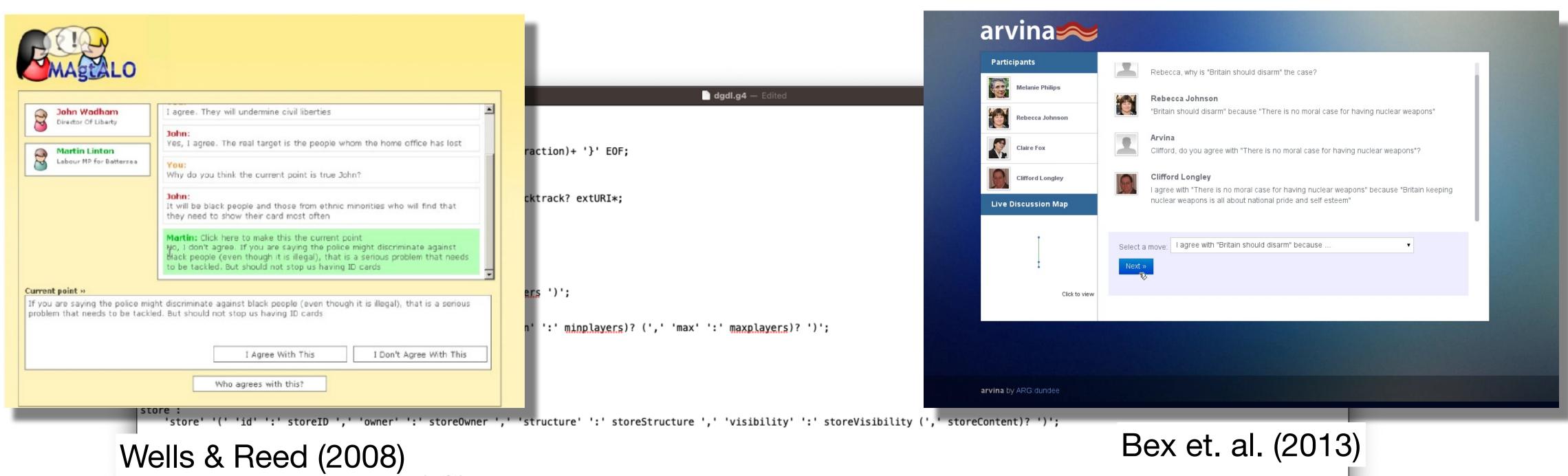


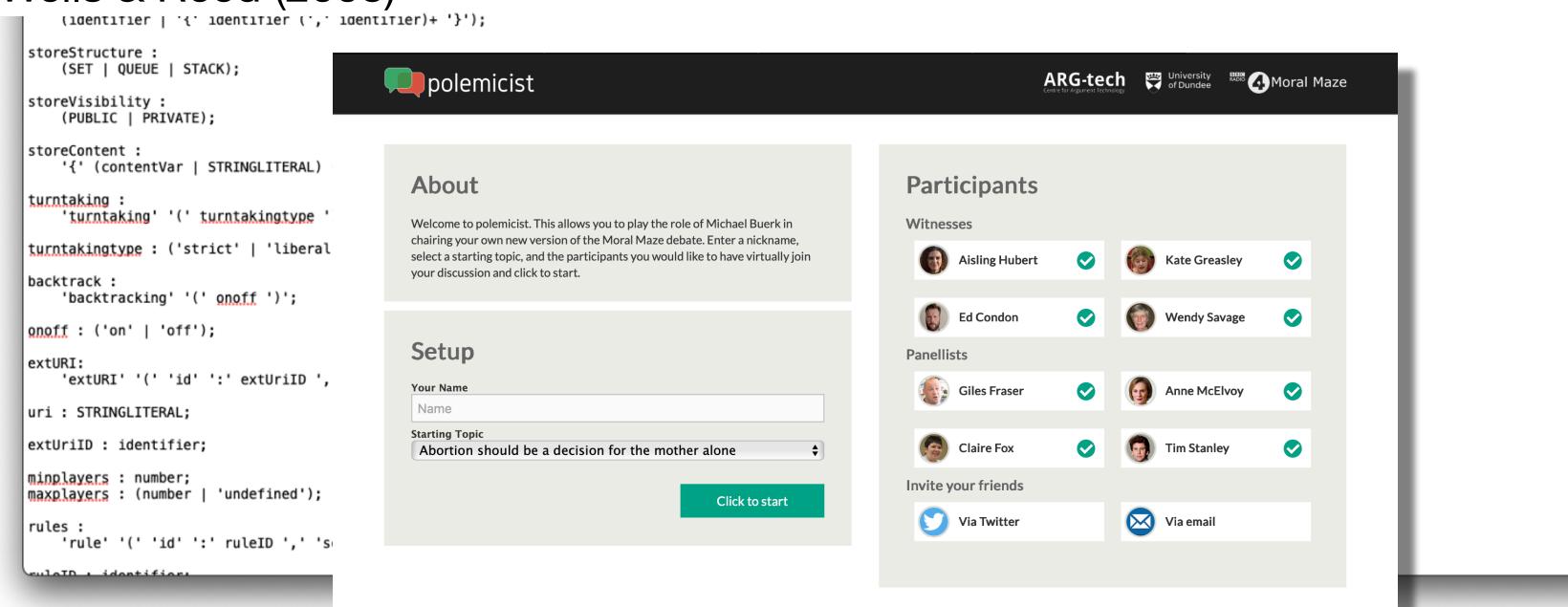
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Bex et. al. (2013)





