

Stanford CS224v Course

Conversational Virtual Assistants with Deep Learning

Lecture 7

Introduction to Agents for Structured and Free-Text Data

Monica Lam & Shicheng Liu

Motivation with an Example

- How do you find a restaurant on Yelp?

Yelp: DB + Free text

Name TEXT	Cuisine TEXT[]	Rating NUM(2,1)	...	Popular_dishes FREE TEXT	Reviews FREE TEXT
Hummus Mediterranean Kitchen	mediterranean, halal, salad	4.0	...	Chicken Kebab Plate, Lamb Beef Gyro, Marinated Chicken Gyros, ...	t l ; d r This is your place if you're looking for a healthy and filling meal whether it's a quick pick-me-up or casual dining, ...
Penny Roma	italian, venues & event spaces	4.0	...	Cacio E Pepe, Agnolotti Dal Plin, Albacore Tartare, ...	My girlfriend was craving pasta on a Monday night. ... We were not expecting such an intimate and romantic dining experience. The restaurant was candle lit, modern, and perfect for a date night. ...

- Blue columns contain structured data
- Yellow columns are free text
- A lot of rows (thousands)

A lot of info is in free-text

DB + Free-Text Combo Example

I need a family-friendly restaurant

→ “family-friendly” in reviews

I need a family-friendly restaurant in Palo Alto

→ “family-friendly” in reviews; Palo Alto in DB

We Need Hybrid Data

	Structured	Free Text
Restaurants	Cuisines, opening hours, address, rating	Reviews, popular dishes
Products	Product ID, cost, ratings, sizes, physical dimensions, color	Descriptions, reviews
Courses	Class number, time offered, instructor, building, pre-requisites	Descriptions, reviews
Business processes	Receipts, statements	Regulations
Medical	Patient demographics Prescription	Diagnosis history

The Next Problem:

Hybrid Data QA

COMBINING
KNOWLEDGE BASES & TEXTUAL QA

Quiz

WHAT IS YOUR APPROACH TO HANDLE
KNOWLEDGE BASES & TEXT?

Goal of this Lecture

- To understand the Hybrid QA problem
 - Discuss 4 major approaches, starting with the simplest
 - HybridQA: dataset requiring composition of DB & Text retrieval

1. **Classify query to decide to retrieve from DB or Text**
2. Retrieve answers from DB and Text separately, choose answer
3. Convert DB to text; use Text Retrieval
4. Retrieve answers from DB and Text separately, use LLM to combine the answers

1. Classify the Question: KB or Text

"What do others think?":

Task-Oriented Conversational Modeling with Subjective Knowledge

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<https://browse.arxiv.org/pdf/2305.12091.pdf>

SK-TOD Dataset

Subject-Knowledge Task-Oriented Dataset

“The first dataset, which contains subjective knowledge-seeking dialogue contexts and manually annotated responses grounded in subjective knowledge sources.”

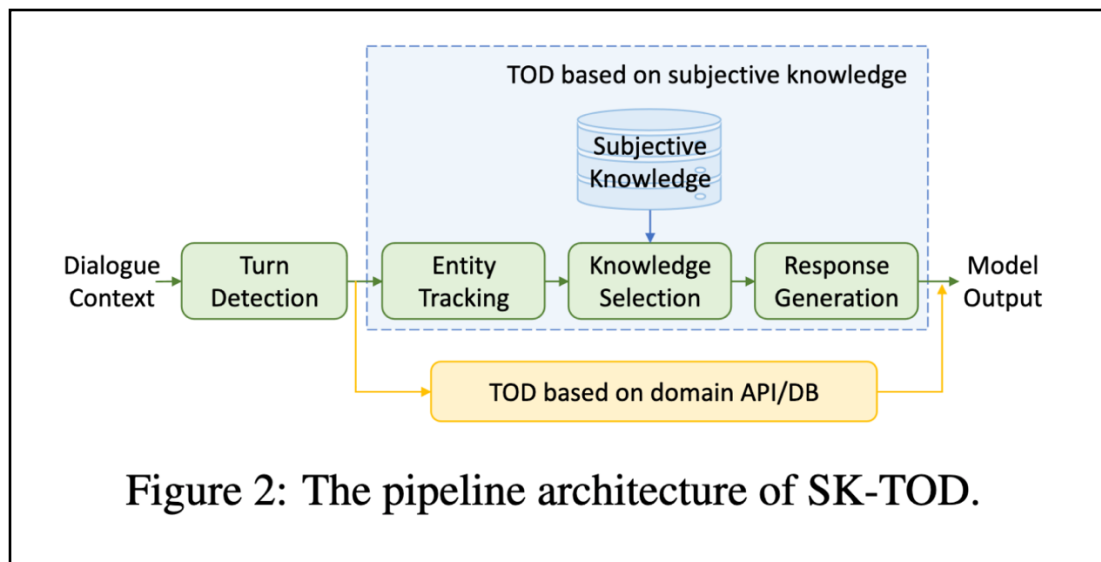
- MultiWOZ restaurant and hotel (in Cambridge area)
 - User goal: search and book restaurants and hotels
 - Structure: 13 slots (easier than SQL)
 - Text: 143 entities and 1,430 reviews (8,013 sentences)

