# Leveraging Large Language Models for Addressing Evolving Cyber Security Issues

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## Agenda

- Introduction
- Motivation
- Background: Leveraging LLMs
- LLM-based Reasoning for Evolving Cyber Security Issues
- Paper: Moderating New Waves of Online Hate with Chain-of-Thought Reasoning in Large Language Models
- Discussion
- Q & A

 Large Language Models have recently garnered significant attention



GPT-4o just Released!

#### • State-of-the-art performance

#### User Can you explain this meme?

Sometimes I just look at pictures of the earth from space and I marvel at how beautiful it all is.



GPT-4 This meme is a joke that combines two unrelated things: pictures of the earth from space and chicken nuggets.

The text of the meme suggests that the image below is a beautiful picture of the earth from space. However, the image is actually of chicken nuggets arranged to vaguely resemble a map of the world.

The humor in this meme comes from the unexpected juxtaposition of the text and the image. The text sets up an expectation of a majestic image of the earth, but the image is actually something mundane and silly.

Simulated exams	GPT-4 estimated percentile
Uniform Bar Exam (MBE+MEE+MPT) <sup>1</sup>	298/400 ~90th
LSAT	<b>163</b> ~88th
SAT Evidence-Based Reading & Writing	<b>710/800</b> ~93rd
SAT Math	700/800 ~89th
Graduate Record Examination (GRE) Quantitative	163/170 ~80th
Graduate Record Examination (GRE) Verbal	<b>169/170</b> ~99th
Graduate Record Examination (GRE) Writing	4/6 ~54th
USABO Semifinal Exam 2020	87/150 99th-100th
USNCO Local Section Exam 2022	36/60
Medical Knowledge Self-Assessment Program	75%
Codeforces Rating	<b>392</b> below 5th
AP Art History	5 86th-100th
AP Biology	5 85th-100th
AP Calculus BC	<b>4</b> 43rd-59th

#### Source: https://openai.com/research/gpt-4

#### • Model size is increasing exponentially



https://huggingface.co/blog/large-language-models

# Introduction Three approaches for language modeling

$$\hat{x_i} = p(\hat{x_i}|x_1, x_2, ..., x_n)$$
 .

Sentence correction (denoising)

$$\hat{x}_{n+1} = p(\hat{x}_{n+1} | x_1, x_2, ..., x_n)$$
 Text completion

$$\hat{x}_{n+1} = p(\hat{x}_{n+1} | x_1, x_2, ..., x_n, D)$$
 . Text translation

# Introduction Parametric architectures for sentence denoising: Encoder



 Parametric architectures for text completion: Decoder



# Introduction Parametric architectures for text translation: Encoder-Decoder



#### • Training LLMs

- -Pre-training
- -Supervised Training

#### -Reinforcement Learning

- "Pure" Reinforcement Learning (cherry)
  - The machine predicts a scalar reward given once in a while.
  - A few bits for some samples

#### Supervised Learning (icing)

- The machine predicts a category or a few numbers for each input
- Predicting human-supplied data
- ► 10→10,000 bits per sample

#### Unsupervised/Predictive Learning (cake)

- The machine predicts any part of its input for any observed part.
- Predicts future frames in videos
- Millions of bits per sample

![](_page_9_Picture_16.jpeg)

# Introduction Several applications!

![](_page_10_Picture_1.jpeg)

- Education
- Customer service / advisor
- Knowledge Management
- Recommendation
- Virtual Assistant

# • LLMs for cybersecurity

#### Give security teams an edge with Microsoft Security Copilot

Powerful new capabilities, new integrations, and industry-leading generative Al-now available in early access.

Read the announcement

Watch the announcement

Supercharge security with generative Al

Google Cloud

![](_page_11_Figure_6.jpeg)

# Palo Alto Networks teases plans for generative AI across security services

The security vendor is taking a restrained approach to deploying generative AI products, but the company's leaders still believe the technology will herald a major shift for cybersecurity.

Published May 31, 2023

• LLMs have a significant number of cyber security applications

# Background Emerging capabilities –ICL / CoT / MM reasoning...

Circulation revenue has increased by 5% in Finland. // Positive

Panostaja did not disclose the purchase price. // Neutral

Paying off the national debt will be extremely painful. // Negative

The company anticipated its operating profit to improve. //

Circulation revenue has increased by 5% in Finland. // Finance

They defeated ... in the NFC Championship Game. // Sports

Apple ... development of in-house chips. // Tech

The company anticipated its operating profit to improve. // \_\_\_\_\_

![](_page_12_Picture_9.jpeg)

#### **Chain-of-Thought Prompting**

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

#### Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

https://arxiv.org/pdf/2201.11903.pdf http://ai.stanford.edu/blog/understanding-incontext/

# LLM-based Reasoning LLMs can be used as reasoners for evolving cybersecurity issues

![](_page_13_Picture_1.jpeg)

