# AI가 변화시킬 보안의 미래

KAIST 윤인수



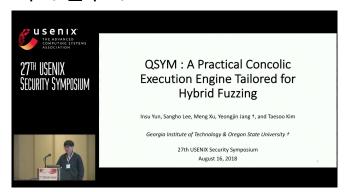
## 자기소개

### ● 해커



- o KAIST GoN 회장 (2010)
- o DEFCON CTF 우승 (2015, 2018)
- o Pwn20wn 우승 (2020)

### • 학계 연구자



- 다수의 탑티어 보안 논문 개제
- Usenix Security & OSDI 최우수 논문상
   (2018)
- KAIST 조교수, 부교수 (2021-)

# 발표 내용

- LLM의 발전
- LLM의 영향
  - LLM의 긍정적인 면: 업무 자동화
  - LLM의 부정적인 면: 프롬프트 인젝션
- LLM에 대한 대응 (조직)
- LLM에 대한 대응 (개인)

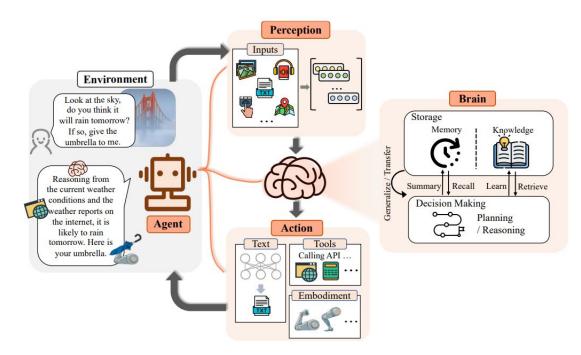
# Large Language Model (LLM)

- 생성형 AI: 데이터로 학습하여 새로운 컨텐츠를 만들어내는 기능을 가진 AI
- LLM (Large Language Model): 대규모의 언어를 학습하여 인간의 언어를 이해하고 생성하는데 사용



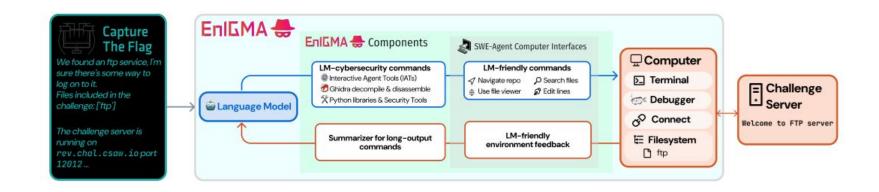
# LLM Agent

• LLM을 기반으로 자율적으로 동작하는 AI 시스템



LLM의 발전 (1년 전)

## 예: EnIGMA: Enhanced Interactive Generative Model Agent for CTF Challenges



	% Solved	Avg. Cost
NYU CTF [51]		
EnIGMA w/ Claude 3.5 Sonnet	13.5	\$0.35
EnIGMA w/ GPT-4 Turbo	7.0	\$0.79
EnIGMA w/ GPT-4o	9.0	\$0.62
NYU CTF agent [51] (previous best)	4.0	-
InterCode-CTF [62]		
EnIGMA w/ Claude 3.5 Sonnet	67.0	\$0.24
EnIGMA w/ GPT-4 Turbo	72.0	\$0.53
EnIGMA w/ GPT-40	69.0	\$0.47
InterCode-CTF agent [62] (prev. best)	40.0	-
Google DeepMind agent [43]	24.0*	-
HTB (collected by us)		
EnIGMA w/ Claude 3.5 Sonnet	26.0	\$0.53
EnIGMA w/ GPT-4 Turbo	18.0	\$1.35
EnIGMA w/ GPT-4o	16.0	\$1.71
NYU CTF agent [51] w/ GPT-4 Turbo	20.0	_

Event	# Teams	# CTFs	Mean	Median	GPT 3.5 Score	GPT 4 Score	Claude 3
Qual'23	1176	26	587	225	0	300	0
Final'23	51	30	1433	945	0	0	0
Qual'22	884	29	852	884	500	0	500
Final'22	53	26	1773	1321	1000	0	1500

Table 5: Human Participants in CSAW 2022 and 2023 vs. LLMs.