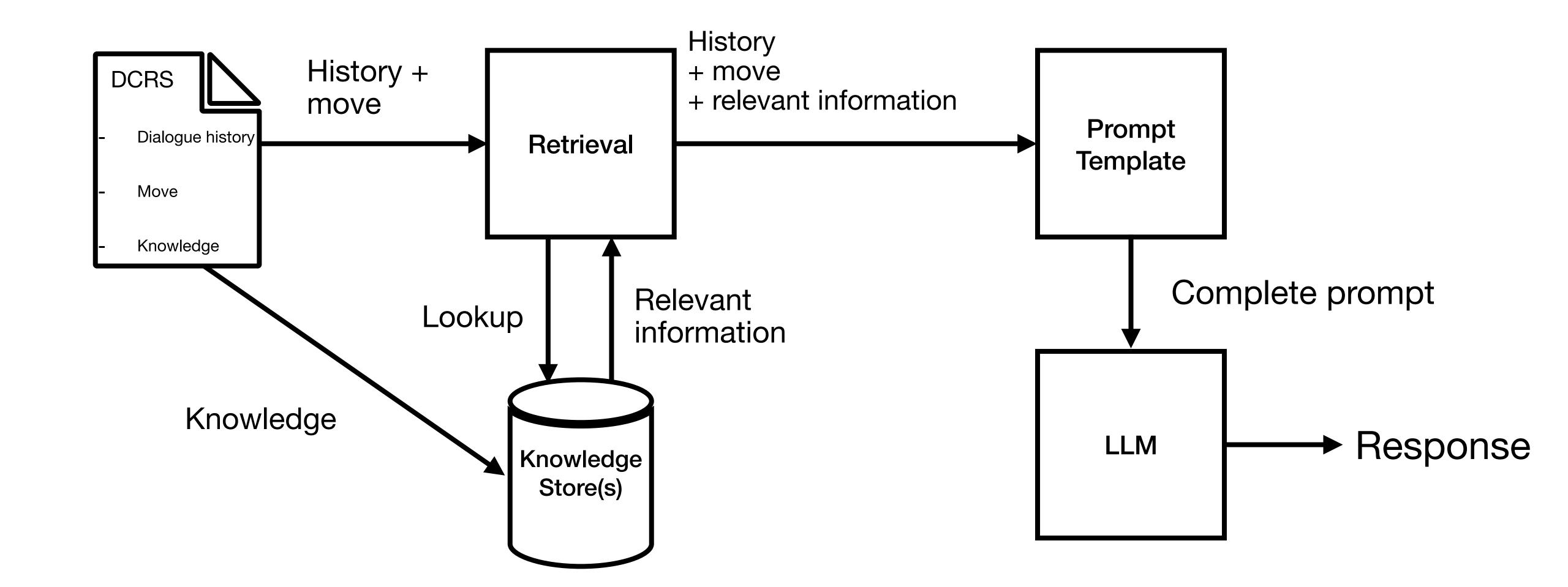
Lawrence et. al. (2022)

