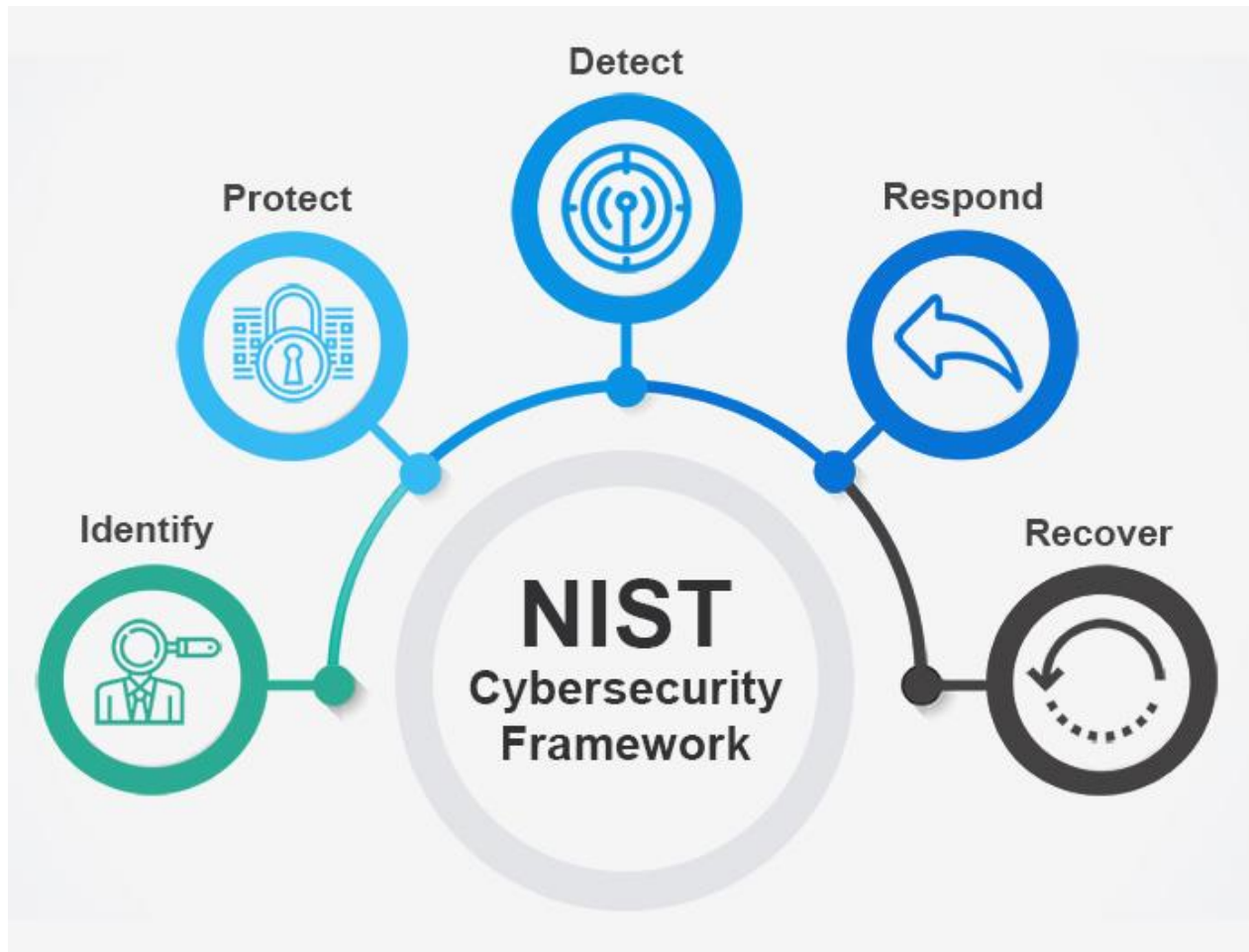


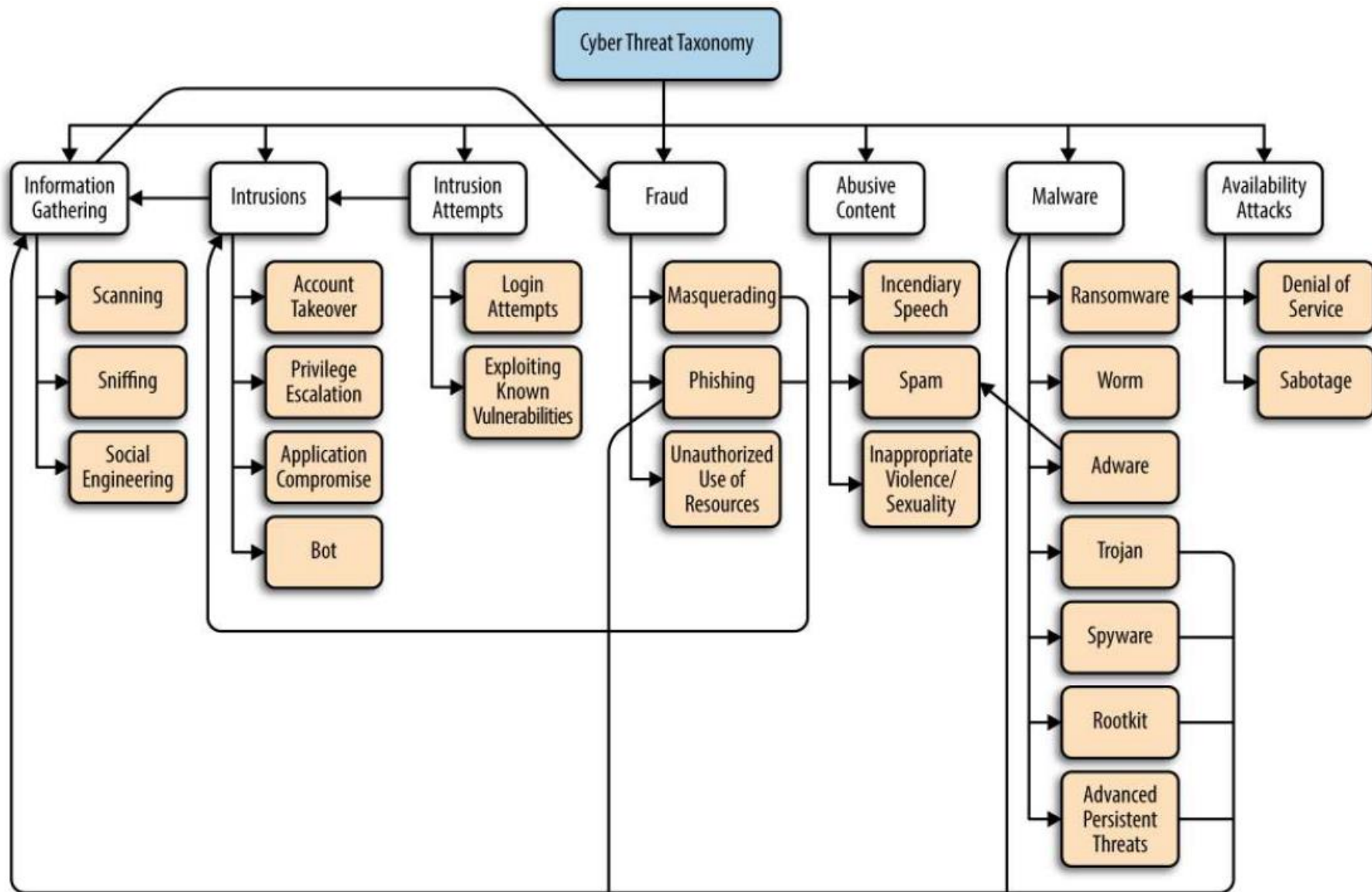
Machine learning and Applications in Cyber Security