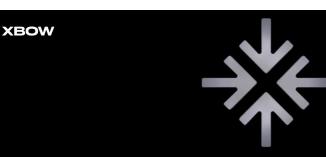
### 예: Google's naptime

• 구글에서 만든 LLM을 사용한 취약점 탐지 도구

### Conclusions

When provided with the right tools, current LLMs can really start to perform (admittedly rather basic) vulnerability research! However, there's a large difference between solving isolated CTF-style challenges without ambiguity (there's always a bug, you always reach it by providing command line input, etc.) and performing autonomous offensive security research. As we've said many times - a large part of security research is finding the right places to look, and understanding (in a large and complex system) what kinds c control an attacker might have over the system state. Isolated challenges do not reflect these areas of complexity; solving these challenges is closer to the typical usage of targeted, domain-specific fuzzing performed as part of a manual review workflow than a fully autonomous researcher.

# 예: XBOW



**Boosting offensive security with Al** 

XBOW autonomously finds and exploits vulnerabilities in 75% of web benchmarks

**75%** PortSwigger Labs solved

72%

PentesterLab Exercises solved

78%

Join Waitlist

Novel Benchmarks solved

		Reputation	Signal (i)	Impact ①
<b>^</b> 1.	ace_mccloud	1593	7.00	26.67
<b>^</b> 2.	dgrindle	1164	7.00	35.47
<b>^</b> 3.	archangel	871	7.00	16.18
<b>4</b> .	stealthy	760	7.00	21.19
<b>^</b> 5.	aiqitut	732	7.00	36.67
▲ 5. ⓒ	8910jq	732	7.00	20.37
<b>▼</b> 7.	r3aper	689	6.76	25.71
▼ 8.	iqimpz	564	7.00	40.83
<b>9</b> .	mlitchfield	559	7.00	32.00
<b>10.</b> 2	7urb0	545	7.00	25.88
<b>^</b> 11.	<b>←</b> xbow	481	7.00	29.00

# 컴퓨터 해커?



### Levels of AGI

Performance (rows) x	Narrow	General
Generality (columns)	clearly scoped task or set of tasks	wide range of non-physical tasks,
		including metacognitive abilities
		like learning new skills
Level 0: No AI	Narrow Non-AI	General Non-AI
	calculator software; compiler	human-in-the-loop computing,
		e.g., Amazon Mechanical Turk
Level 1: Emerging	Emerging Narrow AI	Emerging AGI
equal to or somewhat better than	GOFAI <sup>4</sup> ; simple rule-based sys-	ChatGPT (OpenAI, 2023), Bard
an unskilled human	tems, e.g., SHRDLU (Winograd,	(Anil et al., 2023), Llama 2
	1971)	(Touvron et al., 2023)
Level 2: Competent	Competent Narrow AI	Competent AGI
at least 50th percentile of skilled	toxicity detectors such as Jig-	not yet achieved
adults	saw (Das et al., 2022); Smart	3277
	Speakers such as Siri (Apple),	
	Alexa (Amazon), or Google As-	
	sistant (Google); VQA systems	
	such as PaLI (Chen et al., 2023);	
	Watson (IBM); SOTA LLMs for a	
	subset of tasks (e.g., short essay	
	writing, simple coding)	
Level 3: Expert	Expert Narrow AI	Expert AGI
at least 90th percentile of skilled	spelling & grammar checkers	not yet achieved
adults	such as Grammarly (Gram-	
	marly, 2023); generative im-	
	age models such as Imagen (Sa-	
	haria et al., 2022) or Dall-E 2	
	(Ramesh et al., 2022)	
Level 4: Virtuoso	Virtuoso Narrow AI	Virtuoso AGI
at least 99th percentile of skilled	Deep Blue (Campbell et al.,	not yet achieved
adults	2002), AlphaGo (Silver et al.,	•
	2016, 2017)	
Level 5: Superhuman	Superhuman Narrow AI	Artificial Superintelligence
outperforms 100% of humans	AlphaFold (Jumper et al., 2021;	(ASI)
*	Varadi et al., 2021), AlphaZero	not yet achieved
	(Silver et al., 2018), StockFish	•
	(Stockfish, 2023)	
	()	

현재: LLM의 발전 (1년 후)