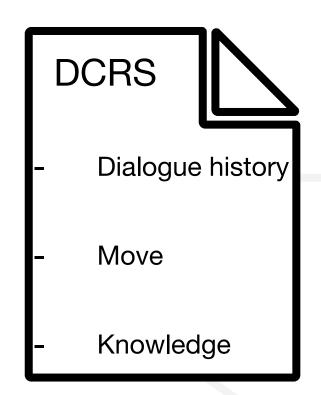
Formal dialogue vs LLMs

Aspect	Formal Dialogue	LLMs	
Structure	Rigid, protocol-driven turns	Free-flowing, unconstrained text	
Goals	Clear purposes (e.g. persuasion, inquiry, negotiation) Flexible, task-agnostic		
Transparency	High: reasoning explicit through moves		
Naturalness	Often stilted and hard for users to engage with	Human-like fluency	
Grounding	Rules and knowledge bases explicitly defined	Implicit in training data	

Formal dialogue vs LLMs

Aspect	Formal Dialogue	LLMs	Formal Dialogue + LLM + RAG
Structure	Rigid, protocol-driven turns	Free-flowing, unconstrained text	Natural expression mapped to structured moves
Goals	Clear purposes (e.g. persuasion, inquiry, negotiation)	Flexible, task- agnostic	Preserve dialogue goals while adapting language
Transparency	High: reasoning explicit through moves	Low: opaque "black box"	Retrieved evidence grounds outputs, explanations possible
Naturalness	Often stilted and hard for users to engage with	Human-like fluency	Formal logic preserved, but phrased naturally
Grounding	Rules and knowledge bases explicitly defined	Implicit in training data	Retrieval ensures domain- specific, up-to-date knowledge from multiple sources

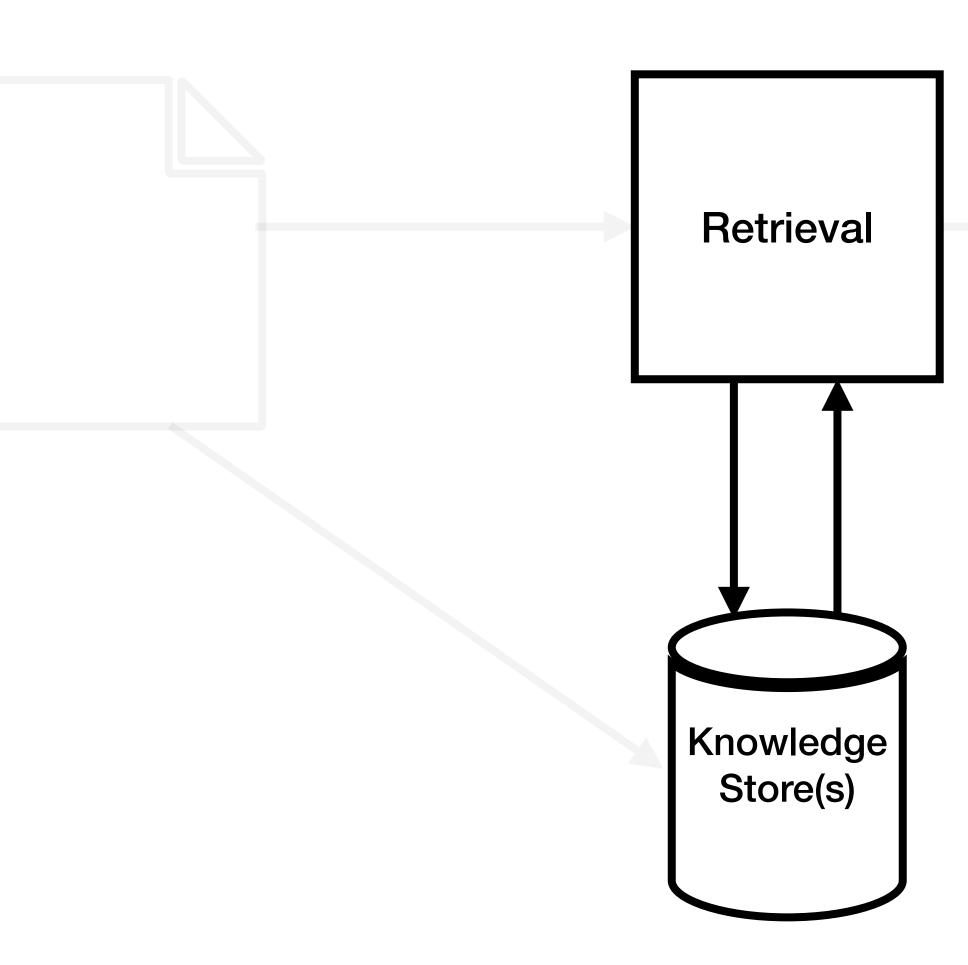




Dialogue Context Request Structure

Contains:

- Knowledge (from the agent)
- Dialogue history (for context)
- Move scaffold (to help the LLM structure its response)



Vector Database(s) - semantic search

Returns *relevant* knowledge based on a query assembled from:

- Dialogue history
- Move scaffold

Four key elements:

- Task description (instructions)
- Dialogue history
- Move scaffold
- Retrieved knowledge
 - And how it should be interpreted

Prompt Template

Prompt Template

You are assisting in a dialogue by generating the next utterance. Use the provided scaffold, dialogue history, and structured knowledge sources below. *Prioritise the provided knowledge sources in generating the next utterance, but if a suitable utterance can't be generated you may use your own knowledge, in which case identify the source as "generated".*

```
## Dialogue History
{{history}}

## Utterance Scaffold
{{Utterance}}
```

You may adapt the scaffold to better match the tone, style, or conversational flow of the dialogue history. The goal is to maintain coherence and sound natural within the ongoing dialogue.

Knowledge Sources

The knowledge provided below includes different structures. Each structure has a name, a formal representation, and a description of how to interpret it.

{{knowledge}}

Prompt Template

You are assisting in a dialogue by generating the next utterance. Use the provided scaffold, dialogue history, and structured knowledge sources below. *Prioritise the provided knowledge sources in generating the next utterance, but if a suitable utterance can't be generated you may use your own knowledge, in which case identify the source as "generated".*

