Face4Rag: Factual Consistency Evaluation for Retrieval Augmented Generation in Chinese

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- Introduction
- Related Works
- Methodology
  - Face4RAG Benchmark
  - Logic-Enhanced Factual Consistency Evaluation
- Experiment
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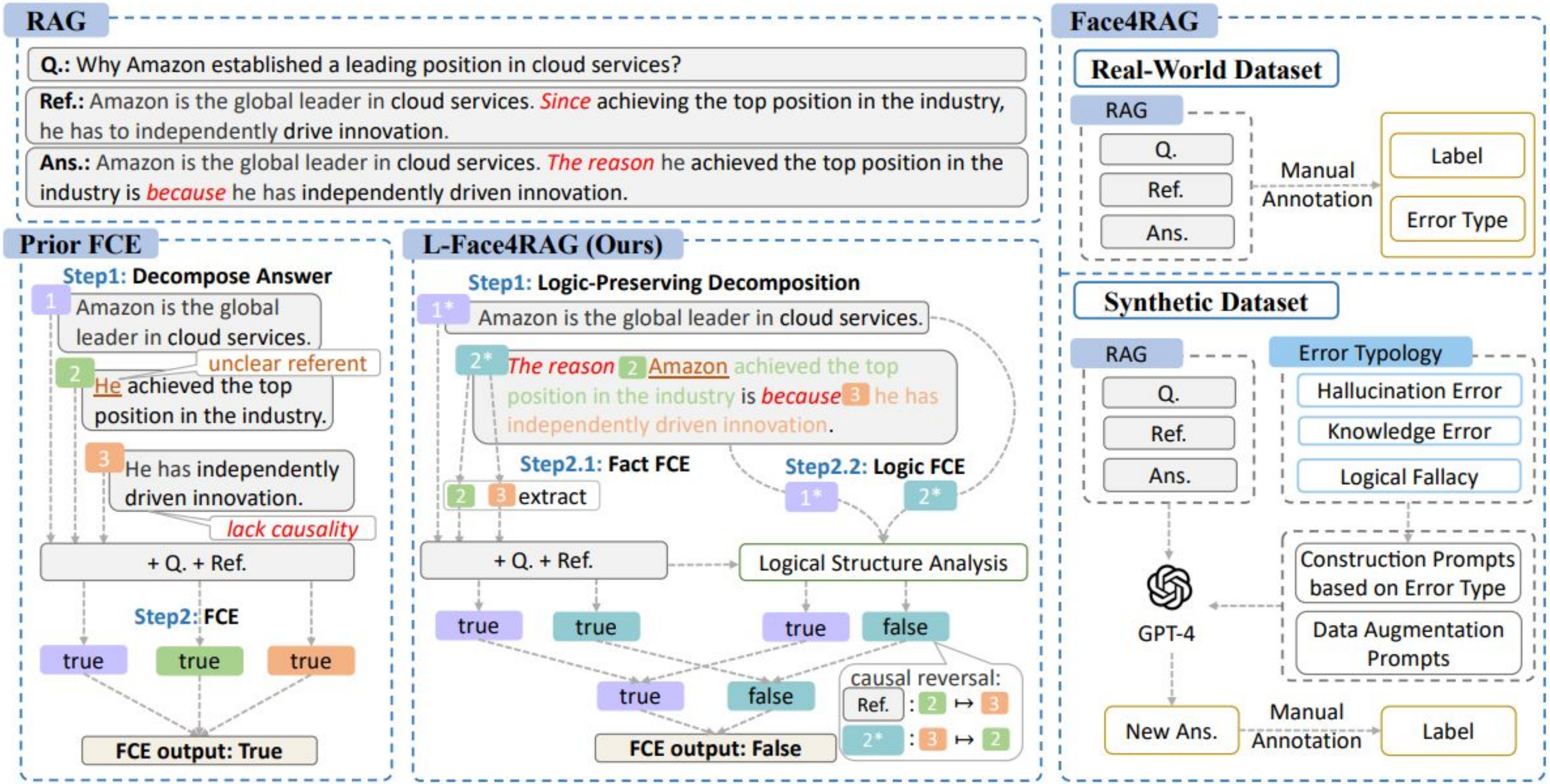
Introduction

- **Background**
  - Retrieval Augmented Generation (RAG): enhances the context of LLMs with relevant passages
  - Passages retrieved from external sources like retrievers or search engines
  - RAG shows strong performance on knowledge-intensive tasks
  - Key applications: open domain conversation and question answering

Introduction

- **Background**
  - Leading RAG systems like Bing Chat and Perplexity: only slightly over 50% factual consistency
  - Many Factual Consistency Evaluation (FCE) methods in RAG tasks evaluated on datasets from specific LLMs
  - Lack of comprehensive benchmarks for testing FCE methods on different LLMs
  - FCE methods may fail to detect error types from other LLMs

Introduction



Outline

Related Works

- **Traditional FCE Methods**
  - Evaluating the factuality of model generated results is widely studied across various language model generation domains, like
    - text summarization [15]
    - dialogue summary [47]
    - question-answering [4].

[4] Yushi Bai, Jiahao Ying, Yixin Cao, Xin Lv, Yuze He, Xiaozhi Wang, Jifan Yu, Kaisheng Zeng, Yijia Xiao, Haozhe Lyu, et al. 2023. Benchmarking Foundation Models with Language-Model-as-an-Examiner. arXiv preprint arXiv:2306.04181 (2023).