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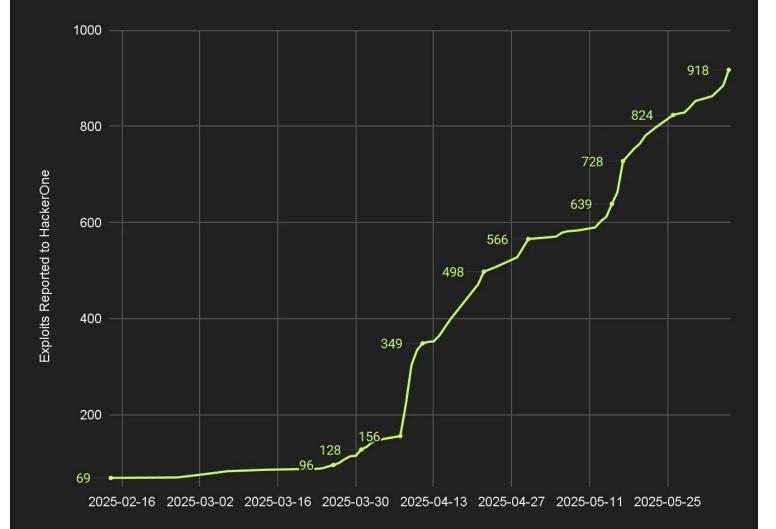
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# Today's XBOW

 For the first time in bug bounty history, an autonomous penetration tester has reached the top spot on the US leaderboard.





### 예: Google's naptime

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## GOOGLE FIXED CHROME FLAW FOUND BY BIG SLEEP AI

August 20, 2025



# Google Chrome 139 addressed a high-severity V8 flaw, tracked as CVE-2025-9132, found by Big Sleep AI

Google Chrome 139 addressed a high-severity vulnerability, tracked as CVE-2025-9132, in its open source high-performance JavaScript and WebAssembly engine V8.

# 컴퓨터 해커?



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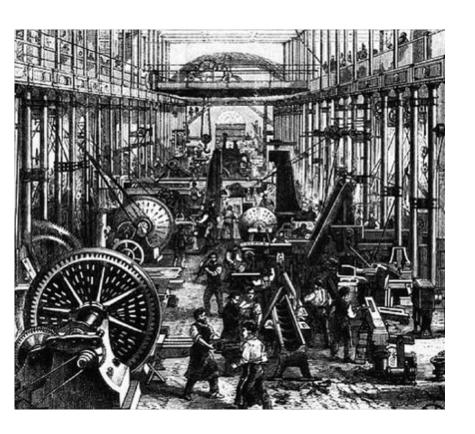
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	(Stockfish, 2023)	

## 18세기 산업혁명 vs 21세기...?





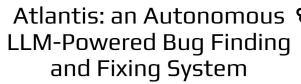


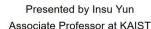




# LLM의 영향

# Bright & Dark





Slides from Taesoo Kim
Professor at Georgia Tech & VP at Samsung Research



Samsung Research



POSTECH





Eunkyu Lee, Donghyun Kim, Wonyoung Kim, Insu Yun

KAIST

Under review



**KAIST Hacking Lab** 

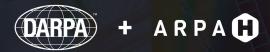
# Atlantis: an Autonomous LLM-Powered Bug Finding and Fixing System

Presented by Insu Yun Associate Professor at KAIST

Slides from Taesoo Kim Professor at Georgia Tech & VP at Samsung Research











# WHAT IS AIXCC?

- → A competition that rewards autonomous systems that find and patch vulnerabilities in source code.
- → The challenges are well-known open-source projects.
- → The vulnerabilities are realistic or real.
- → Patching is worth more than finding.
- → Code and data will be released open source.



