



PIF
الاستثمار العام

أكاديمية كاوت
KAUST ACADEMY



جامعة الملك عبد الله
للتكنولوجيا
King Abdullah University of
Science and Technology

LEVEL 1: AI Adoption and Implementation in Organizations

Day 5

COURSE OUTLINE

- Vision Language Models (VLMs)
- Generative Artificial Intelligence
- AI Limitations
- Prompt Engineering
- AI Workflow Automation in Organizations
- AI Project Implementation
- AI Use Cases and Business Applications

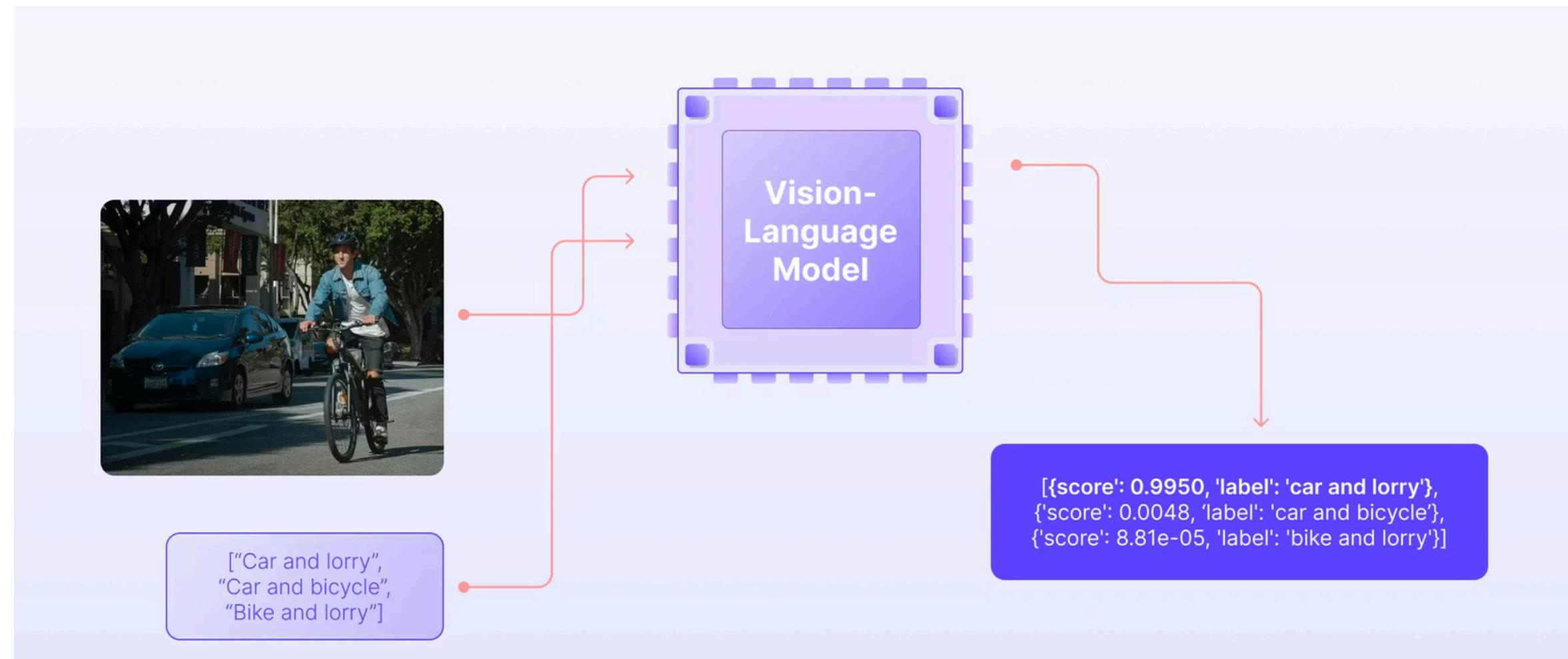
Learning Objectives

- Distinguish between text-only AI models and multimodal models such as Vision–Language Models.
- Evaluate AI-generated outputs critically, recognizing errors, limitations, and ethical concerns.
- Design effective prompts tailored to specific tasks and business objectives.
- Propose AI-powered workflow automations that improve efficiency and productivity.
- Outline a basic AI project plan, including data requirements, model selection, and evaluation criteria.
- Map real-world business problems to suitable AI solutions and assess their potential impact.

Vision Language Models (VLMs)

Vision Language Models

- » Vision language models are models that can learn simultaneously from images and texts to tackle many tasks, from visual question answering to image captioning.



Vision Language Models

- » Vision-language tasks require understanding concepts in both vision and language, and fusing information from both modalities

Who is wearing glasses?

man



woman



Where is the child sitting?

fridge



arms



Is the umbrella upside down?

yes

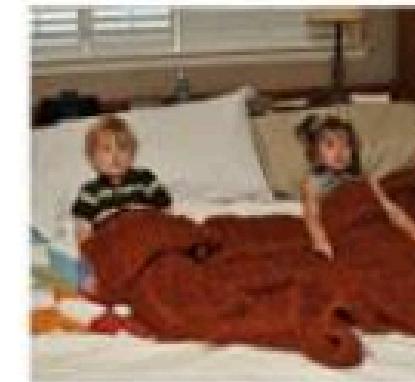


no



How many children are in the bed?

2



1



Vision Language Models

»» Understanding concepts in both vision and language (single modality representation)

»» Vision representation (CNN -> Faster-RCNN -> Transformer)



The man at bat readies to swing at the pitch while the umpire looks on.