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[47] Rongxin Zhu, Jianzhong Qi, and Jey Han Lau. 2023. Annotating and Detecting Fine-grained Factual Errors for Dialogue Summarization. arXiv preprint arXiv:2305.16548 (2023).

Related Works

- **FCE for Long-form Answers**
  - To effectively evaluate factuality of long answers, recent FCE research mostly take a two step approaches [23, 26]
    - In the first step, the long-form answer is decomposed into shorter segments [10, 18, 23, 24, 26, 31, 18]
    - The second step evaluates the verifiability of each segment with respect to the given reference text [25, 26, 45], which can be efficiently done by modern general purpose LLM [9, 31], e.g., GPT4.

Related Works

- **FCE Benchmarks**
  - Prior benchmarks for FCE mostly focus on specialized tasks like summarization [13, 24, 39]. For FCE in RAG, existing benchmarks are derived from specific LLMs, such as Refchecker [18] and FELM [9], which are constrained by the error type distribution of the underlying LLMs.

[9] Shiqi Chen, Yiran Zhao, Jinghan Zhang, I Chern, Siyang Gao, Pengfei Liu, Junxian He, et al. 2023. Felm: Benchmarking factuality evaluation of large language models. arXiv preprint arXiv:2310.00741 (2023).

[13] Shahul Es, Jithin James, Luis Espinosa-Anke, and Steven Schockaert. 2023. Ragas: Automated evaluation of retrieval augmented generation. arXiv preprint arXiv:2309.15217 (2023).

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Methodology - Face4RAG Benchmark

- **Introduction**
  - Error-type-oriented synthetic dataset
    - includes nine types of errors belonging to three main categories
  - A real-world dataset
    - constructed from six commonly used LLMs

Methodology - Face4RAG Benchmark

- **Error Typology in FCE**
  - Hallucination Error
    - Hallucination Error (Hallu.)
  - Knowledge Error
    - Contradiction Error (KCont.)
    - Entity Inversion Error (KInve.)
    - Conflation Error (KConf.)
    - Conceptual Substitution Error (KConc.)

Methodology - Face4RAG Benchmark

Error Type	Original Text	Factual Inconsistent Text
KCont.	功能饮料中的维生素、矿物质等，对于运动后快速补充身体营养，消除疲劳具有一定作用。 The vitamins and minerals in energy drinks play a certain role in quickly replenishing nutrients and eliminating fatigue after exercise.	功能饮料中的元素、微生物等，对于运动后快速补充身体营养，增加疲劳具有一定作用。 The vitamins and minerals in energy drinks play a certain role in quickly replenishing nutrients and inducing fatigue after exercise.
KInve.	一般蚕可以活一个多月，其中从孵化到结茧根据季节不同大约是25-32天，变成蛹后有15-18天，最后成蛾是1-3 天。 A typical silkworm can live for just over a month, during which the period from hatching to cocooning varies roughly from 25 to 32 days depending on the season, followed by 15 to 18 days as a pupa, and finally 1 to 3 days as a moth.	一般蚕可以活一个多月，其中从孵化到结茧根据季节不同大约是15-18天，变成蛹后有25-32天，最后成蛾是1-3 天。 A typical silkworm can live for just over a month, during which the period from hatching to cocooning varies roughly from 15 to 18 days depending on the season, followed by 25 to 32 days as a pupa, and finally 1 to 3 days as a moth.
KConf.	防晒霜中的无机化学物质可以反射或散射皮肤上的光线，而有机（碳基）化学物质可以吸收紫外线。 The inorganic chemicals in sunscreen can reflect or scatter light on the skin, while organic (carbon-based) chemicals can absorb ultraviolet rays.	防晒霜中的无机化学物质和有机（碳基）化学物质都可以反射或散射皮肤上的光线、吸收紫外线。 Both the inorganic chemicals and organic (carbon-based) chemicals in sunscreen can reflect or scatter light on the skin and absorb ultraviolet rays.
KConc.	随着健康意识的增强，越来越多的人开始注重膳食平衡。 With the increasing awareness of health, more and more people are beginning to focus on a balanced diet.	随着健康意识的增强，越来越多的人开始注重膳食的有机质量。 With the increasing awareness of health, more and more people are beginning to focus on the organic quality of their diets.

Methodology - Face4RAG Benchmark

- **Error Typology in FCE**
  - Logical Fallacy
    - Overgeneralization Error (LOver.)
    - Causal Confusion Error (LCaus.)
    - Confusing Sufficient and Necessary Conditions Error (LConf.)
    - Inclusion Relation Error (LIncl.)
    - Other Logical Fallacy (LOthe.)

Methodology - Face4RAG Benchmark

Error Type	Original Text	Factual Inconsistent Text
LOver.	一般的我们平时见到的蜘蛛都是晚上出来。 The spiders that we usually see tend to come out at night.	一般的我们平时见到的昆虫都是晚上出来。 The insects that we usually see tend to come out at night.
LCaus.	随着信息技术的快速发展，大数据在各行各业中的应用越来越广泛。 With the rapid development of information technology, the application of big data across various industries is becoming increasingly widespread.	大数据在各行各业中的应用越来越广泛，这导致了信息技术的快速发展。 The application of big data across various industries is becoming increasingly widespread, leading to the rapid development of information technology.
LConf.	为了获得某项荣誉学生奖学金，学生必须具备以下条件：成绩优秀、品行端正、参加社会实践活动。 To receive a certain honor student scholarship, students must meet the following criteria: excellent academic performance, good moral character, and participation in social practice activities.	学生成绩优秀、品行端正就可以获得某项荣誉学生奖学金。 Students with excellent academic performance and good moral character can receive a certain honorary student scholarship.
LIncl.	坚持锻炼身体可以提高心肺能力，加强肌肉的耐力，提高身体的抗疲劳能力。 Regular exercise can enhance cardiorespiratory fitness, strengthen muscle endurance, and improve the body's resistance to fatigue.	坚持锻炼身体可以提高心肺能力，例如加强肌肉的耐力、提高身体的抗疲劳能力。 Regular exercise can enhance cardiorespiratory fitness, such as strengthening muscle endurance and improving the body's resistance to fatigue.