Cyber Security



Cyber Security

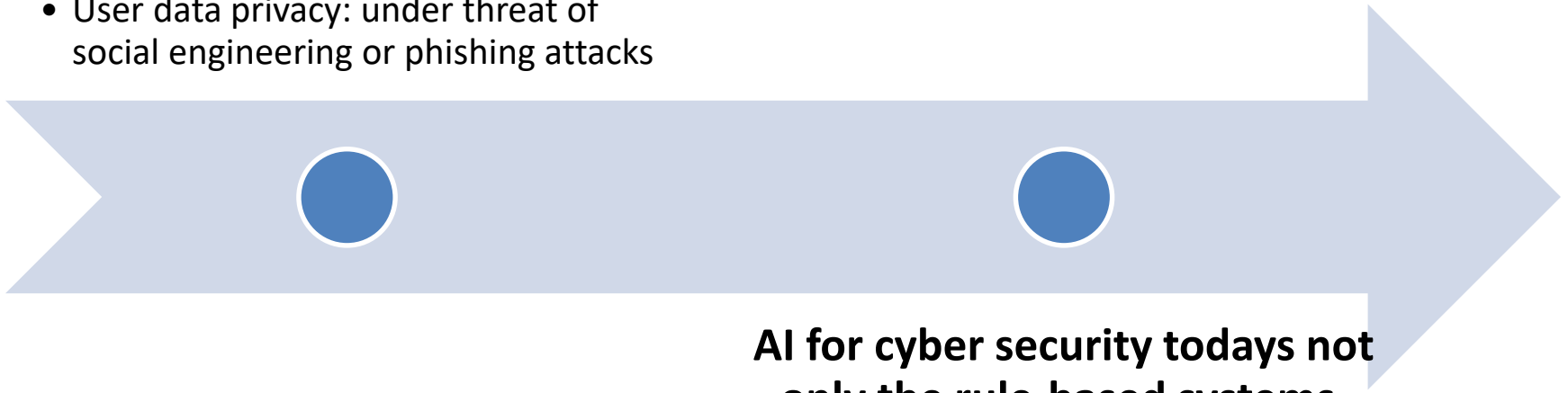




AI in Cyber Security

Threat landscape:

- Changing very fast with billions of connected devices around the world
- Massive, largely automated botnets infecting consumer devices
- User data privacy: under threat of social engineering or phishing attacks

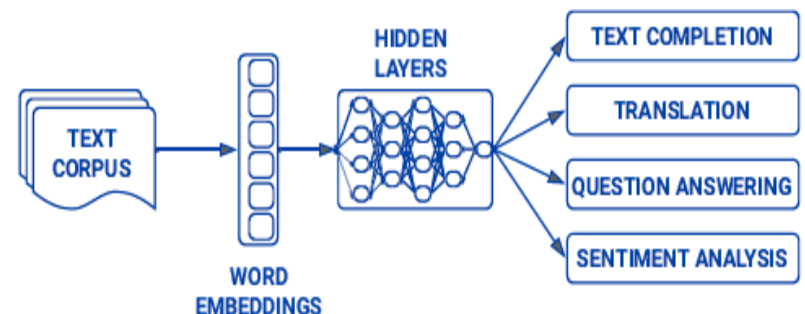
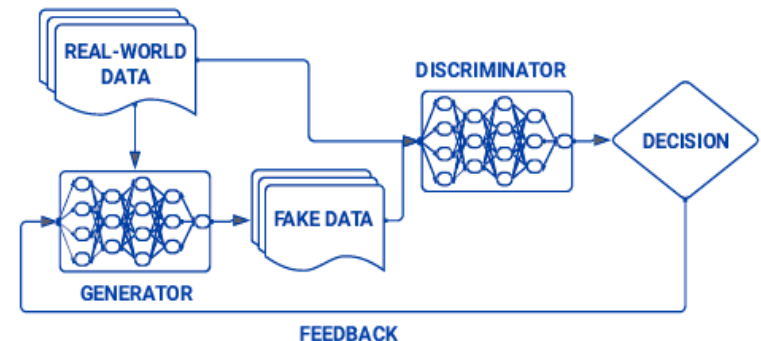
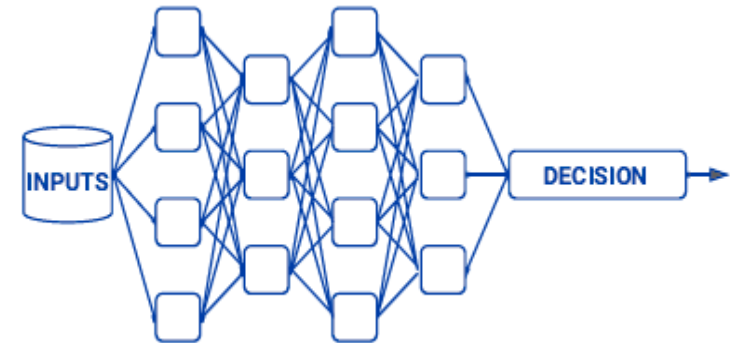


