BA6403
Cybersecurity at VTT
Research overview

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Network Security - BA6403
Research focus & interests

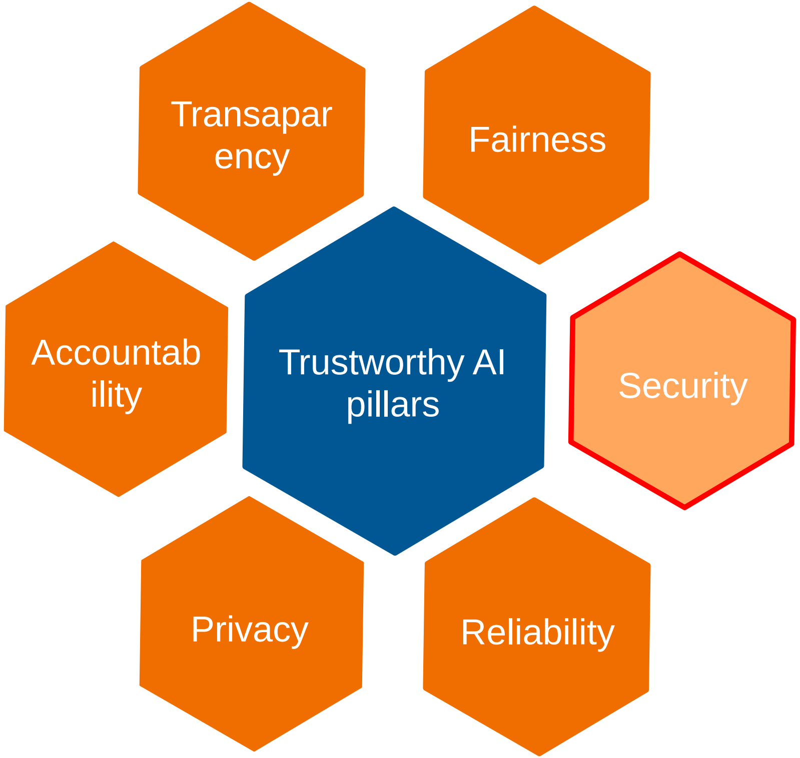
- **Security of future networks**
  - AI for security functions in B5G/6G + mobile networks
  - Security automation in constrained distributed environments (edge security)
  - Secure network architecture
  - B5G/6G networks simulation with *cyber range*

- **AI & security + Trustworthy AI systems**
  - AI automation in security operations
  - Defenses against adversarial AI attacks
  - Secure AI system development & deployment
  - Security assessment for AI systems

- **Cyber insurance for emerging technologies**
  - Security testing and security posture management
  - Security risk and compliance management (NIS2, CR Act, AI act)
  - Security training & security scenarios simulation with *cyber range*
  - Targeted applications: AI, cloud, edge network, critical infrastructures

Secure & Trustworthy AI systems

Trustworthy AI



→ **Resilience against attacks**
- Evasion attack
- Poisoning attack
- Data inference

Security of AI

AI systems are vulnerable against new attacks that only targets them: *adversarial attacks*

