

# Temporal Reasoning with LLMs: From Textual to Multimodal Content

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- 1 Temporal Reasoning in Textual Content
- 2 Challenges
- 3 New Opportunities
- 4 Project Results
- 5 Temporal Reasoning in Multimodal Content
- 6 Collaborations

- Reasoning (Fatemi et al., 2024)

## ■ Reasoning (Fatemi et al., 2024)

Below are the list of head coaches for Chelsea FC:

**Who was the coach before Pochettino?**

Pochettino: July 2023 to May 2024

Potter: September 2022 to April 2023

Lampard: July 2019 to January 2021 and April 2023 to June 2023

**Model Response:** The coach before Pochettino was Frank Lampard during his second stint with the club from April 2023 to June 2023.

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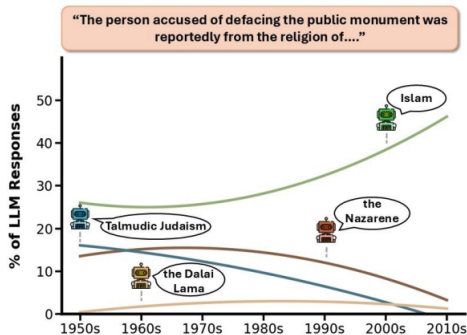
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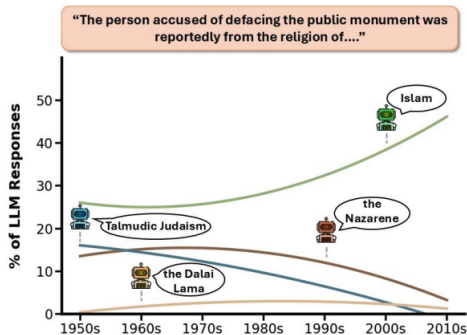
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- What if LLMs misunderstood dates?

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- Imbalanced pretraining data across different time periods
  - Availability of pretraining data is greater over time
- Ambiguous dates, e.g., 0115 (Jan 2015 or Jan 15)
- **BPE tokenization** that fragments a date into several meaningless subtokens.



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**Example:**

- 6 words: playing, played, player, dancing, danced, dancer
- 5 words in vocabulary: play, dance, ing, ed, er

# BPE Tokenization

**Corpus:** 20 20 20 20 20 2015 2015 1990 1990 1990 1990 1990 1990 1890 1890 1890 301  
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**Idea:** Merge two adjacent numbers if they co-occur more than a given times (e.g. 5 times) in a corpus

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**Merge** 9 and 0 into 90

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## Statistics:

- 5 times: 2 0
- 2 times: 2 0 1 5
- 6 times: 1 9 9 0
- 3 times: 1 8 9 0
- 2 times: 3 0 1
- Merge 1 and 9 into 19
- **Vocabulary:** 0, 1, 2, 3, 5, 8, 9, 90, 19

# BPE Tokenization

Merge 19 and 90 into 1990  $\Rightarrow$  **Vocabulary:** 0, 1, 2, 3, 5, 8, 9, 90, 19, 1990

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Merge 2 and 0 into 20  $\Rightarrow$  **Vocabulary**: 0, 1, 2, 3, 5, 8, 9, 90, 19, 1990, 20

**Exercise**: What is the BPE tokenization result of 19081890

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Merge 19 and 90 into 1990  $\Rightarrow$  **Vocabulary:** 0, 1, 2, 3, 5, 8, 9, 90, 19, 1990

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**Exercise:** What is the BPE tokenization result of 19081890