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{{history}}

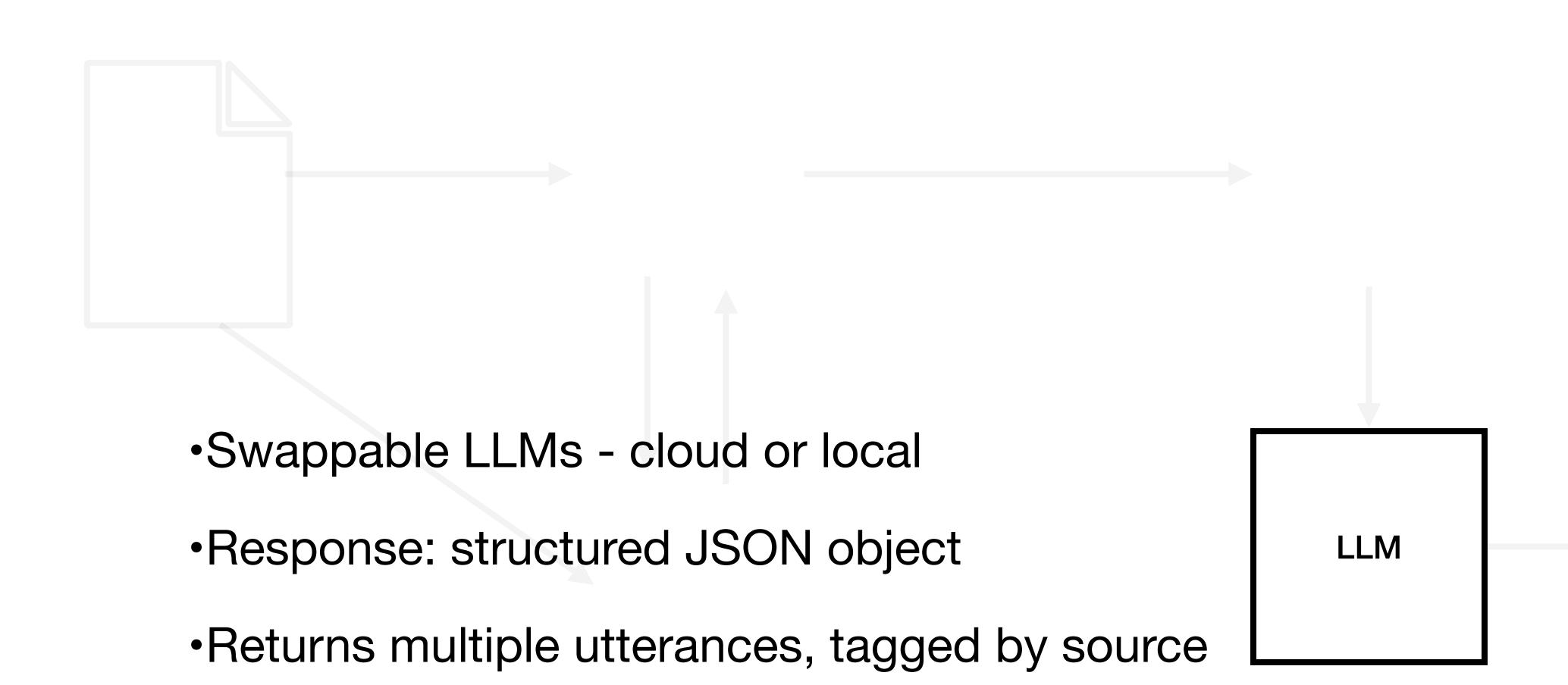
## Utterance Scaffold
{{Utterance}}
```

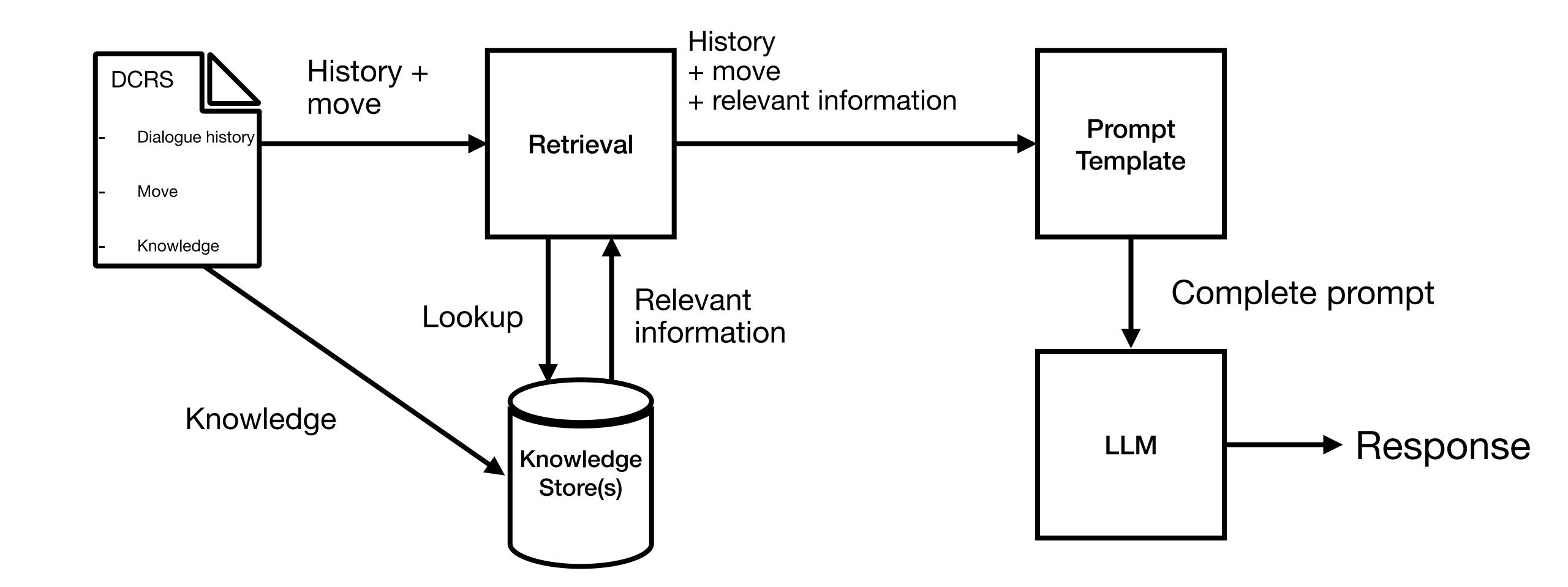
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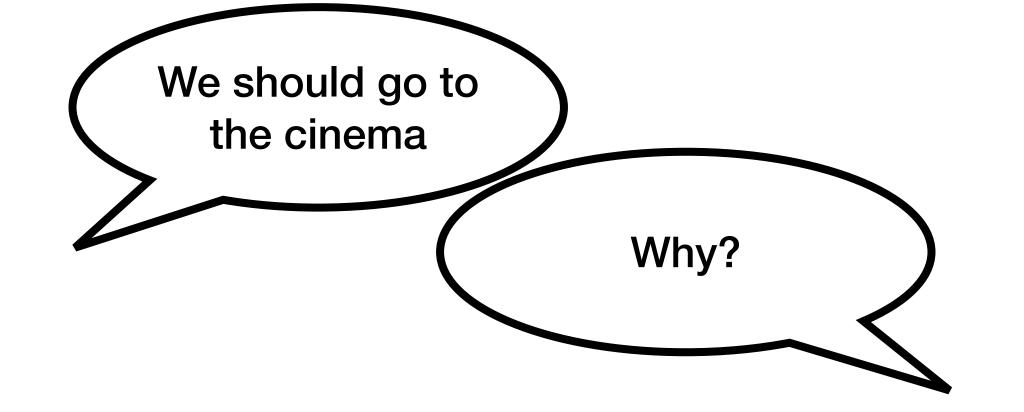
Knowledge Sources

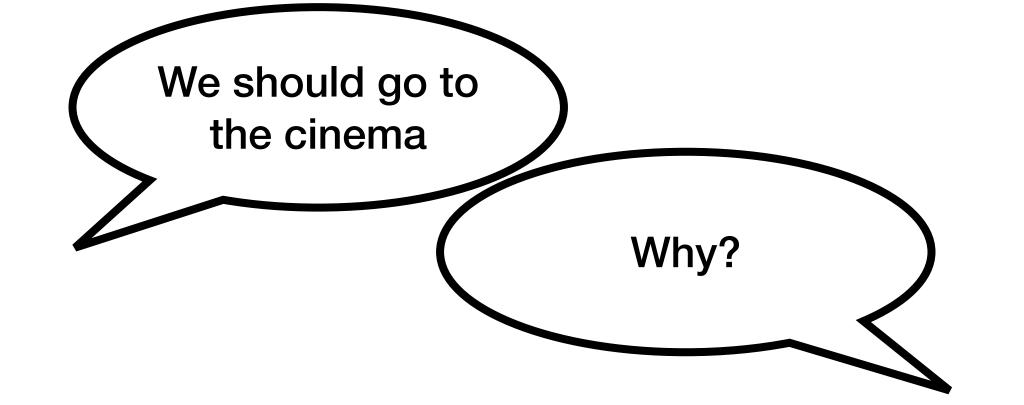
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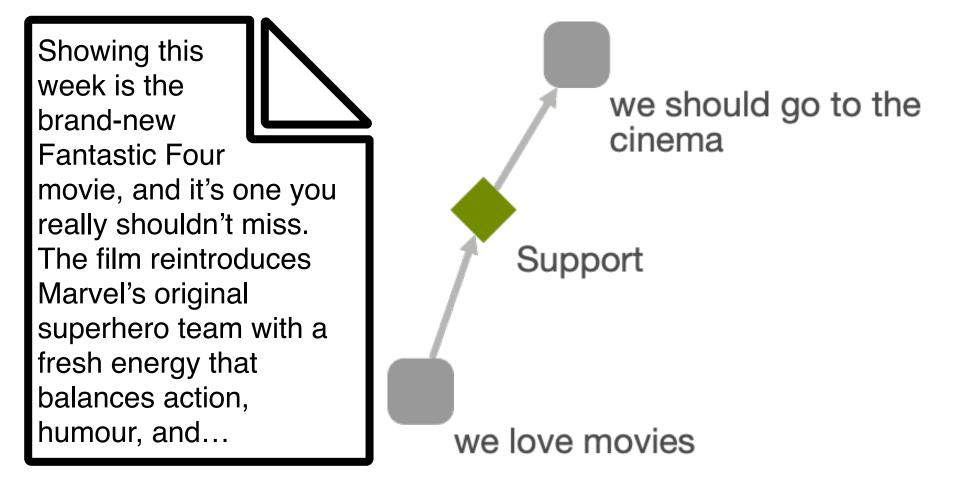
{{knowledge}}

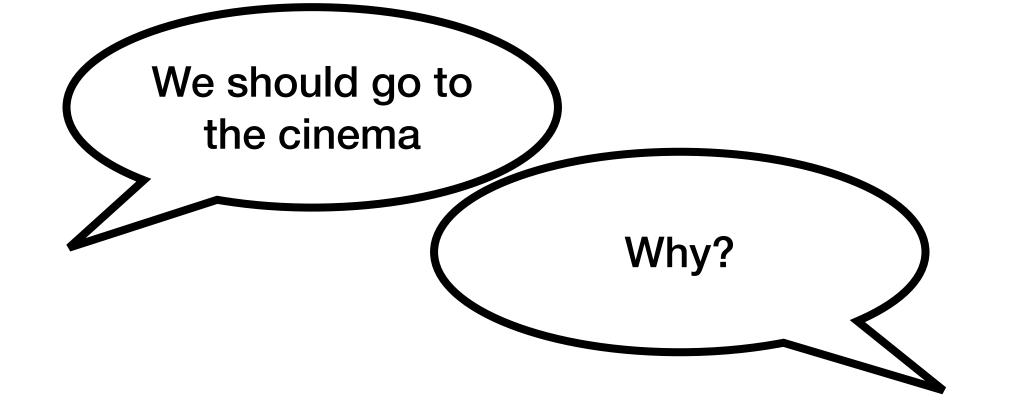










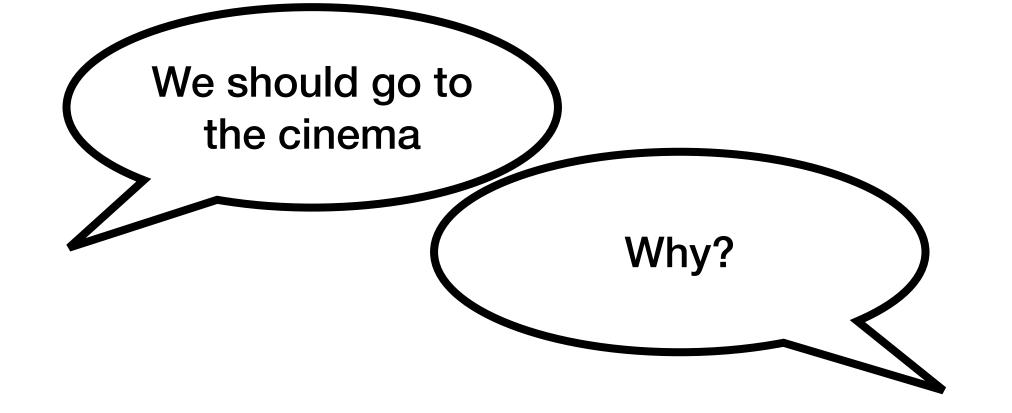


Showing this week is the we should go to the brand-new cinema Fantastic Four movie, and it's one you really shouldn't miss. Support The film reintroduces Marvel's original superhero team with a fresh energy that balances action, humour, and... we love movies

Dialogue history

Alice: We should go to the cinema [assert]

Bob: Why? [challenge]



Showing this week is the we should go to the brand-new cinema Fantastic Four movie, and it's one you really shouldn't miss. Support The film reintroduces Marvel's original superhero team with a fresh energy that balances action, humour, and... we love movies

