VerifAl: Verified Generative Al (Vision)

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- What
- How
- Results
- Opportunities

image

table

2018: GPT-1 and GPT-2

2020: GPT-3 (Wow)

2022: ChatGPT (Amazing)

2023: GPT-4 (Unbelievable)

...

...

...

...

...

text graph



Large Language Models

2017

Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly test time to train. Our model achieves 28.4 BLE (U on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by one 2012 BLE (U on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by one 2012 BLE (U on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by one 2012 BLE (U on the WMT 2014 English-to-German translation task, improving over the existing best results, including the second of the province of th

"Equal contribution. Listing order is random, Jakob proposed explacing RNNs with self-attention and started the effort to evaluate this idea, Ashish, with Illia, designed and implemented the first Transformer models and has been crucially involved in every aspect of this work. Noam proposed scaled dots product attention, multi-bead attention and the parameter-free position representation and became the other person involved in nearly every detail. Niki designed, implemented, tuned and evaluated countless model variants in our original codebase and efficient inference and visualizations. Lukasz and Aldan spent countless long days designing various parts of and efficient inference and visualizations. Lukasz and Aldan spent countless long days designing various parts of and implementing tensor/tensor, replacing our earlier codebase, gently improving results and massively accelerating

[†]Work performed while at Google Brain.

*Work performed while at Google Research.

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

100,000+ citations

(a) ChatGPT for tuple generation/completion/augmentation



You

Please help me fill in the missing values denoted by 'NULL' in this table and provide me with the completed one:

[title]: United States House of Representative Elections 2004 in Ohio

| district | incumbent | candidates |

| Ohio's 1st congressional district | NULL | NULL |

| Ohio's 2st congressional district | NULL | NULL |

| Ohio's 3st congressional district | NULL | NULL |



Do you trust the results?

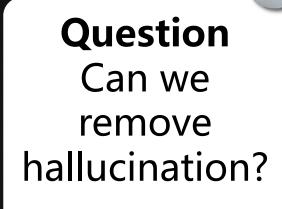
Hallucination

- Inaccurate decision-making
- Spread misinformation
- Privacy violation
- Legal liabilities
- Damage to trust
- •

Downstream tasks? Errors can be propagated ...

- LLMs: Generative Al
 - Learn a distribution from finite data
 - Generalize to infinite data points
- Goals of Generative Al
 - Generalizable and natural
 - Not factual

- LLMs vs. data compression models?
 - Is not
 - Can not



NO



- What: Verify the outputs of LLMs (True/False)
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Generative Al

(a) ChatGPT for

tuple generation/completion/augmentation



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district	incumbent	candidates
Ohio's 1st congressional district	Steve Chabot (R)	Steve Chabot (R), John Cranley (D), James Berns (Libertarian)
Ohio's 2nd congressional district	Rob Portman (R)	Rob Portman (R), Charles W. Sanders (D), Edward S. Focke (Green)
Ohio's 3rd congressional district	Tony P. Hall (D)	Tony P. Hall (D), Richard E. Stobbs (R), John Fockler (Libertarian)



(b) ChatGPT for text generation

MC Does Meagan Good play a role in Stomp the Yard?



No, Meagan Good does not appear in the 2007 film "Stomp the Yard." "Stomp the Yard" is a dance drama film directed by Sylvain White, and Meagan Good is not listed as part of the main cast or credited with a role in the film. The main cast of "Stomp the Yard" includes actors such as Columbus Short, Chris Brown, Ne-Yo, and Brian White, among others. Meagan Good is an American actress known for her roles in films such as "Think Like a Man," "Eve's Bayou," and "Waist Deep," but she did not appear in "Stomp the Yard."