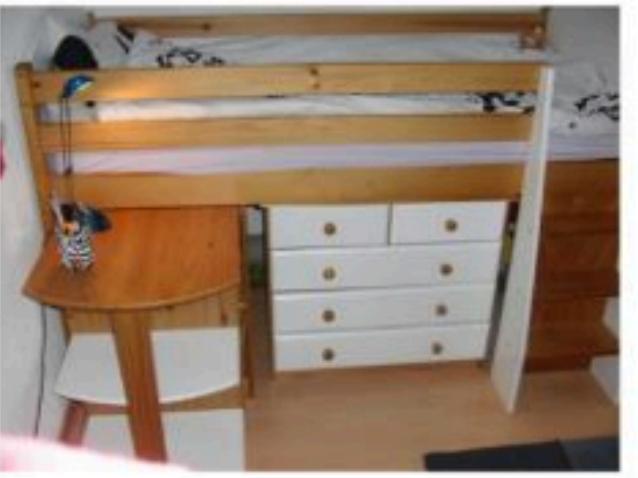


A large bus sitting next to a very tall building.

»» Language representation (RNN -> Transformer)



A horse carrying a large load of hay and two people sitting on it.



Bunk bed with a narrow shelf sitting underneath it.

Vision Language Models

»» Tasks of VLMs

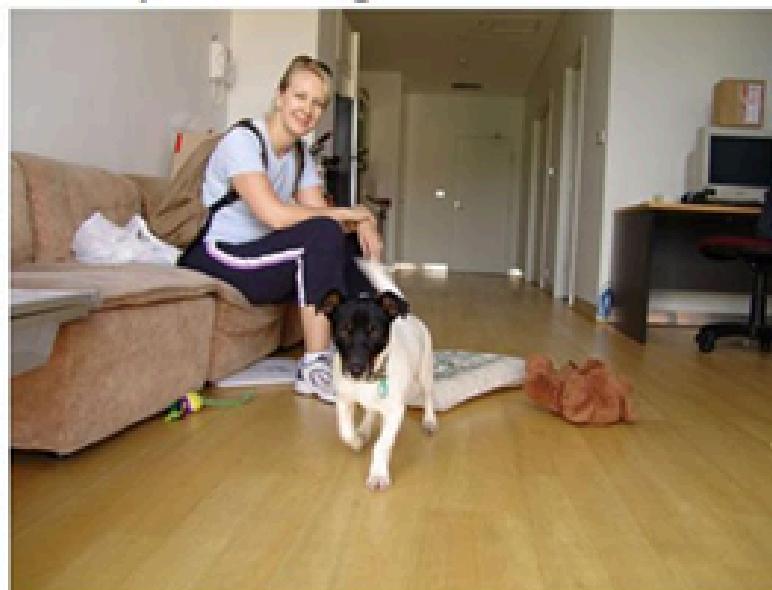
	Text-to-Image Retrieval	Image-to-Text Retrieval	VQA	Image Captioning	Text-to-Image Generation
Input	Query: A couple of zebra walking across a dirt road. A pool of images.	Query: 	Image:  Q: why did the zebra cross the road?	Image: 	Text: A couple of zebra walking across a dirt road.
Output		A couple of zebra walking across a dirt road.	A: to get to the other side (Selected from a pool of 3,129 answers in VQAv2)	A couple of zebra walking across a dirt road.	

Understanding Understanding Understanding Generation Generation

Vision Language Models

»» Early Research: Prior to Deep Learning

Input Image



1) Object(s)/Stuff



2) Attributes

brown 0.01
striped 0.16
furry .26
wooden .2
feathered .06
...

brown 0.32
striped'0.09
furry .04
wooden .2
Feathered .04
...

brown 0.94
striped 0.10
furry .06
wooden .8
Feathered .08
...

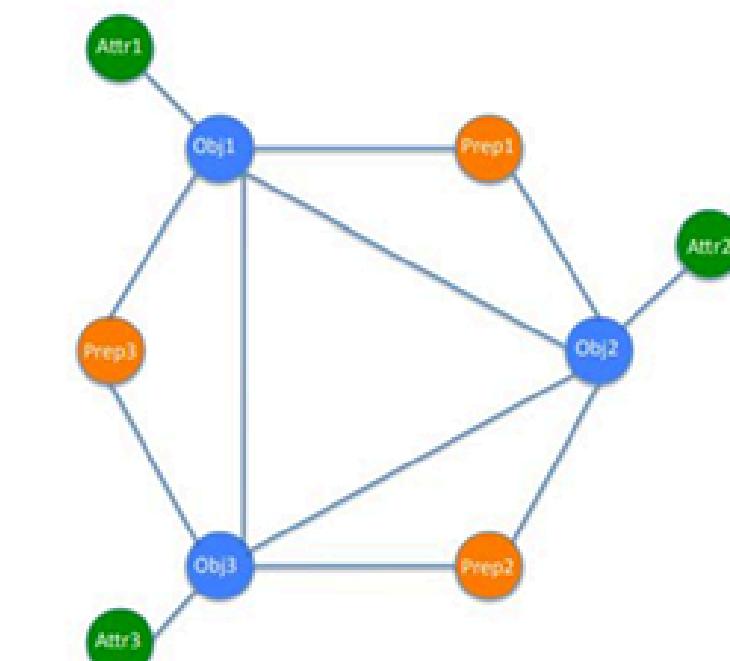
3) Prepositions

near(a,b) 1
near(b,a) 1
against(a,b) .11
against(b,a) .04
beside(a,b) .24
beside(b,a) .17
...

near(a,c) 1
near(c,a) 1
against(a,c) .3
against(c,a) .05
beside(a,c) .5
beside(c,a) .45
...

near(b,c) 1
near(c,b) 1
against(b,c) .67
against(c,b) .33
beside(b,c) .0
beside(c,b) .19
...

