

AI for Security and Security for AI

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Presentation Focus:

AI is transforming cybersecurity. AI is now used for defense, automation, and decision-making, but it is also becoming a target for attackers.

Key Message:

AI is not only changing cybersecurity tools; it is changing the nature of cyber threats.



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AI AND ML FOR SCIENTIFIC APPLICATIONS THROUGH SECURE COMMUNICATIONS FOR 5G/6G

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“Data Science - Machine Learning for Scientific Applications”

subarea **“Beyond Supervised Learning”**

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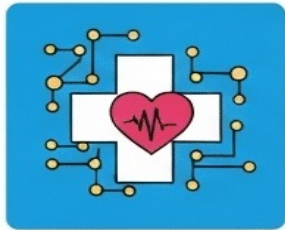


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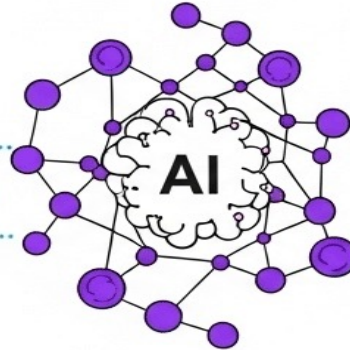
APPLICATIONS OF ARTIFICIAL INTELLIGENCE WITH REAL WORLD EXAMPLES



HEALTICARE



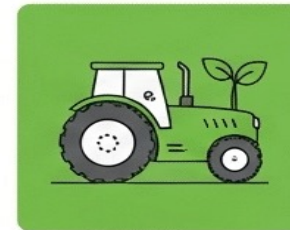
FINANCE



AUTONOMOUS
VEHICLES



AGRICULTURE



**AI Is
Transforming
the Digital
World?**

**AI Is Becoming
Operational
Infrastructure!**

Healthcare:

AI supports diagnosis, medical image analysis, patient monitoring, and treatment recommendations.

Finance:

Banks use AI for fraud detection, credit risk analysis, transaction monitoring, and automated customer support.

Industry:

Manufacturing uses AI for predictive maintenance, quality control, robotics, and process optimization.

Cybersecurity

AI helps detect malware, identify abnormal behavior, analyze threats, and automate incident response.

Key Point:

As AI becomes essential to operations, attacking AI systems becomes more attractive to cybercriminals.



Evolution

Introduction

Motivation

Why Cybersecurity Must Evolve?

Traditional Security Faces New Challenges!

Static software is easier to protect:

Traditional systems usually behave in predictable ways and can be protected with rules, signatures, and access controls.

AI systems are dynamic:

AI models may change after retraining, new data, or deployment in new environments.

AI decisions can be hard to explain:

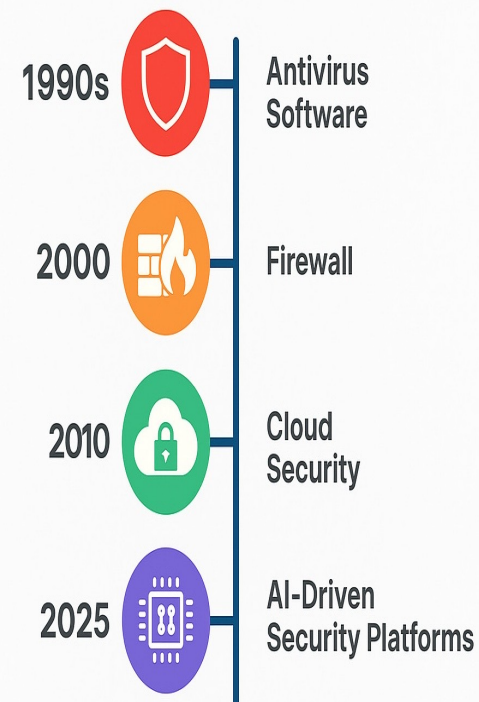
Many AI systems operate as black boxes, making it difficult to understand why they made a decision.

Attack surfaces are expanding:

Attackers can target data, models, APIs, prompts, users, and deployment pipelines.

EVOLUTION OF CYBERSECURITY

TIMELINE



Core Question:

How do we secure systems that learn, adapt, and make autonomous decisions?

AI as a Cybersecurity Tool?