(a) ChatGPT for

tuple generation/completion/augmentation



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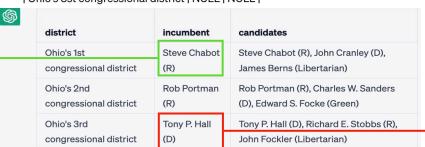
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| Ohio's 1st congressional district | NULL | NULL |

| Ohio's 2st congressional district | NULL | NULL |

| Ohio's 3st congressional district | NULL | NULL |





(b) ChatGPT for text generation

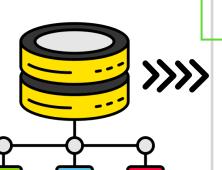
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Data Lake

Generative Al



Steve Chabot

Article Talk

From Wikipedia, the free encyclopedia

Steven Joseph Chabot ([fabet] SHAB-et; born January 22, 1953) is an American politician and lawyer who represented Ohio's 1st congressional district in the United States House of Representatives from 1995 to 2009 and again from 2011 to 2023. A member of the Republican Party, he lost his 2022 reelection bid to Democrat Greg Landsman. Until his election loss, he was the dean of Ohio's GOP delegation to the House of Representatives, after the retirement of former Speaker John Boehner. [1]



General election results [edit]

Ohio's 3rd Congressional District election, 2004^[1]

Cinc Conditional District Circuit, 2001			
Party	Candidate	Votes	%
Republican	Mike Turner (Incumbent)	197,290	62.29
Democratic	Jane Mitakides	119,448	37.71
	Total votes	316,738	100
Benublican hold			

Stomp the Yard

Article Talk

From Wikipedia, the free encyclopedia

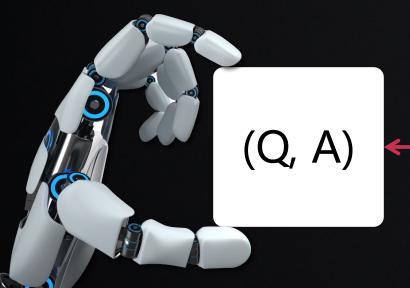
The film stars Columbus Short, Meagan Good, Darrin Henson, Brian White, Laz Alonso, and Valarie Pettiford, with Harry Lennix, and, in their film debuts, R&B singers Ne-Yo & Chris Brown. Stomp the Yard was filmed in Atlanta, Georgia, on the campuses of Morris Brown College, Georgia Institute of Technology, Morehouse College, and Clark Atlanta University, and in the MAK Historic District of Decatur, Georgia. Elsewhere Short, Alonso and Brown had also starred together in the film This Christmas.

Meagan Good's Filmography

Film [edit]

Year ≑	Title +	Role +	Notes +
	Brick	Kara	
2005	Venom	Cece	
	Roll Bounce	Naomi Phillips	
0000	Miles from Home	Natasha Freeman	
2006	Waist Deep	Coco	
2007	Stomp the Yard	April Palmer	

- What: Verify the outputs of LLMs (True/False)
- How
- Results
- Opportunities



Retrieve relevant dataset(s) to verify factual (not subjective) answers



- textual files
- table
- (sub)graphs
- images
- HTML files
- a combination

- What: Verify the outputs of LLMs (True/False)
- How: Retrieval
- Results
- Opportunities

- Retrieval-augmented generation (RAG)
- VerifAI: Retrieval-based matching

- Question-Answer Similarity
- Answer-Answer Similarity (matching)