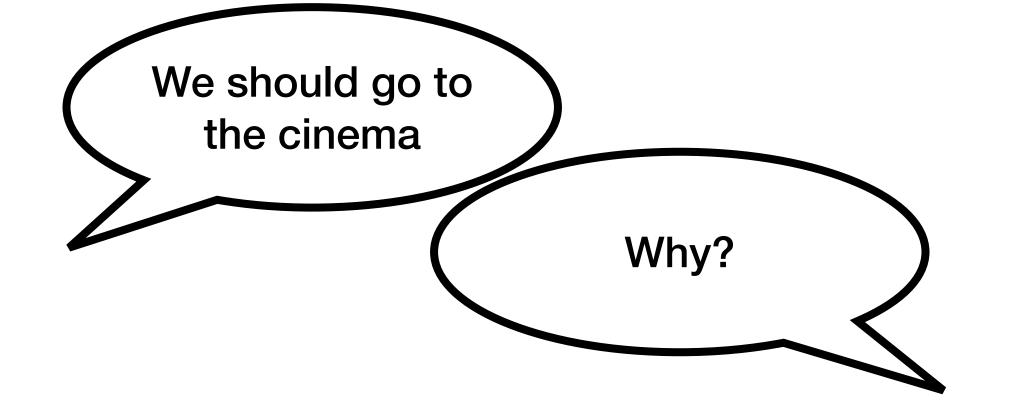
Dialogue history

Alice: We should go to the cinema [assert]

Bob: Why? [challenge]

Scaffold

"We should go to the cinema because \$p"



Showing this week is the we should go to the brand-new cinema Fantastic Four movie, and it's one you really shouldn't miss. The film reintroduces Support Marvel's original superhero team with a fresh energy that balances action, humour, and... we love movies

Natural language text to interpret. Rephrase if needs be to make short responses using this source.

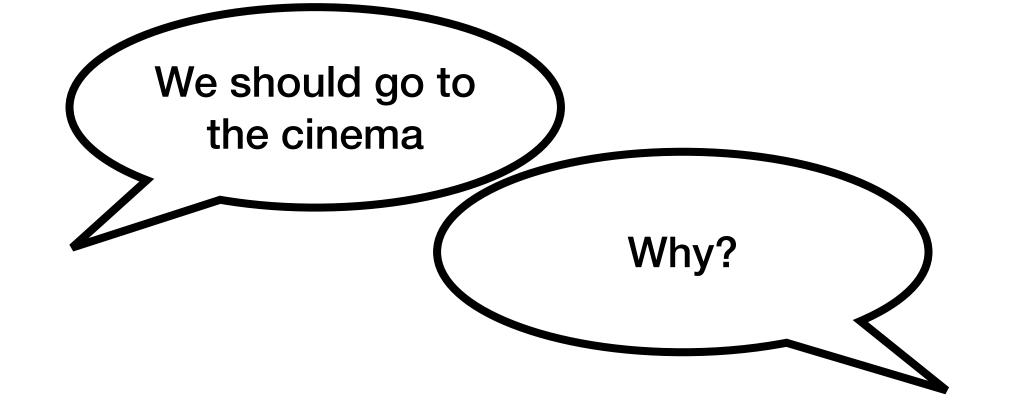
Dialogue history

Alice: We should go to the cinema [assert]

Bob: Why? [challenge]

Scaffold

"We should go to the cinema because \$p"



Showing this week is the brand-new Fantastic Four movie, and it's one you really shouldn't miss. The film reintroduces Marvel's original superhero team with a fresh energy that balances action, humour, and...

Dialogue history

Alice: We should go to the cinema [assert]