Methodology - Face4RAG Benchmark

- **Synthetic Dataset**
  - Based on WebCPM [36]
  - Negative Samples
  - Positive Samples
  - Human Annotation Refinement

[36] Yujia Qin, Zihan Cai, Dian Jin, Lan Yan, Shihao Liang, Kunlun Zhu, Yankai Lin, Xu Han, Ning Ding, Huadong Wang, et al. 2023. WebCPM: Interactive Web Search for Chinese Long-form Question Answering. arXiv preprint arXiv:2305.06849 (2023).

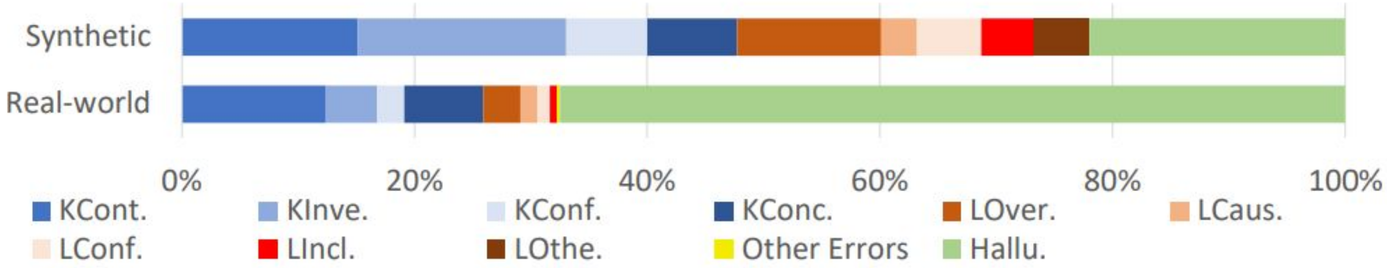
Methodology - Face4RAG Benchmark

- **Real-World Dataset**
  - gpt-3.5-turbo (GPT-3.5) [33]
  - gpt-4-turbo (GPT-4) [2]
  - Baichuan2- 13B-Chat (Baichuan2) [5]
  - ChatGLM3 [44]
  - Qwen-14B-Chat (Qwen) [3]
  - Chinese-Alpaca-2-13B-16k(Alpaca2 (CH)) [11]

Methodology - Face4RAG Benchmark

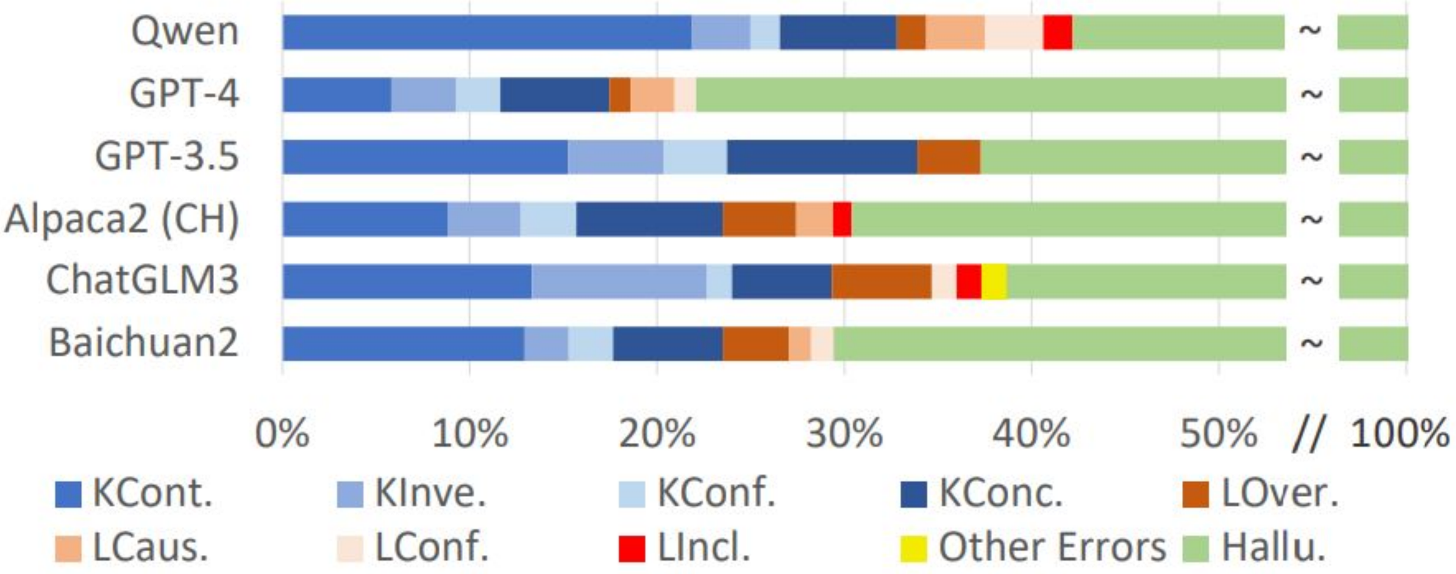
- **Overall Error Type Distribution**

Statistics	Synthetic Dataset		Real-world Dataset	
	Answer	Segment	Answer	Segment
Num. Samples	1299	6737	1200	6143
Avg. Length	289.3	45.4	307.7	45.2
Positive Rate	30.3%	55.8%	63.3%	85.6%



