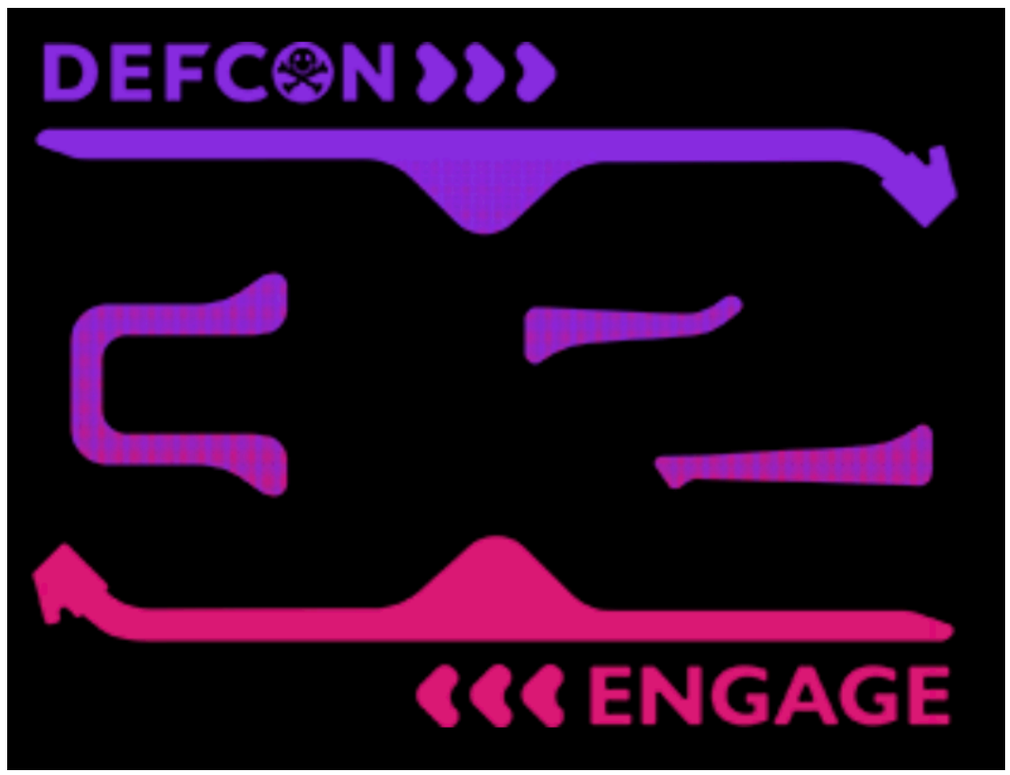
Machine Learning for N00bs



Sam Bowne

Aug 9, 2024

Whoami

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- Corporate trainer
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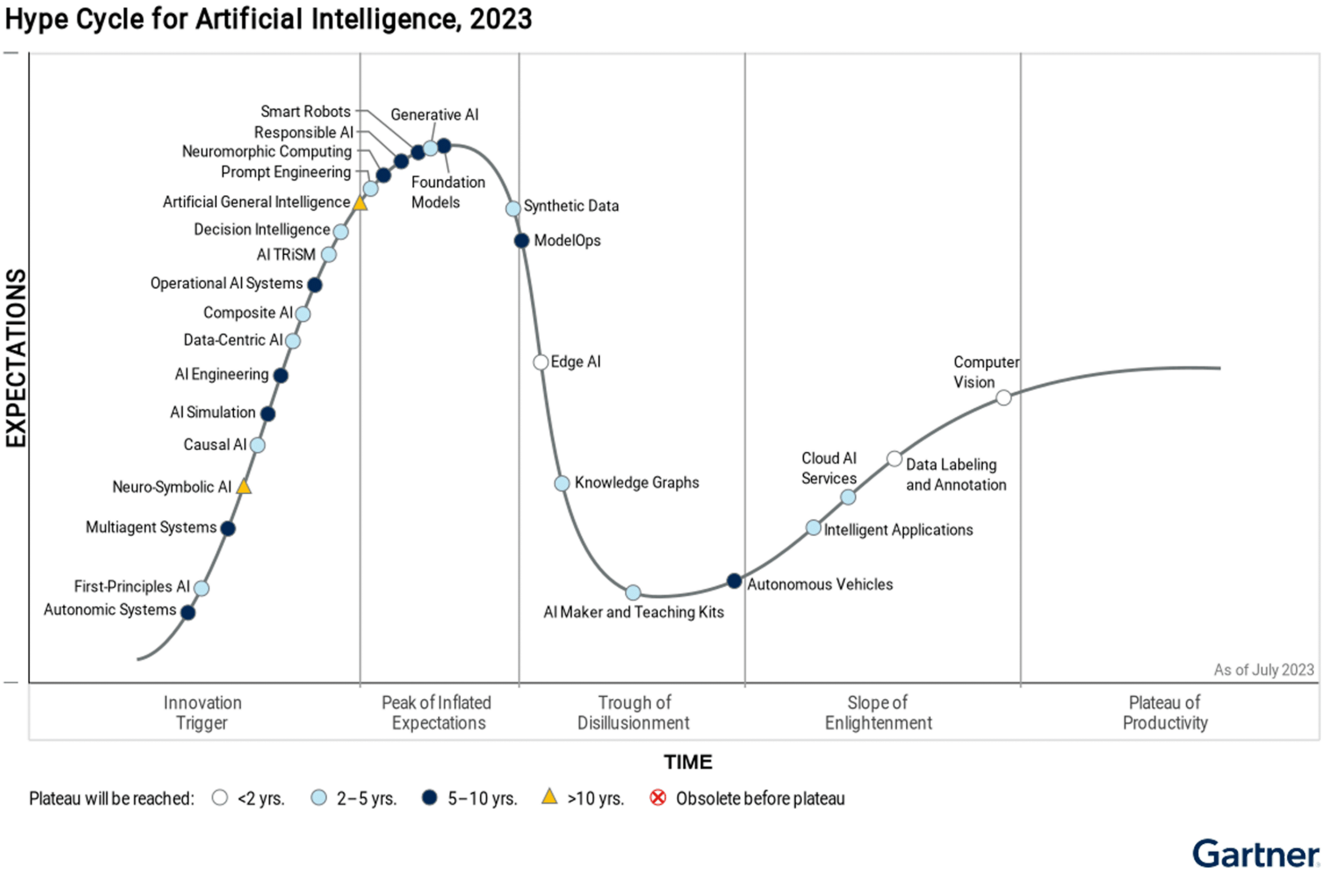
Figure 1: Hype Cycle for Artificial Intelligence, 2023