Largest TOD Dataset with Subjective Knowledge

	Size	Manual	Dial	TOD	Query	Aspect	Senti	Mul-Knwl	Senti-%
Semeval/MAMS (2016; 2019)	5K/22K	✓	✗	n/a	✗	✓	✓	✗	n/a
Space (2021)	1K	✓	✗	n/a	✗	✓	✓	✓	✗
Yelp/Amazon (2019; 2020)	200/180	✓	✗	n/a	✗	✗	✓	✓	✗
Justify-Rec (2019)	1.3M	✗	✗	n/a	✗	✓	✗	✓	✗
AmazonQA (2016)	309K	✗	✗	n/a	✓	✗	✗	✗	n/a
SubjQA (2020)	10K	✗	✗	n/a	✓	✓	✓	✗	n/a
Holl-E (2018)	9K	✓	✓	✗	✗	✗	✗	✓	✗
Foursquare (2018)	1M	✗	✓	✗	✗	✗	✗	✓	n/a
SK-TOD (Ours)	20K	✓	✓	✓	✓	✓	✓	✓	✓

Table 1: Comparison between SK-TOD and other benchmarks based on the subjective content. We consider if the dataset is manually annotated, dialogue-based, task-oriented, and query-focused. We also list if it considers aspect and sentiment, multiple knowledge snippets (Mul-Knwl), and the proportion of two-sided sentiments (Senti-%).

Binary Classifier (IR vs Semantic Parsing)



Turn detection: binary classification

INFORMATION RETRIEVAL (IR)

Entity Tracking

Fuzzy n-gram matching between dialogue & entities. (A few entities in MultiWOZ)

Knowledge Selection

Calculate relevant knowledge score between dialogue context & knowledge snippets

Response Generation

Use pretrained GPT-2/Bart

2. Choose Later: Stanford Chirpy Cardinal

Neural Generation Meets Real People: Building a Social, Informative Open-Domain Dialogue Agent

Ethan A. Chi*, Ashwin Paranajpe*, Abigail See*, Caleb Chiam*, Trenton Chang, Kathleen Kenealy, Swee Kiat Lim, Amelia Hardy, Chetanya Rastogi, Haojun Li, Alexander Iyabor, Yutong He, Hari Sowrirajan, Peng Qi, Kaushik Ram Sadagopan, Nguyet Minh Phu, Dilara Soylu, Jillian Tang, Avanika Narayan, Giovanni Campagna, and Christopher D. Manning

- Alexa Social Bot Prize Runner up, 2021
- Different modules to handle different kinds of questions
- Run generators in parallel
- Choose at the end