AI Strengthens Cyber Defense!

Threat detection:

AI can analyze large amounts of security data and identify suspicious patterns faster than humans.

Malware classification:

Machine learning can classify unknown files by detecting behavioral or structural similarities.

Fraud detection:

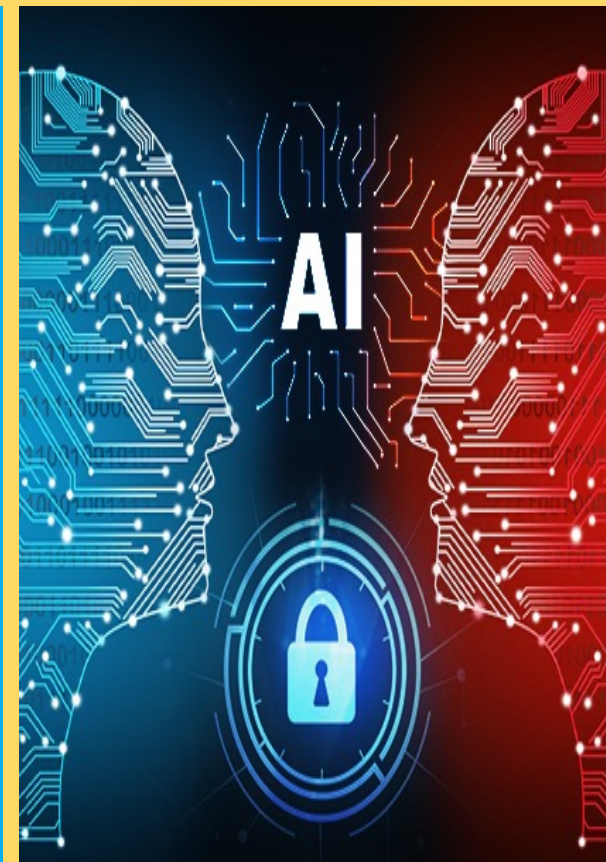
AI identifies unusual financial transactions and suspicious user behavior.

Security automation:

AI can prioritize alerts, reduce analyst workload, and support faster incident response.

Key Benefit:

AI improves speed, scalability, and accuracy in modern cybersecurity operations



AI as a Cybersecurity Target?

AI Systems Are
Also Vulnerable!

Models can be attacked:

Attackers may manipulate inputs to force incorrect predictions.

Training data can be corrupted:

If attackers poison training data, the model may learn harmful behavior.

APIs can expose models:

Repeated queries to AI services can reveal model behavior or enable model theft.

AI supply chains can be compromised:

Pre-trained models, datasets, plugins, and libraries may contain hidden risks.

Key Message:

AI is both a defensive tool and a new target for cyber attacks.



The Modern AI Threat Landscape

New Categories of AI Threats

Adversarial examples:

Inputs are carefully modified so an AI system makes wrong decisions.

Data poisoning:

Attackers inject malicious or misleading data into training datasets.

Model extraction:

Attackers steal or imitate a model by repeatedly querying it.

Prompt injection:

Malicious prompts manipulate generative AI systems into unsafe behavior.

Key Observation:

Many AI threats target trust, decision reliability, and data integrity.



Adversarial AI Attacks

Fooling Intelligent Systems

What they are:

Adversarial attacks modify input data in subtle ways to mislead AI models.

Why they work:

AI models often rely on statistical patterns rather than human-like understanding.

Example — images:

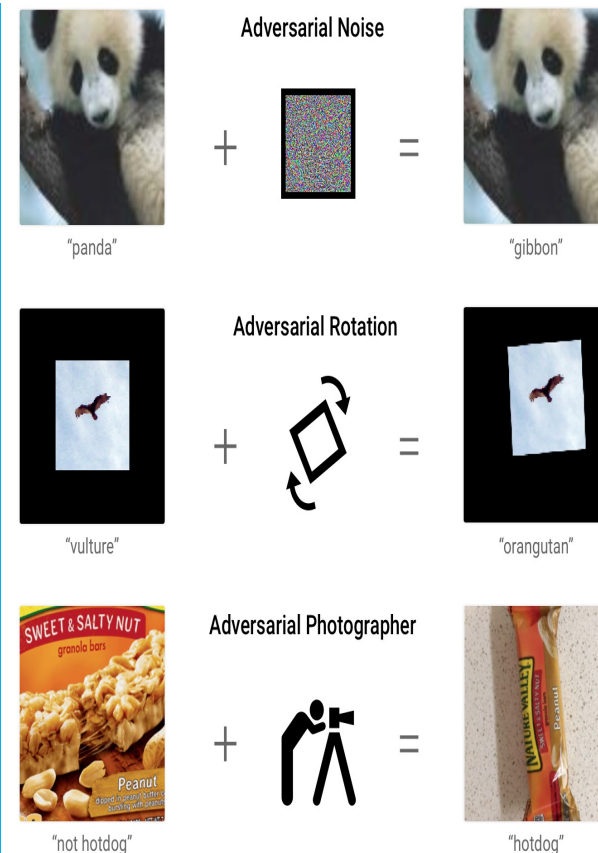
A tiny change in pixels may cause an image classifier to misidentify an object.

Example — autonomous systems:

A modified traffic sign could cause a self-driving system to make a wrong decision.

Main Risk:

Small changes can lead to large consequences in safety-critical systems.



Real-World Impact of Adversarial AI

Small Changes,
Major
Consequences

Autonomous vehicles:

A manipulated road sign may cause incorrect navigation or unsafe driving behavior.

Medical AI:

Small image changes may influence diagnosis, leading to incorrect clinical decisions.

Biometric systems:

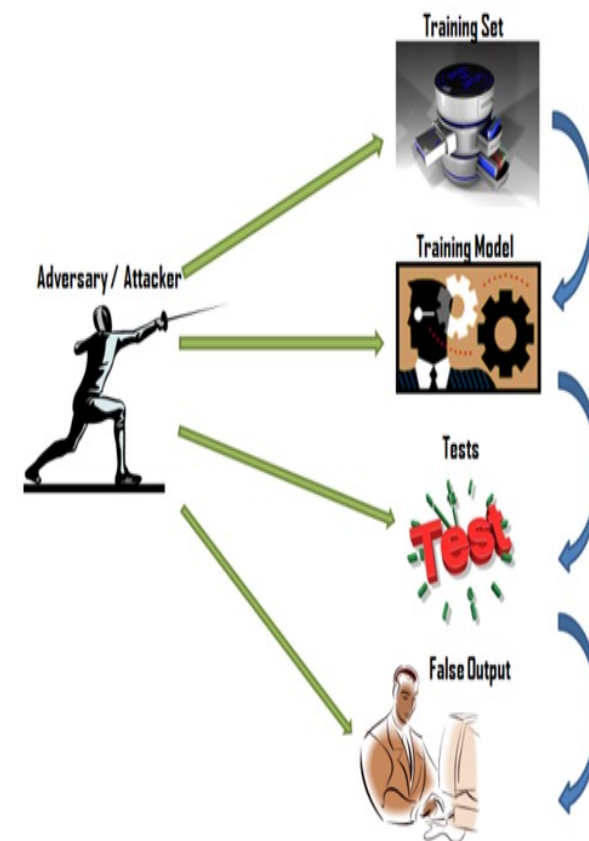
Facial recognition can potentially be bypassed using adversarial patterns.

Fraud systems:

Attackers may slightly change transaction behavior to avoid detection.

Key Message:

Adversarial AI attacks can move from digital manipulation to real-world harm.



Data Poisoning Attacks

Attacking the Learning Process

What happens:

Attackers manipulate training data so the AI learns incorrect or harmful behavior.

Why it is dangerous:

The attack becomes embedded inside the model and may remain hidden after deployment.