AI for cyber security today's not only the rule-based systems, but also ML- based ones

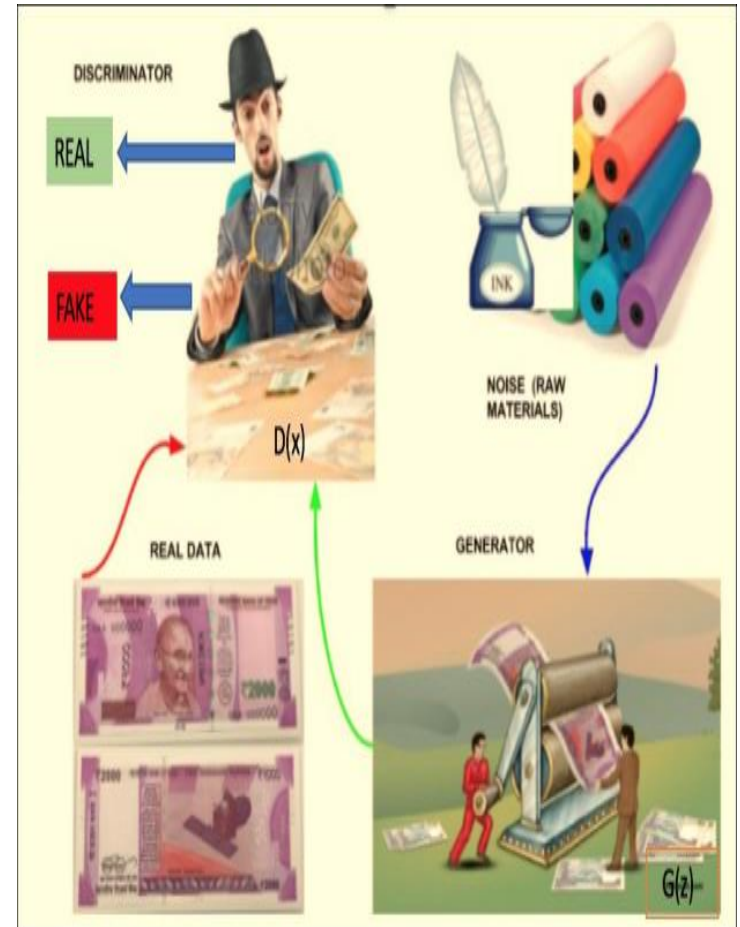
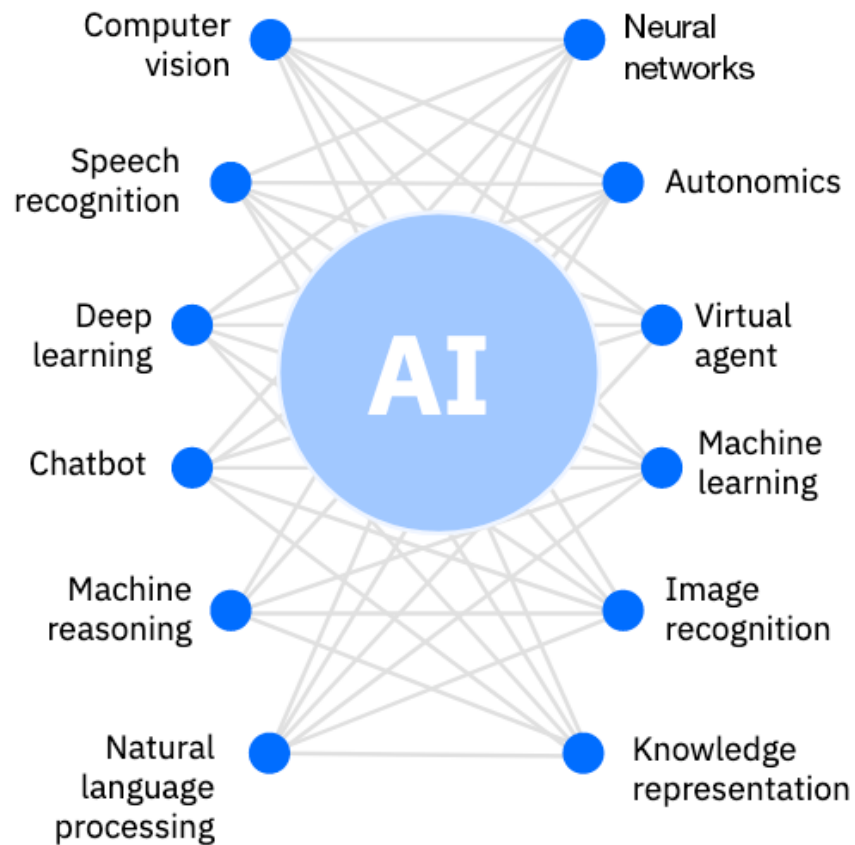
Main categories: Pattern recognition and Classification

AI in Cyber Security

- 1. Spam mail and phishing page detection
- 2. Anomaly detection
- 3. DoS and DDoS attack detection
- 4. Malware detection and identification
- 5. Detection of advanced persistent threats
- 6. Detection of information leakage
- 7. Detection of hidden channels
- 8. Detection of software vulnerabilities.
- 9. Biometric recognition
- 10. User identification and authentication
- 11. Detection of identity theft
- 12. Social media analytics



AI: Cutting Edges



AI in Cyber Security

	Pre-1990s	1990s	2000s	2010s
SPAM DETECTION	1978: First spam email	Spam continues to worsen due to growth in email 1996: First spam blockers	2002: Machine learning methods first proposed for spam detection 2003: First attempts to regulate spam in the United States	Machine learning spam detection widely embedded in email services Emergence of deep learning-based classifiers
INTRUSION DETECTION	1980: First intrusion detection systems 1986: Anomaly detection systems combine expert rules and statistical analysis	Early 1990s: Neural networks for anomaly detection first proposed 1999: DARPA creates datasets to study intrusion detection systems	Machine learning further studied as a possible tool for misuse-based and anomaly-based intrusion detection	Late 2010s: Emergence of large-scale, cloud-based intrusion detection systems Deep learning studied for intrusion detection
MALWARE DETECTION	Early 1980s: First viruses found "in the wild" Late 1980s: First antivirus companies founded	Early 1990s: First polymorphic viruses 1996: IBM begins studying machine learning for malware detection	Early 2000s: First metamorphic viruses Wide number of traditional machine learning methods studied to detect malware	Rise of "next-gen" antivirus detection Emergence of ML-focused antivirus companies

AI in Cyber Security

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AI to power spam-prevention technology

Today, Google uses TensorFlow to block **100 million spam emails a day**. The use of machine learning means that there's a transition from pattern recognition in spam emails to self-learning and optimizing systems.