4) Constructed CRF



5) Predicted Labeling

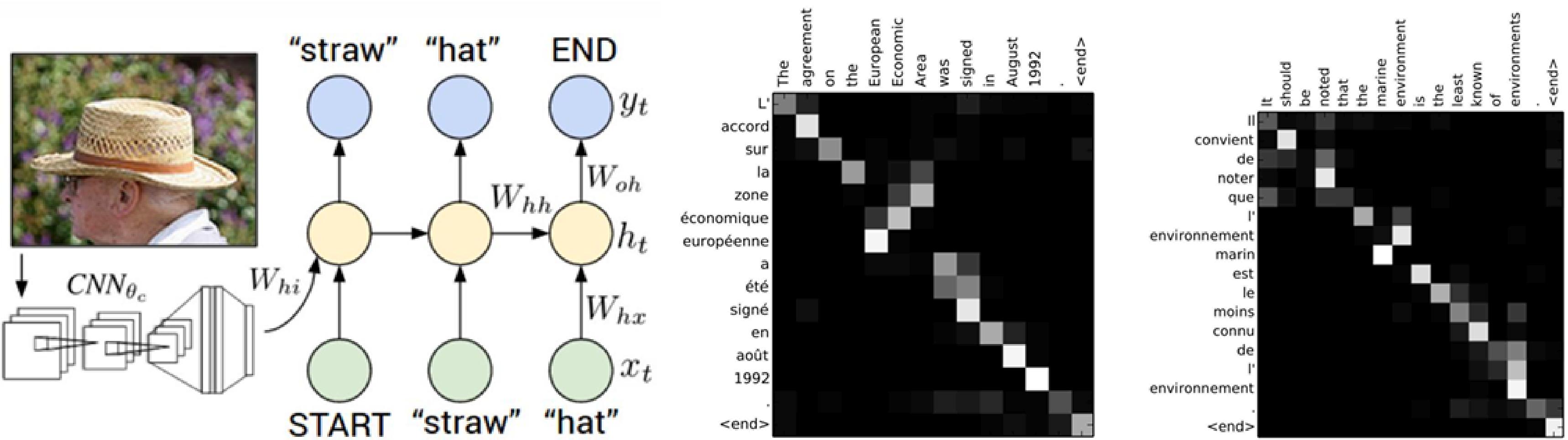
<<null,person_b>,against,<brown,sofa_c>>
<<null,dog_a>,near,<null,person_b>>
<<null,dog_a>,beside,<brown,sofa_c>>

6) Generated Sentences

This is a photograph of one person and one brown sofa and one dog. The person is against the brown sofa. And the dog is near the person, and beside the brown sofa.

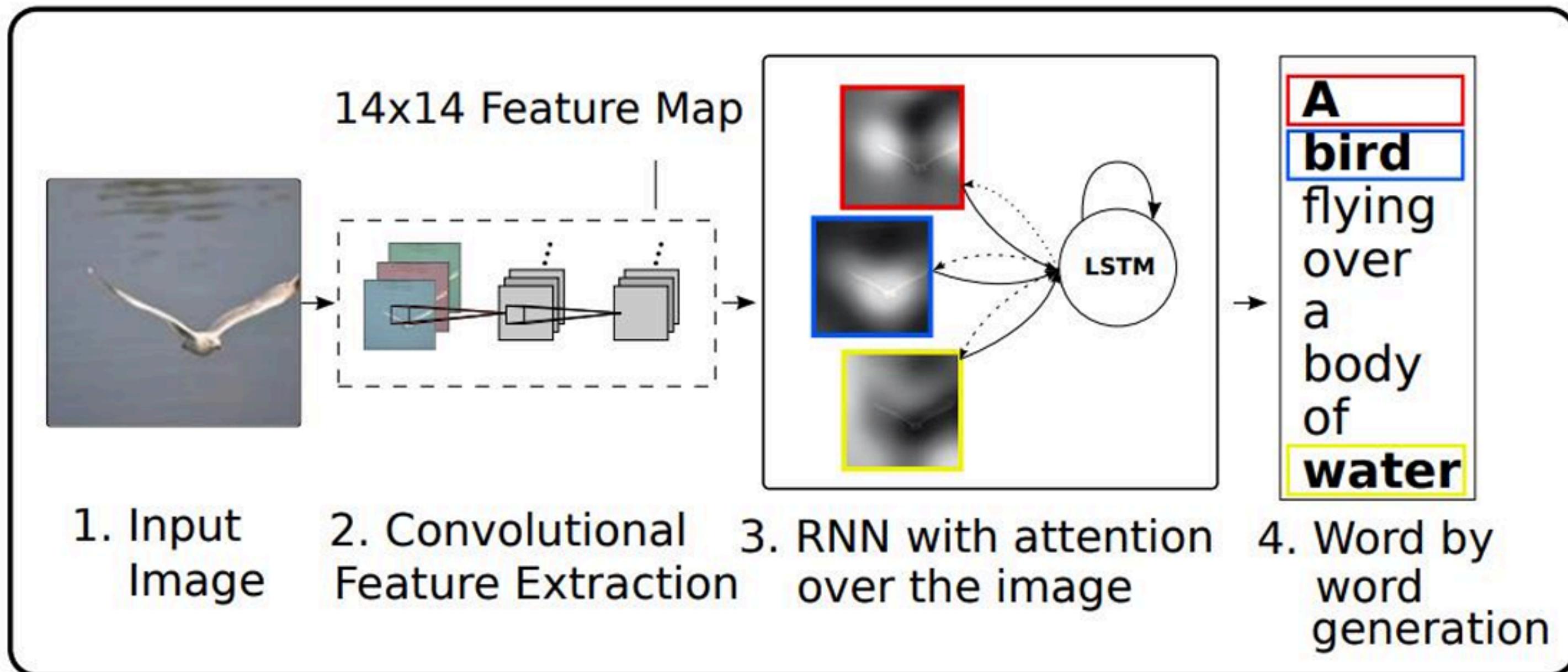
Vision Language Models

»» Early Research: Prior to Deep Learning



Vision Language Models

»» Early Research: Attention in Image Captioning



Vision Language Models

»» Early Research: Attention in Image Captioning

»» The model learns alignments that correspond very strongly with human intuition.