Gartner

Types of Machine Learning Systems

Supervised Learning

- Training data has labels
  - Indicating desired solution

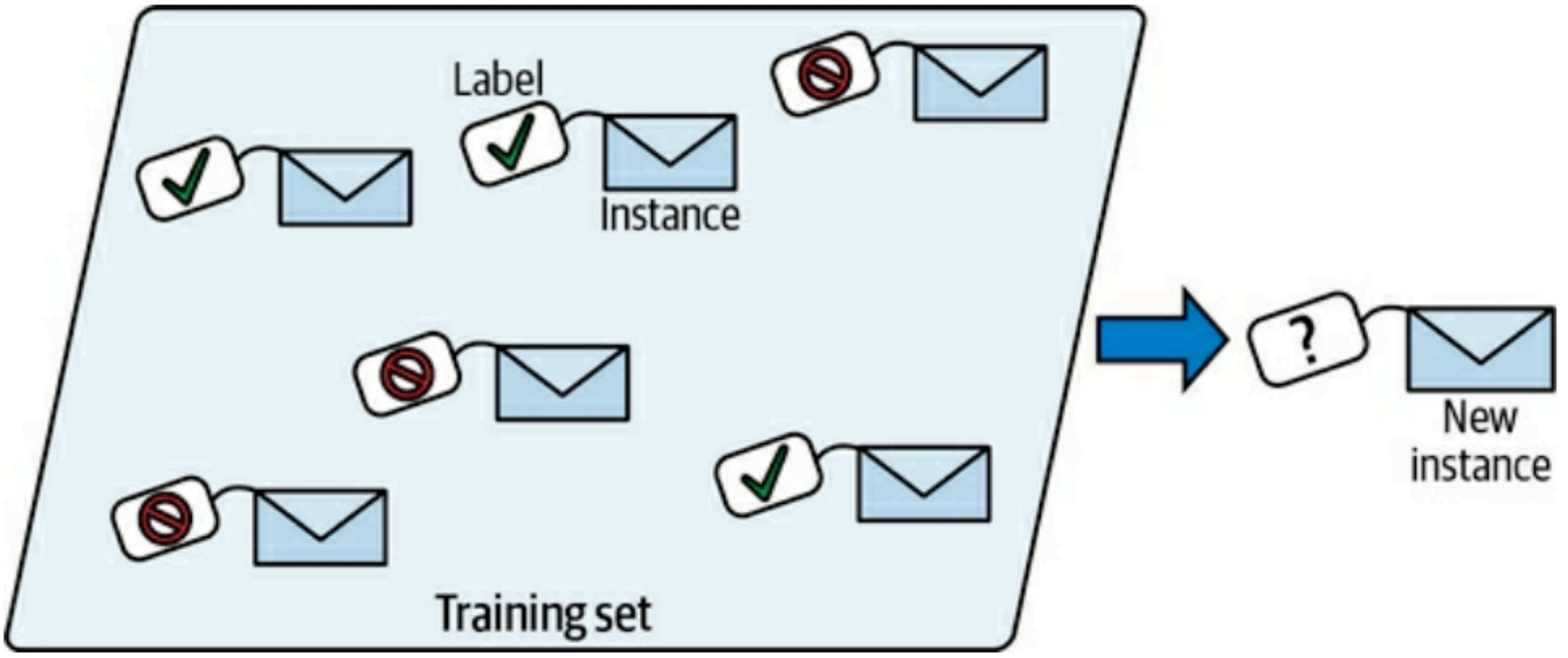


Figure 1-5. A labeled training set for spam classification (an example of supervised learning)