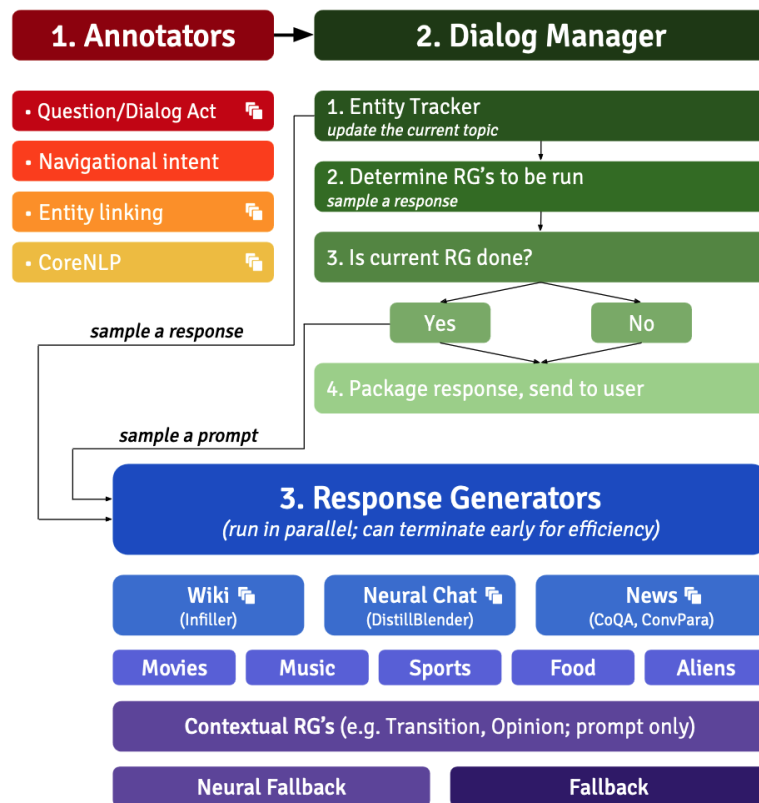


Figure 4: Overall system design.

QUIZ

WHAT IS THE WEAKNESS OF
CHOOSING JUST THE KB OR TEXT?

What if We Need Both to Answer the Questions?



Hey! Can you recommend me an Italian restaurant with a romantic atmosphere?

Name TEXT	Cuisine TEXT[]	Rating NUM(2,1)	...	Popular_dishes FREE TEXT	Reviews FREE TEXT
Hummus Mediterranean Kitchen	Mediterranean, halal, salad	4.0	...	Chicken Kebab Plate, Lamb Beef Gyro, Marinated Chicken Gyros, ...	t ; d r This is your place if you're looking for a healthy and filling meal whether it's a quick pick-me-up or casual dining, ...
Penny Roma	Italian, venues & event spaces	4.0	...	Cacio E Pepe, Agnolotti Dal Plin, Albacore Tartare, ...	My girlfriend was craving pasta on a Monday night. ... We were not expecting such an intimate and romantic dining experience. The restaurant was candle lit, modern, and perfect for a date night. ...

- Is it common? Yes!
 - Real-user queries about restaurants: 55/100 need a combo
- Separate modules cannot answer these questions

Goal of this Lecture

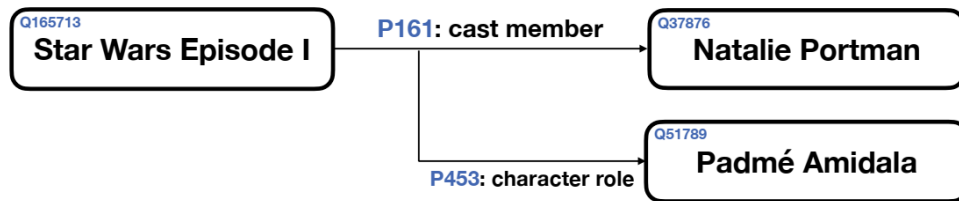
- To understand the Hybrid QA problem
 - Discuss 4 major approaches, starting with the simplest
 - HybridQA: dataset requiring composition of DB & Text retrieval
1. Classify query to decide to retrieve from DB or Text
 2. Retrieve answers from DB and Text separately, choose answer
 - 3. Convert DB to text; use Text Retrieval**
 4. Retrieve answers from DB and Text separately, use LLM to combine the answers

3. Converting All to Text

- Unified Knowledge Question Answering (UniK-QA)
- Converts everything to text
 - Text
 - Semi-structured data e.g. Wikipedia lists, tables and info boxes
 - Knowledge base
- Then uses the usual pipeline designed for textual QA

Wikipedia Tables / Wikidata

- Wikipedia tables are linearized simply by concatenating cell values with special tokens to separate rows
- Wikidata:



Converted Text:

Star Wars Episode I cast member Natalie Portman, and character role Padmé Amidala .