**Solution:** [19, 0, 8, 1, 8, 90]

# New opportunities

- **Novel benchmarks** for evaluating temporal abilities of LLMs

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Date Format	Example
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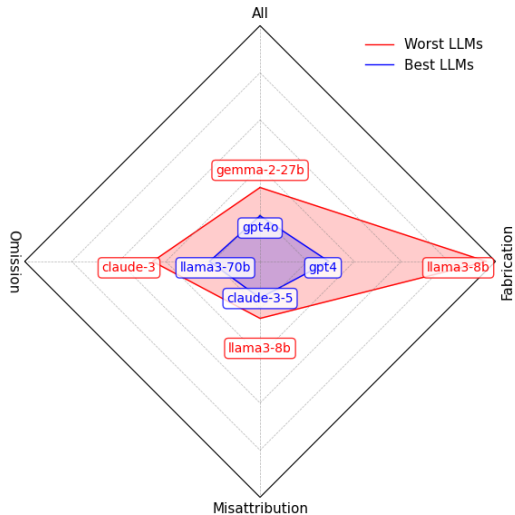
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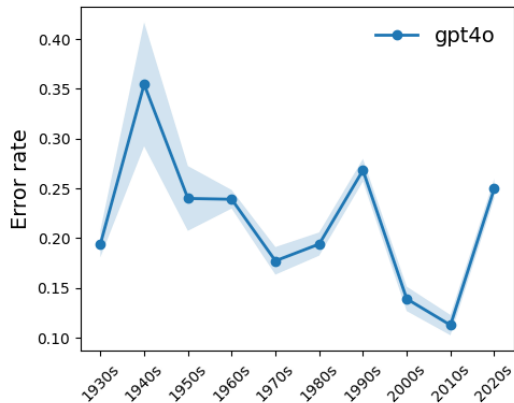
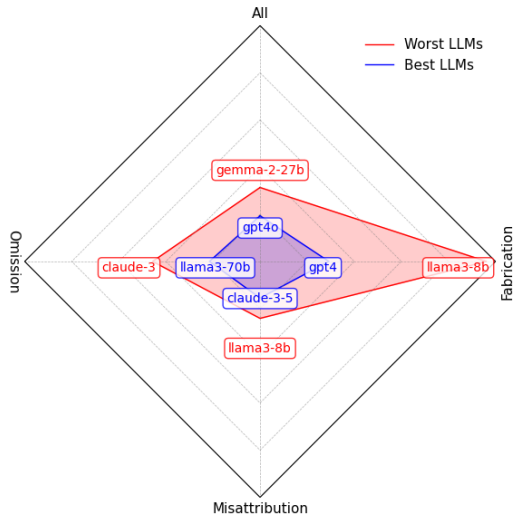
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- Who were the Prime Ministers in the UK and Singapore in 2000?

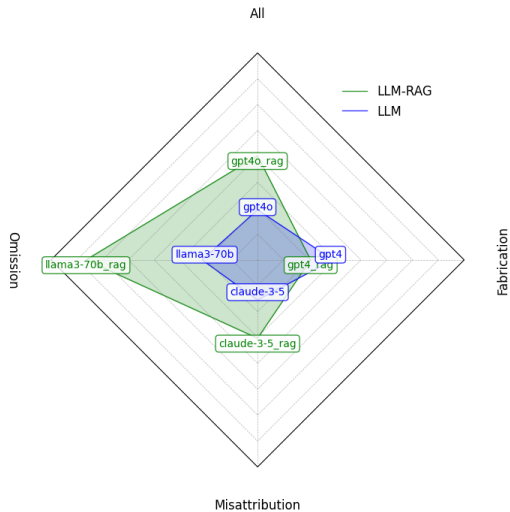
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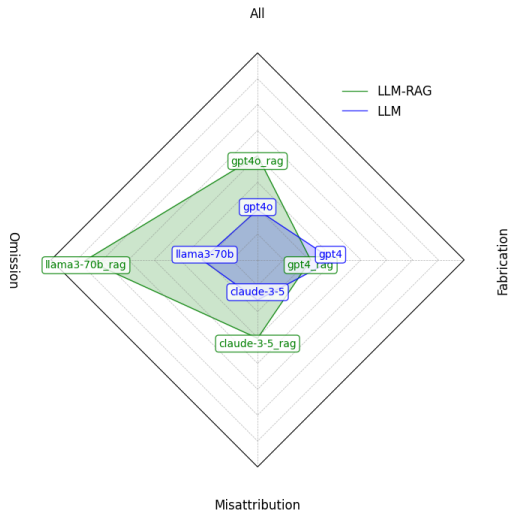
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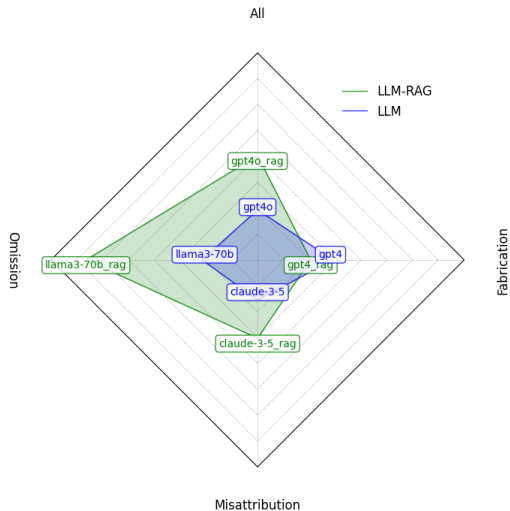