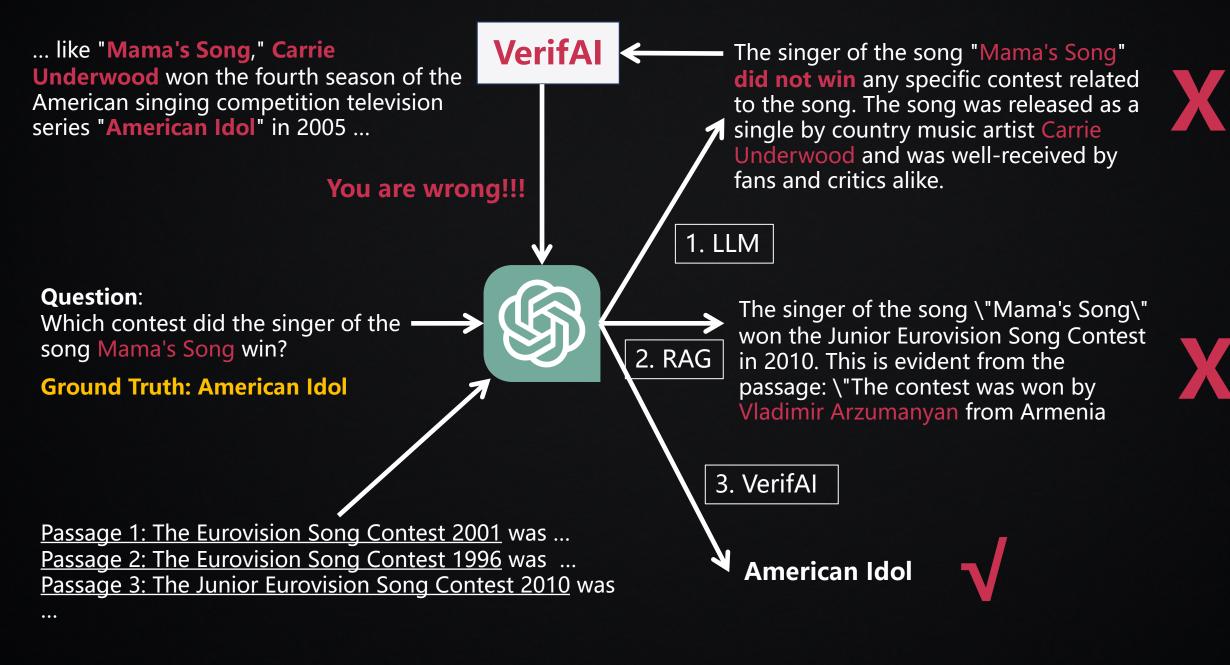
A Deep Look into Neural Ranking Models for Information Retrieval

Jiafeng Guo^{a,b}, Yixing Fan^{a,b}, Liang Pang^{a,b}, Liu Yang^c, Qingyao Ai^c, Hamed Zamani^c, Chen Wu^{a,b}, W. Bruce Croft^c, Xueqi Cheng^{a,b}

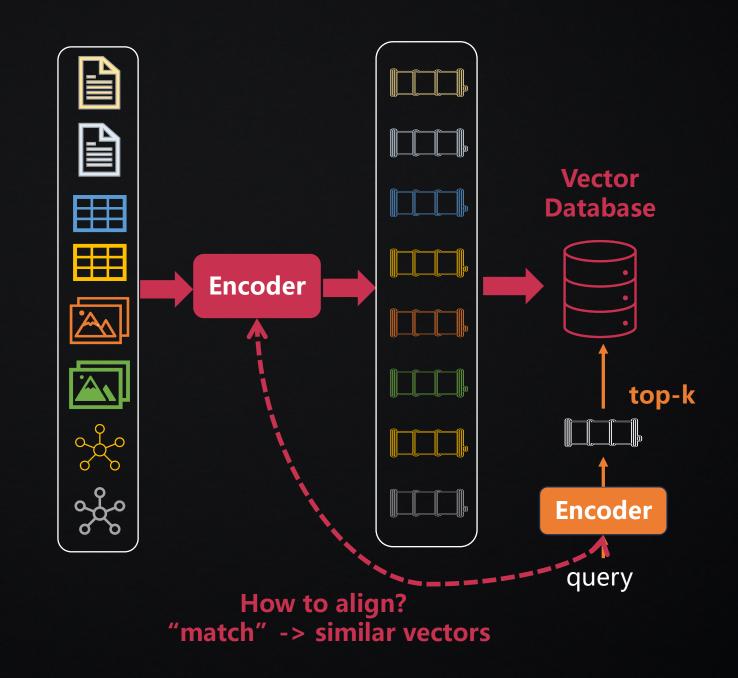
^a University of Chinese Academy of Sciences, Beijing, China
^b CAS Key Lab of Network Data Science and Technology, Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China
^c Center for Intelligent Information Retrieval, University of Massachusetts Amherst, Amherst, MA. USA

