Enhancing Uncertainty-Based Hallucination Detection with Stronger Focus

Tianhang Zhang[1], Lin Qiu[2], Qipeng Guo[2], Cheng Deng[1], Yue Zhang[3], Zheng Zhang[2], Chenghu Zhou[4], Xinbing Wang[1], Luoyi Fu[1]

[1]Shanghai Jiaotong University [2]Amazon AWS AI [3]Westlake University [4]IGSNRR, Chinese Academy of Sciences
{zhangtianhang, davendw, xwang8, yiluofu}@sjtu.edu.cn {quln, gqipeng, zhaz}@amazon.com zhangyue@westlake.edu.cn

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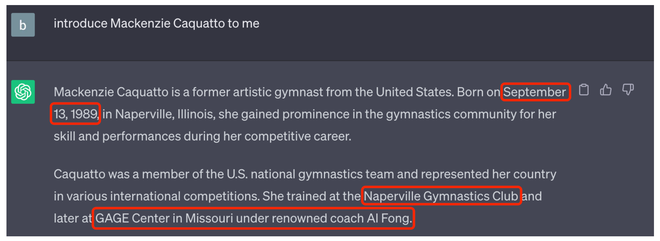
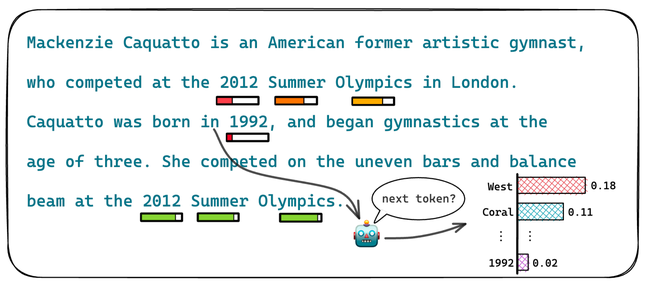
Introduction

Task: Finding hallucinations in LLM generated text

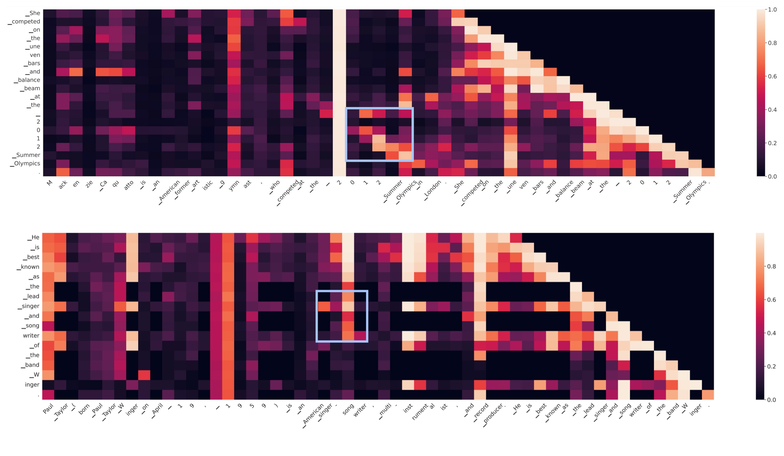


- Hallucinations can undermine the reliability and trustworthiness of LLMs, especially in scenarios where accuracy and veracity are essential.
- We focus on hallucinations that conflict with knowledge in the real world.

Problems of Existing Uncertainty-Based Methods

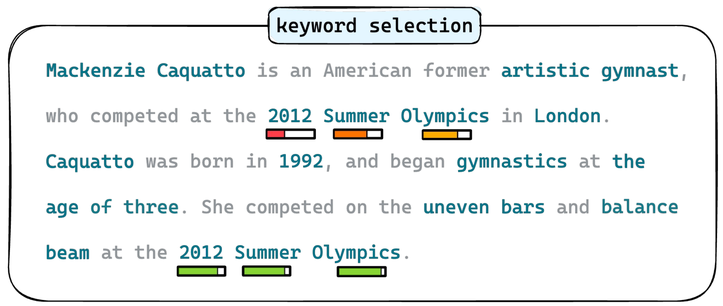


- Given a model response, calculate the generation probability of each token. If the text is from a black-box LLM, we can use a proxy model for estimation.
- However, such method may introduce noise when calculating sentence-level hallucination scores.
- The probability may exhibit "overconfidence".
- The probability sometimes demonstrate "underconfidence"