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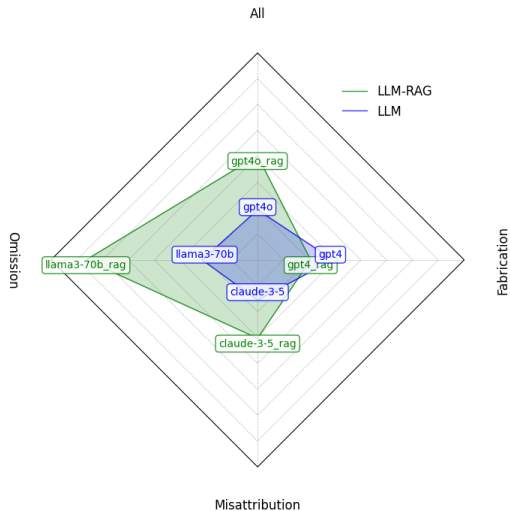
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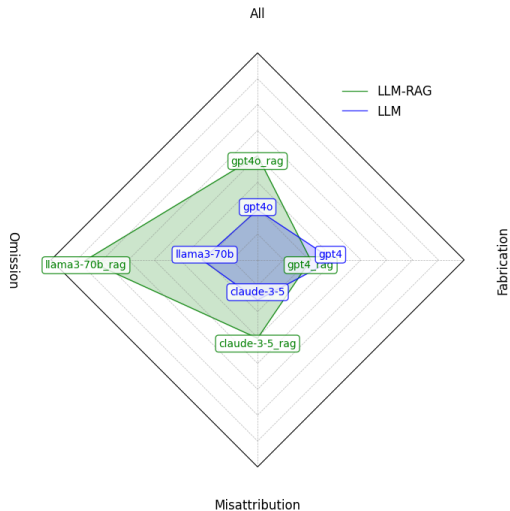
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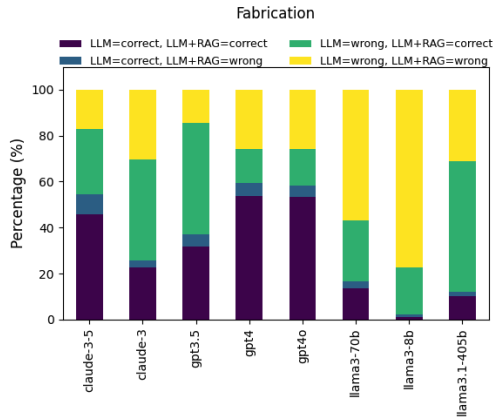