Unsupervised Learning

- Training data is unlabeled

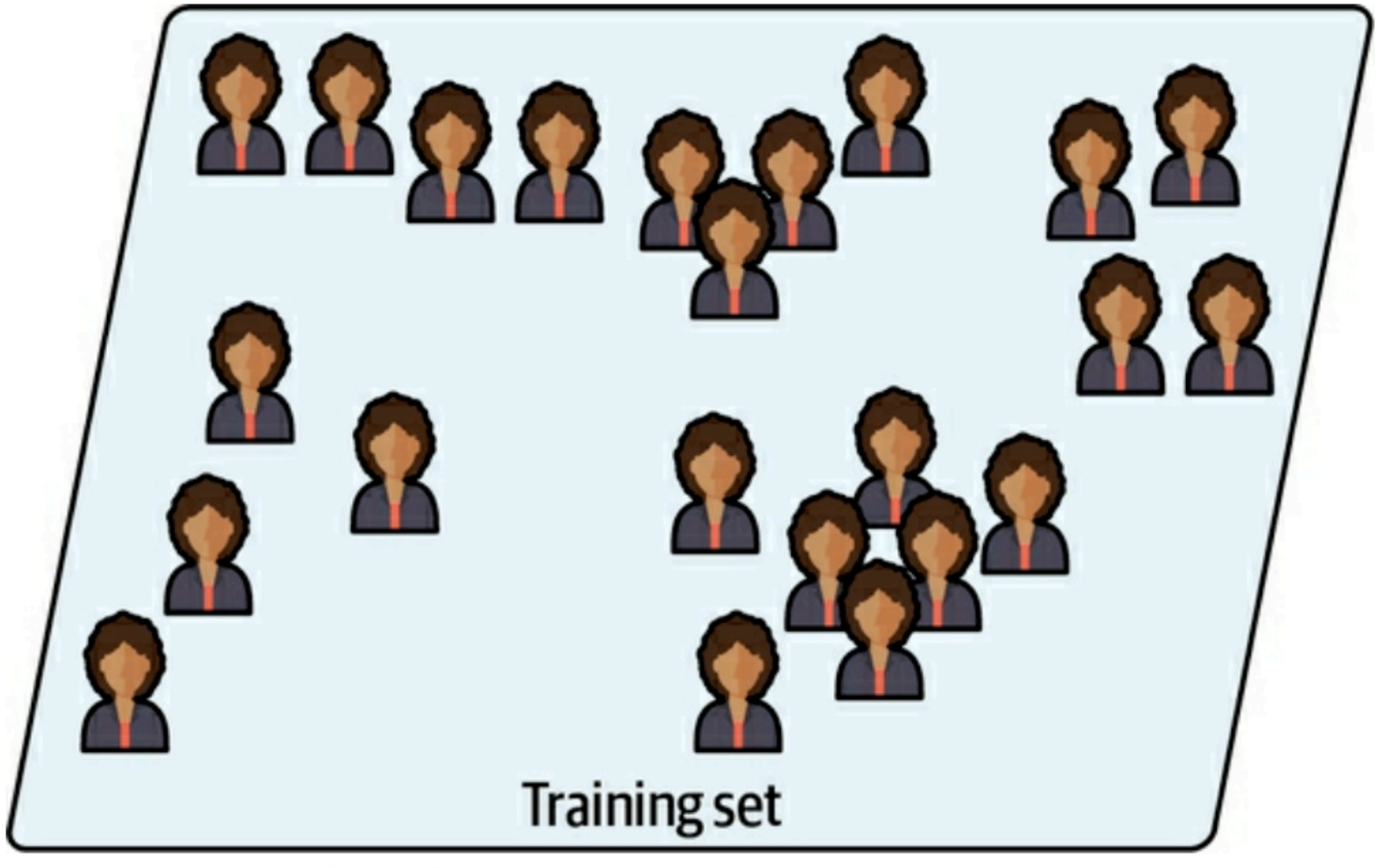


Figure 1-7. An unlabeled training set for unsupervised learning

Unsupervised Learning

- **Clustering** algorithm
  - Sorts data into groups

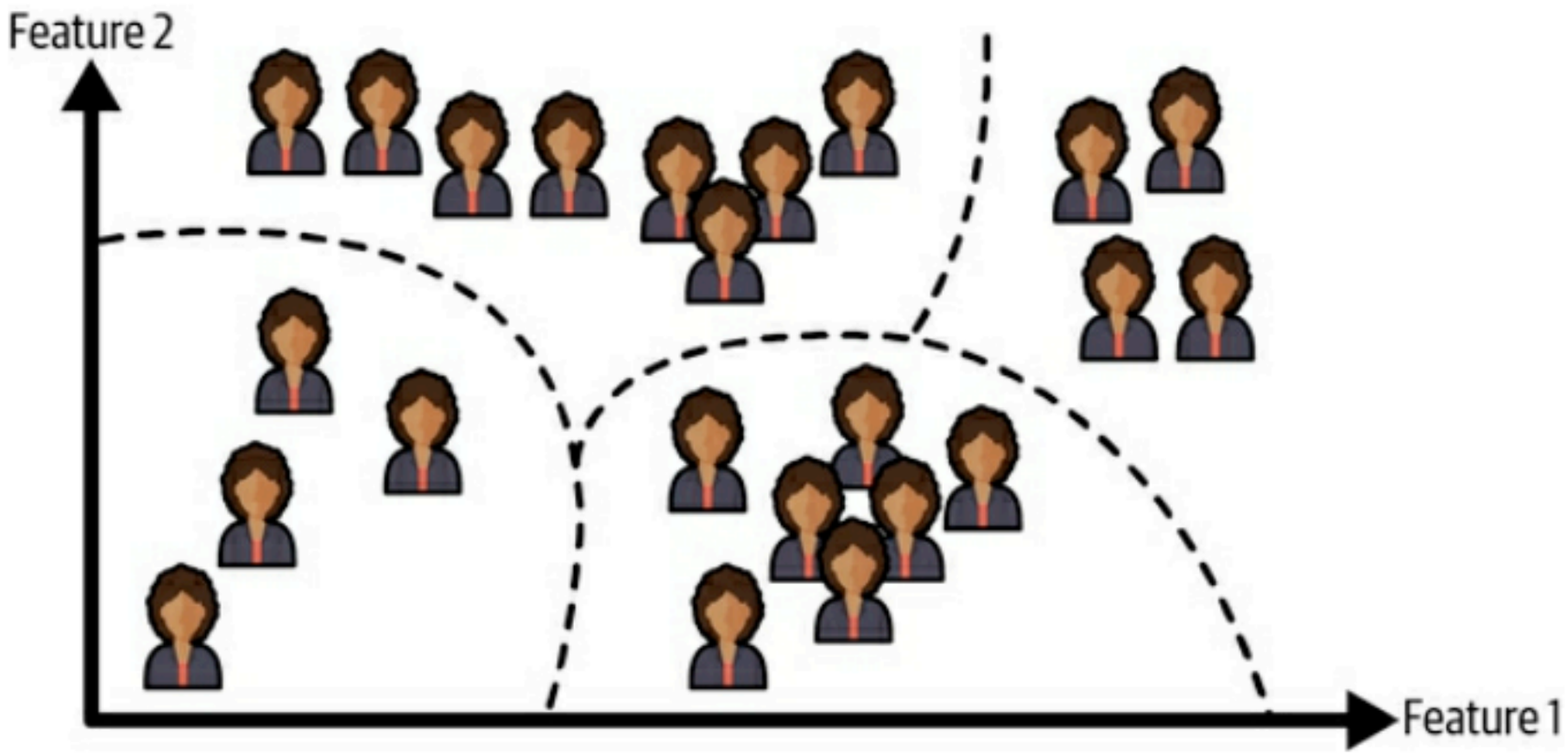


Figure 1-8. Clustering

Unsupervised Learning

- **Anomaly detection**
  - Find unusual credit card transactions
  - Find manufacturing defects

