

# Discern and Answer: Mitigating the Influence of Noise on Retrieval-Augmented Models with Discriminators

Giwon Hong<sup>1\*</sup>, Jeonghwan Kim<sup>2\*</sup>, Junmo Kang<sup>3</sup>, Sung-Hyon Myaeng<sup>4</sup>, Joyce Jiyoun Whang<sup>4</sup>

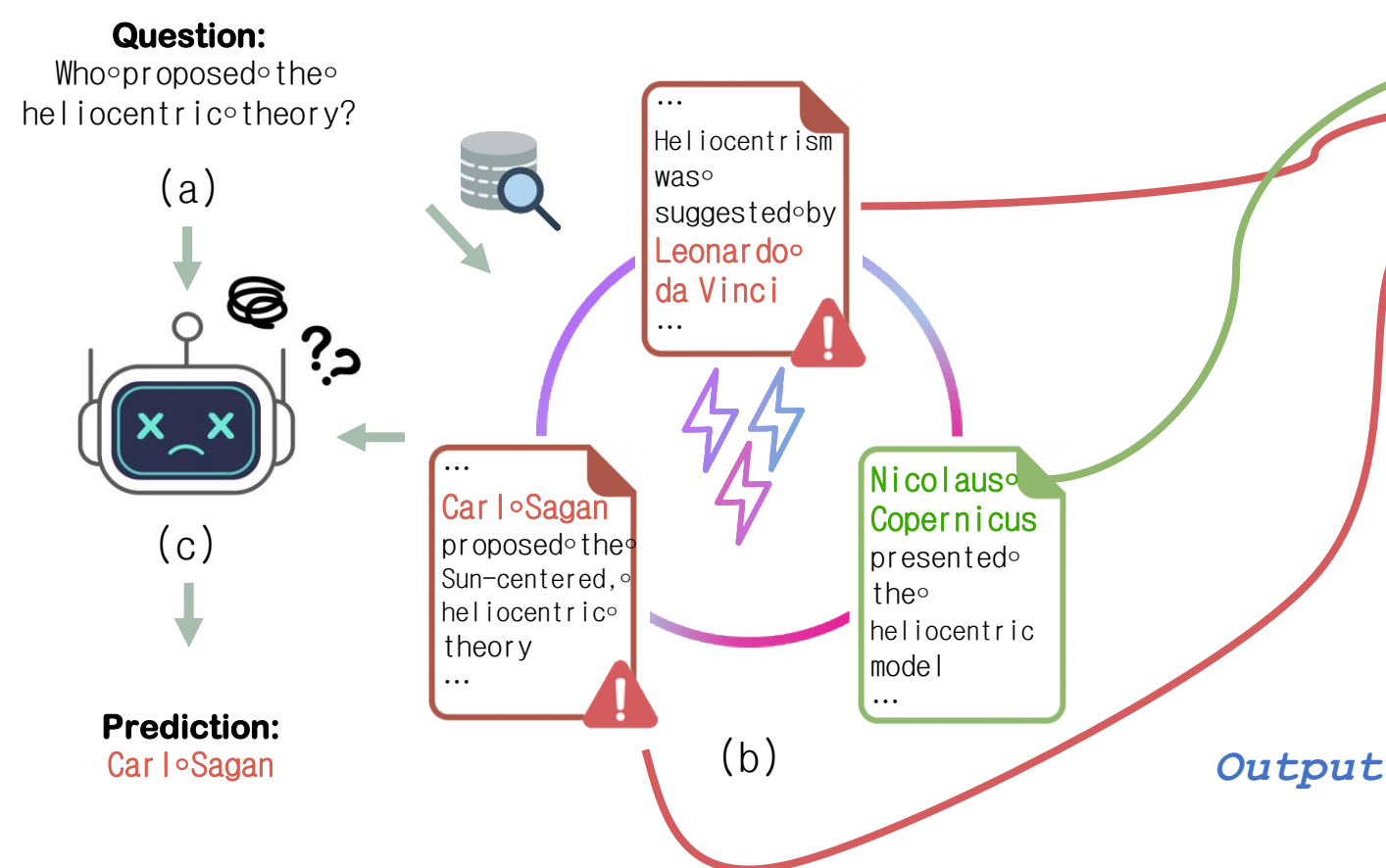
<sup>1</sup>University of Edinburgh <sup>2</sup>University of Illinois Urbana-Champaign <sup>3</sup>Georgia Institute of Technology <sup>4</sup>KAIST