Methodology - Face4RAG Benchmark

- **Real-World Dataset - Error Distribution of Various Models**



Outline

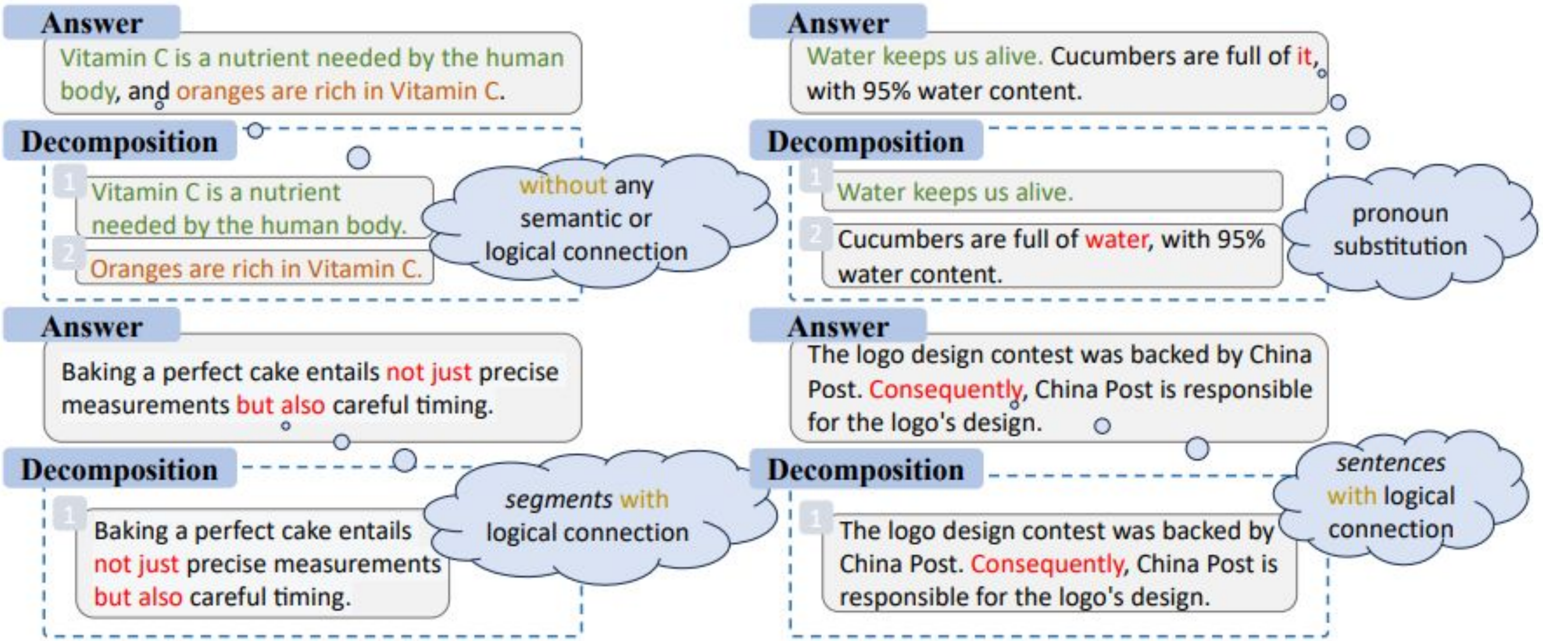
Methodology - Logic-Enhanced Factual Consistency Evaluation

- **Introduction**
  - Logical fallacy accounts for a considerable proportion of factual errors in real-world RAG scenarios.
  - Existing FCE pipelines neglect the logical connections between segments in the original answer, which may result in wrong factual consistency evaluation result for samples with logical fallacy.

Methodology - Logic-Enhanced Factual Consistency Evaluation

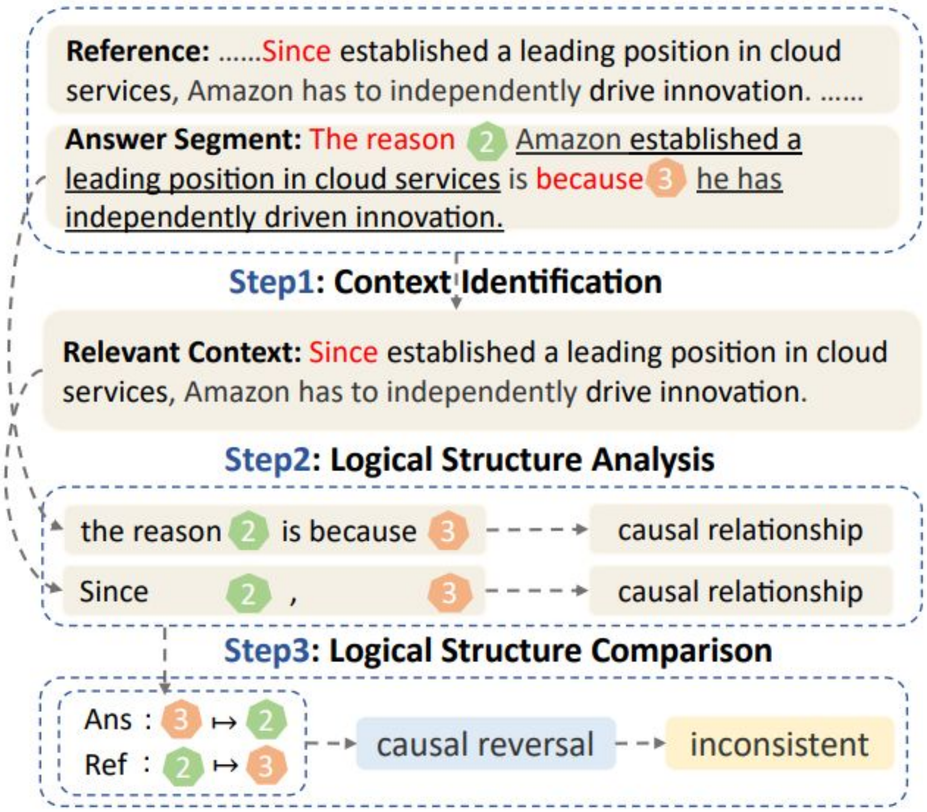
- **Logic-Preserving Answer Decomposition**
    - Logical Connection
    - Pronoun Substitution
    - Unique Format