AI in Cyber Security

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AI in Cyber Security

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Example: Spam detection

the Spam Detection Rate (SDR) and the False Alarm Rate (FAR) seems to be most obvious criteria to measure the effectiveness of a spam detection resolution.

The final purpose of any Anti-Spam approach is to maximize the SDR and to minimize the FAR as much as possible.



[Knowledge and Systems Engineering](#) pp 211–221 | [Cite as](#)

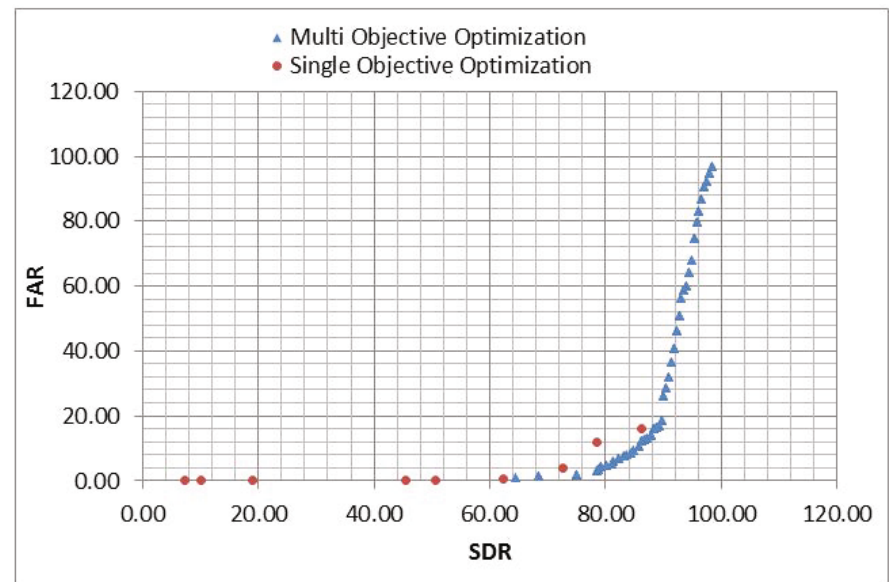
A Multi-objective Approach for Vietnamese Spam Detection

[Minh Tuan Vu](#) , [Quang Anh Tran](#), [Quang Minh Ha](#) & [Lam Thu Bui](#)

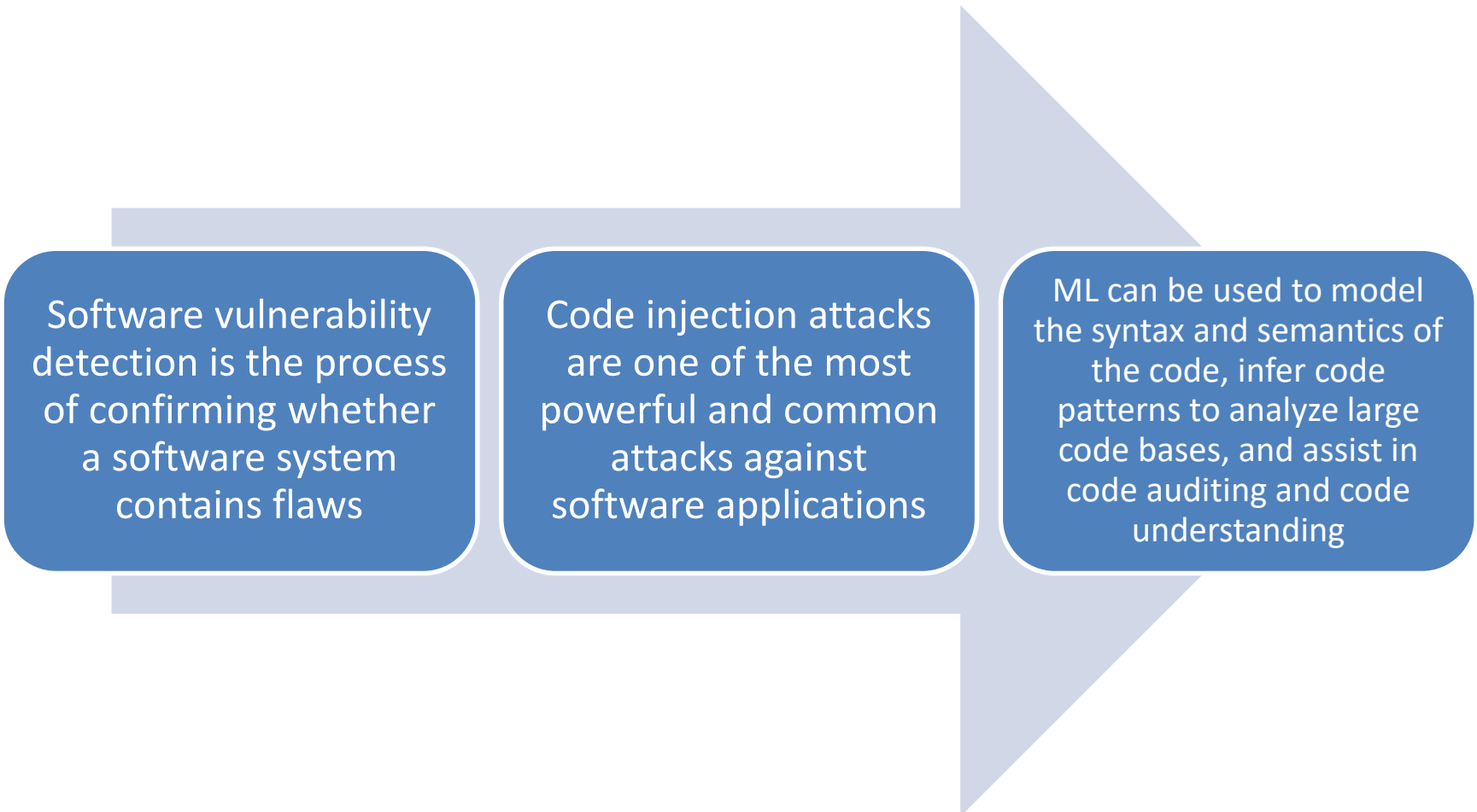
Conference paper

959 Accesses

Part of the [Advances in Intelligent Systems and Computing](#) book series (AISC, volume 245)