Example:

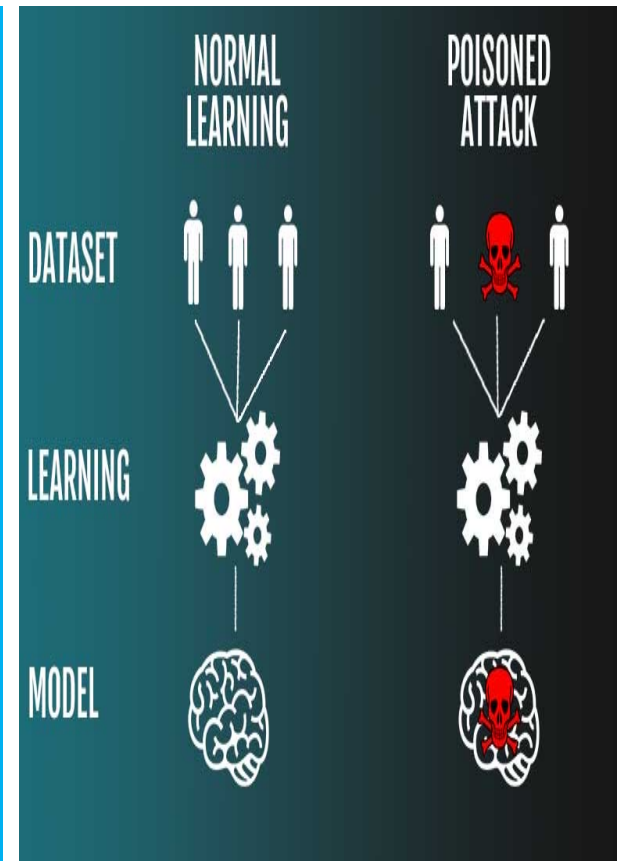
A poisoned dataset may teach an AI system to misclassify certain objects or users.

Impact:

Poisoning can reduce accuracy, create bias, or introduce hidden vulnerabilities.

Key Point:

AI security begins with trusted, verified, and well-governed data.



Backdoor Attacks

Hidden Triggers Inside AI Systems

What is a backdoor:

A hidden behavior inside an AI model that activates only when a specific trigger appears.

Normal behavior:

The model may perform well during ordinary testing and appear safe.

Triggered behavior:

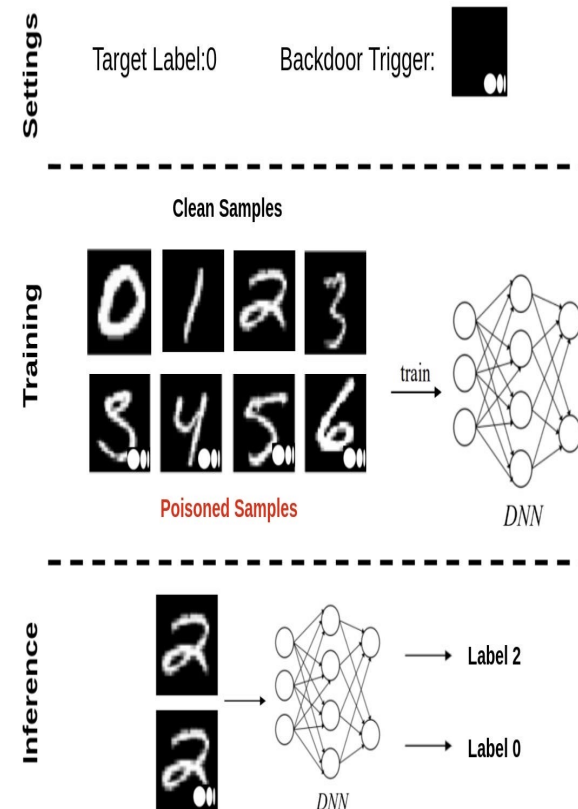
When the hidden trigger appears, the model may make a malicious or incorrect decision.

Example triggers:

A sticker, symbol, phrase, image pattern, or specific input sequence.

Key Risk:

Backdoors are difficult to detect because they remain inactive most of the time.



Model Theft and Extraction

AI Models as Strategic Assets

Why models are valuable:

Large AI models require expensive data, computing power, expertise, and time.

API abuse:

Attackers can repeatedly query a model and learn how it behaves.

Model replication:

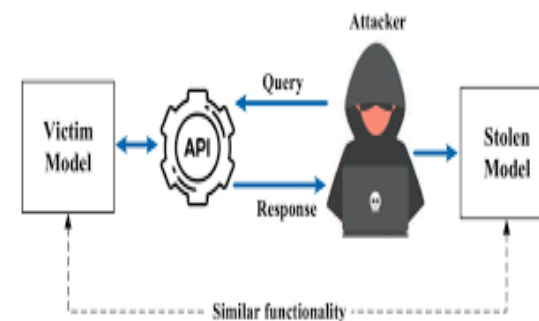
The attacker may build a copy that performs similarly to the original model.