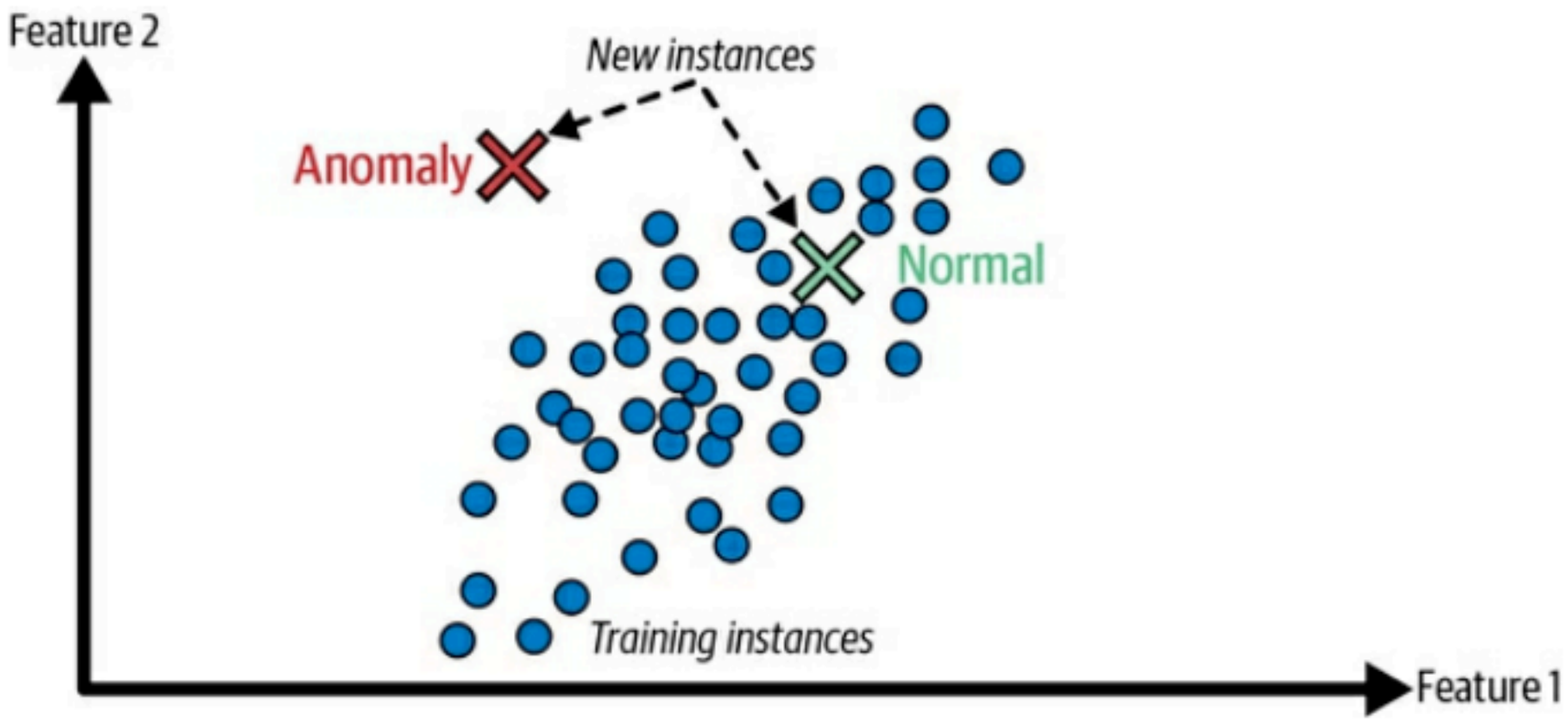


Figure 1-10. Anomaly detection

Self-Supervised Learning

- Generates a labeled dataset from an unlabeled one
    - Example: mask part of an image, train a model to recover the original image

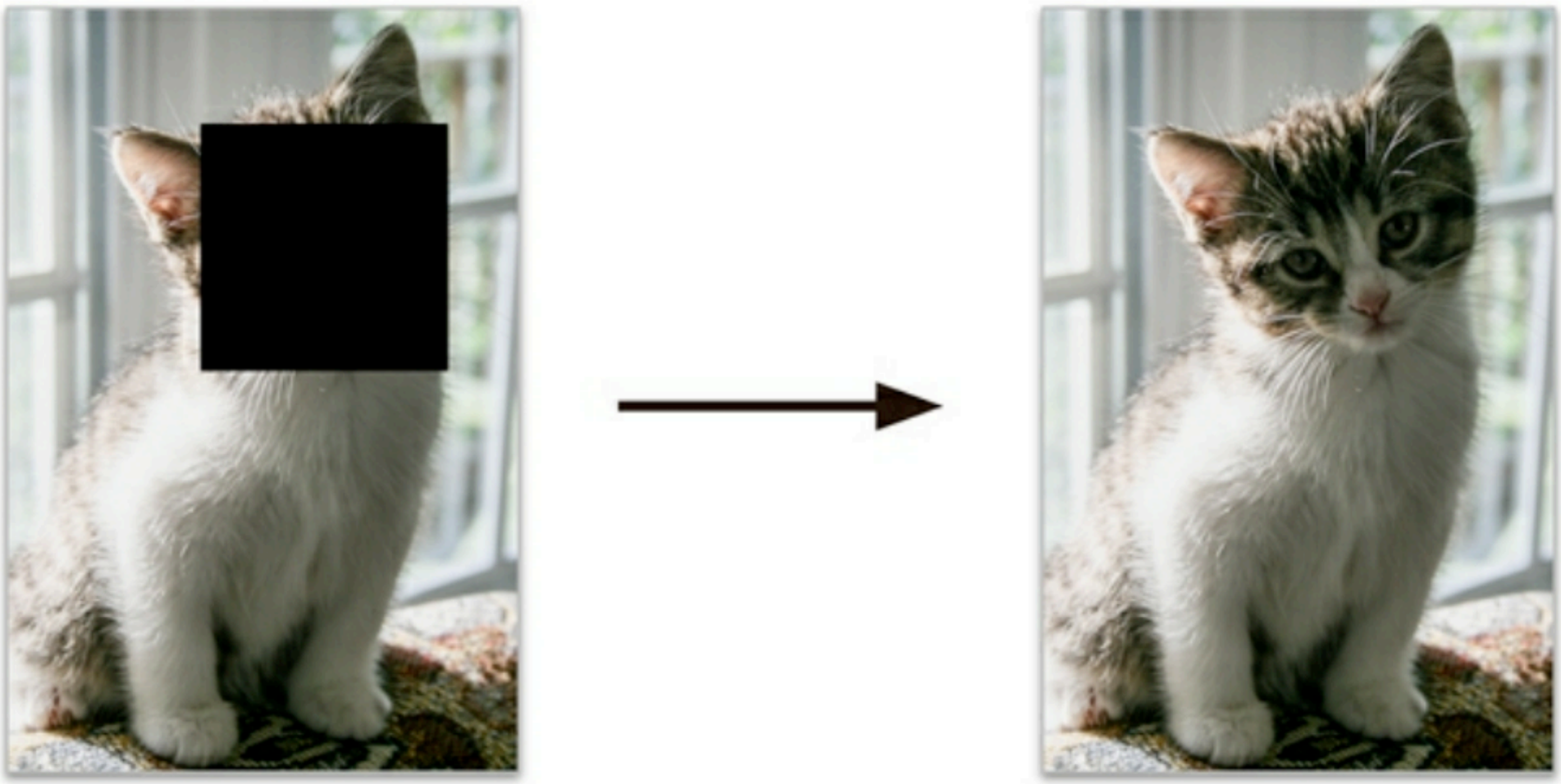


Figure 1-12. Self-supervised learning example: input (left) and target (right)

Large Language Models

- Start with sentences written by humans
- Randomly mask some words
- Learn to predict the masked word

```
0.32 can        artificial intelligence can take over the world.
0.18 will       artificial intelligence will take over the world.
0.06 to         artificial intelligence to take over the world.
0.05 ##s        artificial intelligences take over the world.
0.05 would      artificial intelligence would take over the world.
```

```python
from transformers import pipeline
unmasker = pipeline('fill-mask', model='bert-base-uncased')
result = unmasker("Artificial Intelligence [MASK] take over the world.")
print()
for r in result:
   print(round(r['score'], 2), r['token_str'], "\t", r['sequence'])
```

Securing AI Systems

April 12, 2024

NIST AI 100-1


Artificial Intelligence Risk Management
Framework (AI RMF 1.0)
NIST
NATIONAL INSTITUTE OF
STANDARDS AND TECHNOLOGY
U.S. DEPARTMENT OF COMMERCE

Harm to People

- Individual: Harm to a person's civil liberties, rights, physical or psychological safety, or economic opportunity.
- Group/Community: Harm to a group such as discrimination against a population sub-group.
- Societal: Harm to democratic participation or educational access.