Example: Detection of software vulnerabilities

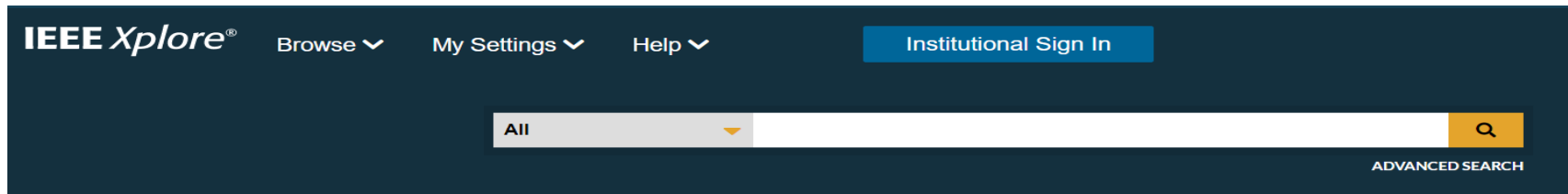


Software vulnerability detection is the process of confirming whether a software system contains flaws

Code injection attacks are one of the most powerful and common attacks against software applications

ML can be used to model the syntax and semantics of the code, infer code patterns to analyze large code bases, and assist in code auditing and code understanding

Example: Detection of software vulnerabilities



Conferences > 2017 IEEE 29th International ... ?

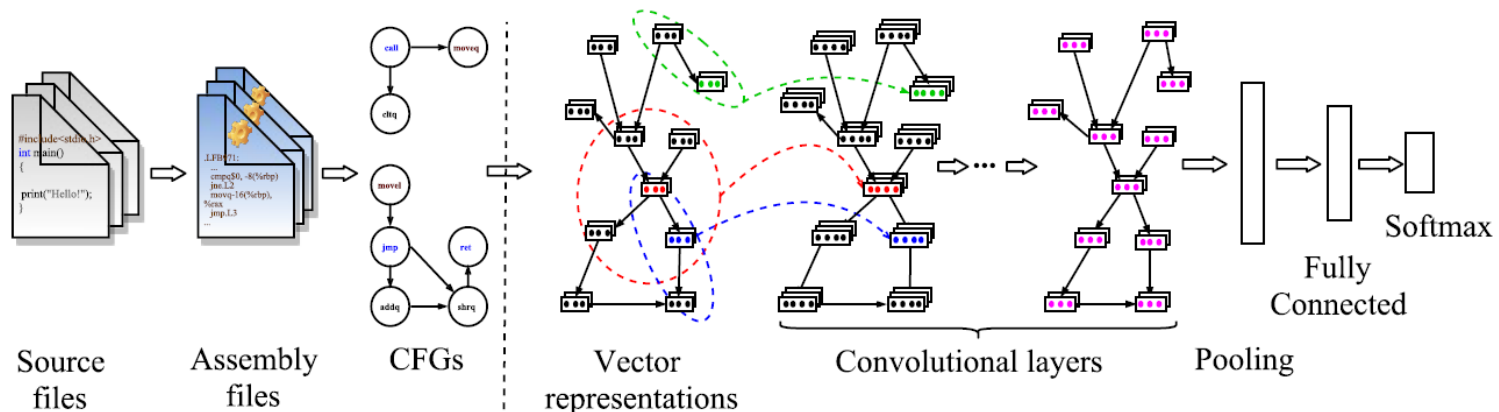
Convolutional Neural Networks over Control Flow Graphs for Software Defect Prediction

Publisher: IEEE

[Cite This](#)

[PDF](#)

Anh Viet Phan ; Minh Le Nguyen ; Lam Thu Bui [All Authors](#)



(a) Building Control Flow Graphs

(b) The convolutional neural network on directed graphs

Fig. 3: The overview of our approaches for software defect prediction using convolutional neural networks on Control Flow Graphs of assembly code.

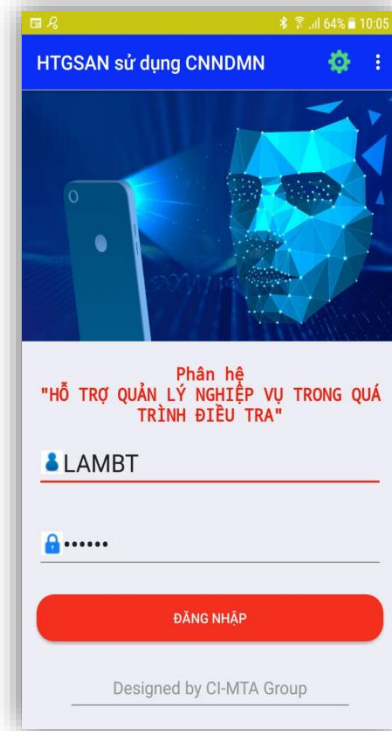
Example: Biometric recognition

Modality	Features	ML techniques
Face	Distance between eyes, DCT, Fourier transform, Ratio of distance between eyes and nose, Principal components,	PCA, LDA, Kernel PCA, Kernel LDA, SVM, Deep neural network
Iris	DCT, Fourier transform, Wavelet transform, Principal components, Texture features,	PCA, LDA,
Fingerprint	Delta, Core points, Ridge ending, Island, Bifurcation, Minutiae, FFT	Artificial neural networks, Support vector machine, Genetic algorithms, Bayesian training, Probabilistic models
Finger vein	LBP, Minutiae, Bifurcation and end points, Pixel information	SVM, Deep learning
Palm print	Shape, Texture, Palm lines, PCA, LDA coefficients, DCT	Naive Bayes, k-nearest neighbor, HMM
Palm vein	LBP, Minutiae, Bifurcation and end points, Pixel information	SVM, Deep learning
Voice	Linear prediction coefficient (LPC), Cepstral coefficient (CC), MFCC features	Gaussian mixture models, HMM, ANN, SVM deep learning