Model poisoning / backdooring
- Adversarial data to cause skew in model decision

ML model *integrity*

Model evasion
- Input maliciously crafted to be misclassified

Prediction *integrity*

Model stealing
- Uncovering ML models via probing

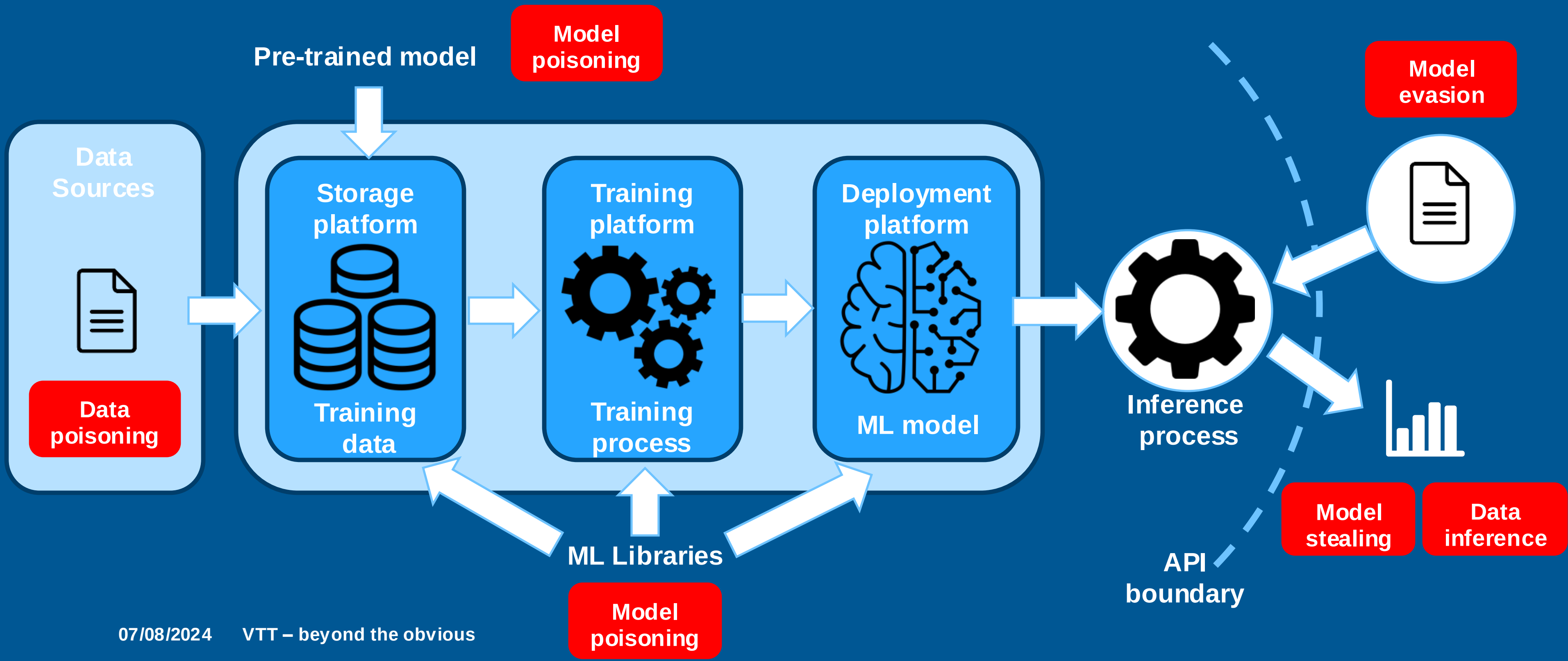
ML model *confidentiality*

Data inference
- Uncovering private data from ML models

Training data *confidentiality*

Inference attacks

Adversarial ML: attack surface



Research interests in AI security

<u>RQ1</u>: How to ensure and provide evidence that AI systems are secure?

Security assessment & certification for AI systems

- Metrics to quantify the security level of AI systems
- Methods and tools for security testing (to compute security metrics)

<u>RQ2</u>: How to make AI systems resilient against adversarial attacks?

Detection of and protection against adversarial attacks

- Detection approach against evasion attacks
- Protection against poisoning attacks in federated learning

<u>RQ3</u>: How to make AI systems resilient against the main cybersecurity threats?

Mitigation of supply chain attacks against AI systems

- Identification of AI-specific supply chain attacks
- Definition of conventional and novel mitigation approaches

Security assessment & certification for AI systems

Security assessment for AI
Evasion attacks

Aimed functionalities

- Produce quantifiable measures of security/resilience
- Provide an upper bound estimation for security vulnerability
- Implement realistic attacker capabilities
- Applicability against virtually any ML model

Main targeted applications

- Identify and fix vulnerabilities in ML models before deployment
- Select the most secure + reliable (+ explainable + etc.) ML model
  - Evaluate the performance/security(/explainability) trade-off
- Document the performance and the security posture of ML-based systems
  - Support for AI risk management
  - Evidence for security compliance