QUIZ

WHAT IS THE WEAKNESS OF
CONVERTING DATABASES TO TEXT?

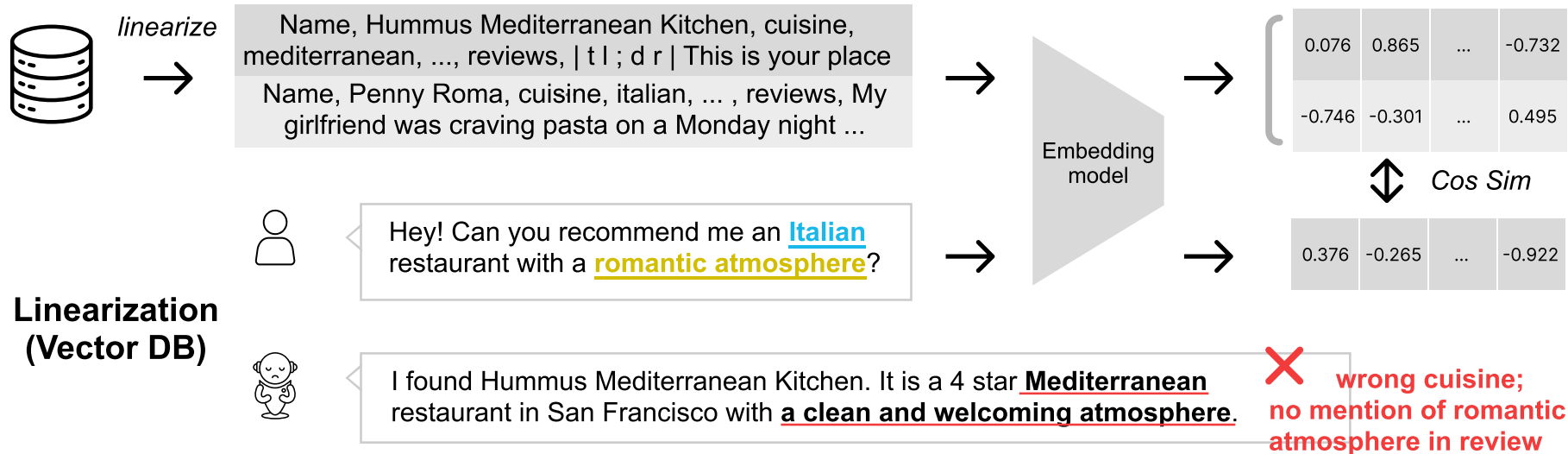
Unified Knowledge Question Answering (UniK-QA)

- Retrieve and read QA pipeline with SOTA components
 - Neural retriever; T5 reader
- Exact match scores:

Knowledge Source	Natural Questions	TriviaQA	WebQuestions
Wikipedia Text	49.0	64.0	50.6
Wikipedia Tables	36.0	34.5	41.0
Wikidata	27.9	35.4	55.6
Text + Tables	54.1	65.1	50.2
Text + Tables + Wikidata	54.0	64.1	57.8

Quiz: What do you observe?

Testing with Yelp



Problems with Linearization

- How to combine different clauses together?
(Algebraic operators handle them naturally)
 - e.g. multiple clauses: "Are there any restaurants that have **a great view of the Golden Gate bridge** in **San Francisco**?"
- Hard to do column computations
(rank, max, min, average, count) on flattened data
 - e.g. "what is the **top-rated** Chinese restaurant?"

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HybridQA Dataset

HybridQA: A Dataset of Multi-Hop Question Answering over Tabular and Textual Data

Wenhu Chen, Hanwen Zha, Zhiyu Chen, Wenhan Xiong, Hong Wang, William Wang

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{zhiyuchen, hongwang600, william}@cs.ucsb.edu

Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1026–1036

November 16 - 20, 2020. ©2020 Association for Computational Linguistics

Earlier than SK-TOD. Note: this is not conversational

HybridQA Dataset

Wikipedia Tables

hyperlinked

Wikipedia Pages

The 2016 Summer Olympics officially known as the Games of the XXXI Olympiad (Portuguese : Jogos da XXXI Olimpíada) and commonly known as **Rio 2016** , was an international multi-sport event

Name	Year	Season	Flag bearer
XXXI	2016	Summer	Yan Naing Soe
XXX	2012	Summer	Zaw Win Thet
XXIX	2008	Summer	Phone Myint Tayzar
XXVIII	2004	Summer	Hla Win U
XXVII	2000	Summer	Maung Maung Nge
XX	1972	Summer	Win Maung

Yan Naing Soe (born **31 January 1979**) is a Burmese judoka . He competed at the 2016 Summer Olympics in the **men 's 100 kg event** , He was the flag bearer for Myanmar at the **Parade of Nations** .