Abstract

Ranking models lie at the heart of research on information retrieval (IR). During the past decades, different techniques have been proposed for constructing ranking models, from traditional heuristic methods, probabilistic methods, to modern machine learning methods. Recently, with the advance of deep learning technology, we have witnessed a growing body of work in applying shallow or deep neural networks to the ranking problem in IR, referred to as neural ranking models in this paper. The power of neural ranking models lies in the ability to learn from the raw text inputs for the ranking problem to avoid many limitations of hand-crafted features. Neural networks have sufficient capacity to model complicated tasks, which is needed to handle the complexity of relevance estimation in ranking. Since there have been a large variety of neural ranking models proposed, we believe it is the right time to summarize the current status, learn from existing methodologies, and gain some insights for future development. In contrast to existing reviews, in this survey, we will take a deep look into the neural ranking models from different dimensions to analyze their underlying assumptions, major design principles, and learning strategies. We compare these models through benchmark tasks to obtain a comprehensive empirical understanding of the existing techniques. We will also discuss what is missing in the current literature and what are the promising and desired future directions.

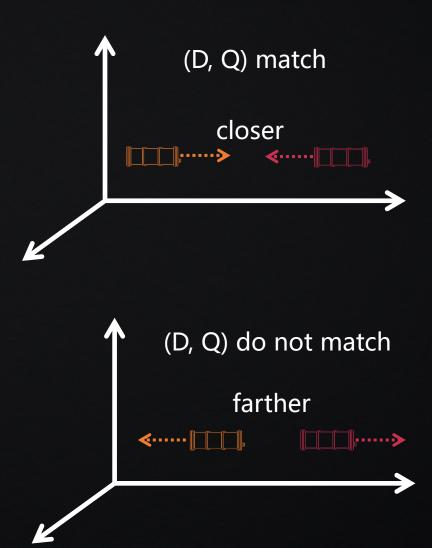


- Given a query, find
- textual files
- table (tuples)
- (sub)graphs
- images
- HTML files
- or a combination thereof