Methodology - Logic-Enhanced Factual Consistency Evaluation



Methodology - Logic-Enhanced Factual Consistency Evaluation

- **Fact-Logic FCE**
  - Fact Consistency Evaluation
    - Informational Points Extraction
    - Context Identification
    - Fact Consistency Check
  - Logic Consistency Evaluation
    - Context Identification
    - Logical Structure Analysis
    - Logical Structure Comparison



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Experiment

- **Baselines:**
    - FACTSCORE [31]
    - FELM [9]
    - Ragas [13]
    - Refchecker [18]

Experiment

- **Performance Comparison on Face4RAG - Synthetic Dataset**
  - L-Face4RAG shows significant performance improvement over other baselines
  - Particularly strong in detecting logical fallacy errors

Method	Total	Pos.	Negative samples									
			Hallu.	KCont.	KInve.	KConf.	KConc.	LOver.	LCaus.	LConf.	LIncl.	LOthe.
FACTSCORE(GPT-3.5)	70.36	37.31	90.45	**100**	94.44	55.56	94.29	78.57	64.29	68.00	46.34	86.07
FACTSCORE(GPT-4)	71.82	33.50	93.97	**100**	96.30	68.25	97.14	87.5	60.71	72.00	51.22	88.37
FELM	68.05	77.67	42.21	99.27	91.98	22.22	88.57	69.64	42.86	54.00	4.88	32.56
RAGAS(GPT-3.5)	69.59	70.81	76.89	98.54	71.60	49.21	87.14	54.46	39.29	48.00	34.15	44.19
RAGAS(GPT-4)	76.37	73.60	93.97	99.27	79.01	52.38	90.00	58.93	50.00	50.00	**53.66**	72.09
RefChecker	78.52	76.14	95.48	**100**	87.65	63.49	92.86	55.36	50.00	52.00	36.59	67.44
L-Face4RAG (Ours)	**93.38**	**96.19**	**96.98**	**100**	**98.77**	**76.19**	**98.57**	**90.18**	**92.86**	**80.00**	51.22	**90.70**

Experiment

- **Performance Comparison on Face4RAG - Real-world Dataset**
  - L-Face4RAG significantly outperforms other baseline FCE methods in overall accuracy

Method	Total	Baichuan2	ChatGLM3	GPT-3.5	GPT-4	Alpaca2 (CH)	Qwen
FACTSCORE(GPT-3.5)	53.33	54.0	55.5	47.5	51.5	59.0	52.5
FACTSCORE(GPT-4)	54.67	55.0	59.5	46.5	52.5	63.0	51.5
FELM	55.00	49.6	56.0	56.8	52.0	55.6	60.0
RAGAS(GPT-3.5)	65.92	64.5	68.5	64.5	60.0	65.0	73.0
RAGAS(GPT-4)	72.92	72.5	74.0	71.5	68.5	76.5	74.5
RefChecker	68.25	62.0	72.0	66.5	63.0	74.5	71.5
L-Face4RAG (Ours)	**87.75**	**90.0**	**88.0**	**81.5**	**86.0**	**93.5**	**87.5**

Experiment

- **Performance Comparison on Existing FCE Benchmark**
  - L-Face4RAG achieved SOTA (state-of-the-art) results on 6 out of 7 datasets

Method	Avg.	RAG		Summ.		Dial.		Fact Verif.
		RAGAS[13]	RefChecker[18]	FRANK[34]	SummEval[14]	Q^2[17]	DialFact[16]	VitaminC[37]
FACTSCORE(GPT-4)	70.5	70	61	80	65	74	72	71
FELM	74.2	71	63	70	<u>82</u>	<u>83</u>	**79**	72
RAGAS(GPT-4)	76.9	<u>88</u>	69	**87**	80	77	69	69
RefChecker	<u>78.4</u>	86	**73**	85	80	80	72	<u>73</u>
L-Face4RAG (Ours)	**84.2**	**91**	**73**	**87**	**90**	**84**	<u>77</u>	**88**

Experiment

- **Ablation Study**
  - Evaluating the Answer Decomposition Module. (A.D.)
  - Evaluating the Introduction of COT.(w/o COT)
  - Evaluating the Stage of Logical Consistency Evaluation. (w/o logi. eval)

	L-Face4RAG	A.D.	w/o COT	w/o logi.eval
Overall	93.38	76.44	79.60	88.99
-Positive	96.19	91.62	51.27	97.46
-Negative	92.15	69.83	91.93	85.30