#### Moderating New Waves of Online Hate with Chain-of-Thought Reasoning in Large Language Models

IEEE S&P 2024 ("Oakland"), San Francisco, CA

<u>Nishant Vishwamitra</u><sup>\*</sup>, Keyan Guo<sup>†</sup>, Farhan Tajwar Romit<sup>\*</sup>, Isabelle Ondracek<sup>†</sup>, Long Cheng<sup>‡</sup>, Ziming Zhao<sup>†</sup>, **Hongxin Hu**<sup>†</sup>

![](_page_14_Picture_3.jpeg)

![](_page_14_Picture_4.jpeg)

![](_page_14_Picture_5.jpeg)

#### **New Waves of Online Hate**

- We live in a world with rapidly evolving events
- These rapidly evolving events consequently affect the global digital landscape
  - COVID-19 pandemic
  - 2021 insurrection of the US Capitol
  - 2022 Russian invasion of Ukraine
- Emotions of anger and anxiety, and rhetoric from these events also spill over into our global digital landscape

![](_page_15_Picture_7.jpeg)

![](_page_15_Picture_8.jpeg)

![](_page_15_Picture_9.jpeg)

#### **New Waves of Online Hate**

#### New waves of online hate

![](_page_16_Figure_2.jpeg)

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9168424/

![](_page_16_Picture_4.jpeg)

**UN News** Nations Global perspective Human stories

AUDIO HUB

Violence, rhetoric, hate speech, drive atrocity crimes in Ukraine and beyond, Security Council hears

https://news.un.org/en/story/2022/06/1120972

#### Facebook bungled efforts to curb explosion of hate speech ahead of Capitol attack

Pressure on social network increases as internal documents reveal it fell short in implementing content safeguards

https://www.ft.com/content/abaf9ea7-c5dc-4ba7-8f80-48b488aee5ae

#### Dataset

• X (Twitter) dataset (31,549 tweets)

New Wave Type	Number of hateful tweets	Number of non hateful tweets			
COVID-19 tweets	1,096	1,600			
US Capitol Insurrection tweets	314	390			
Russian Invasion of Ukraine tweets	237	363			
Total tweets	1,647	2,353			

Annotated new wave datasets with 4,000 tweets

#### **Motivation**

• Temporal patterns in usage of hateful hashtags

![](_page_18_Figure_2.jpeg)

As current events evolve, new waves of online hate occur in the global digital landscape

#### **Motivation**

#### Using Existing Tools Against New Waves of Online Hate

Precision	Recall	F1-score
0.69	0.16	0.27
0.49	0.31	0.38
0.54	0.21	0.31
	<b>Precision</b> 0.69 0.49 0.54	Precision         Recall           0.69         0.16           0.49         0.31           0.54         0.21

#### Zero-shot (or few-shot) learning to adapt to rapid changes in concept?

![](_page_19_Figure_4.jpeg)

#### **HateGuard Design**

Reasoning-based decision-making for detection:

![](_page_20_Figure_2.jpeg)

- Learning non-no or lew new samples
  - Updated with *no samples* or *only a few* samples
  - Automatic policy update and zero-shot learning by updating

#### **HateGuard Overview**

![](_page_21_Figure_1.jpeg)

![](_page_22_Figure_1.jpeg)

![](_page_23_Figure_1.jpeg)

- Identity-based hate: targets are based on several *identities*, such as race, nationality, political affiliation, religion, etc
- Hate against individuals: *name* or *username* of the individual is mentioned

![](_page_24_Figure_1.jpeg)

![](_page_25_Figure_1.jpeg)

![](_page_26_Figure_1.jpeg)

![](_page_27_Figure_1.jpeg)

#### **Evaluation**

![](_page_28_Figure_1.jpeg)

Deploying HateGuard in the period of 2020 (COVID-19), 2021 (US Capitol insurrection), and 2022 (Russian invasion) shows that new wave peaks are significantly reduced (green line)

![](_page_29_Figure_0.jpeg)

HateCoT for new waves decision-making (3) compared to traditional RoBERTa hate speech detection model (1) and general prompting (2)