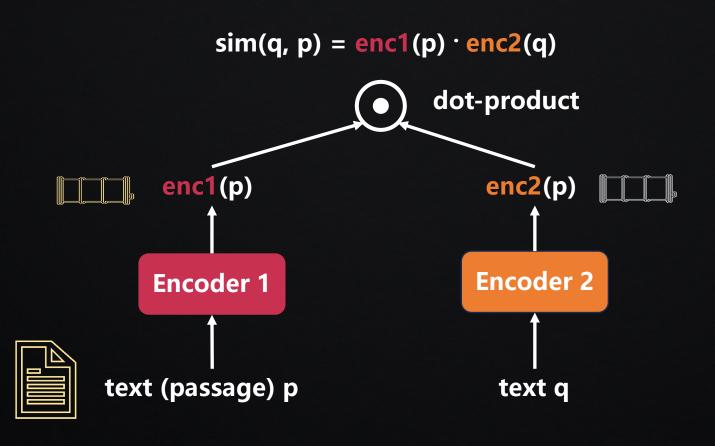




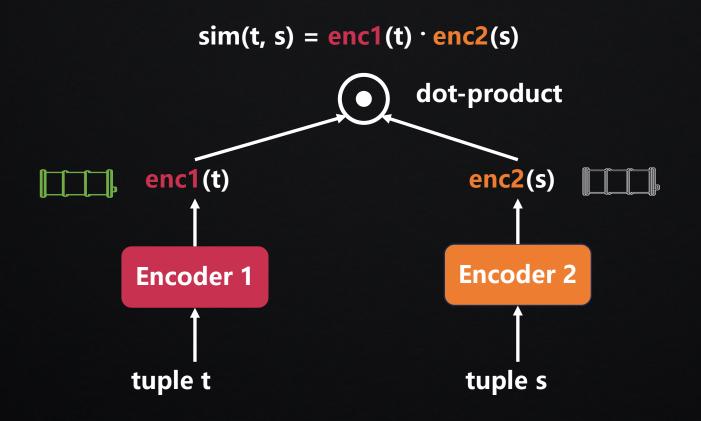




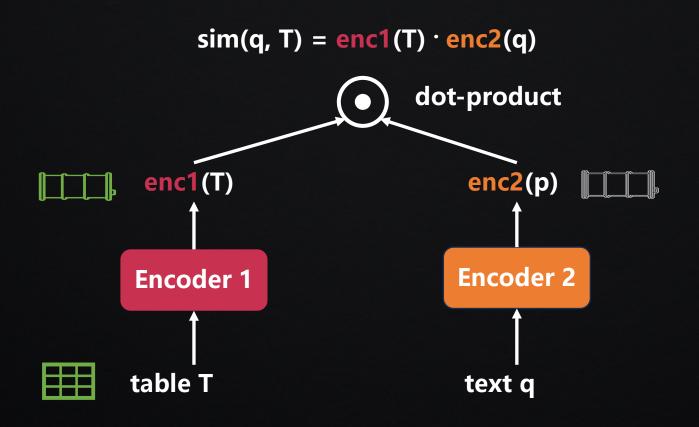
Dense Passage Retriever (DPR) for Text-Text



Dense Passage Retriever (DPR) for Tuple-Tuple

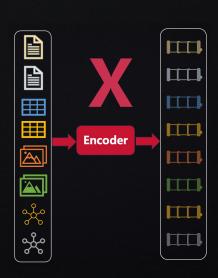


Dense Passage Retriever (DPR) for Text-Table



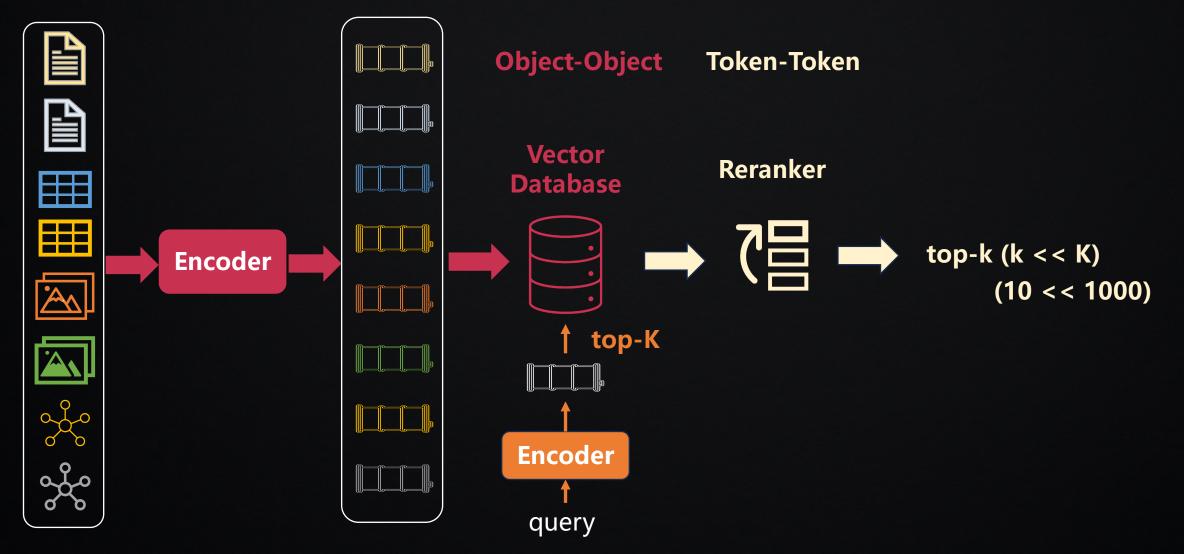
Retrieval over multi-modal data lakes

- We know (a little bit about) how to
 - align two encoders of the same/different data modalities
 - the main effort is to find positive/negative pairs
- We do not know how to
 - align multiple encoders
 - encode/index large tables
 - encode/index large graphs