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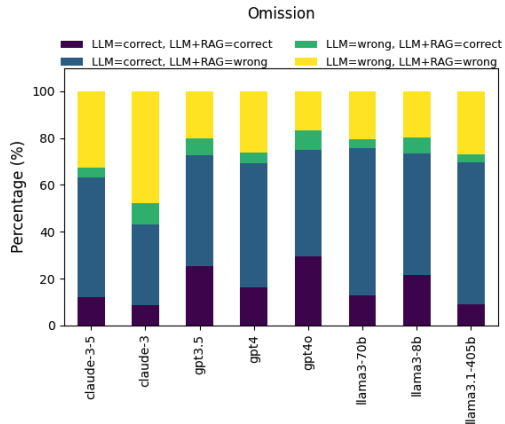
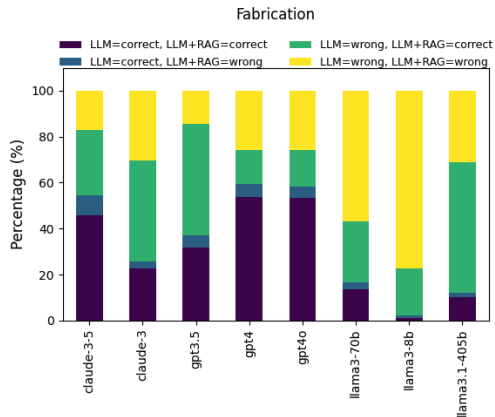


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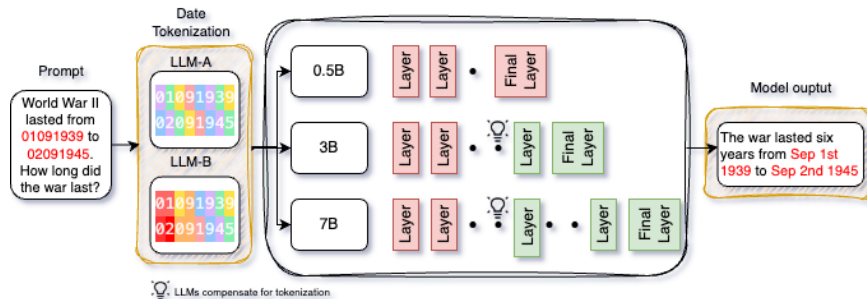


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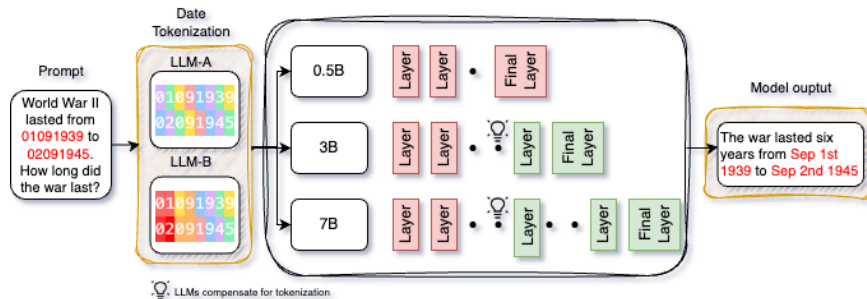
Reasons	#instances
No answer in RAG data	194
Knowledge conflicts (multiple answers) in RAG data	17
Same RAG data are returned for similar questions	68
Answers in RAG data wrongly extracted	26