			<u>'O'</u>							0							
	Method —	Qu	Quarter 1 (Jan-Mar)			Quarter 2 (Apr-Jun)			Quarter 3 (Jul-Sep)				Quarter 4 (Oct-Dec)				
Wave Type		# of Tweets	Acc- uracy	Prec- ision	Rec- all	# of Tweets	Acc- uracy	Prec- ision	Rec- all	# of Tweets	Acc- uracy	Prec- ision	Rec- all	# of Tweets	Acc- uracy	Prec- ision	Rec- all
						-	Overall	Results -									
T. (. 1	HATEGUARD		0.95	0.95	0.94		0.94	0.94	0.93		0.94	0.94	0.93		0.94	0.95	0.92
(2020 2022)	BERT-base	928	0.74	0.81	0.34	893	0.82	0.76	0.71	1148	0.84	0.82	0.79	1031	0.83	0.86	0.8
(2020-2022)	Tweet-NLP		0.7	0.73	0.23		0.83	0.79	0.77		0.84	0.83	0.8		0.83	0.84	0.8
						- Ca	tegory-w	ise Resul	ts -								
Ageism (2020)	HATEGUARD		0.94	0.91	0.92		0.95	0.95	0.95		0.95	0.95	0.95		0.95	0.94	0.96
	BERT-base	186	0.82	0.6	0.44	117	0.8	0.68	0.53	114	0.79	0.68	0.6	161	0.74	0.72	0.76
	Tweet-NLP		0.79	0.5	0.15		0.87	0.79	0.72		0.86	0.74	0.83		0.72	0.79	0.57
A	HATEGUARD		0.96	0.96	0.97		0.93	0.93	0.93		0.94	0.95	0.94		0.95	0.94	0.98
Asian (2020)	BERT-base	179	0.68	0.91	0.35	296	0.84	0.79	0.8	331	0.85	0.86	0.87	262	0.87	0.88	0.92
	Tweet-NLP		0.63	0.77	0.29		0.84	0.84	0.72		0.84	0.86	0.84		0.85	0.91	0.86
Mask (2020)	HATEGUARD		0.99	0.99	0.99		0.94	0.96	0.88		0.98	0.95	0.97		0.96	0.97	0.94
	BERT-base	16	0.75	0	0	64	0.79	0.78	0.39	249	0.85	0.75	0.66	199	0.8	0.75	0.86
	Tweet-NLP		0.94	0.67	0.99		0.86	0.85	0.61		0.87	0.75	0.78		0.84	0.8	0.88
Vaccine (2020)	HATEGUARD		0.98	0.99	0.96		0.92	0.9	0.92		0.93	0.93	0.91		0.94	0.95	0.92
	BERT-base	78	0.76	0.92	0.38	114	0.78	0.68	0.7	104	0.85	0.79	0.83	226	0.84	0.75	0.79
	Tweet-NLP		0.72	0.77	0.35		0.75	0.6	0.83		0.8	0.75	0.73		0.88	0.83	0.82
US Capitol (2021)	HATEGUARD		0.91	0.91	0.88		0.99	0.97	0.99		0.9	0.89	0.9		0.9	0.9	0.9
	BERT-base	311	0.68	0.79	0.31	112	0.85	0.85	0.83	158	0.82	0.85	0.76	123	0.84	0.78	0.89
	Tweet-NLP		0.63	0.7	0.16		0.83	0.79	0.87		0.82	0.87	0.72		0.78	0.75	0.79
Russia	HATEGUARD		0.95	0.95	0.93		0.94	0.95	0.92		0.94	0.95	0.93		0.9	0.92	0.9
-Ukraine	BERT-base	158	0.8	0.85	0.37	190	0.8	0.72	0.62	192	0.82	0.82	0.81	60	0.83	0.82	0.87
(2022)	Tweet-NLP		0.77	0.92	0.24		0.84	0.82	0.65		0.86	0.88	0.84		0.85	0.89	0.81

#### **HateGuard Against Evolving Online Hate**

Comparing HateGuard against the existing benchmarks

#### **Conclusion and Future Work**

- Conclusion
  - A large-scale experiment to study the nature of new waves of online hate
  - Examining the capabilities of the existing moderation tools
  - A novel framework to address the problem of new waves of online hate
- Future work
  - Multilingual new waves of online hate
  - Multimodal scenarios, such as hateful memes
  - Auto-prompting methodologies

# Discussion

- LLMs for addressing evolving cyber security issues
  - -Fake news/Disinformation
  - -Zero-day attacks
  - -Phishing attacks
  - -Advanced Persistent Threats

### Discussion

Method	Paper	Source
Chain-of-Thought	Chain-of-Thought Prompting Elicits Reasoning in Large Language Models	NeurIPS 2022
Self-consistency	Self-Consistency Improves Chain of Thought Reasoning in Language Models	ICLR 2023
Least-to-Most	Least-to-Most Prompting Enables Complex Reasoning in Large Language Models	ICLR 2023
Tree of Thought	Tree of Thoughts: Deliberate Problem Solving with Large Language Models	ArXiv 2023
In-Context Learning	Teaching Algorithmic Reasoning via In-context Learning	NeurIPS 2022
Analogical Prompting	Large Language Models as Analogical Reasoners	ArXiv 2023
PromptBreeder	Promptbreeder: Self-Referential Self-Improvement Via Prompt Evolution	ArXiv 2023
Autoprompt	AUTOPROMPT: Eliciting Knowledge from Language Models with Automatically Generated Prompts	EMNLP 2020

#### Thank you !

![](_page_34_Picture_1.jpeg)

![](_page_34_Picture_2.jpeg)

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![](_page_34_Picture_4.jpeg)

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![](_page_34_Picture_6.jpeg)

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