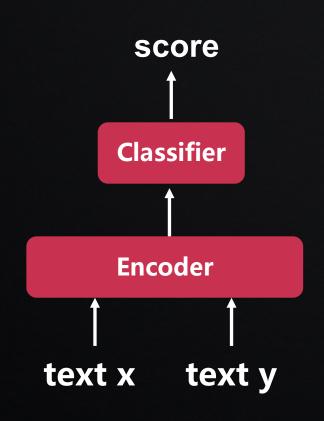
- What: Verify the outputs of LLMs (True/False)
- How: Retrieval Rerank
- Results
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Retrieval (Coarse-grained) -> Rerank (Fine-grained)

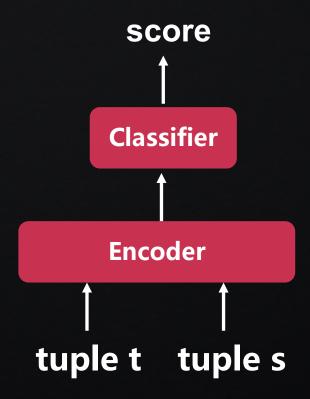


Rerank

Text-Text: Cross-Encoder (monoBERT)



Tuple-Tuple



Rerank

Text-Table: Cross-Encoder-Decoder (monoT5)

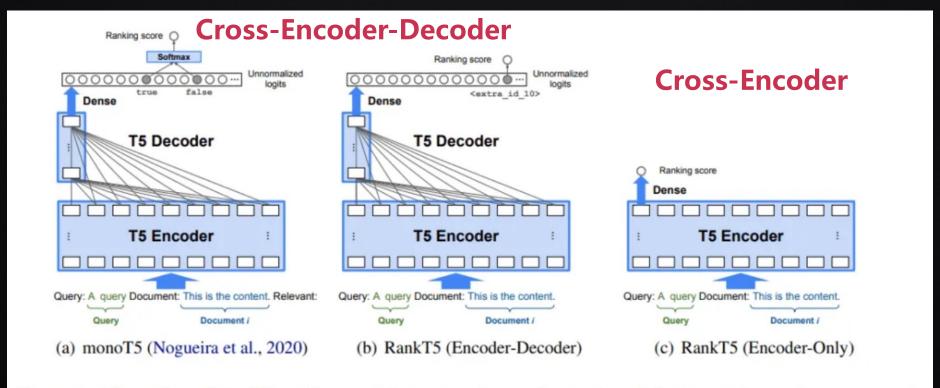


Figure 1: Illustration of the T5 ranking model structure from prior work and the two variants of our proposed RankT5 model. The differences in training mechanism is not reflected in this illustration.

Note: Figure from the Google paper "RankT5: Fine-Tuning T5 for Text Ranking with Ranking Losses"

- What: Verify the outputs of LLMs (True/False)
- How: Retrieval Rerank Verifier



- What: Verify the outputs of LLMs (True/False)
- How: retrieval, rerank, verifier
- Results
- Opportunities

Verify Tuple(s) via retrieving Tuple and Text

(S)	Generated Tuple	e: members of	the 20th dáil	
	constituency	name	party	
	1 1		1	
	Clare	Brendan Daly	Fianna Fáil (generated	value)
		156 160 -1		
Retri	eved Evidence an	d Verification		
E1 : B	rendan Daly (2 Fel	oruary 1940 – 6	July 2023) was an Irish Fi	anna
Fáil politician. He was a long-serving Teachta Dála(TD) for				
the C	lare constituency,	a government n	ninister, and Senator.	