Experiment

- **Ablation Study**
  - Removing the logical validation phase caused a **significant drop in logical performance**

		L-Face4RAG	A.D.	w/o logi. eval
Hallucination	Hallu.	96.98	90.45	96.98
Knowledge	KCont.	100.00	100.00	100.00
	KInve.	98.77	74.07	97.53
	KConf.	76.19	41.27	66.67
	KConc.	98.57	90.00	94.29
Logical	LOver.	90.18	42.86	83.93
	LCaus.	92.86	32.14	35.71
	LConf.	80.00	34.00	64.00
	LIncl.	51.22	31.71	29.27
	LOth.	90.70	44.19	65.12

Outline

Conclusion

- **Contribution**
  - Construct a comprehensive benchmark to enable the evaluation of FCE methods independent of the underlying LLM, which is called Face4RAG.
  - Propose a new FCE method called L-Face4RAG to better detect the logic fallacy in the examined answer

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SoWork – Lottery Post Recognition

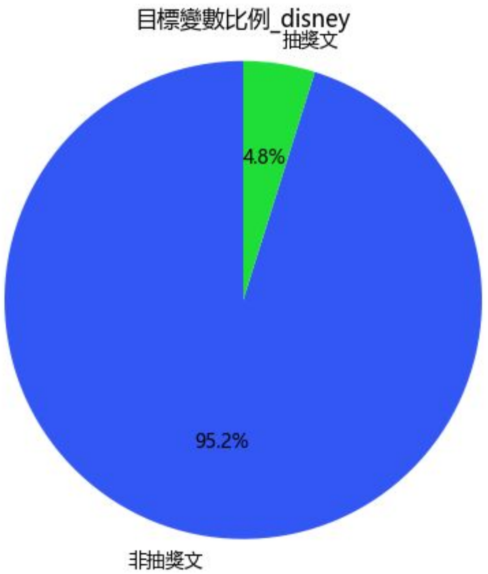
Presenter: Cheng Jhe Lee
National Cheng Kung University

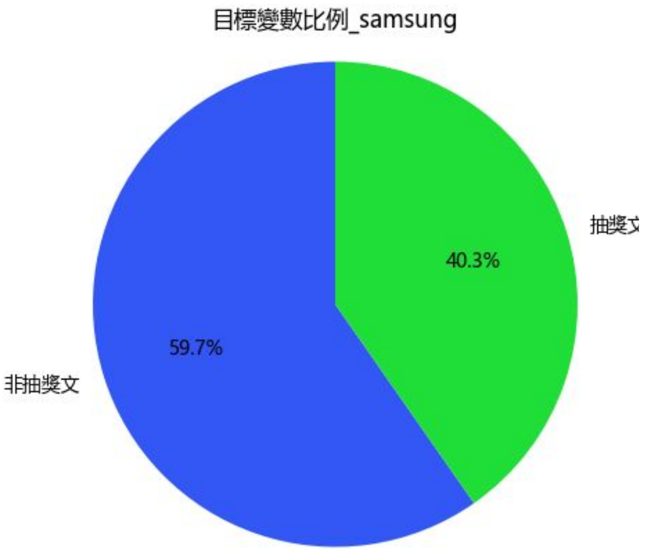
Data Analysis

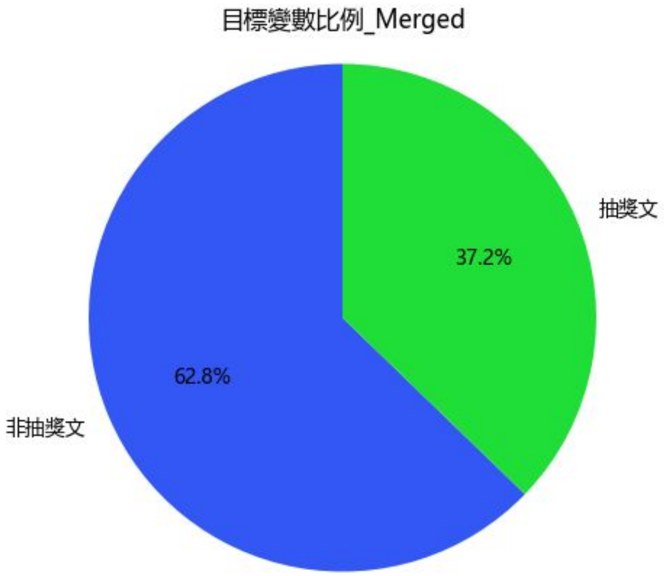
- **Data Information**
  - Two dataset, Disney+ dataset and Samsung dataset
  - Disney+ has **30 columns**, while samsung dataset only has **25 columns**, the former has 5 more columns, `['C', 'URL', '合併', '日期', '時間']`
  - Merged dataset has **25 columns** with **32809 rows**

Data Analysis

- **Label Distribution**







Data Analysis

- **Feature Extraction**

Most significant	**討論串總則數(OpView收錄回文文章數)**
Important	來源、作者、頻道屬性標籤、頻道內容標籤、網站、按讚/觀看、正面強度、負面強度
Minor	分享/轉貼數/評級、FB_讚、FB_大心、FB_哈、FB_哇、FB_嗚、FB_怒、中立強度、監測主題、發布時間、標題、內容、主文/回文、情緒標記、原始連結