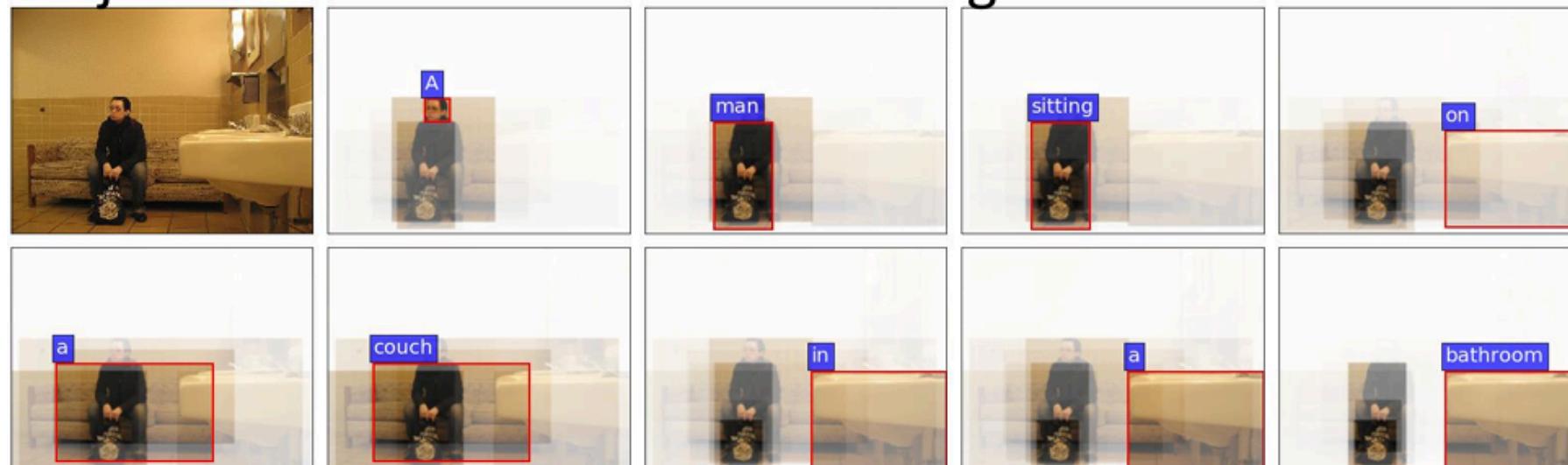
Vision Language Models

»» Attention Empowered by Objects Detection

Grid feature: A man sitting on a **toilet** in a bathroom.



Object-centric feature: A man sitting on a **couch** in a bathroom.



Vision Language Models

»» Overview of Open Source VLMs

Model	Permissive License	Model Size	Image Resolution	Additional Capabilities
LLaVA-1.6 (Hermes)	✓	34B	672 × 672	—
DeepSeek-VL-7B-Base	✓	7B	384 × 384	—
DeepSeek-VL-Chat	✓	7B	384 × 384	Chat
Moondream2	✓	~2B	378 × 378	—
CogVLM-Base	✓	17B	490 × 490	—
CogVLM-Chat	✓	17B	490 × 490	Grounding, Chat
Fuyu-8B	✗	8B	300 × 300	Text detection within image
KOSMOS-2	✓	~2B	224 × 224	Grounding, zero-shot object detection
Qwen-VL	✓	4B	448 × 448	Zero-shot object detection
Qwen-VL-Chat	✓	4B	448 × 448	Chat
Yi-VL-34B	✓	34B	448 × 448	Bilingual (English, Chinese)