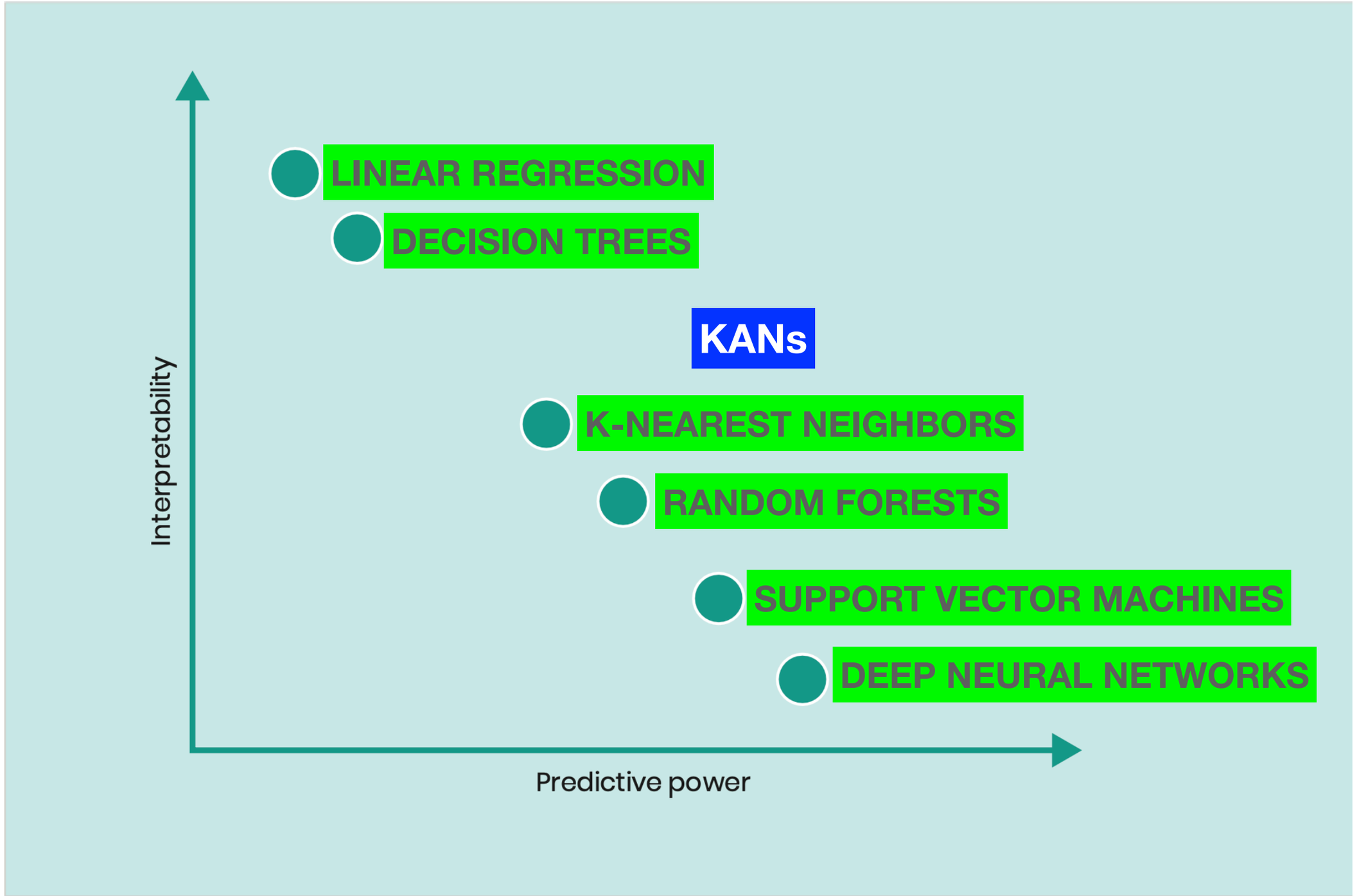
Harm to an Organization

- Harm to an organization's business operations.
- Harm to an organization from security breaches or monetary loss.
- Harm to an organization's reputation.

Harm to an Ecosystem

- Harm to interconnected and interdependent elements and resources.
- Harm to the global financial system, supply chain, or interrelated systems.
- Harm to natural resources, the environment, and planet.

Inscrutability



Principles for the security of machine learning

Version 1

Published August 2022

National Cyber Security Centre

a part of GCHQ

Section 1
Prerequisites and wider considerations

Section 2
Requirements and development

Inception

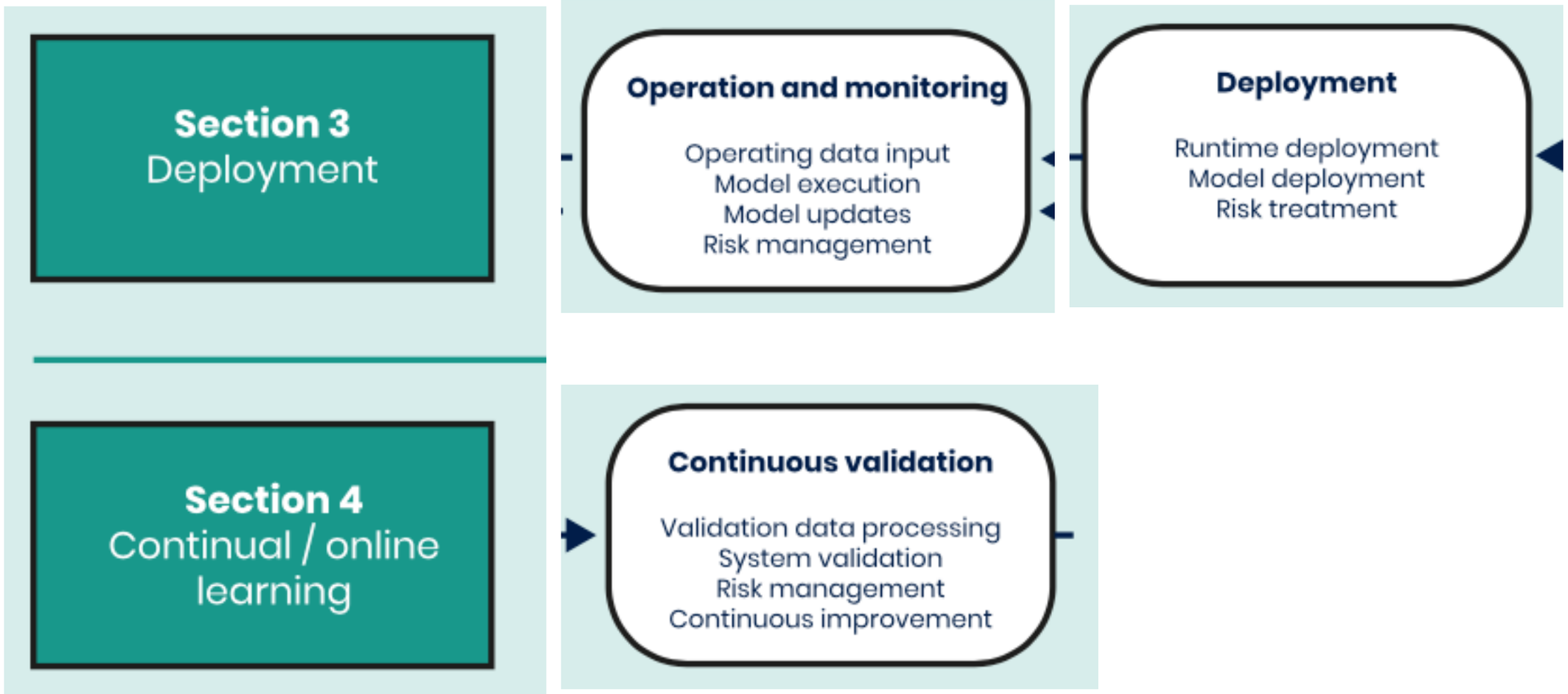
Objectives
High level requirements
Risk assessment
Policies and compliance