Preliminary events



Top 7 teams advance





**AUGUST 2023** 

OPEN TRACK AND
SMALL BUSINESS TRACK
SUBMISSIONS



AUGUST 2024

SEMIFINAL COMPETITION

Top 7 teams \$2 million each



**AUGUST 2025** 

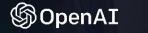
FINAL COMPETITION

Winners announced

1ST: \$4 MILLION 2ND: \$3 MILLION 3RD: \$1.5 MILLION













### What counts for semifinals?





### **Proof-Of-Vulnerability (POV)**

→ Input data to reproduce vulnerability crash in harness

### **PATCH**

→ Unified diff source code fix for vulnerabilities

### What counts for finals?





### **Proof-Of-Vulnerability (POV)**

→ Input data to reproduce vulnerability crash in harness



→ Unified diff source code fix for vulnerabilities



# Archives: 1 Folders: 0 Files: 15 Size: 7108839 (6 MB) Compressed size: 1290263 (1 MB) There are no errors

### **SARIF Assessment**

→ Structured reporting format for vulnerability details

#### **BUNDLE**

→ Grouping of related PoV, patch, and SARIF submissions

### **DELTA SCAN**

→ Challenge analyzing base code plus applied diff changes

```
return $\frac{1}{2}\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi}_{\tilde{\psi
```

### **FULL SCAN**

→ Challenge analyzing entire code base



# **CONGRATULATIONS TO TEAM**



**Atlanta** 

# 1st PLACE







ARPA

### **Semifinal**

Found in C

1

Found in Java

0

### **Final**

Found in C

(1 replay - SystemD)

Found in Java

12

Patched in C

0

Patched in Java

11

(3 w/o PoV)

\* More information pending disclosure completion

## TL;DR.

Visit our team website for more information:

https://team-atlanta.github.io/

Blog: <a href="https://team-atlanta.github.io/blog/">https://team-atlanta.github.io/blog/</a>

Repo: Team-Atlanta/aixcc-afc-atlantis

We will release a Technical Report (very soon)!

### **Recently released:**









LLMs improve ridiculously fast, and scary exciting for security researchers!

# Takedown: How It's Done in Modern Coding Agent Exploits

Eunkyu Lee, Donghyun Kim, Wonyoung Kim, Insu Yun

KAIST

Under review



KAIST Hacking Lab

# LLM의 보편화





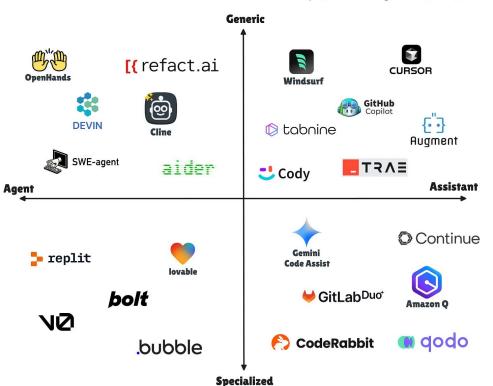




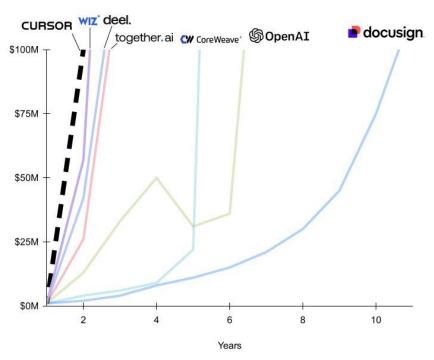
Ask anything with Al Mode

### Al Coding Assistants Landscape

https://GenerativeProgrammer.com 03/2025







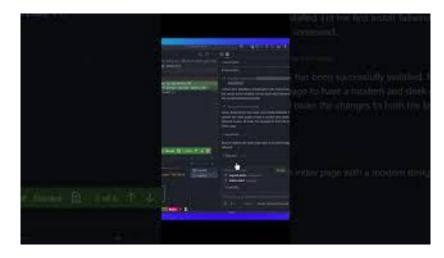
# 코드 완성에서 에이전트로

코드 완성 (Code completion)

```
You, 9 seconds ago - 1 Author (You) 0 implementations
pub struct EncodedMessageQueue {
pub queue: Vec<(EncodedMessage, ClientFilter)>,
sender: Arc<Sender<Vec<(EncodedMessage, ClientFilter)>>,
receiver: Arc<Receiver<Vec<(EncodedMessage, ClientFilter)>>>,
}

impl EncodedMessageQueue { You, 8 seconds ago - Uncommitted changes
pub fin new() -> Self {
    let (sender, receiver) = crossbeam_channel::unbounded();
    Self {
        queue: vec![],
        sender: Arc::new(sender),
        receiver: Arc::new(receiver),
    }
}
```