Conclusion

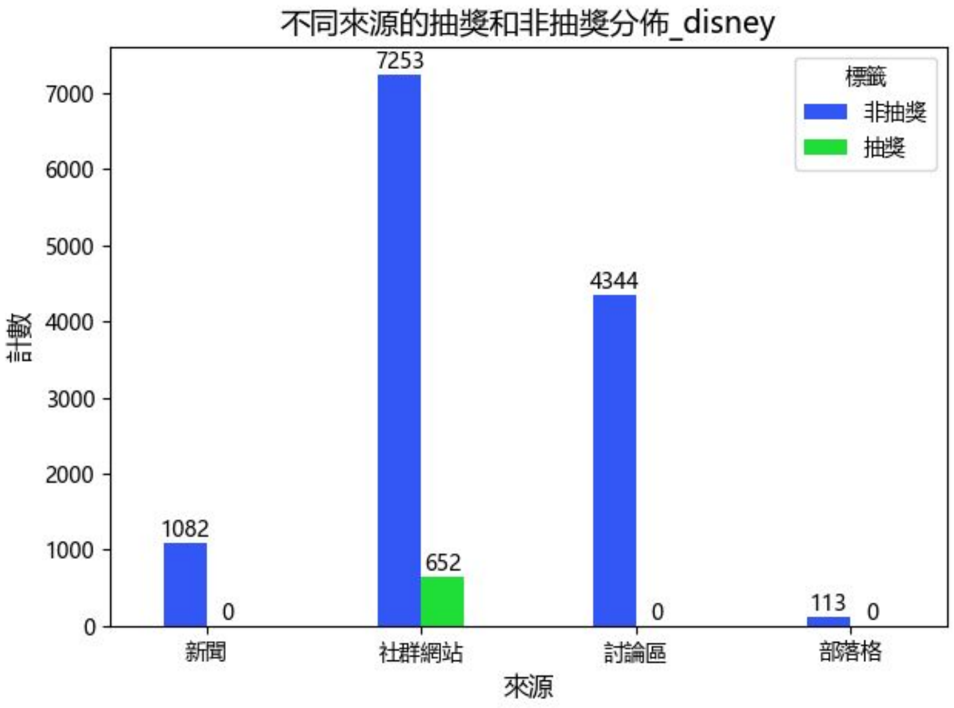
- Merged dataset has **25 columns** with **32809 rows**

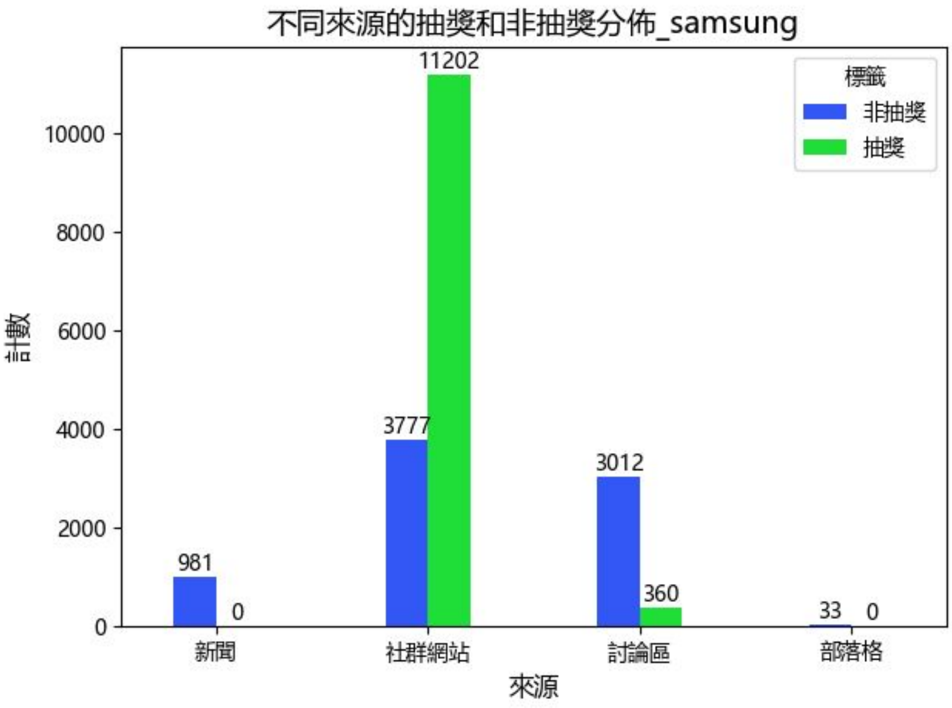
- Most significant feature is '**討論串總則數(OpView收錄回文文章數)**', which is **consistent with the description provided by Sowork**

- After classifying three datasets with a decision tree and analyzing their precision, accuracy, and recall, the lowest score was **93%**