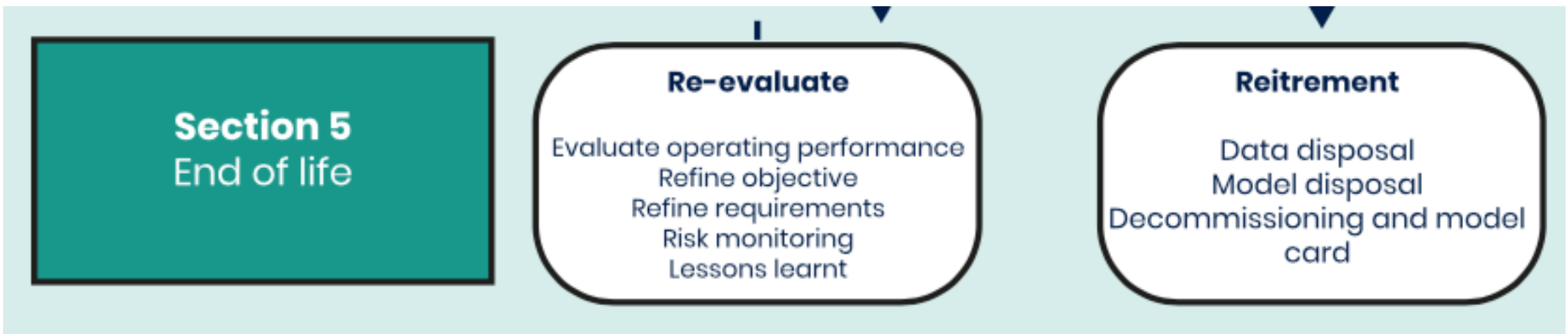
Design and development

Approach
Technical requirements
Architecture
Gathering of training data
Code for data processing
Model creation
Risk treatment

Verification and validation

Verification of data processing
System verification
Risk monitoring and review


Section 3
Deployment
Operation and monitoring
Operating data input
Model execution
Model updates
Risk management
Deployment
Runtime deployment
Model deployment
Risk treatment
Section 4
Continual / online learning
Continuous validation
Validation data processing
System validation
Risk management
Continuous improvement


Section 5
End of life
Re-evaluate
Evaluate operating performance
Refine objective
Refine requirements
Risk monitoring
Lessons learnt
Reitrement
Data disposal
Model disposal
Decommissioning and model card

OWASP Top Ten Machine Learning Risks

- ML01:2023 Input Manipulation Attack
- ML02:2023 Data Poisoning Attack
- ML03:2023 Model Inversion Attack
- ML04:2023 Membership Inference Attack
- ML05:2023 Model Theft
- ML06:2023 AI Supply Chain Attacks
- ML07:2023 Transfer Learning Attack
- ML08:2023 Model Skewing
- ML09:2023 Output Integrity Attack
- ML10:2023 Model Poisoning

- https://owasp.org/www-project-machine-learning-security-top-10/

- **ML01:2023 Input Manipulation Attack**
  - An attacker deliberately alters input data to mislead the model
  - This attack is also called **evasion**
  - Example: a model is trained to tell cat images from dog images. An attacker modifies a cat image so it is misclassified as a dog.
- **ML02:2023 Data Poisoning Attack**
  - An attacker manipulates the training data to cause the model to behave in an undesirable way
- **ML03:2023 Model Inversion Attack**
  - An attacker reverse-engineers the model to extract information from it
  - Example: a model is trained to recognize faces. An attacker inputs images of individuals into the model and and recovers the personal information of the individuals from the model's predictions, such as their name, address, or social security number.

- **ML04:2023 Membership Inference Attack**
  - An attacker manipulates the model's training data in order to cause it to behave in a way that exposes sensitive information
  - Example: A malicious attacker trains a machine learning model on a dataset of financial records and uses it to query whether or not a particular individual's record was included in the training data.
- **ML05:2023 Model Theft**
  - An attacker gains access to the model's parameters
  - Example: Stealing a machine learning model from a competitor
- **ML06:2023 AI Supply Chain Attacks**
  - An attacker modifies or replaces a machine learning library or model that is used by a system

- **ML07:2023 Transfer Learning Attack**
  - An attacker trains a model on one task and then fine-tunes it on another task to cause it to behave in an undesirable way
  - Example: An attacker trains a machine learning model on a malicious dataset that contains manipulated images of faces. The attacker then transfers the model's knowledge to a target face recognition system. As a result, the face recognition system starts making incorrect predictions, allowing the attacker to bypass the security and gain access to sensitive information.
- **ML08:2023 Model Skewing**
  - An attacker manipulates the distribution of the training data to cause the model to behave in an undesirable way.
  - Example: The attacker provides fake feedback data to a loan-approving machine learning system. As a result, the model's predictions are skewed, and the attacker's chances of getting a loan approved are significantly increased.

- **ML09:2023 Output Integrity Attack**
  - An attacker aims to modify or manipulate the output of a machine learning model in order to change its behavior or cause harm to the system it is used in.
  - Example: An attacker has gained access to the output of a machine learning model that is being used to diagnose diseases in a hospital. The attacker modifies the output of the model, making it provide incorrect diagnoses for patients.
- **ML10:2023 Neural Net Reprogramming**
  - An attacker manipulates the model's parameters to cause it to behave in an undesirable way.
  - Example: A bank is using a machine learning model to identify handwritten characters on cheques. An attacker manipulates the parameters of the model by altering the images in the training dataset or directly modifying the parameters in the model. This can result in the model misidentifying characters, leading to incorrect amounts being processed.

OWASP Top 10 for LLM Applications

VERSION 1.1

Published: *October 16, 2023*

https://owasp.org/www-project-top-10-for-large-language-model-applications/

LLM01: Prompt Injection

This manipulates a large language model (LLM) through crafty inputs, causing unintended actions by the LLM. Direct injections overwrite system prompts, while indirect ones manipulate inputs from external sources.

LLM02: Insecure Output Handling

This vulnerability occurs when an LLM output is accepted without scrutiny, exposing backend systems. Misuse may lead to severe consequences like XSS, CSRF, SSRF, privilege escalation, or remote code execution.

LLM03: Training Data Poisoning

This occurs when LLM training data is tampered, introducing vulnerabilities or biases that compromise security, effectiveness, or ethical behavior. Sources include Common Crawl, WebText, OpenWebText, & books.

LLM04: Model Denial of Service

Attackers cause resource-heavy operations on LLMs, leading to service degradation or high costs. The vulnerability is magnified due to the resource-intensive nature of LLMs and unpredictability of user inputs.