Verification result: True. Explanation: The attribute 'party' value for

Brendan Daly is Fianna Fáil, which matches with the claim.

Retrieved Evidence and Verification

E2: members of the 20th dáil



Verification result: Not Related. Explanation: The evidence talks about the members of the 20th Dáil and the TDs elected by constituencies Tipperary South and Clare. It mentions Brendan Griffin as a member of the 20th Dáil from Tipperary South constituency, but it does not provide any information about Brendan Daly's party affiliation.

Verify Tuple(s) via retrieving Tuple and Text

Generative AI task: tuple completion

100 tuples with missing values

ChatGPT's accuracy in completion: 0.52

Data lake: 13,796 textual files and 19,498 tables containing 269,622 tuples

Retrieval	Recall@3	both	Vanifi an	Δ
Tuple	0.99			Accuracy
Text	0.58		ChatGPT	0.88

Verify Text using via retrieving Tables



Claim: In 1954 u.s. open (golf), the cash prize for tommy bolt,

fred haas, and ben hogan was 960 in total.

(**Ground Truth**: a false claim that should be **Refuted**)

Retrieved Evidence and Verification

Table E1: 1954 u.s. open (golf)

I place I player I country I score I to par I money I

| 11 | ed furgol | united states | 71 + 70 + 71 + 72 = 284 | + 416000 |

 $1t2 \, Igene \, littler \, Iunited \, states \, I70 + 69 + 76 + 70 = 285 \, I + 5 \, I3600 \, I$

| t3 | lloyd mangrum | united states | 72 + 71 + 72 + 71 = 286 | + 6 | 1500 |

| t3 | dick mayer | united states | 72 + 71 + 70 + 73 = 286 | + 6 | 1500 |

| t5 | bobby locke | south africa | 74 + 70 + 74 + 70 = 288 | + 8 | 960 |

 $1 \text{ t6 } | \text{ fred haas } | \text{ united states } | 73 + 73 + 71 \div 72 = 289 | + 9 | 570 |$

| t6 | ben hogan | united states | 71 + 70 + 76 + 72 = 289 | + 9 | 570 |

I t6 I shelley mayfield I united states I 73 + 75 + 72 + 69 = 289 I + 9 | 570 I

Verification result: **Refuted**. **Explanation:** The cash prize for Tommy Bolt, Fred Haas, and Ben Hogan was \$570 each, totaling \$1710.

Table E2: 1959 u.s. open (golf)

I player I country I year (s) won I total I to par I finish I

I ben hogan I united states I 1948, 1950, 1951, 1953 | 287 | + 7 | t8 |

I cary middlecoff I united states I 1949, 1956 | 294 I + 14 | t19 I

| liack fleck | united states | 1955 | 294 | + 14 | t19 |

| liulius boros | united states | 1952 | 297 | + 17 | t28 |

I tommy bolt I united states | 1958 | 301 | + 21 | t38 | V2:

Verification result: Not related.

Verify Text using via retrieving Tables

A controlled study: 1,300 textual claims from TabFact benchmark Retrieved from 19K Wikipedia Tables

	Verifier	Reference	Accuracy
	ChatGPT		0.54
>	ChatGPT	Tables	0.91

Retrieval	Recall@5
Table	0.88

- What: Verify the outputs of LLMs (True/False)
- How: retrieval, rerank, verifier
- Results
- Opportunities

Opportunities (DB)

- 1. Table learning using LLMs
- 2. Table reasoning using LLMs
- 3. Table retrieval (small tables, large tables, database tables)
- 4. Cross-modal data discovery (aligning multiple encoders)
- 5. Cross-modal matching
- 6. Cross-modal reranking
- 7. Cross-modal reasoning