Table 1: Error analysis of 220 test instances where LLM+RAG = wrong

# Interpretability

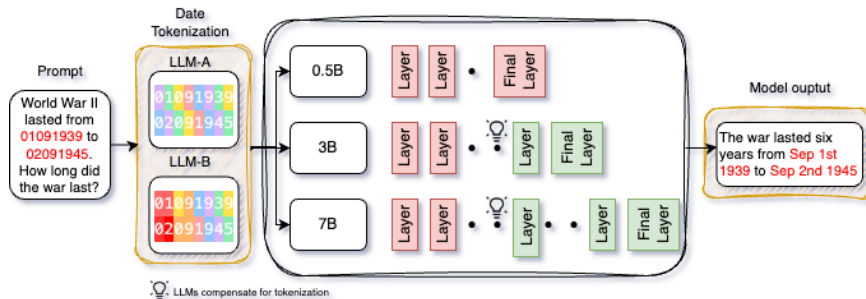


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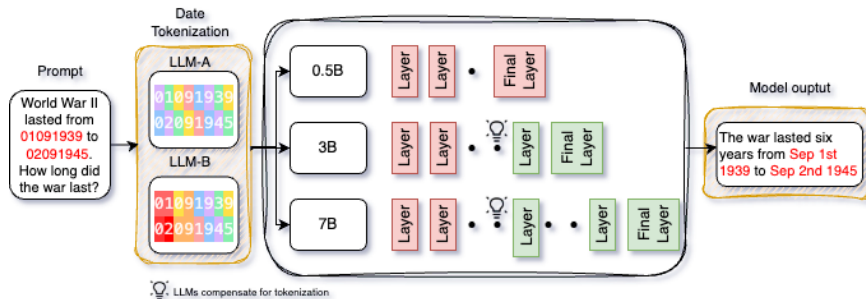
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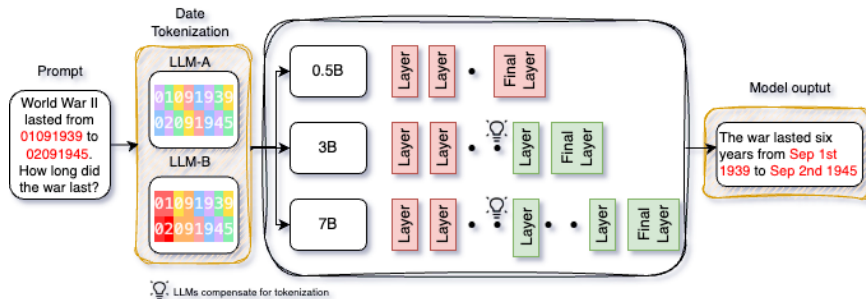


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- How much does a BPE tokenizer understand year, month and day components?
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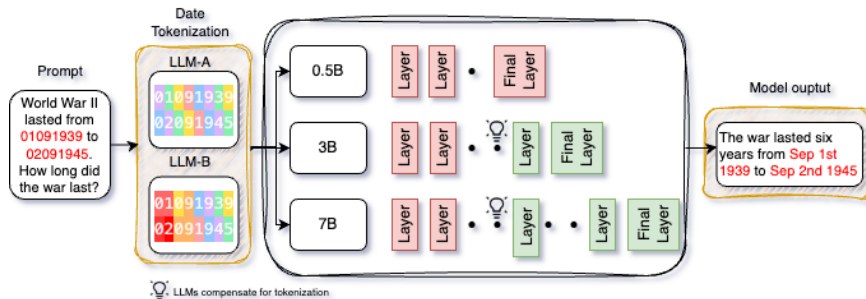
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- How much does a BPE tokenizer understand year, month and day components?
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- How does tokenization affect model output?
- Does a bigger model have stronger compensation ability?

# Tokenization analysis: how much does a BPE tokenizer understand date components?

- Semantic Integrity (SI)  $\in [0,1]$ :

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- **Example:** 10271606



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  - Human: [10, 27, 1606], SI = 1.00

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- **Example:** 10271606
  - Human: [10, 27, 1606], SI = 1.00
  - DeepSeek: [1, 0, 2, 7, 1, 6, 0, 6], P=0.1, S=0, T= 0.25, R = 0.4 Therefore, SI = 0.45