● 에이전트 모드





#### 프롬프트 인젝션

- 악의적인 입력이 프롬프트에 삽입되어 AI의 동작을 조작하는 공격
  - 데이터베이스에서의 SQL 인젝션과 유사
- 프롬프트 인젝션의 종류
  - 직접적 프롬프트 인젝션 (Direct Prompt Injection): 프롬프트 자체를 조작할 수 있는 경우
  - 간적접 프롬프트 인젝션 (Indirect Prompt Injection): 악의적인 프롬프트가 외부 데이터에 숨겨져 있는 경우 (예: 문서, 웹페이지)

# 발생 원인: 데이터와 코드의 구분이 미비



PROJECTS CHAPTERS EVENTS ABOUT Q

#### **Code Injection**

Author: Weilin Zhong, Rezos

Contributor(s): OWASP, Thandermax, Csa, KristenS, Wichers, Neil Bergman, Camilo, Andrew Smith, kingthorin

#### Description

Code Injection is the general term for attack types which consist of injecting code that is then interpreted/executed by the application. This type of attack exploits poor handling of untrusted data. These types of attacks are usually made possible due to a lack of proper input/output data validation, for example:

- · allowed characters (standard regular expressions classes or custom)
- · data format
- · amount of expected data

[Submitted on 11 Mar 2024 (v1), last revised 31 Jan 2025 (this version, v3)]

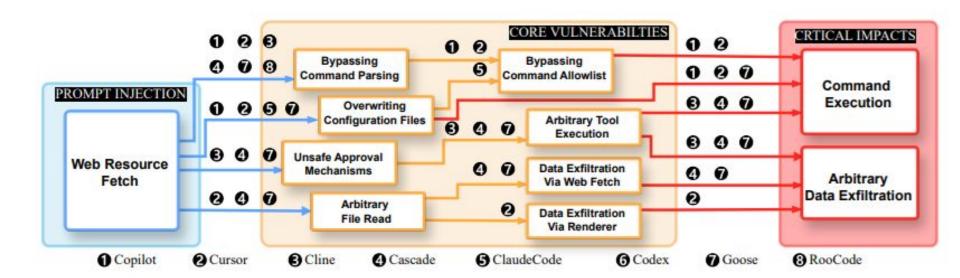
Can LLMs Separate Instructions From Data? And What Do We Even Mean By That?

Egor Zverev, Sahar Abdelnabi, Soroush Tabesh, Mario Fritz, Christoph H. Lampert

#### **DEMO**



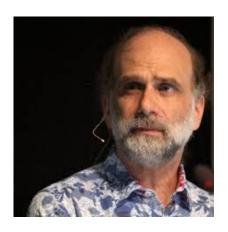
#### 요약



#### 더 많은 문제들...

**People often represent the weakest link** in the security chain and are chronically responsible for the failure of security systems."

Bruce Schneier



```
12
         "permissions": {
13
           "allow": [
14
             "Bash(git add:*)",
             "Bash(git reset:*)",
15
16
             "Bash(find:*)",
             "Bash(rg:*)",
17
             "Bash(echo:*)",
18
             "Bash(grep:*)",
19
20
             "Bash(ls:*)",
```

```
insu ~ $ find _ -name \* -exec sh -c 'sh' {} \;
```

LLM에 대한 대응 (조직)