Empirical security diagnosis for evasion attacks

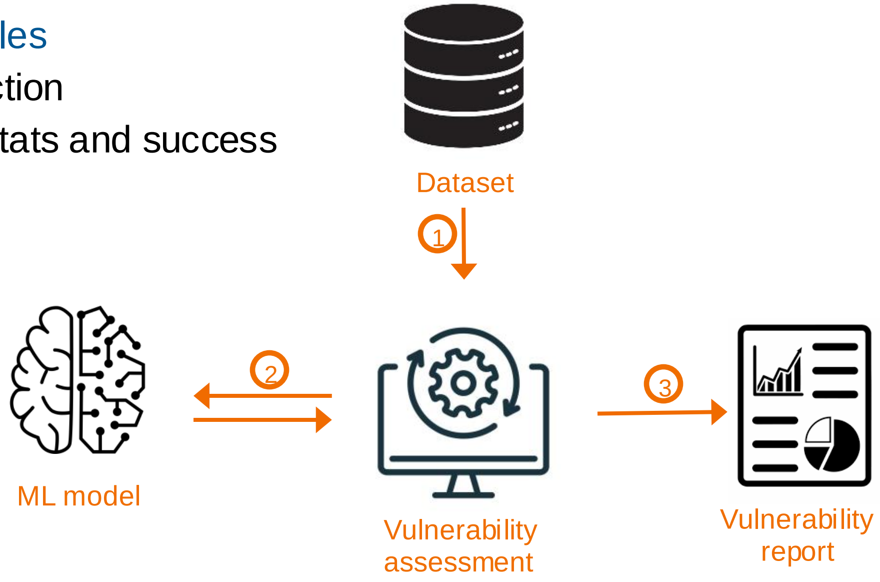
Process

- Generate synthetic queries: adversarial examples
- Analyze model outputs: correct/incorrect prediction
- Compute resilience metrics based on attacks stats and success
- Generate vulnerability/resilience report

Implements several blackbox evasion attacks

Computes 3 resilience metrics

- Impact
- Complexity
- Detectability



Protection against poisoning attacks in federated learning

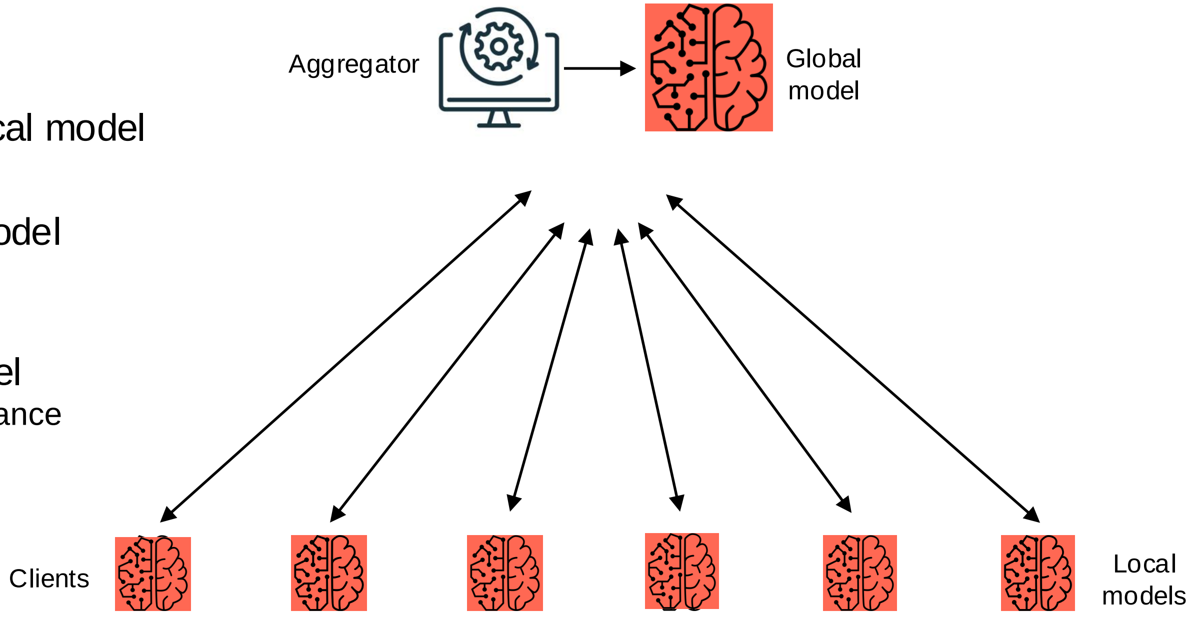
Poisoning attacks in federated learning

Attack process

- Malicious client(s) craft poisoned local model
- Send update to aggregator
- Aggregation compromises global model

Impact of attack

- Compromise integrity of global model
  - Decrease in overall accuracy / performance
  - Embedding of backdoors
- Affect all model users