LLM05: Supply Chain Vulnerabilities

LLM application lifecycle can be compromised by vulnerable components or services, leading to security attacks. Using third-party datasets, pre- trained models, and plugins can add vulnerabilities.

LLM06: Sensitive Information Disclosure

LLMs may inadvertently reveal confidential data in their responses, leading to unauthorized data access, privacy violations, and security breaches. It’s crucial to implement data sanitization and strict user policies to mitigate this.

LLM07: Insecure Plugin Design

LLM plugins can have insecure inputs and insufficient access control. This lack of application control makes them easier to exploit and can result in consequences like remote code execution.

LLM08: Excessive Agency

LLM-based systems may undertake actions leading to unintended consequences. The issue arises from excessive functionality, permissions, or autonomy granted to the LLM-based systems.

LLM09: Overreliance

Systems or people overly depending on LLMs without oversight may face misinformation, miscommunication, legal issues, and security vulnerabilities due to incorrect or inappropriate content generated by LLMs.

LLM10: Model Theft

This involves unauthorized access, copying, or exfiltration of proprietary LLM models. The impact includes economic losses, compromised competitive advantage, and potential access to sensitive information.

Copilot Security: Ensuring a Secure Microsoft Copilot Rollout

This article describes how Microsoft 365 Copilot's security model works and the risks that must be mitigated to ensure a safe rollout.

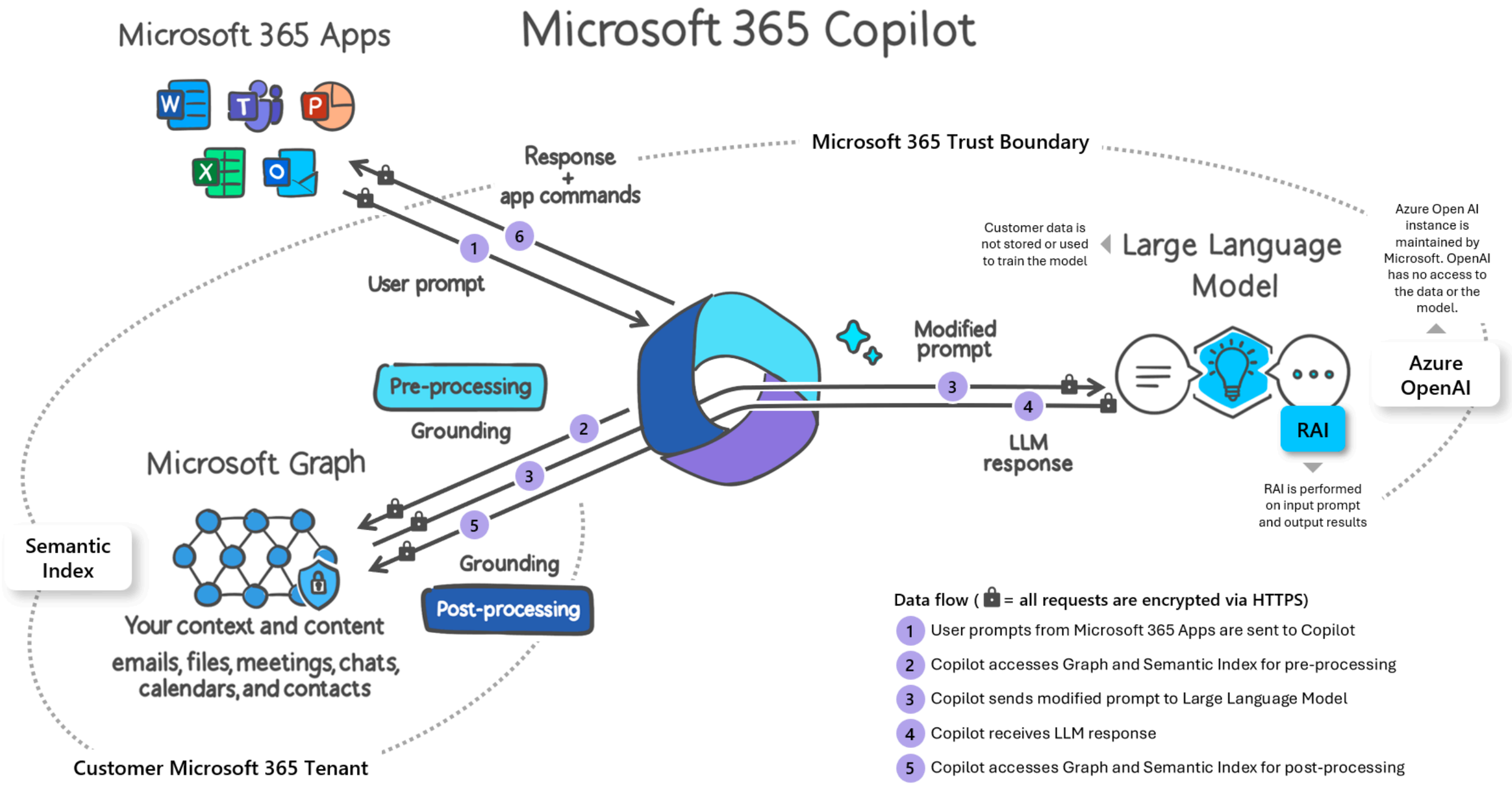
Rob Sobers | 5 min read | Last updated April 11, 2024

Microsoft 365 Copilot Use Cases

+ Copilot can join your Teams meetings and summarize in real time what's being discussed, capture action items, and tell you which questions were unresolved in the meeting.
+ Copilot in Outlook can help you triage your inbox, prioritize emails, summarize threads, and generate replies for you.
+ Copilot in Excel can analyze raw data and give you insights, trends, and suggestions.

- Writes documents for you
  - Based on data found in your Email, documents, spreadsheets, and other files you have access to
  - In the Microsoft365 cloud
  - **Based on your Microsoft365 permissions**

Microsoft 365 Copilot



Data flow (= all requests are encrypted via HTTPS)

1. User prompts from Microsoft 365 Apps are sent to Copilot
2. Copilot accesses Graph and Semantic Index for pre-processing
3. Copilot sends modified prompt to Large Language Model
4. Copilot receives LLM response
5. Copilot accesses Graph and Semantic Index for post-processing
6. Copilot sends the response, and app command back to Microsoft 365 Apps

What Microsoft Handles for You

+ **Tenant isolation.** Copilot only uses data from the current user's M365 tenant. The AI tool will not surface data from other tenants that the user may be a guest, in nor any tenants that might be set up with cross-tenant sync.

+ **Training boundaries.** Copilot **does not** use any of your business data to train the foundational LLMs that Copilot uses for all tenants. You *shouldn't* have to worry about your proprietary data showing up in responses to other users in other tenants.

