University of Piraeus MSc Cybersecurity & Data Science

How AI is transforming Cybersecurity

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>whoami.

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- 15+ years of experience as a product leader and analytics expert in startups and NASDAQ-listed companies in the US and Greece
- 8 years of experience in applying analytics to prevent financial crime and ad fraud

Studies

- PhD (2009), Data Warehousing & Mining Techniques for MOD, University of Piraeus
- MSc (2004), Information Systems Engineering, UMIST
- o BSc (2003), Informatics, University of Piraeus

Cybersecurity in the Al era.

New technologies like AI, IoT, cloud computing, and microservices create great opportunities to deliver business transformation. At the same time, they also create significant new challenges for security teams. Let's focus on AI:

- Attackers use AI for nefarious purposes
- Security teams leverage AI to enhance defense systems
- Al-powered systems need to be protected

Offensive Al.

- Attackers begin to use ML and other AI techniques to power their attacks: phishing, deepfakes, discovery of new vulnerabilities, design of new payloads, evasion, etc.
- Researchers have started to use some curation on Al publications and code because of the potential use for malicious activity
 - OpenAl initially withheld the full version of GPT-2, a text-generation system that has the ability to generate coherent text from minimal prompts, as it could be used for malicious purposes

Offensive Al.

MIT Technology Review (2021): 96% of C-level executives said they are preparing for Al-based cyberattacks, 68% expect to see Al used to impersonate humans and launch spear phishing attacks.



- Cyxtera (2018): built an ML-based phishing attack generator that trained on more than 100 million historic attacks to optimize and automatically generate effective scam links and emails.
 - They we able to bypass an AI-based detection system 15% of the time,
 whereas traditional approaches achieved this only 0.3% of the time.

Defensive Al.

- Security techniques evolve from rule-based only to AI and ML-based that augment security analysts
- Model-driven security and real-time data streaming to match data attributes to known patterns resulting in deviation scores with a threshold that trigger automated actions in front-line cyber controls in milliseconds
- Supervised, unsupervised, and reinforcement learning can be successfully used in security today to detect malware, phishing, network anomalies, unauthorized access of sensitive data, user behavior analytics, vulnerability prioritization etc

Use case: Payment fraud.

Objective: prevent fraudsters from draining clients' bank accounts.

| Legacy systems | Fraud prevention in the Al-era | | | |
|------------------------------|-------------------------------------------------|--|--|--|
| Simple scorecards based on | Machine Learning models that take into account: | | | |
| accumulated domain knowledge | Device fingerprinting | | | |
| | Extended client profiles | | | |
| | Recent transactions and account services | | | |
| Tuned once a year | Models trained once a day or even several times | | | |
| | per day | | | |

Use case: Ad fraud.

Objective: prevent wasted media spend



Source: Integral Ad Science

Use case: Ad fraud.

Prevention techniques have evolved from rule-based to:

- Browser and device analysis
 - Machine learning allows us to identify fraudulent activity by matching browser features to the user agent.
- Behavioral and network analysis
 - Distinguish real user behavior from bot behavior by looking at anomalies within site visitation patterns.
 - Cohorts of bots tend to visit the same cluster of domains over and over because their behavior is automated.

Al-Powered Systems are vulnerable.

- There are a growing number of vulnerabilities in ML, and its use increases the attack surface of existing systems.
- Data Scientists should be aware of the potential risks associated with AI-Powered systems, and put in place systems for cross-checking and verifying information
- Prevention:
 - Adversarial training
 - Switching models
 - Generalized models

Gartner: Through
2022, 30% of all Al
cyberattacks will
leverage training-data
poisoning, Al model
theft or adversarial
samples to attack
Al-powered systems.

The MITRE ATLAS matrix.

Adversarial Threat Landscape for Al Systems

| Reconnaissance 2 techniques | Resource Development 6 techniques | Initial Access 1 technique | ML Model Access 4 techniques | Execution 1 technique | Persistence 2 techniques | Defense Evasion 1 technique | Discovery 3 techniques | Collection 1 technique | ML Attack Staging 5 techniques | Exfiltration 1 technique | Impact 6 techniques |
|----------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------|-----------------------------------------------|-----------------------------------|------------------------------------------------------------------------------------------------|---------------------------|-------------------------------------------------------------------------------------------------------------------------|-----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------|
| Search for Victim's Publicly Available Research Materials Search for Publicly Available Adversarial Vulnerability Analysis | Acquire Public ML Artifacts Obtain Capabilities: Adversarial ML Attack Implementations Develop Capabilities: Adversarial ML Attack Implementations Acquire Infrastructure: Attack Development and Staging Workspaces Publish Poisoned Datasets Poison Training Data | ML Supply Chain Compromise | ML Model Inference API Access ML-Enabled Product or Service Physical Environment Access Full ML Model Access | User Execution: Unsafe ML Artifacts | Poison Training Data Poison ML Model | Evade ML Model | Discover ML Model Ontology Discover ML Model Family Discover ML Artifacts | ML Artifact Collection | Train Proxy ML Model Replicate ML Model Poison ML Model Verify Attack Craft Adversarial Data | Exfiltration via ML Inference API | Evade ML Model Denial of ML Service Spamming ML System with Chaff Data Erode ML Model Integrity Cost Harvesting ML Intellectual Property Theft |



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Thank you!

Appendix

INFOSEC WHEEL