Example: Biometric recognition

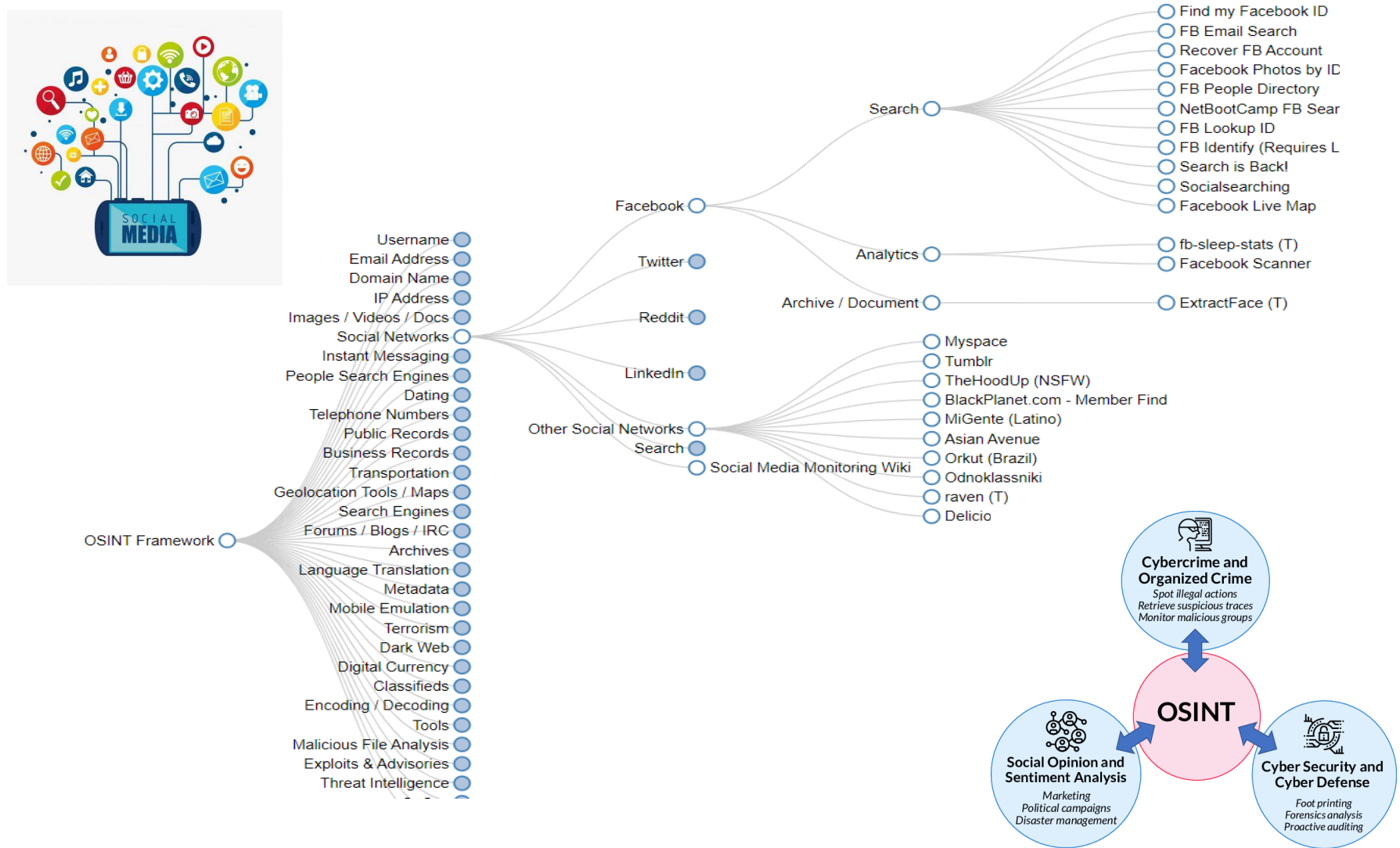
Related problems

1. **Face reconstruction:**
using Generative Adversary Networks GAN
2. **Facial detection**
YOLO và Haar-like
3. **Facial recognition**
FaceNet
4. **Frame selection:**
entropy based selection



Social media analytics and OSINT

← → ↻ osintframework.com



OSINT

← → ↻ osintframework.com



Facebook

Search

- Find my Facebook ID
- FB Email Search
- Recover FB Account
- Facebook Photos by ID
- FB People Directory
- NetBootCamp FB Sear
- FB Lookup ID
- FB Identify (Requires L
- Search is Back!
- Socialsearching
- Facebook Live Map



Web crawler



Information
extraction



STT
Speech 2 Text



OCR



OSINT Framework

- Search Engines
- Forums / Blogs / IRC
- Archives
- Language Translation
- Metadata
- Mobile Emulation
- Terrorism
- Dark Web
- Digital Currency
- Classifieds
- Encoding / Decoding
- Tools
- Malicious File Analysis
- Exploits & Advisories
- Threat Intelligence

- Raven (1)
- Delicio



**Cybercrime and
Organized Crime**

Spot illegal actions
Retrieve suspicious traces
Monitor malicious groups

OSINT

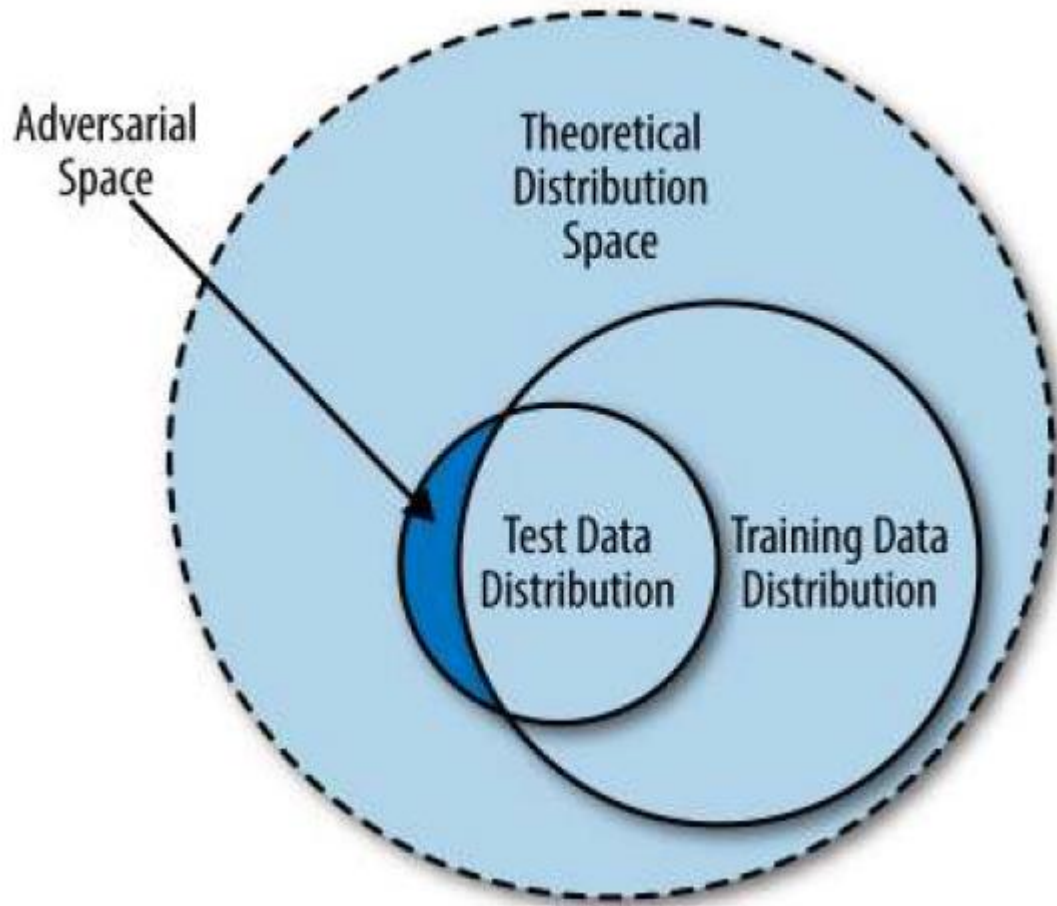
**Social Opinion and
Sentiment Analysis**