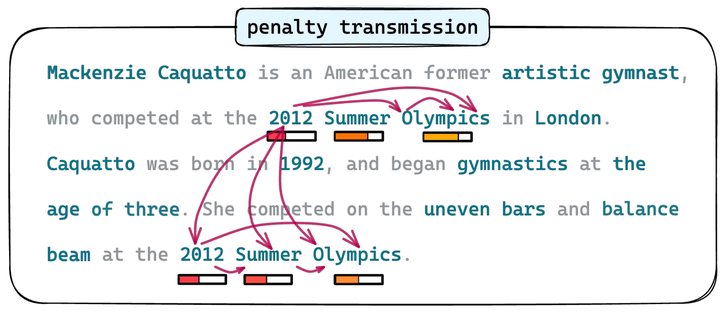
Our Method: Focus

Keyword Selection: The keywords that express salient information will be extracted for calculation



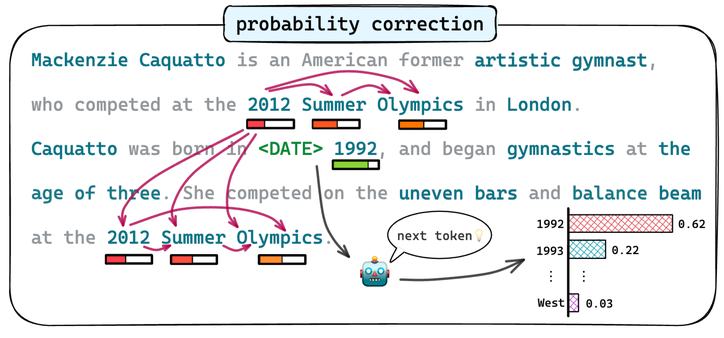
- The keywords are the named entities and nouns recognized by Spacy.

Penalty Transmission: The uncertainties of previous tokens will be transmitted to the subsequent ones



- The attention weight is the max-pooling results for all the layers and attention heads.

Probability Correction: The token generation probability will be adjusted according to the token properties



- The predicted token probability is conditioned on its entity type (if any) and adjusted by its inverse document frequency (IDF).
- The token frequency is estimated using the sampled RedPajama dataset.

Experiments

Hallucination Detection in Large Language Model

Wikibio-GPT3

Method	Sentence-level Metrics NonFact	NonFact*	Factual	Passage-level Metrics Pearson	Spearman
GPT-3 Uncertainties					
Avg($-\log p$)	83.21	38.89	53.97	57.04	53.93
Avg($\mathcal{H}$)	80.73	37.09	52.07	55.52	50.87
Max($-\log p$)	87.51	35.88	50.46	57.83	55.69
Max($\mathcal{H}$)	85.75	32.43	50.27	52.48	49.55
SelfCheckGPT					
BERTScore	81.96	45.96	44.23	58.18	55.90
QA	84.26	40.06	48.14	61.07	59.29
Unigram (max)	85.63	41.04	58.47	64.71	64.91
Combination	87.33	44.37	61.83	69.05	67.77
Ours					
LLaMA-7B$_{focus}$	84.26	40.20	57.04	64.47	54.73
LLaMA-13B$_{focus}$	87.90	43.84	62.46	70.62	63.03
LLaMA-30B$_{focus}$	89.79	**48.80**	**65.69**	**77.15**	**73.24**
LLaMA-65B$_{focus}$	**89.94**	48.69	64.90	76.80	73.01

Method	NoFac	NoFac*	Fact	Pear.	Spear.
avg(h)	82.07	41.47	47.22	51.03	37.29
+keyword	83.01	41.57	45.82	56.07	44.77
+penalty	86.68	45.27	54.93	59.08	55.84
+entity type	88.89	46.92	65.12	76.82	71.49
+token idf	**89.79**	**48.80**	**65.69**	**77.15**	**73.24**

LLaMA-30b

Method	NoFac	NoFac*	Fact	Pear.	Spear.
avg(h)	79.72	37.50	32.37	34.00	27.47
+keyword	80.55	37.62	35.13	45.45	38.11
+penalty	87.26	47.22	44.88	47.67	52.01
+entity type	87.11	45.74	57.60	68.25	62.46
+token idf	**88.11**	**46.95**	**58.14**	**68.63**	**64.66**

Falcon-40b

- Our proposed method achieves SOTA performance on the WikiBio-GPT-3 dataset across various models with different scales.
- Our method show effectiveness across **22** different proxy models such as OPT, GPT-J and Falcon.

Hallucination Detection in Small Language Models

XSumFaith

Method	NonFact	Fact	Balanced-Acc
avg(h)	92.79	11.75	57.65
+keyword	92.65	14.19	56.24
+penalty	92.34	14.97	57.77
+entity type	94.98	18.46	64.77
+token idf	**95.13**	**18.86**	**64.81**

FRANK

Method	NonFact	Fact	Balanced-Acc
avg($-logp$)	89.82	79.00	78.79
+penalty	89.87	78.37	79.46
+entity type	**90.44**	79.78	80.31
+token idf	90.12	**80.00**	**80.70**

- Our method also shows effectiveness in detecting hallucinations within summaries generated by small language models.