Zaw Win Thet (born **1 March 1991** in Kyonpyaw , Patheingyi District , Ayeyarwady Division , Myanmar) is a Burmese runner who

Myint Tayzar Phone (Burmese : မြင့်တင်ဇော်ဖုန်း) born **July 2 , 1978**) is a sprint canoer from Myanmar who competed in the late 2000s .

.....
Win Maung (born **12 May 1949**) is a Burmese footballer . He competed in the men 's tournament at the 1972 Summer Olympics ...

Q: In which year did the judoka bearer participate in the Olympic opening ceremony?

A: 2016

Q: Which event does the does the XXXI Olympic flag bearer participate in?

A: men's 100 kg event

Q: Where does the Burmese judoka participate in the Olympic opening ceremony as a flag bearer?

A: Rio

Q: For the Olympic event happening after 2014, what session does the Flag bearer participate?

A: Parade of Nations

Q: For the XXXI and XXX Olympic event, which has an older flag bearer?

A: XXXI

Q: When does the oldest flag Burmese bearer participate in the Olympic ceremony?

A: 1972

Hardness



Flag bearers of
Myanmar
at the Olympics

Type I (T->P) Q: Where was the XXXI Olympic held? A: Rio	<table> <tr> <th>Name</th><th>Event year</th></tr> <tr> <td>XXXI → 2016</td><td></td></tr> </table> ... commonly known as Rio 2016 , was an international multi-sport event	Name	Event year	XXXI → 2016					
Name	Event year								
XXXI → 2016									
Type II (P->T) Q: What was the name of the Olympic event held in Rio ? A: XXXI	<table> <tr> <th>Name</th><th>Event year</th></tr> <tr> <td>XXXI ← 2016</td><td></td></tr> </table> ... commonly known as Rio 2016 , was an international multi-sport event	Name	Event year	XXXI ← 2016					
Name	Event year								
XXXI ← 2016									
Type III (P->T->P) Q: When was the flag bearer of Rio Olympic born? A: 31 January 1979	<table> <tr> <th>Flag Bearer</th><th>Event year</th></tr> <tr> <td>Yan Naing Soe (born 31 January 1979) ... → Yan Naing Soe ← 2016</td><td></td></tr> </table> ... commonly known as Rio 2016 , was an international	Flag Bearer	Event year	Yan Naing Soe (born 31 January 1979) ... → Yan Naing Soe ← 2016					
Flag Bearer	Event year								
Yan Naing Soe (born 31 January 1979) ... → Yan Naing Soe ← 2016									
Type IV (T&S) Q: Which male bearer participated in Men's 100kg event in the Olympic game? A: Yan Naing Soe	<table> <tr> <th>Flag Bearer</th><th>Gender</th></tr> <tr> <td>Yan Naing Soe ... Men's 100kg event → Yan Naing Soe ←</td><td>Male</td></tr> <tr> <td>Zaw Win Thet ... Men's 400m running → Zaw Win Thet ←</td><td>Male</td></tr> </table>	Flag Bearer	Gender	Yan Naing Soe ... Men's 100kg event → Yan Naing Soe ←	Male	Zaw Win Thet ... Men's 400m running → Zaw Win Thet ←	Male		
Flag Bearer	Gender								
Yan Naing Soe ... Men's 100kg event → Yan Naing Soe ←	Male								
Zaw Win Thet ... Men's 400m running → Zaw Win Thet ←	Male								
Type V (T-Compare P-Compare) Q: For the 2012 and 2016 Olympic Event, when was the younger flag bearer born? A: 1 March 1991	<table> <tr> <th>Flag Bearer</th><th>Event year</th></tr> <tr> <td>Yan Naing Soe (born 31 January 1979) ... → Yan Naing Soe ← 2016</td><td></td></tr> <tr> <td>Zaw Win Thet (born 1 March 1991) → Zaw Win Thet ← 2012</td><td></td></tr> </table>	Flag Bearer	Event year	Yan Naing Soe (born 31 January 1979) ... → Yan Naing Soe ← 2016		Zaw Win Thet (born 1 March 1991) → Zaw Win Thet ← 2012			
Flag Bearer	Event year								
Yan Naing Soe (born 31 January 1979) ... → Yan Naing Soe ← 2016									
Zaw Win Thet (born 1 March 1991) → Zaw Win Thet ← 2012									
Type VI (T-Superlative P-Superlative) Q: When did the youngest Burmese flag bearer participate in the Olympic opening ceremony? A: 2012	<table> <tr> <th>Flag Bearer</th><th>Event year</th></tr> <tr> <td>Yan ... 31 January 1979) ... → Yan Naing Soe → 2016</td><td></td></tr> <tr> <td>Zaw ... 1 March 1991) ... → Zaw Win Thet → 2012</td><td></td></tr> <tr> <td>Myint ... July 2 , 1978) ... → Phone Myint Tayzar → 2008</td><td></td></tr> </table>	Flag Bearer	Event year	Yan ... 31 January 1979) ... → Yan Naing Soe → 2016		Zaw ... 1 March 1991) ... → Zaw Win Thet → 2012		Myint ... July 2 , 1978) ... → Phone Myint Tayzar → 2008	
Flag Bearer	Event year								
Yan ... 31 January 1979) ... → Yan Naing Soe → 2016									
Zaw ... 1 March 1991) ... → Zaw Win Thet → 2012									
Myint ... July 2 , 1978) ... → Phone Myint Tayzar → 2008									