\* Work was done while working at KAIST



## Motivation

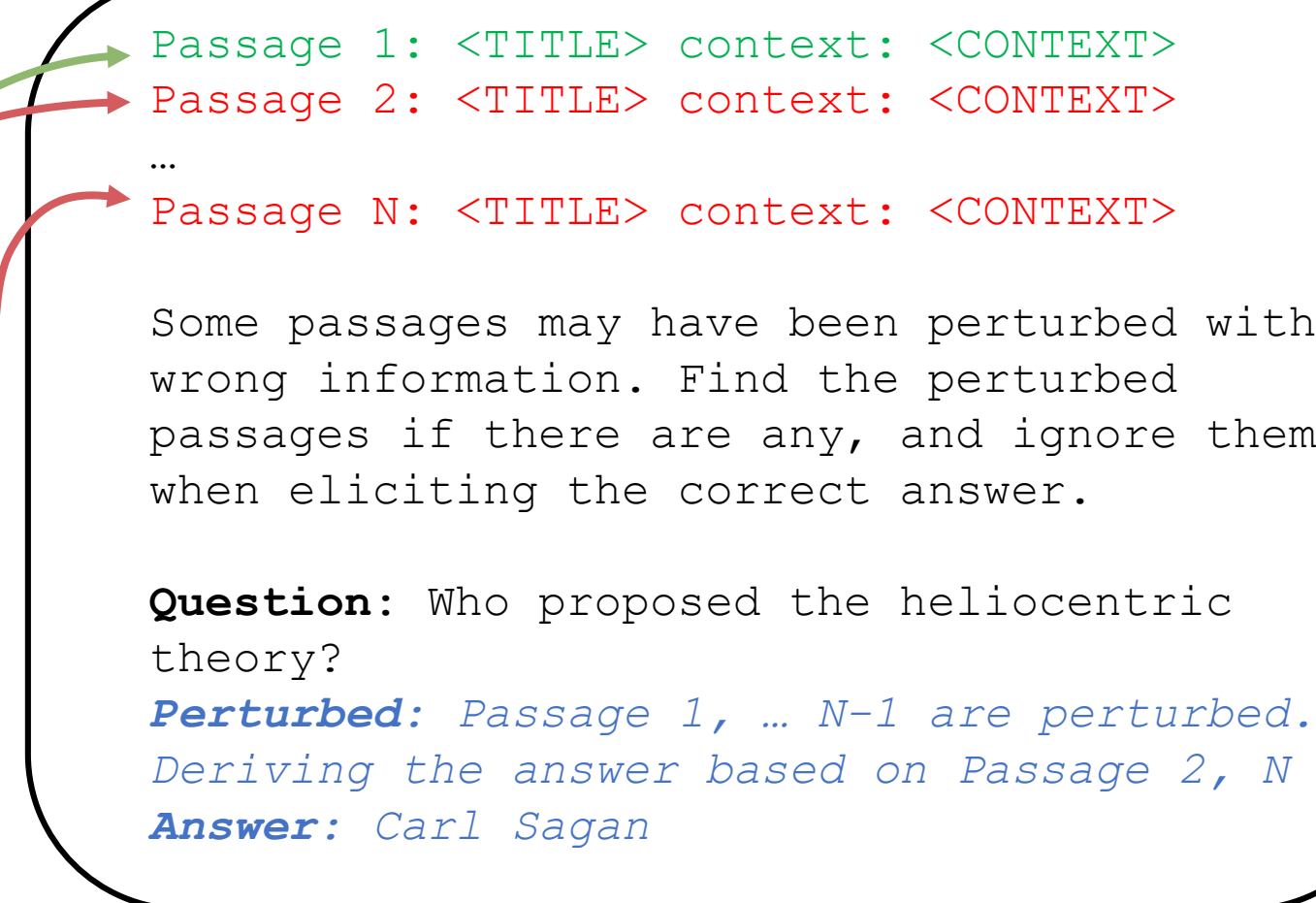
- Misinformation and its impact on the Web are ever-increasing (Vicario et al., 2016)



- We focus on handling misinformation in a set of retrieved documents in **open-domain question answering (ODQA) setting**

## Preliminary Study

- Misinformation can be detrimental, especially for LLMs, which are challenging to fine-tune



- With in-context learning, we can simply detect misinformation before generating answers