What You Need to Manage

+ **Permissions.** Copilot surfaces all organizational data to which individual users have at least view permissions.
+ **Labels.** Copilot-generated content *will not* inherit the MPIP labels of the files Copilot sourced its response from.
+ **Humans.** Copilot's responses aren't guaranteed to be 100% factual or safe; humans must take responsibility for reviewing AI-generated content.

Multicloud environments are complex

40,000+
permissions to manage

>50%
are **high-risk**

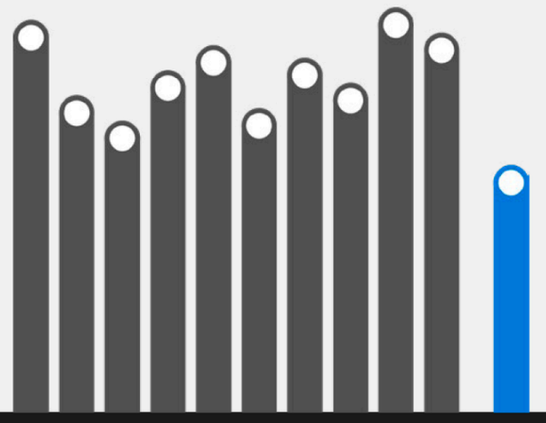
After analyzing over

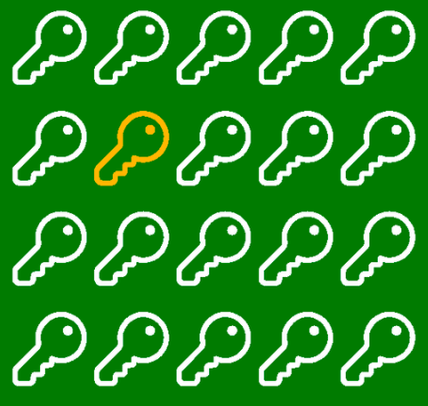
500 risk assessments,

we found that **most identities are greatly over-permissioned**, putting organizations' critical environments at risk for accidental or malicious permission misuse

Workload identities accessing cloud environments are increasing, now outnumbering human identities

10:1





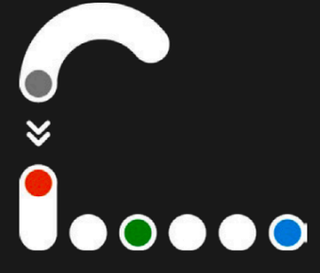
1%
of permissions granted are actually used

>50%
of identities are super admins, meaning they have **access to all permissions and resources**

Microsoft Security

Learn how to implement least privilege and reduce permission risks across multicloud at

aka.ms/PermissionsManagement

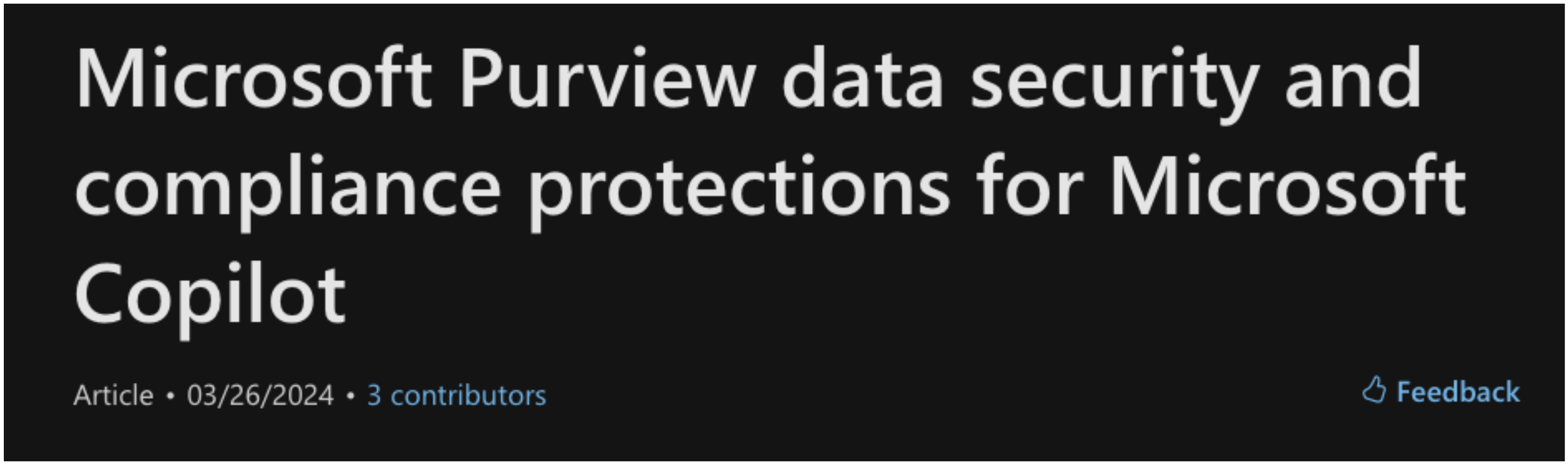


The Average M365 Tenant has

+ 40+ million unique permissions
+ 113K+ sensitive records shared publicly
+ 27K+ sharing links

Why Does This Happen?

+ Direct user permissions
+ Microsoft 365 group permissions
+ SharePoint local permissions (with custom levels)
+ Guest access
+ External access
+ Public access
+ Link access (anyone, org-wide, direct, guest)



- But you must enable sensitivity labels
  - For SharePoint and OneDrive
- If humans fail to apply and update labels, the system fails

How to Weaponize Microsoft Copilot for Cyberattackers

At Black Hat USA, security researcher Michael Bargury released a "LOLCopilot" ethical hacking module to demonstrate how attackers can exploit Microsoft Copilot — and offered advice for defensive tooling.

Jeffrey Schwartz, Contributing Writer

August 8, 2024

Using the tool, Bargury can add a direct prompt injection to a copilot, jailbreaking it and modifying a parameter or instruction within the model. For instance, he could embed an HTML tag into an email to replace a correct bank account number with that of the attacker, without changing any of the reference information or altering the model with, say, white text or a very small font.

Meta's AI safety system defeated by the space bar

'Ignore previous instructions' thwarts Prompt-Guard model if you just add some good ol' ASCII code 32

Thomas Claburn

Mon 29 Jul 2024 // 21:01 UTC

Home Users are Safe. Right?

Microsoft

Retrace your steps with Recall

Search across time to find the content you need. Then, re-engage with it. With Recall, you have an explorable timeline of your PC's past. Just describe how you remember it and Recall will retrieve the moment you saw it. Any photo, link, or message can be a fresh point to continue from. As you use your PC, Recall takes snapshots of your screen. Snapshots are taken every five seconds while content on the screen is different from the previous snapshot. Your snapshots are then locally stored and locally analyzed on your PC. Recall's analysis allows you to search for content, including both images and text, using natural language. Trying to remember the name of the Korean restaurant your friend Alice mentioned? Just ask Recall and it retrieves both text and visual matches for your search, automatically sorted by how closely the results match your search. Recall can even take you back to the exact location of the item you saw.