T: Table
P: Passage

Quiz: How many total # of types can there be?

HYBRIDQA

A GOOD DATASET THAT ILLUSTRATES
THE NATURALNESS OF HYBRID DATA QUERIES

NEED TO SUPPORT FULL COMPOSITIONALITY THOUGH

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SOTA Model in 2023

S³HQA: A Three-Stage Approach for Multi-hop Text-Table Hybrid Question Answering

**Fangyu Lei^{1,2}, Xiang Li^{1,2}, Yifan Wei^{1,2},
Shizhu He^{1,2}, Yiming Huang^{1,2}, Jun Zhao^{1,2}, Kang Liu^{1,2}**

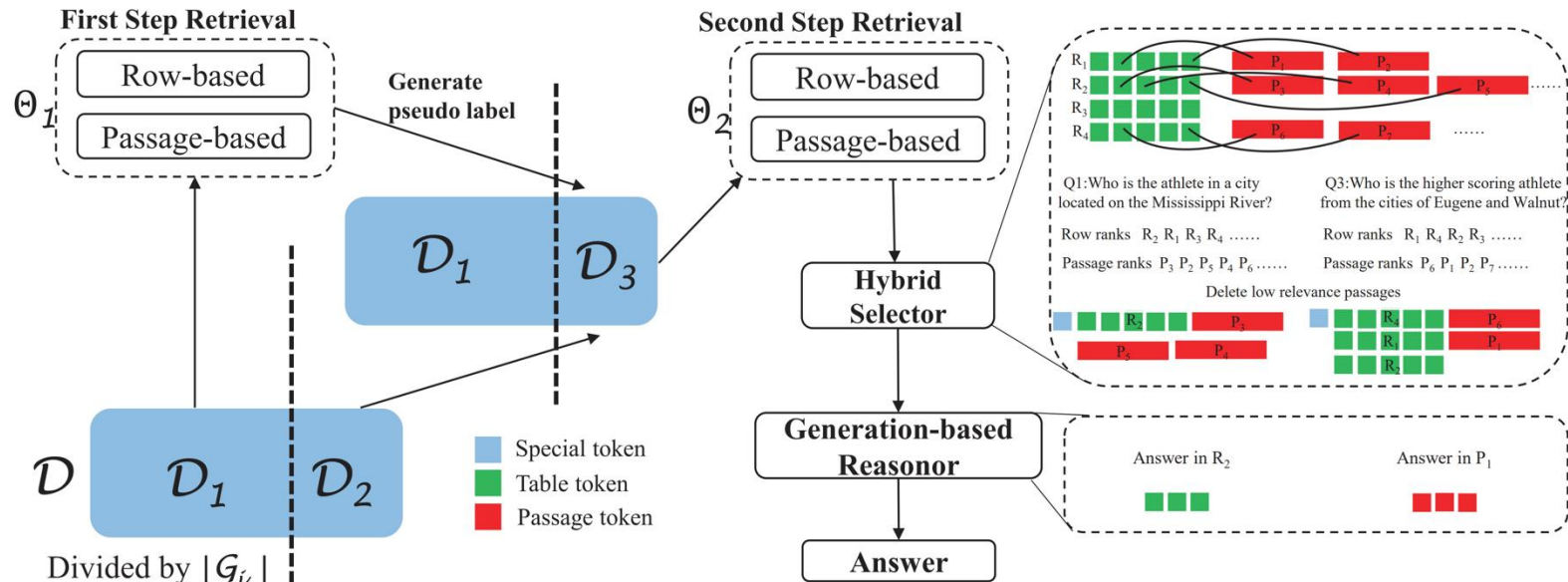
¹The Laboratory of Cognition and Decision Intelligence for Complex Systems
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<https://browse.arxiv.org/pdf/2305.11725.pdf>