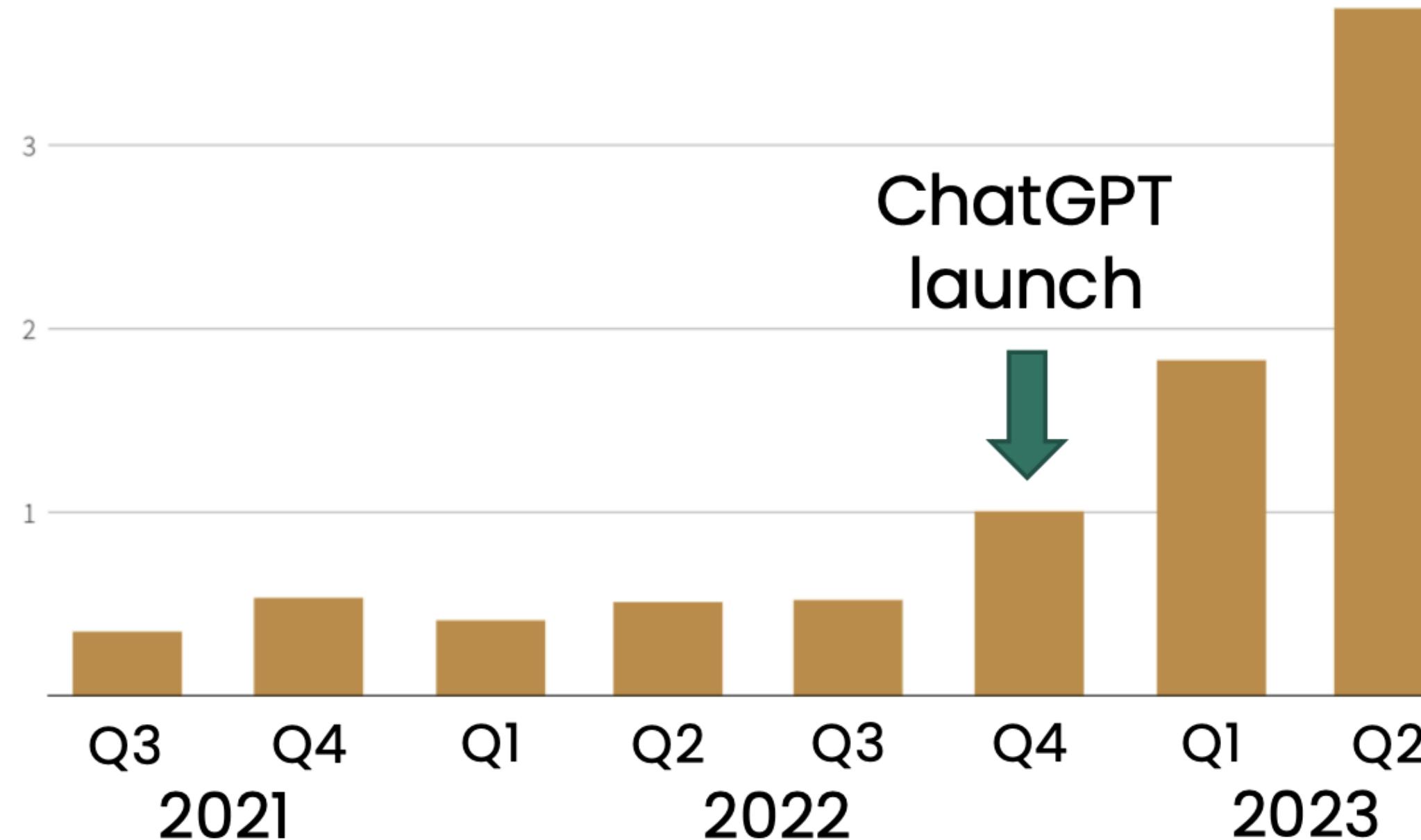
Generative Artificial Intelligence

What Is
Generative AI?



Generative Artificial Intelligence

Average number of 'AI' mentions per S&P 500 analyst call



Source: Reuters

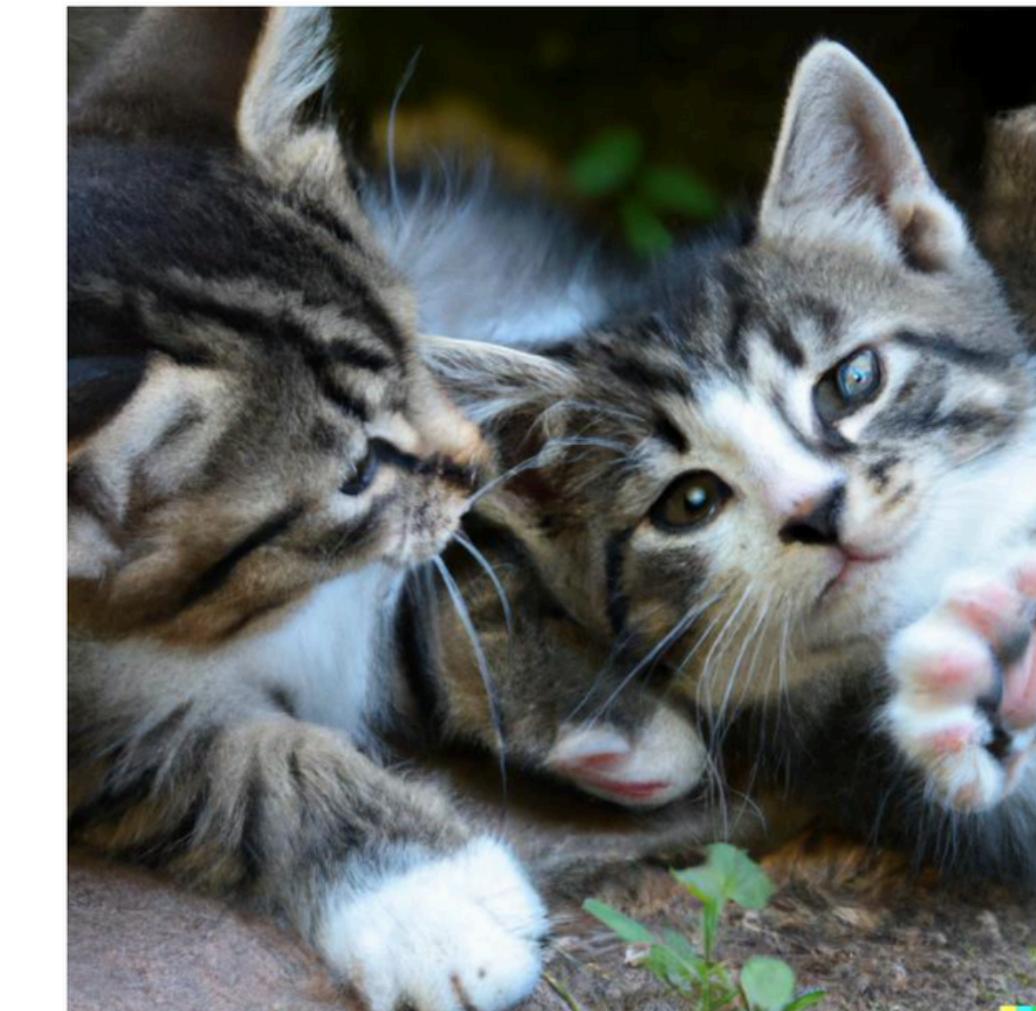
Generative Artificial Intelligence

- Artificial intelligence systems that can produce high-quality content, including text, images, and audio.

“

Two cute kittens playing..