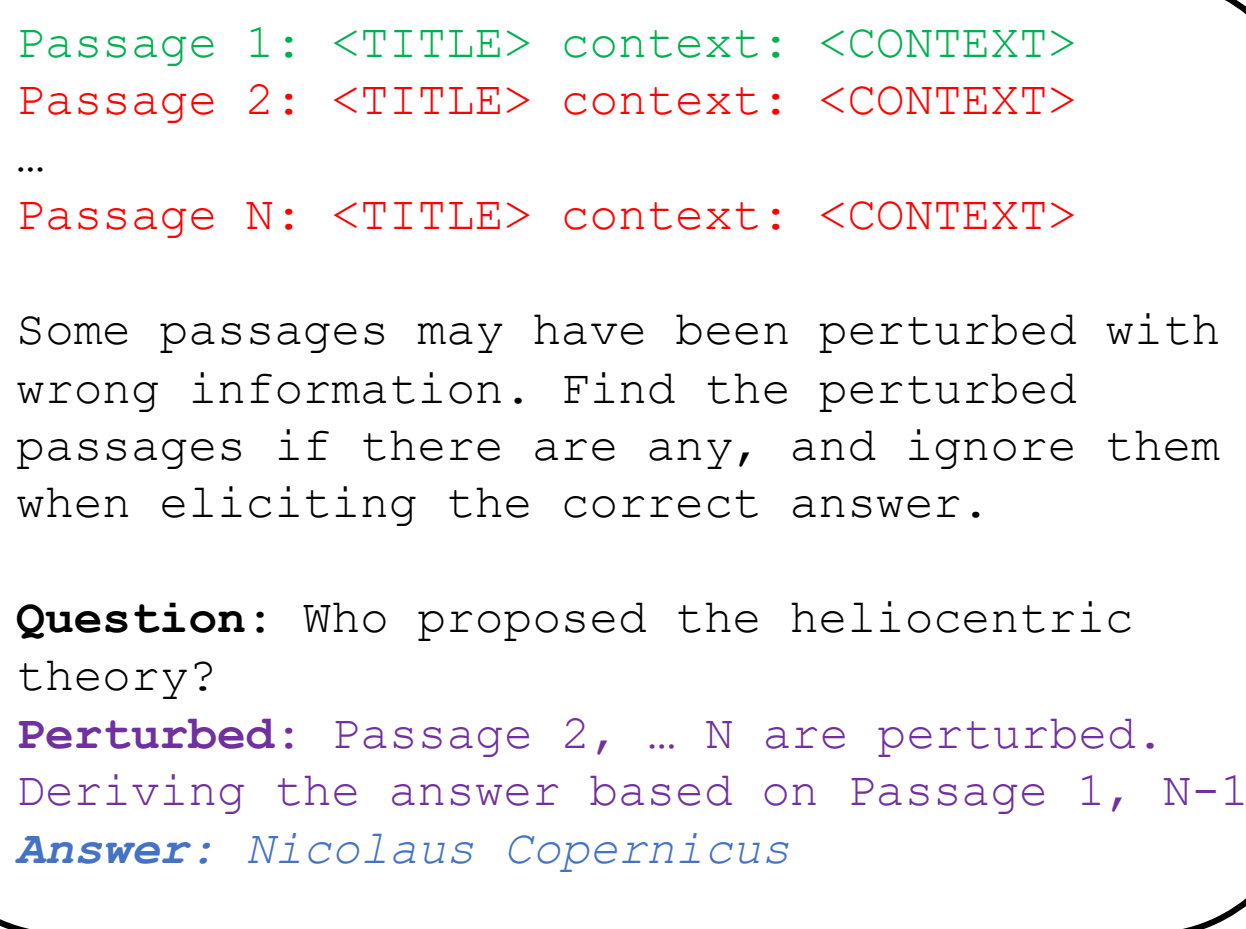
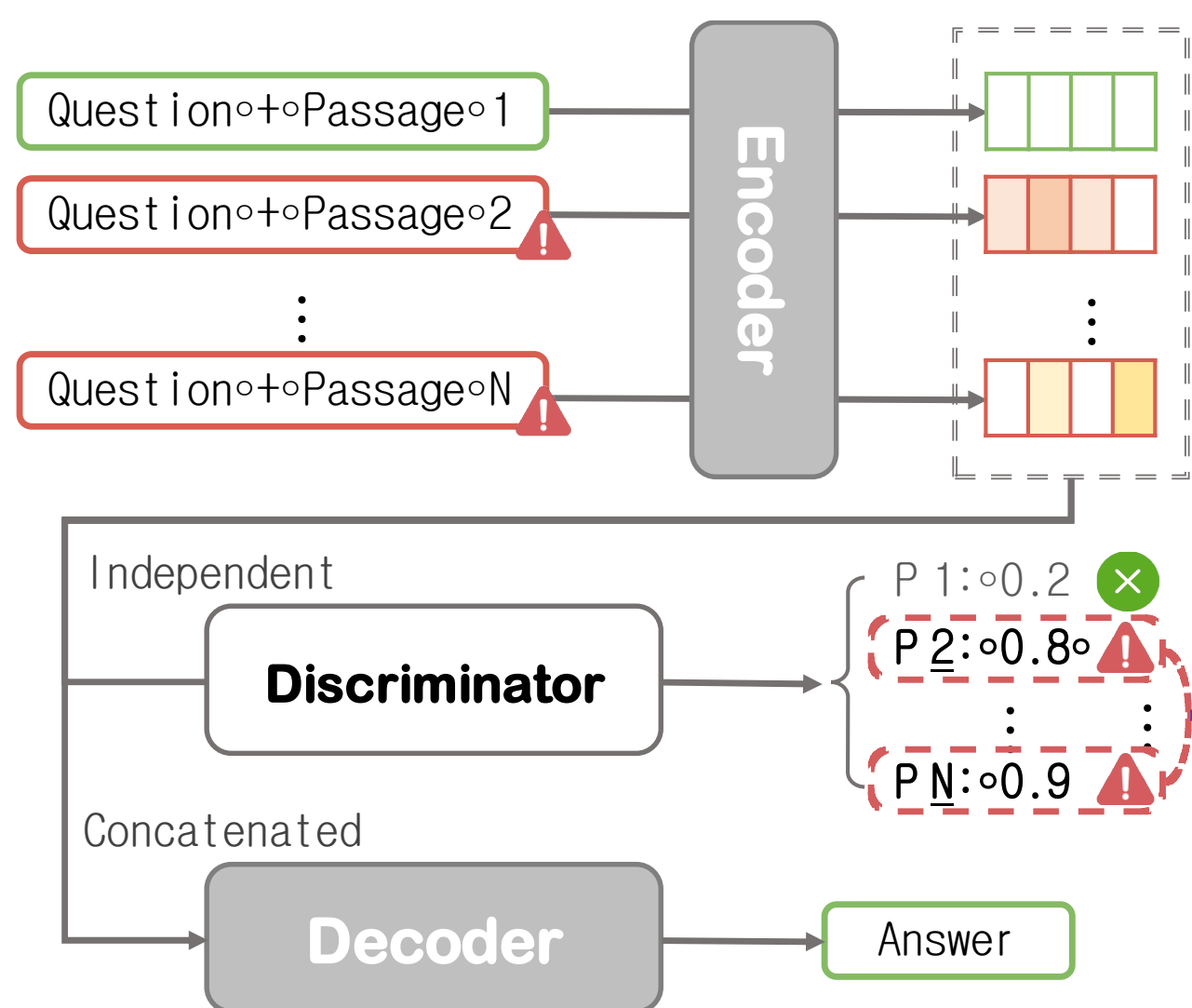
- However, **LLMs** exhibit limited ability to classify misinformation