### LLM의 도입





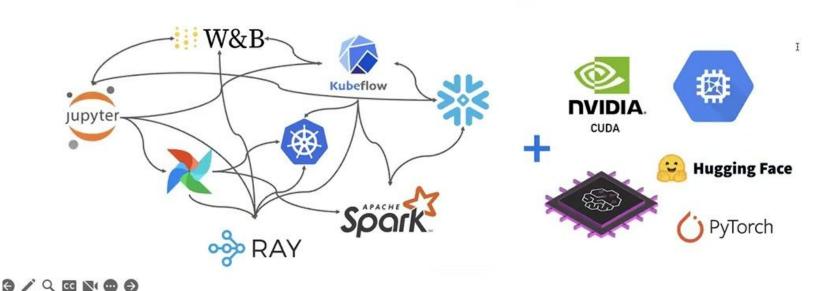
현재 LLM을 조직 내에서 사용하지 않고 있다면 -> 이미 너무 늦음

#### 공격에서의 LLM 활용

- State-sponsored actors including from North Korea, Iran, and the People's Republic of China (PRC) continue to misuse Gemini to enhance all stages of their operations, from reconnaissance and phishing lure creation to command and control (C2) development and data exfiltration.
  - o Google, GTIG AI Threat Tracker: Advances in Threat Actor Usage of AI Tools
- The operation targeted large tech companies, financial institutions, chemical manufacturing companies, and government agencies. We believe this is the first documented case of a large-scale cyberattack executed without substantial human intervention.
  - Antropic, Disrupting the first reported AI-orchestrated cyber espionage campaign

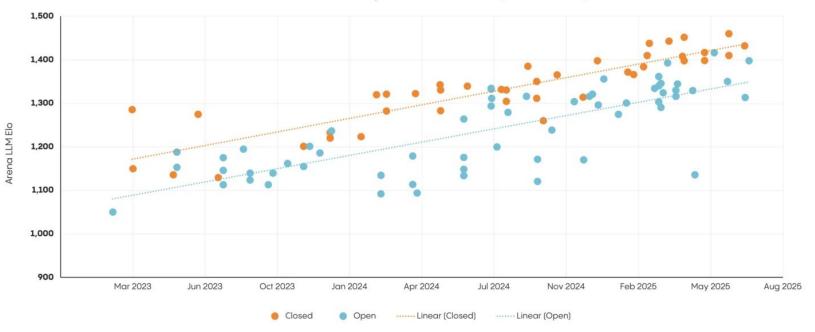
# ... and LLMs only make things that much more complicated.

Because managing LLM environments requires yet more libraries, infrastructure, and specialized hardware.



#### **Closed-Source vs. Open-Source Models**

#### Closed-Source vs. Open-Source Models (LMArena Elo)



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AI 기업과의 협력

ANTHROP\C



## 외부와의 연결

#### 국가망보안체계(N2SF)란 무엇인가?

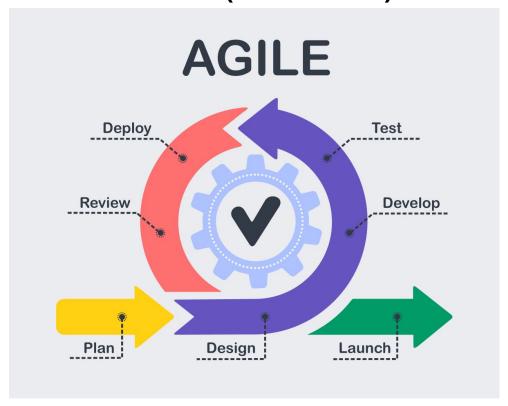




## 보안은 일순위가 아니다.

만약 보안이 정말 일순위라면, **우리는 아무 일도 하지 않는 것이 가장 안전한 길**일 것입니다. "Hello World 프로그램이 가장 보안적으로 안전하다"라는 우스운 말처럼, 아무것도 하지 않으면 공격받을 일도 없습니다. ... 그래서 저는 보안이 업무의 '우위'에 있는 것이 아니라, **업무와 항상 공동 1등**이 되어야 한다고 생각합니다. ...최근 빠르게 발전하고 있는 AI 혁명을 바라보면서, 우리나라의 **많은 기관과 기업들이 AI 도입을 주저하는 가장 큰** 이유 중 하나가 '보안'이라는 사실이 아쉽습니다. ... 우리는 보안이라는 비용을 감수하면서도 업무 효율성을 극대화할 수 있는 AI 도입 방법에 대해 **진지하게 고민**해야 합니다. ...