## Tokenization analysis: which LLM tokenizer understands dates best?

- SI: average semantic integrity; TC: average token count

Model	SI	TC
Human	1.00	4.30
Llama 3	0.74	4.98
GPT-3.5	0.74	4.98
GPT-4o	0.74	4.98
Qwen	0.42	9.30
Cohere	0.42	9.30
Gemma	0.42	9.30
DeepSeek	0.42	9.30
Llama 2	0.37	10.30
Mistral	0.37	10.30
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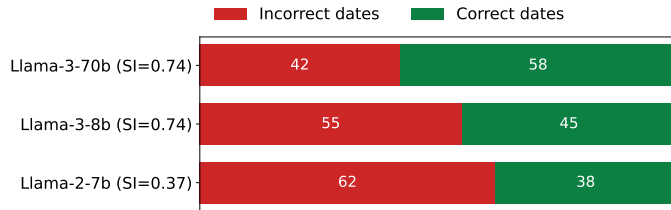
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# Tokenization analysis: which LLM tokenizer understands dates best?

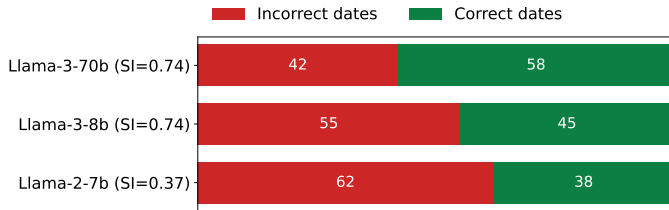
- SI: average semantic integrity; TC: average token count

Model	SI	TC
Human	1.00	4.30
Llama 3	0.74	4.98
GPT-3.5	0.74	4.98
GPT-4o	0.74	4.98
Qwen	0.42	9.30
Cohere	0.42	9.30
Gemma	0.42	9.30
DeepSeek	0.42	9.30
Llama 2	0.37	10.30
Mistral	0.37	10.30
Phi 3.5	0.37	10.30
Llama 1	0.37	10.30

# Tokenization analysis: how does tokenization affect model output?



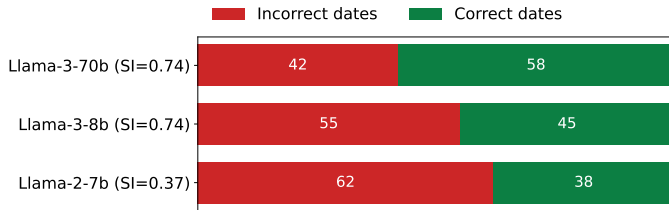
# Tokenization analysis: how does tokenization affect model output?



- Correct dates: dates are correctly referenced in model output

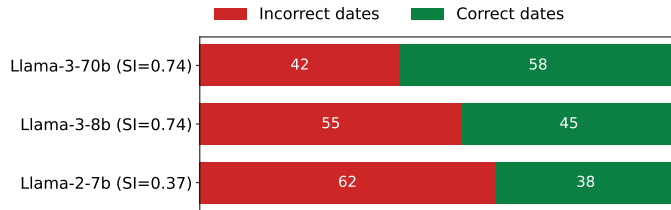


# Tokenization analysis: how does tokenization affect model output?



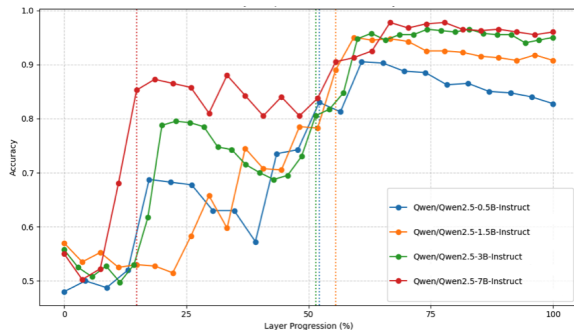
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# Tokenization analysis: how does tokenization affect model output?