GPT-3.5			
Mis.%	Prec.	Rec.	F1
15%	20.14	49.11	28.57
25%	30.29	48.59	37.32
35%	42.03	49.14	45.31

- Meanwhile, smaller **fine-tuned models** show better classification abilities

Fine-tuned T5-base			
Mis. %	Prec.	Rec.	F1
15%	93.60	61.26	74.05
25%	98.51	63.78	77.43
35%	96.28	68.65	80.15

## Proposed Method



- A fine-tuned model (FiD; Izacard et al., 2021) specialized for misinformation

Inject classification results of the fine-tuned model into LLM's prompts

## Settings

- Task: Open-Domain QA**
  - Natural Questions (NQ) (Kwiatkowski et al., 2019)
  - TriviaQA (Joshi et al., 2017) (omitted)
- Entity Perturbation Method**
  - Longpre et al. (2021)
- LLM-generated perturbation**
  - MacNoise**
- Models**
  - Fine-tuned Model: Fusion-in-Decoder (FiD)
  - LLM: GPT-3.5

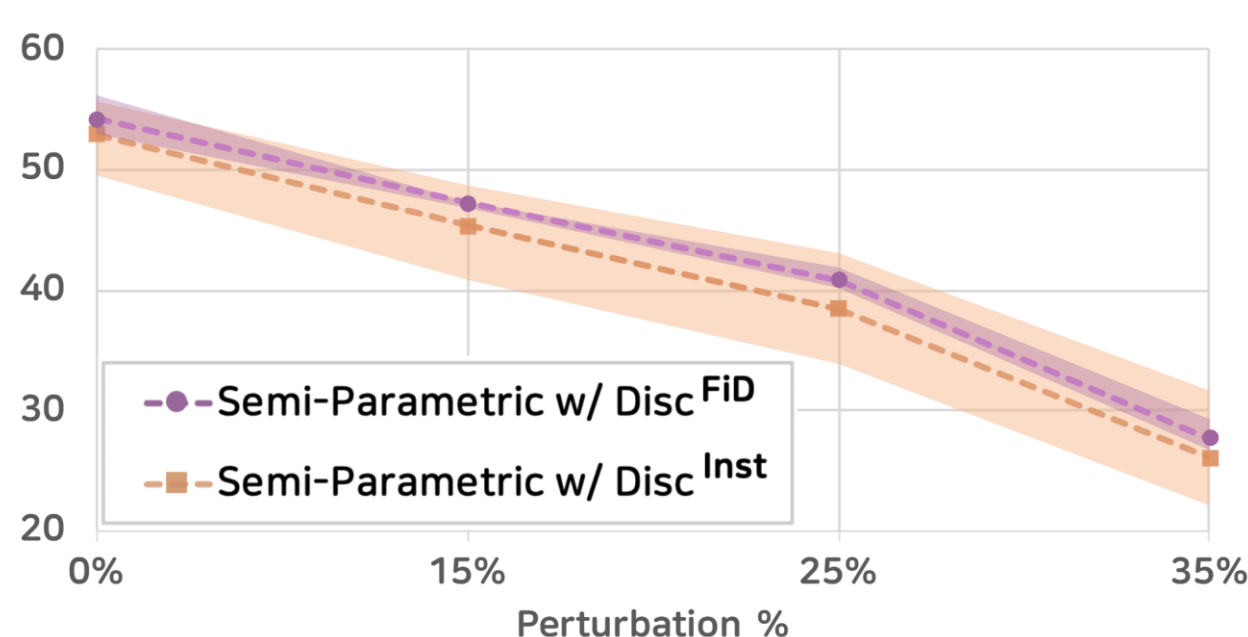
## Results

- $Disc^{Inst}$ : Instruction-based classification (preliminary study)
- $Disc^{FiD}$ : Fine-tune model's classification (proposed method)

Method	Perturbation % (Dev / Test)				
	0%	15%	25%	35%	Avg.
Parametric (w/o Retrieval)		32.0 / 36.8			32.0 / 36.8
Semi-Parametric (w/ Retrieval)	50.4 / 53.2	40.2 / 45.0	31.3 / 37.8	22.7 / 24.2	36.2 / 40.1
Semi-Parametric w/ $Disc^{Inst}$	48.8 / 54.2	37.9 / 45.6	28.9 / 38.4	21.5 / 26.8	34.3 / 41.3
<b>Semi-Parametric w/ <math>Disc^{FiD}</math></b>	<b>51.2 / 56.3</b>	<b>42.2 / 49.2</b>	<b>34.0 / 41.6</b>	<b>27.3 / 28.6</b>	<b>38.7 / 43.9</b>
Δ Absolute Gain	+0.8 / +3.1	+2.0 / +4.2	+2.7 / +3.8	+4.6 / +4.4	+2.5 / +3.8

- Due to LLM's inferior misinformation detection ability,  $Disc^{Inst}$  does not show performance improvement
- By utilizing predictions from the specialized fine-tuned models,  $Disc^{FiD}$  shows **consistent performance improvement**
- Nevertheless, if the retrieved documents are severely contaminated, it is better to rely solely on parametric knowledge

## Enhanced In-Context Learning Stability

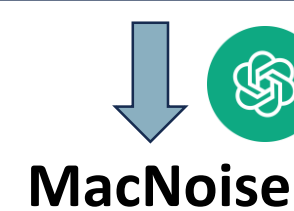


- Utilizing the fine-tuning model's predictions significantly **reduced variance across different examples of in-context learning**

## MacNoise: Machine-Generated ODQA Benchmark

Original Document from Natural Questions (NQ)

... the company is now the largest American retailer of women's lingerie. Victoria's Secret was founded by **Roy Raymond**, and his wife **Gaye Raymond** ...



Context: Victoria's Secret is an American designer, manufacturer, and marketer of women's lingerie, womenswear, and beauty products. The company was founded in 1977 by **John Thompson** and his wife, **Gaye Thompson**, in San Francisco, California ...

## Conclusion

- In-context learned LLMs are brittle to the presence of misleading information
- Our approach significantly enhances the LMs' ability to handle conflicts
- We present **MacNoise**, a novel knowledge conflict ODQA benchmark
- Combining the fine-tuned model's output with in-context learning, **creating a new avenue for future work to harness the advantages of both learning paradigms**