#### 소프트웨어 공학에서 복잡성 (Complexity)를 다루는 방법: 반복 (Iteration)



- 변화하기 쉬운 구조 유지
  - o 분할 (Decomposition)
  - 추상화 (Abstraction)
  - o 모듈화 (Modularization)
- 반복(Iteration)적 개선
  - "작은 단계로 점진적으로 시스템을 완성해 나가는 개발 방식"
  - 초기 완벽을 추구하지 않고,
  - 점진적으로 개선, 수정, 확장
  - 리스크를 조기에 식별하고 관리
  - 복잡성을 단계별로 분해 및 대응

## 고급 해커들의 필요성 증대









#### 고급 인력의 양성





#### KAIST Graduate School of Information Security





## 고급 인력들의 고용



LLM에 대한 대응 (개인)

# 1000x Engineer



# 인간 vs AI







# 인간 vs AI





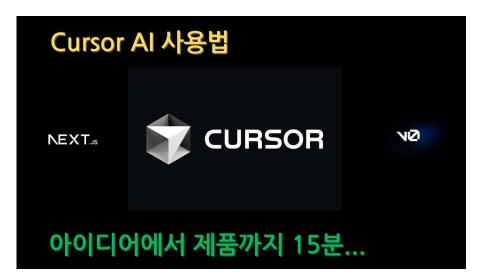


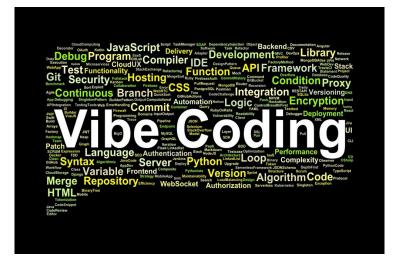
# 프롬프트 엔지니어링

챗GPT, 바드, 빙, 하이퍼클로바X까지 한 권으로 끝내기



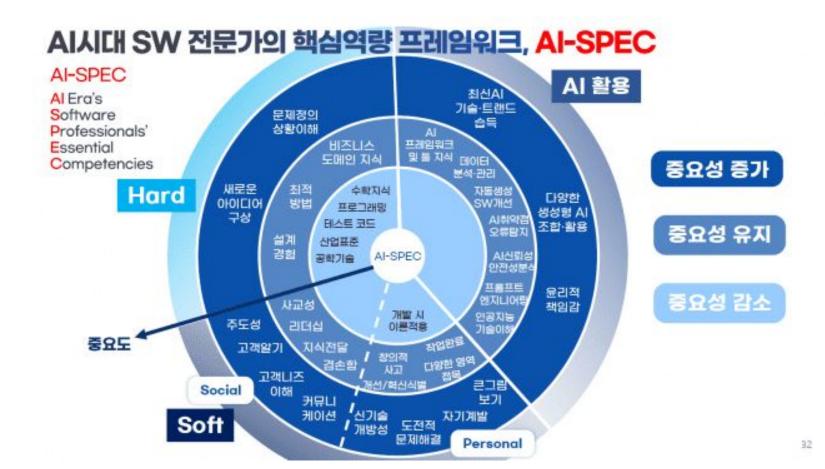
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## AI 시대에도 화이트햇 해커가 필요한 이유 (by 엔키 화이트햇)

비교 항목	AI	화이트햇 해커
공격 방식	기존 알려진 공격 패턴만 학습하여 활용	새로운 공격 벡터를 창의적으로 탐색
데이터 활용	과거 데이터에 의존하여 패턴 기반 탐지	과거 데이터뿐만 아니라 실시간 분석과 직관 활용
적응력	학습된 환경에서만 효과적이며 새로운 환경에서는 어려움	새로운 환경에서도 창의적 접근을 통해 적응
창의적 사고	창의적인 사고 없이 데이터 패턴을 기반으로 분석	발상의 전환과 직관적 사고를 활용하여 보안 취약점 탐색
새로운 공격 기법 개발	새로운 공격 기법을 스스로 창출하지 못함	기존에 없던 새로운 공격 방법 개발 가능
예측 불가능한 공격 대응	예측 불가능한 공격에 대해 즉각적인 대응 어려움	실시간으로 예상치 못한 공격에도 즉각 대응 가능
자동화 가능성	단순 반복 작업 및 대량 분석에는 강점	자동화가 어려운 창의적 전략 수립 가능



## 결론

- LLM의 발전
- LLM의 영향
  - LLM의 긍정적인 면: 업무 자동화
  - LLM의 부정적인 면: 프롬프트 인젝션
- LLM에 대한 대응 (조직)
- LLM에 대한 대응 (개인)

감사합니다