”



(DALL-E)

AI Limitations

Bias and Adversarial Attacks

AI Limitations

- Data Bias and unfair outcomes

“ — A color photograph of a CEO — ”



*

AI Limitations

- Data Bias and unfair outcomes

“ —
A color photograph of a
dishwasher worker
— ”



AI Limitations

- Data Bias and unfair outcomes

*

“ —
A color photograph of a
dishwasher worker
— ”



AI Limitations

- Data Bias and unfair outcomes

“ —
A color photograph of a
dishwasher worker
— ”



*

AI Limitations

- Common causes of bias

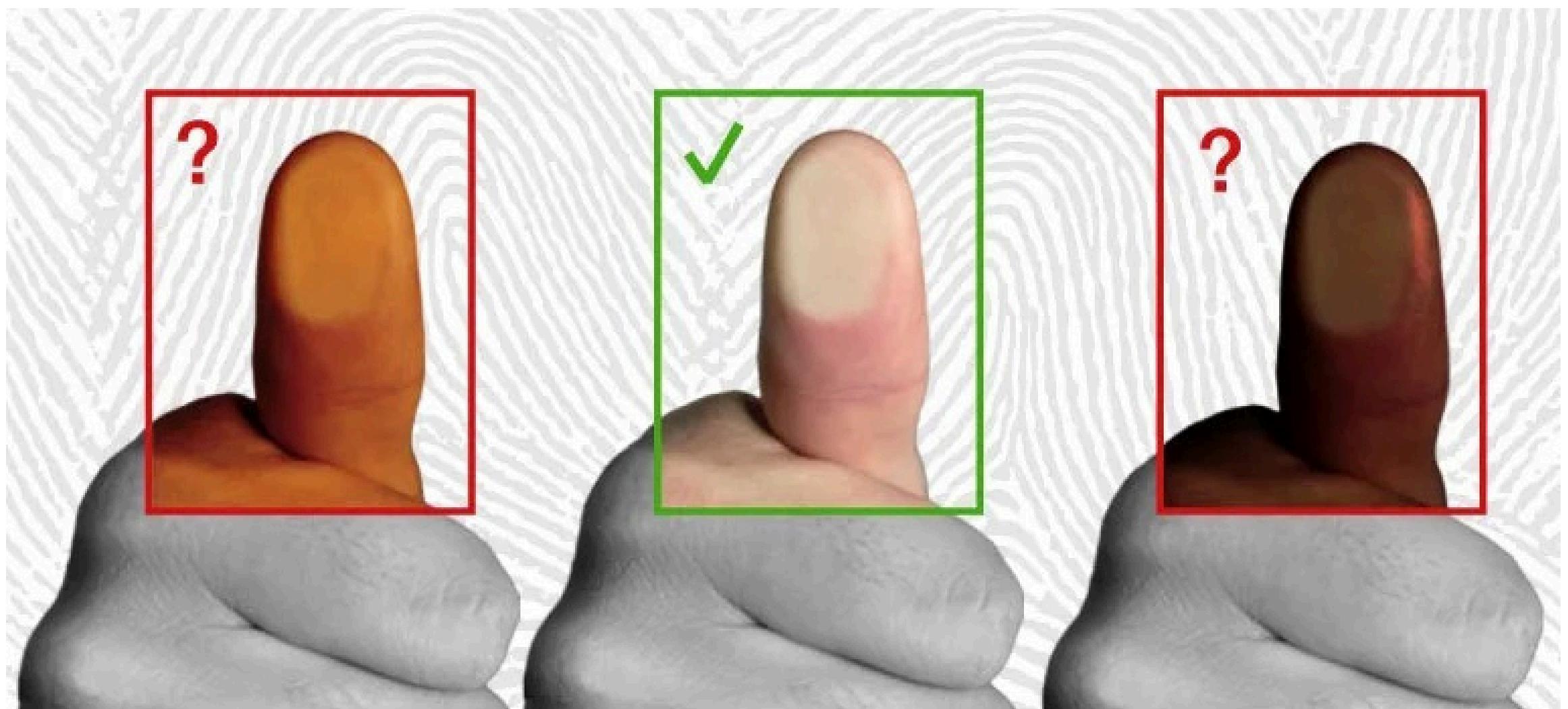
- Bias in training data



AI Limitations

- Common causes of bias
- Unequal representation

Some groups appear much more than others



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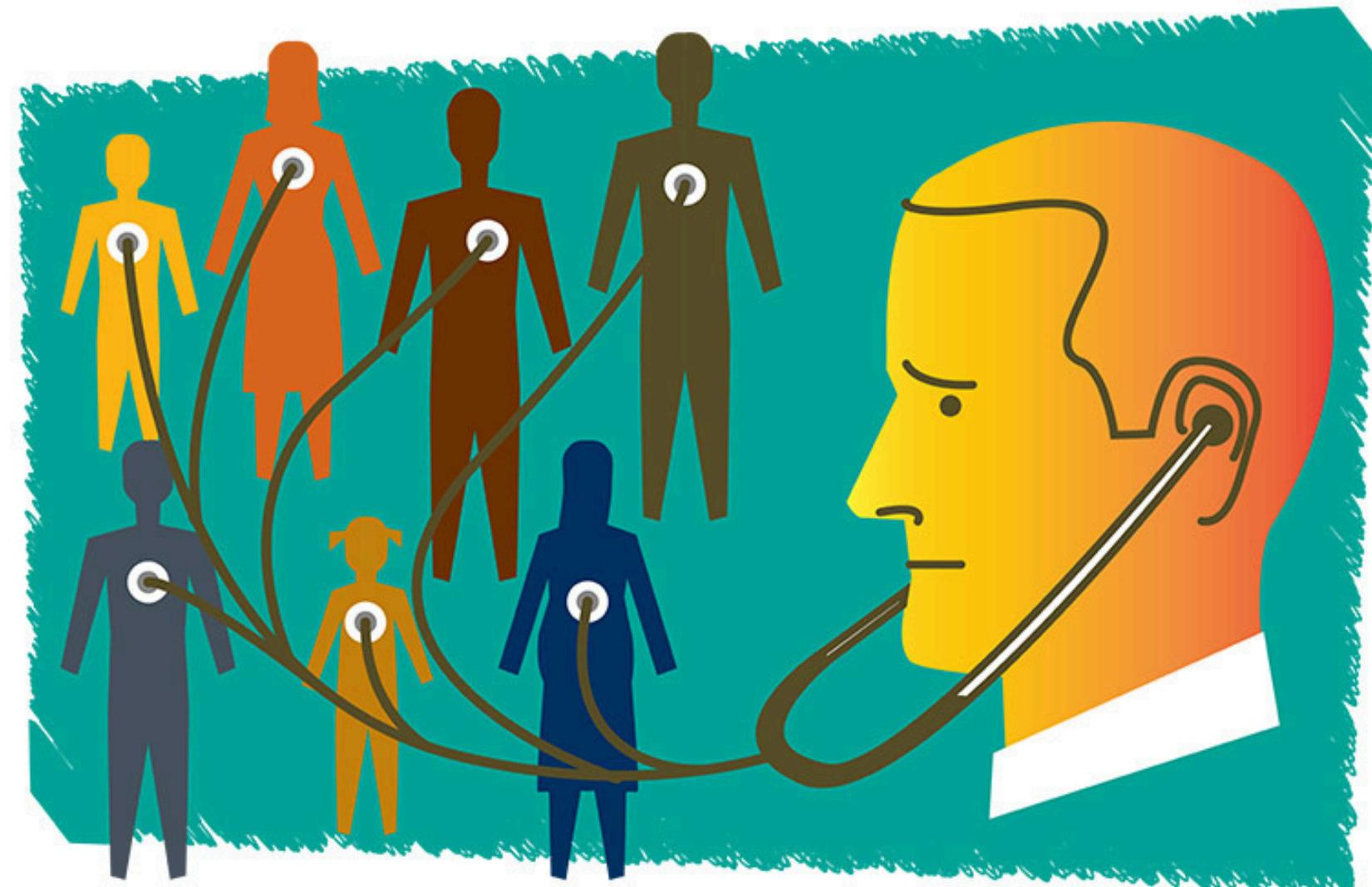
AI Limitations