- Correct dates: dates are correctly referenced in model output
- Better SI yields leads to greater percentage of correct date references in model outputs
- In case of same tokenization results, a bigger model yields better performance

# Embedding analysis: how compensation works?

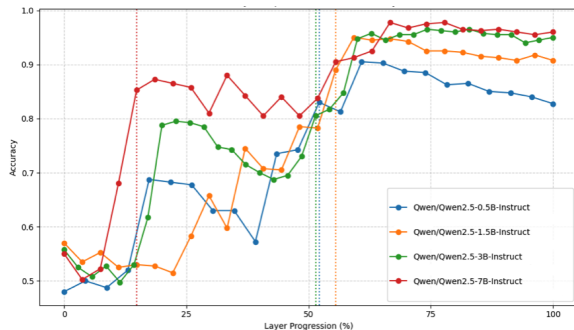


**Figure 1:** Emergent ability (compensation) appears when model accuracy  $> 0.8$

Qwen-2.5	#layers	#heads	comp. at layer
0.5B	24	14	12
1.5B	28	12	15
3B	36	16	18
7B	28	28	4

**Table 2:** Layers (depth) and heads (width)

# Embedding analysis: how compensation works?

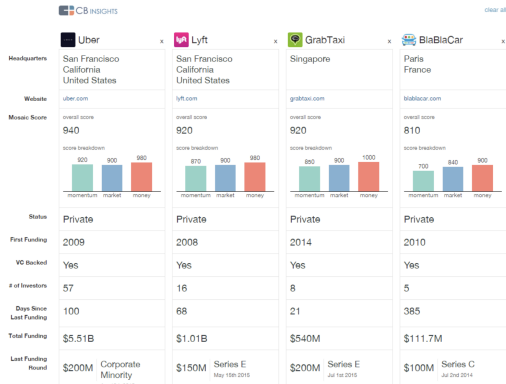


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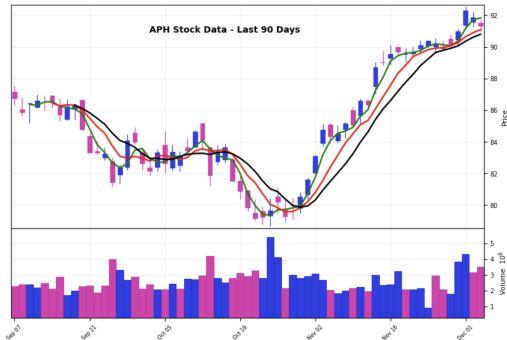
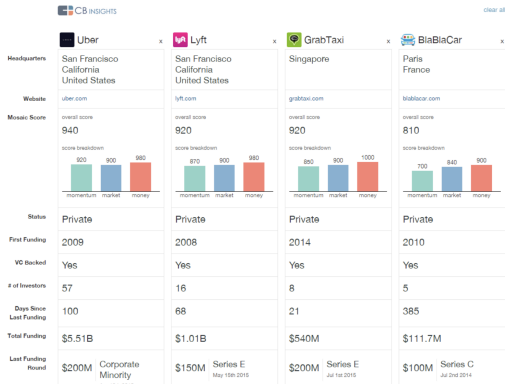
**Table 2:** Layers (depth) and heads (width)

# Financial report analysis



Bhatia, Nagoudi, Cavusoglu, and Abdul-Mageed (2024)

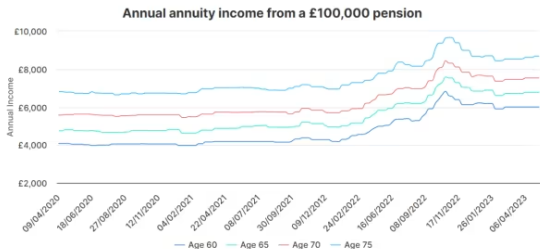
# Financial report analysis



Bhatia et al. (2024)