Bob: Why? [challenge]

- sadface-inference
Format: p1,...,pn=>q
Description: p1,...,pn are
premises that together
support the conclusion q

Scaffold

"We should go to the cinema because \$p"

Natural language text to interpret. Rephrase if needs be to make short responses using this source.

we should go to the

cinema

Support

we love movies

Showing this

week is the

brand-new

Fantastic Four

Marvel's original

fresh energy that

balances action,

humour, and...

really shouldn't miss.

The film reintroduces

superhero team with a

```
"responses": [
                     "response": "We should go to the cinema because the brand-new Fantastic
               Four movie is showing this week, with great effects and a fun team dynamic
               that's best enjoyed on the big screen.",
        Knov
                     "source": "text"
                                                                                                 o to the use $p"
                   },
movie, and it's one you
                     "response": "We should go to the cinema because we love movies, and
               it's a perfect chance to enjoy one together.",
                     "source": "sadface"
```

fold

Ongoing and future work

- Evaluation Two types:
 - Is the LLM giving "good" responses?
 - How "good" are the responses from different LLMs?
- Combining knowledge sources in a single response
 - Currently limited to one source per response
- Strategic support LLM judgement of the "best" response to put forward

DiSCoAl - Dialogue-based Structured Conversational Al 2025-2028

- Automated implementation of computational dialogue games from real (human-human) examples
- Underpinning conversational systems with formal dialogue without the design and development overhead
- When combined with RAG pipeline = rapid development of rich and immersive systems across a wide variety of domains





Summary

- LLM and RAG-based pipeline for generated responses in formal dialogue
- Knowledge, history and move scaffold used to ground the response
- Bridges the vocabulary gap to make formal dialogue responses more natural

Thank you