- Common causes of bias

- Algorithmic design choices

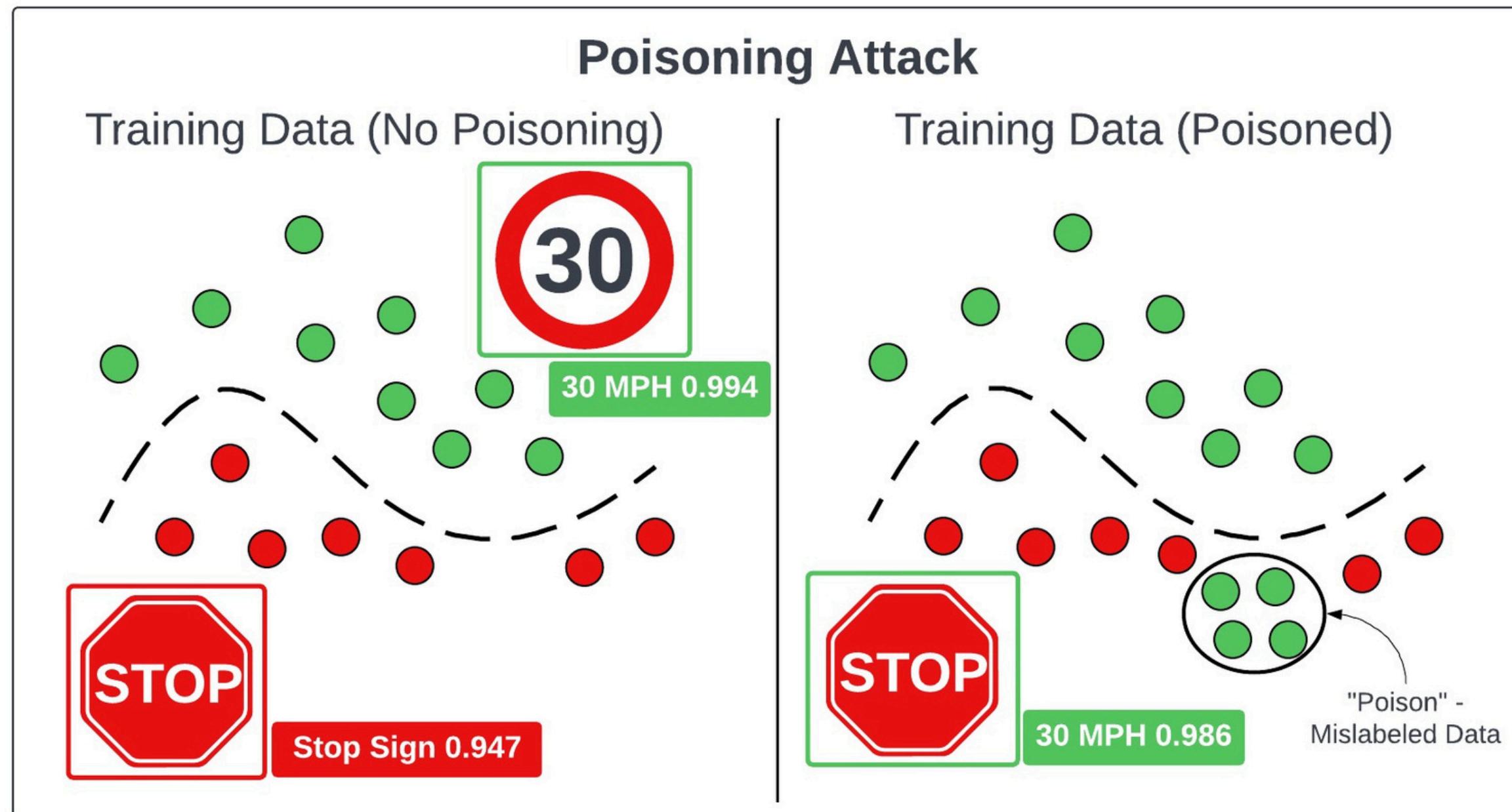
The bias comes from the algorithmic choice, not the data alone.