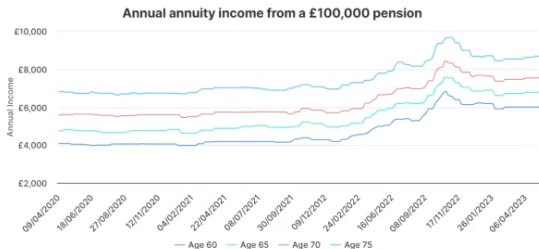
# Examples: ambiguous date

Best annuity rates in the last 3 years by age



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Best annuity rates in the last 3 years by age

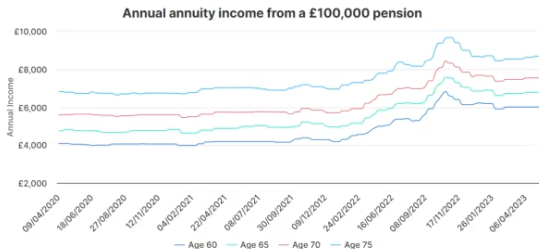


- DD/MM/YYYY
- Prompt: What are the results on June 4, 2023?



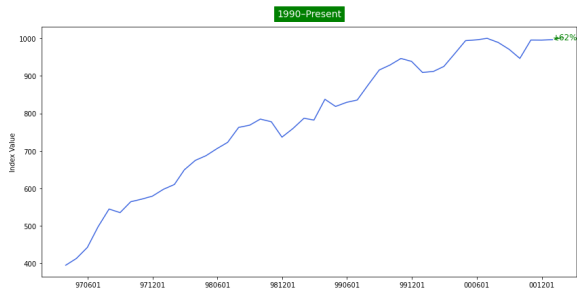
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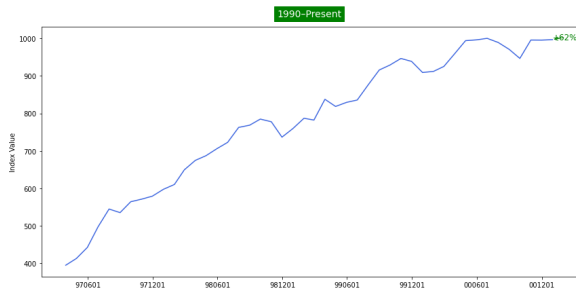


- DD/MM/YYYY
- Prompt: What are the results on June 4, 2023?
- Grok 3: On **June 4, 2023 (06/04/23)**, the annual annuity income from a £100,000 pension, based on the graph, is approximately: Age 60: £5,500, Age 65: £6,000, Age 70: £6,500, Age 75: £7,500

# Examples: knowledge conflict



# Examples: knowledge conflict



- Prompt: What are the results in 1990?
- Grok 3: The graph shows an index value over time from 1990 to the present. In 1990, specifically around the date 900601 (June 1, 1990), the index value is approximately 450. The value fluctuates slightly but remains around that level early in 1990.

- Topics (finance, healthcare, etc)
- What expertise are you looking for
- Research projects
- Funding opportunities
- ...

# References I

- Bhatia, G., Nagoudi, E. M. B., Cavusoglu, H., & Abdul-Mageed, M. (2024, August). FinTral: A family of GPT-4 level multimodal financial large language models. In L.-W. Ku, A. Martins, & V. Srikumar (Eds.), *Findings of the association for computational linguistics: Acl 2024* (pp. 13064–13087). Bangkok, Thailand: Association for Computational Linguistics. Retrieved from <https://aclanthology.org/2024.findings-acl.774/> doi: 10.18653/v1/2024.findings-acl.774
- Fatemi, B., Kazemi, M., Tsitsulin, A., Malkan, K., Yim, J., Palowitch, J., ... Perozzi, B. (2024). Test of time: A benchmark for evaluating llms on temporal reasoning. *ArXiv, abs/2406.09170*. Retrieved from <https://api.semanticscholar.org/CorpusID:270440657>