Marketing
Political campaigns
Disaster management

**Cyber Security and
Cyber Defense**

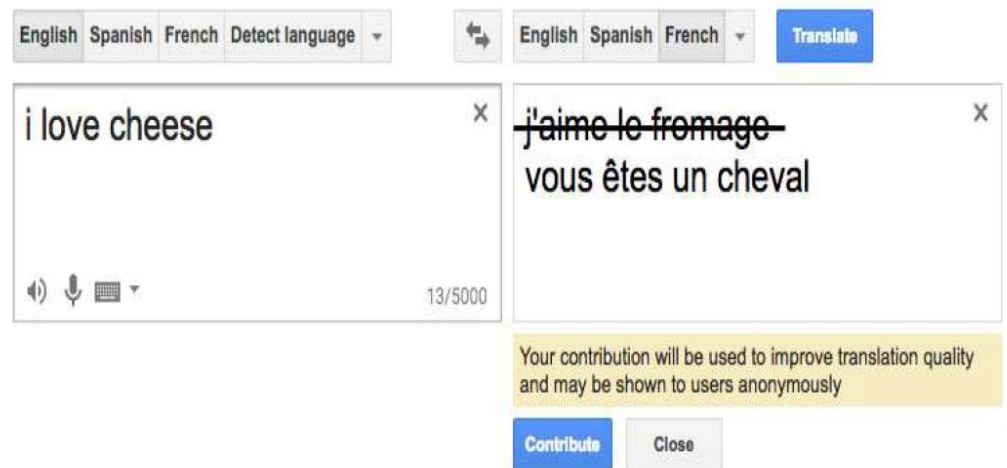
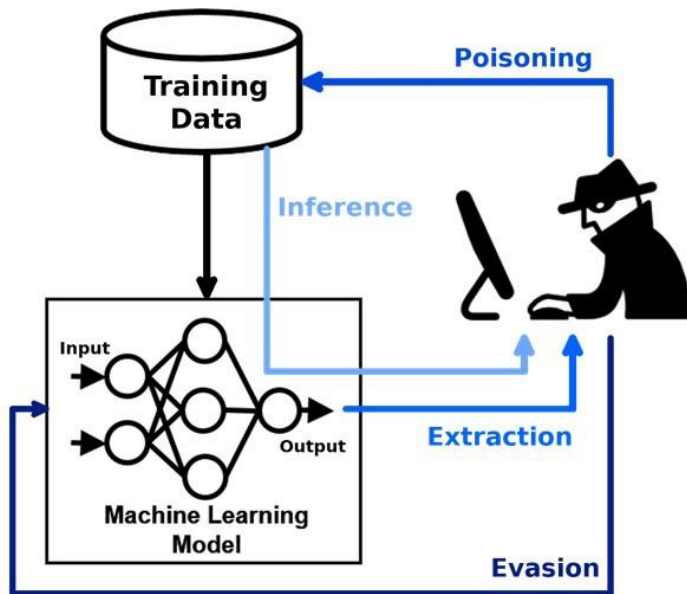
Foot printing
Forensics analysis
Proactive auditing