Appendix

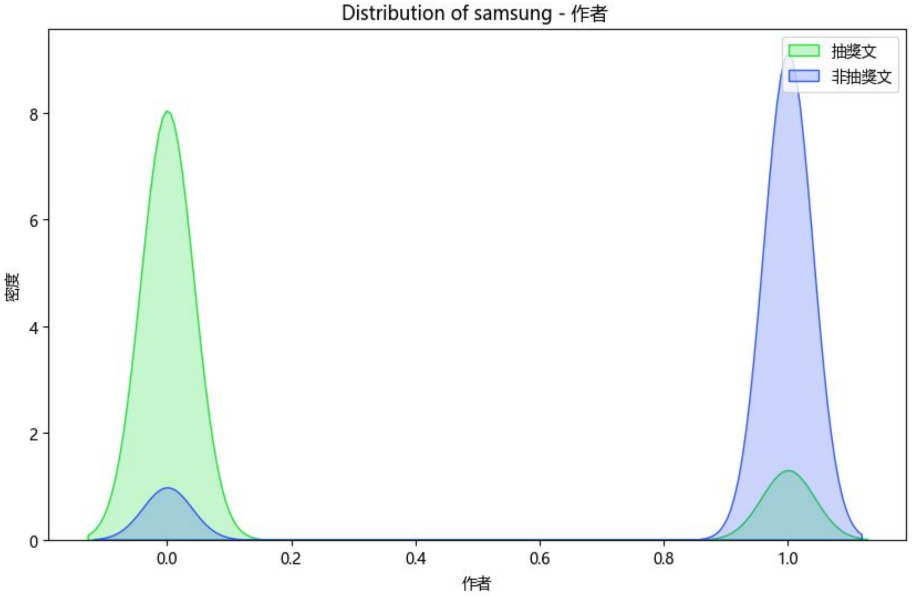
- **column '來源'**

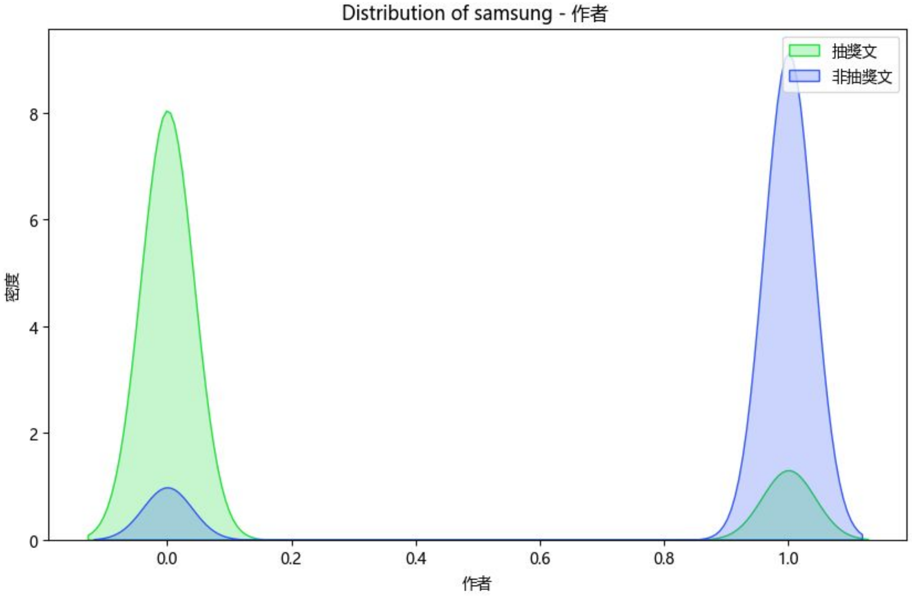




Appendix

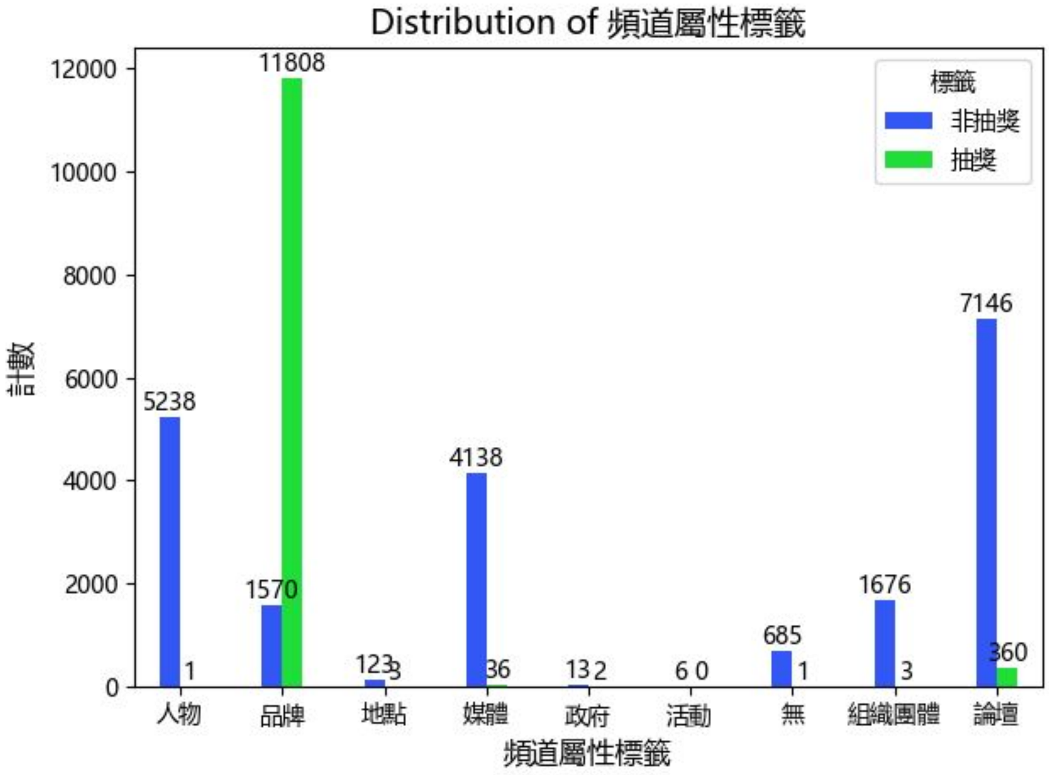
- column '作者'





Appendix

- **(merged) column '頻道屬性標籤'**



Appendix

- **Decision tree visualization**