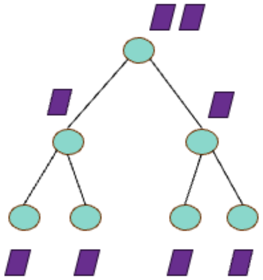
Defenses against FL poisoning

FLAME [1] + SafeLearn [2] against federated learning poisoning

- Privacy-preserving process implemented in aggregator
- Cluster local models to discard obviously malicious updates
- Adaptive clipping to limit negative impact of any single model
- Adaptive noising to mitigate targeted changes to global model

Protection in hierarchical federated learning [3]

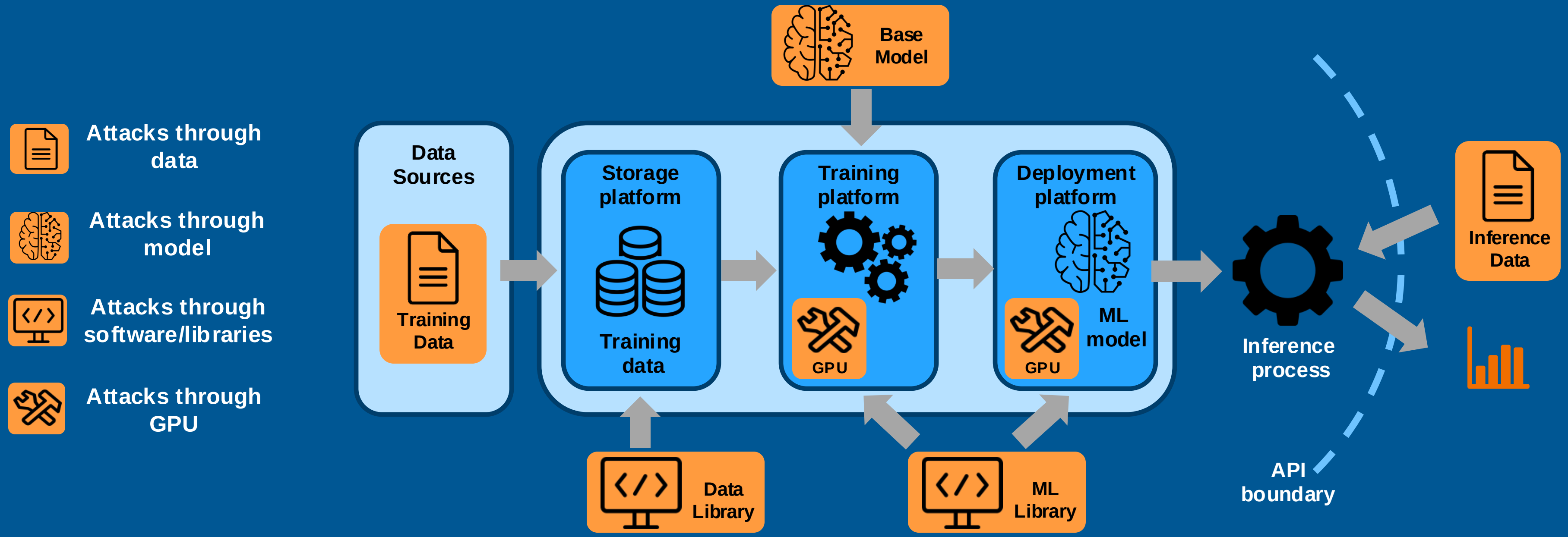
- Adapt process with intermediate aggregation layers



[1] FLAME: Taming backdoors in federated learning. In 31st USENIX Security Symposium (USENIX Security 22)
[2] SafeLearn: Secure aggregation for private federated learning. In 2021 IEEE Security and Privacy Workshops (SPW)
[3] Robust Technique against Poisoning Attacks in Hierarchical Federated Learning. In 2024 IEEE CCNC

Mitigation of supply chain attacks against AI systems

Supply chain attack vectors



Securing the AI supply chain

Vectors for ML supply chain attacks to secure

- Training data
  - Data integrity and quality is difficult to enforce and verify
- Pre-trained ML models
  - Complex ML models can be compromised with backdoors or biased
  - ML model integrity is very hard to verify (just weights…)
- ML software & libraries
  - ML library compromise is more subtle and difficult to detect
  - E.g., change in objective function can compromise ML algorithm
- ML hardware, e.g., GPU
  - Lesser risk, might be harder to compromise