Business impact:

This can lead to intellectual property loss, competitive damage, and revenue loss.

Key Message:

AI models should be protected like critical digital assets.



AI in Critical Infrastructure

High-Stakes AI Security

Energy systems:

AI supports grid monitoring, demand prediction, and fault detection.

Transportation:

AI supports routing, autonomous vehicles, traffic control, and logistics.

Healthcare:

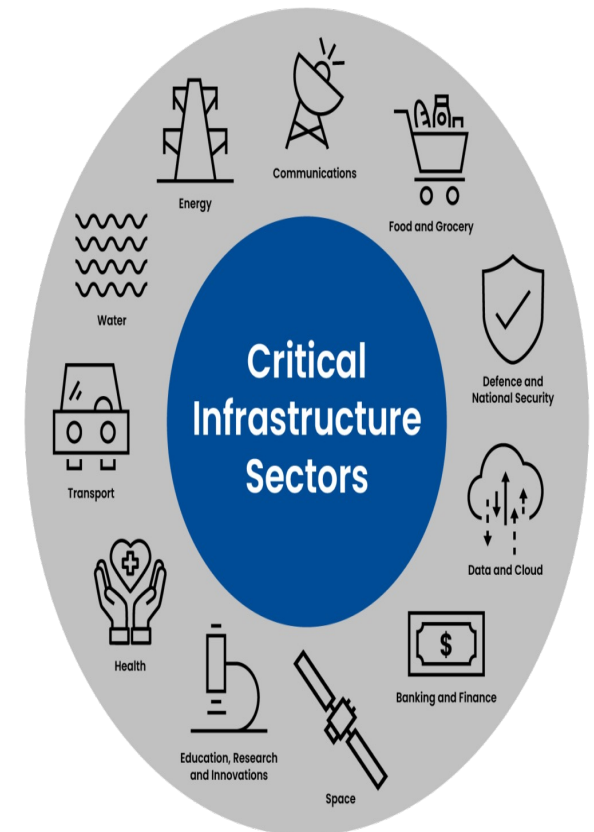
AI supports diagnosis, triage, patient monitoring, and clinical decision support.

Industrial automation:

AI controls robotics, quality assurance, and predictive maintenance.

Key Risk:

Compromised AI in critical infrastructure can cause physical, economic, and societal harm.



Security-by-Design for AI

Security Must Be Integrated Early

Secure data collection:

Datasets should be verified, documented, and protected from manipulation.

Secure model design:

Architectures should consider robustness, privacy, and explainability from the beginning.

Secure training:

Training pipelines should include access control, logging, and integrity checks.

Secure deployment:

Models should be protected through API security, monitoring, and access restrictions.



Key Message:

Security should be built into AI systems, not added after deployment.

Adversarial Robustness

Making AI Harder to Manipulate

Adversarial training:

Models are trained using adversarial examples to improve resistance.

Input sanitization:

Inputs are checked or transformed before reaching the AI model.

Ensemble learning:

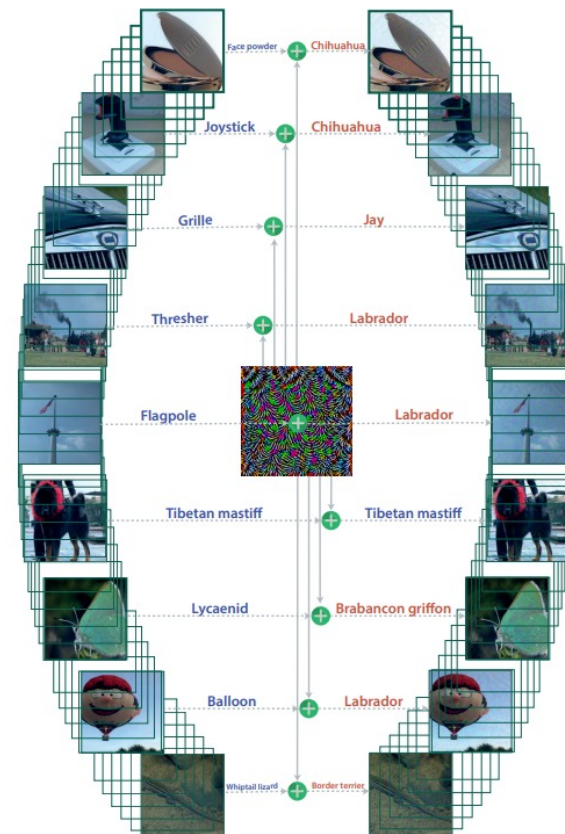
Multiple models are combined to reduce dependence on one vulnerable model.