Security of machine learning models



Security of machine learning models

- Poisoning Attacks



Security of machine learning models

- Evasion Attacks

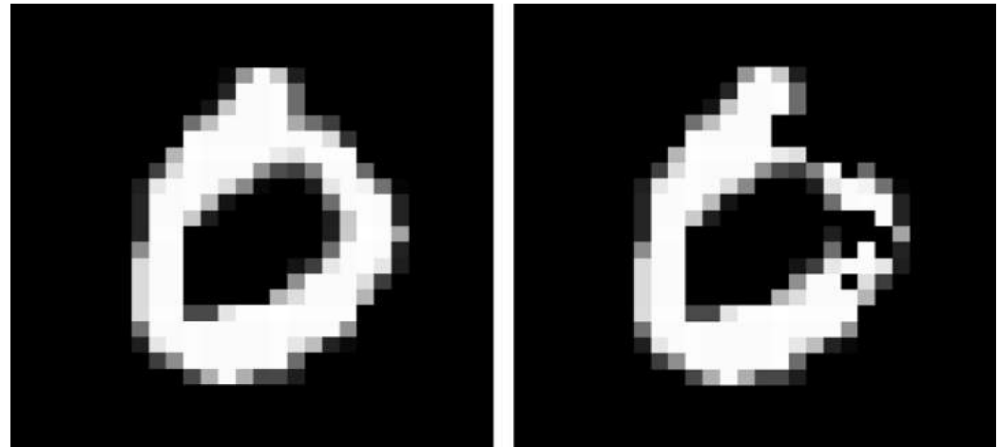
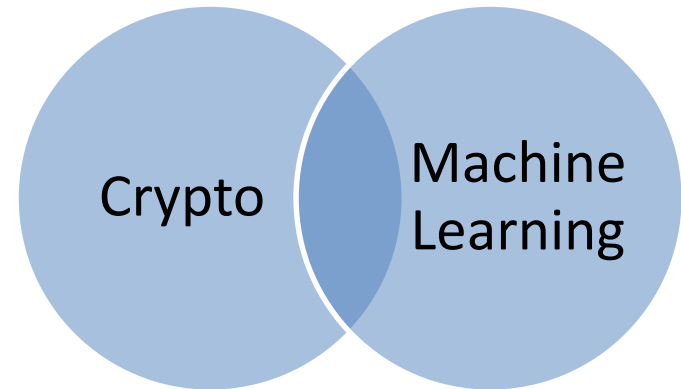
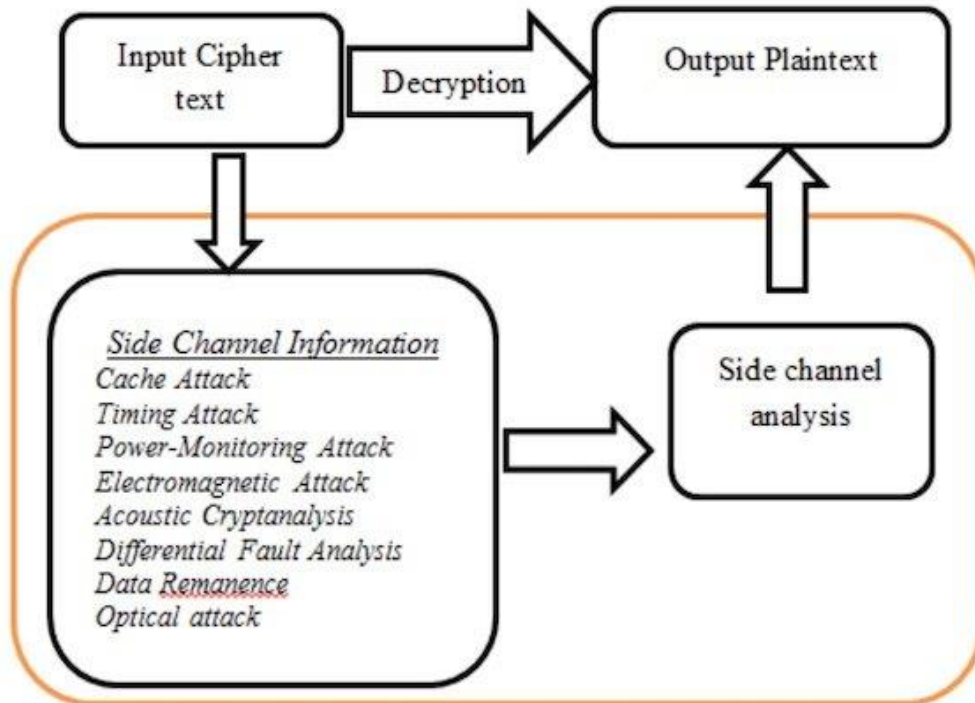


Figure 8-9. Comparison of the unaltered MNIST handwritten digit of a 0 (left) with the adversarially perturbed version (right)

Cryptography and Machine Learning

- ML for Cryptography
 - Side channel attacks



Non Profiled attacks

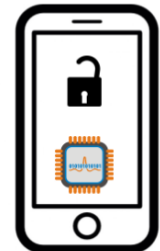
Target device (closed)



- Differential Power Analysis (DPA)
- Correlation Power Analysis (CPA)
- Mutual Information Analysis (MIA)

Profiled attacks

Profiling device (open)



Target device (closed)



- Template attacks
- Support Vector Machine
- Random Forests
- Deep Learning

Cryptography and Machine Learning

• M



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Inp

EFFICIENT CNN-BASED PROFILED SIDE CHANNEL ATTACKS

Ngoc Quy Tran

Academy of Cryptography Techniques, Hanoi, Vietnam

Hong Quang Nguyen

DOI: <https://doi.org/10.15625/1813-9663/37/1/15418>

Keywords: Side channel attack, Convolutional neural network, Grey Wolf Optimizer, Profiled attack, Points of interest

ABSTRACT

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attacks

Target device
(closed)



attacks
ector Machine

- Correlation Power Analysis (CPA)
- Mutual Information Analysis (MIA)

- Random Forests
- Deep Learning

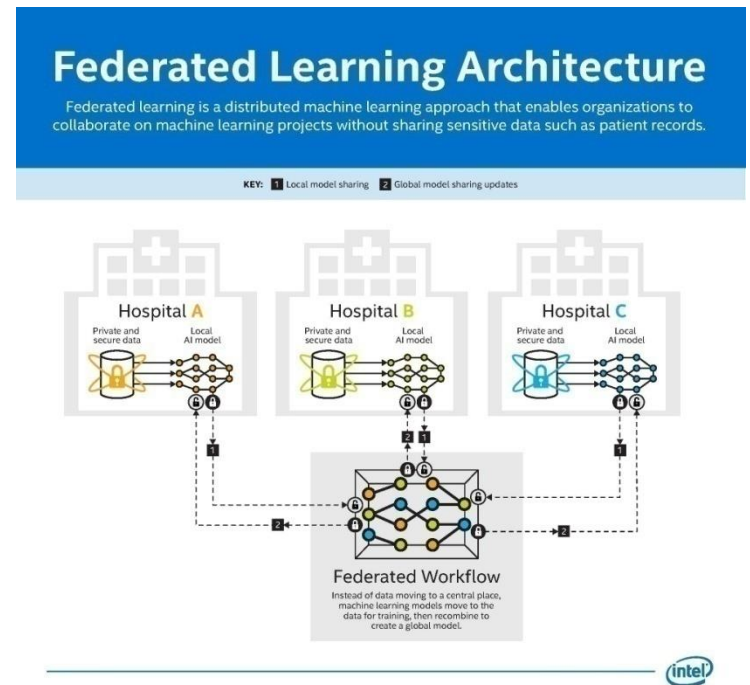
Side
Cache
Timing
Power
Elect
Acoust
Differ
Data
Optic

Cryptography and Machine Learning

- Crypto for ML
 - Security for training data: Data encrypted

Security of Machine Learning models

- Security for training data: distributed learning
- Machine Learning as a Service (MLaaS)



Conclusion

- Machine Learning and Cryptography have a natural similarity
- The application of AI in cryptography and information security is inevitable.
- Challenges: Data for model training.