Hybrid Retrievers



Only uses LLM in the "generation-based reasoner" step

<https://github.com/wenhuchen/HybridQA#recent-papers>

SOTA model: <https://arxiv.org/abs/2305.11725>

3 Steps

1. Retrieve information from DV and Free Text
 - Extra complexity to recover from annotation errors
2. Hybrid selector
 - Sort and filter based on relevance
3. LLM-Based Reasoner
 - Combines the filtered information from DV and Free Text
 - Question types: Count, compare
 - Use lexical analysis to identify the question type
 - Chain-of-thought prompting

SOTA Result

	Table				Passage				Total			
	Dev		Test		Dev		Test		Dev		Test	
	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
Unsupervised-QG (Pan et al., 2021)	-	-	-	-	-	-	-	-	25.7	30.5	-	-
HYBRIDER (Chen et al., 2020b)	54.3	61.4	56.2	63.3	39.1	45.7	37.5	44.4	44.0	50.7	43.8	50.6
DocHopper (Sun et al., 2021)	-	-	-	-	-	-	-	-	47.7	55.0	46.3	53.3
MuGER ² (Wang et al., 2022b)	60.9	69.2	58.7	66.6	56.9	68.9	57.1	68.6	57.1	67.3	56.3	66.2
POINTR (Eisenschlos et al., 2021)	68.6	74.2	66.9	72.3	62.8	71.9	62.8	71.9	63.4	71.0	62.8	70.2
DEHG (Feng et al., 2022)	-	-	-	-	-	-	-	-	65.2	76.3	63.9	75.5
MITQA (Kumar et al., 2021)	68.1	73.3	68.5	74.4	66.7	75.6	64.3	73.3	65.5	72.7	64.3	71.9
MAFiD (Lee et al., 2023)	69.4	75.2	68.5	74.9	66.5	75.5	65.7	75.3	66.2	74.1	65.4	73.6
S³HQA	70.3	75.3	70.6	76.3	69.9	78.2	68.7	77.8	68.4	75.3	67.9	75.5
Human	-	-	-	-	-	-	-	-	-	-	88.2	93.5

Table 1: Performance of our model and related work on the HybridQA dataset.

Quiz: What do you observe?

Problem

- Data are retrieved in just one hop
 - Cannot solve cascading multi-hop questions, where the data to retrieve depends on the 1st hop answer
- Imprecision with the lexical analysis
- Lacks completeness and compositionality
 - Just one “count” or one “compare” operation

Conclusion

- **Many questions require composition of information retrieved from DB and Text**
- **Structure OR Text: is inadequate**
 1. Binary classifier up front (SK-TOD, 2023)
 2. Pick afterwards (Stanford Chirpy Cardinal, 2021)
- **Different approaches to combine structures and free-text**
 3. Structures → Text: Linearization (one hop)
 4. Hybrid: Retrieve from both and combine (one hop each)