Certified robustness:

Mathematical guarantees are used to prove resistance within limited attack boundaries.

Limitation:

No single method provides complete protection against all adversarial attacks.



Resilient AI Architectures

Future Security Approaches

Adaptive resilience:

AI systems should detect changes and adjust defenses automatically.

Randomized defenses:

Introducing controlled randomness can make attacks harder to predict and repeat.

Noise-driven architectures:

Noise can be used strategically to increase unpredictability and reduce exploitability.

Self-healing systems:

Future AI systems may detect compromise and recover without full human intervention.



Research Connection:

Unconventional cybersecurity approaches for securing AI-integrated systems.

The Future of AI Security

What Comes Next?

AI for Security vs Security for AI:

Future attacks and defenses may both be powered by autonomous AI systems.

Autonomous cyber defense:

AI may detect, respond to, and recover from threats in real time.

Secure multi-agent systems:

As AI agents collaborate, new risks emerge around coordination, trust, and control.

Quantum-era cybersecurity:

Future advances in computing may change encryption, data protection, and AI security.

Key Question:

Can AI systems eventually defend themselves against intelligent attackers?



Research Challenges

Open Problems in AI Security

Unknown attack vectors:

New AI capabilities will create threats that are not yet understood.

Supply-chain security:

Datasets, models, libraries, and plugins all introduce hidden dependencies.

Robustness-performance trade-off:

More secure models may require more computation or may reduce accuracy.

Multi-agent risks:

AI agents interacting with each other may create unpredictable security failures.

AI Security Risks

A large percentage of organizations are exposed to AI security risks.

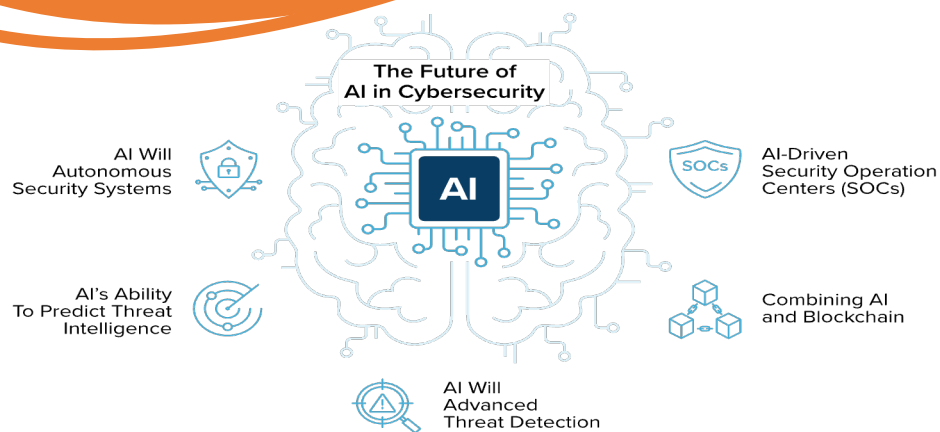


Key Message:

AI cybersecurity remains an open and rapidly evolving research field.

Conclusion

Final Thoughts



AI creates opportunities:

It improves automation, detection, productivity, and decision-making.

AI creates risks:

It introduces new attack surfaces across data, models, APIs, users, and governance.

Traditional security is insufficient alone:

AI requires adaptive, lifecycle-based, and resilience-oriented security.

Collaboration is essential:

Researchers, industry, policymakers, and security professionals must work together.

Final Statement:

“The future of trustworthy artificial intelligence depends on how effectively we secure it today.”

Thank You

Questions, suggestions & discussion! Now or on

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