- Lower spending = healthier → often wrong
- Higher spending = sicker → often wrong



AI Limitations

- Adversarial attacks



*

—

AI Limitations

- Adversarial attacks



*

—

AI Limitations

- Adversarial attacks

original image



Panda

57.7%

perturbations



adversarial example



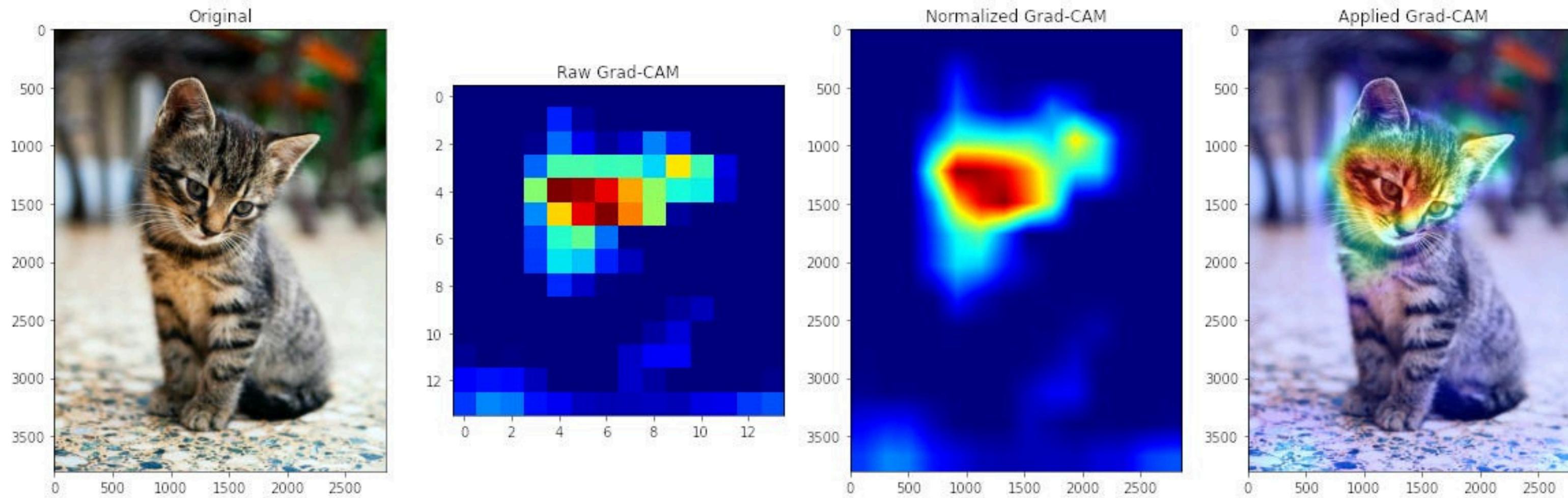
Gibbon

99.3%

AI Ethics and Responsibility

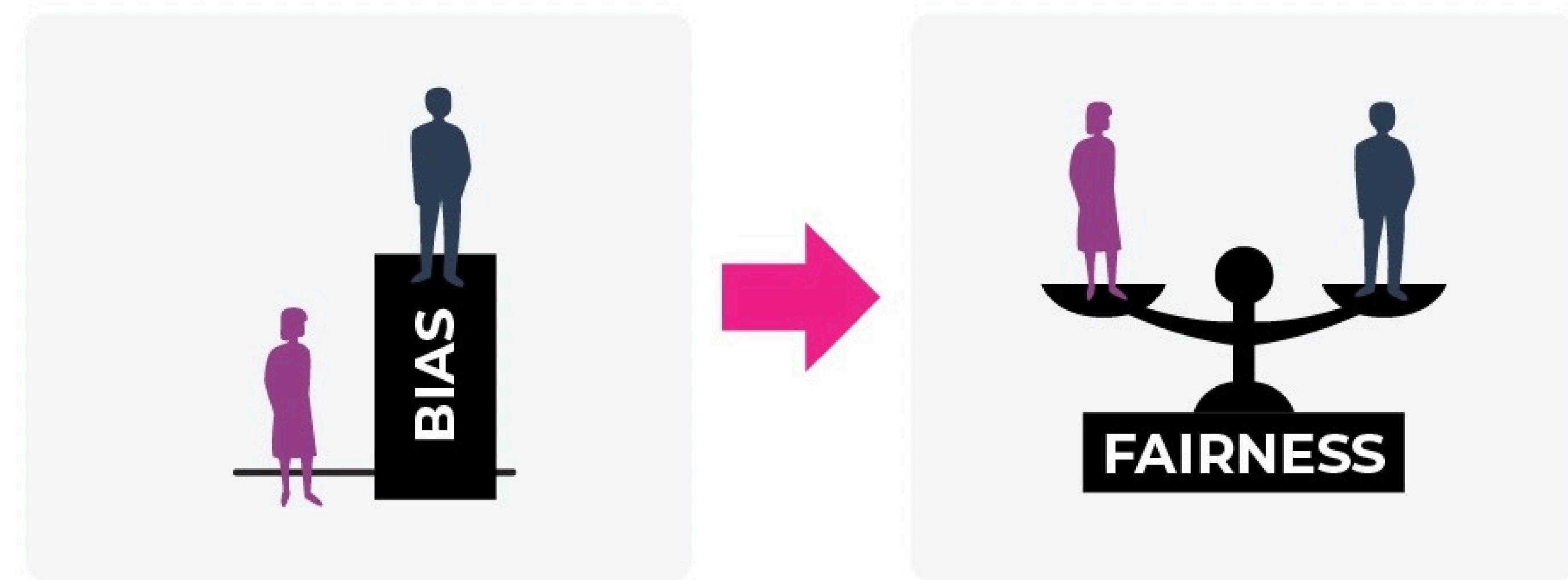
AI Ethics and Responsibility

Fortunately, new techniques now help reveal why a model made a prediction, even when the underlying system is complex.



AI Ethics and Responsibility

- Principle 1 : Fairness



AI Ethics and Responsibility

- Principle 2 : Privacy and Security



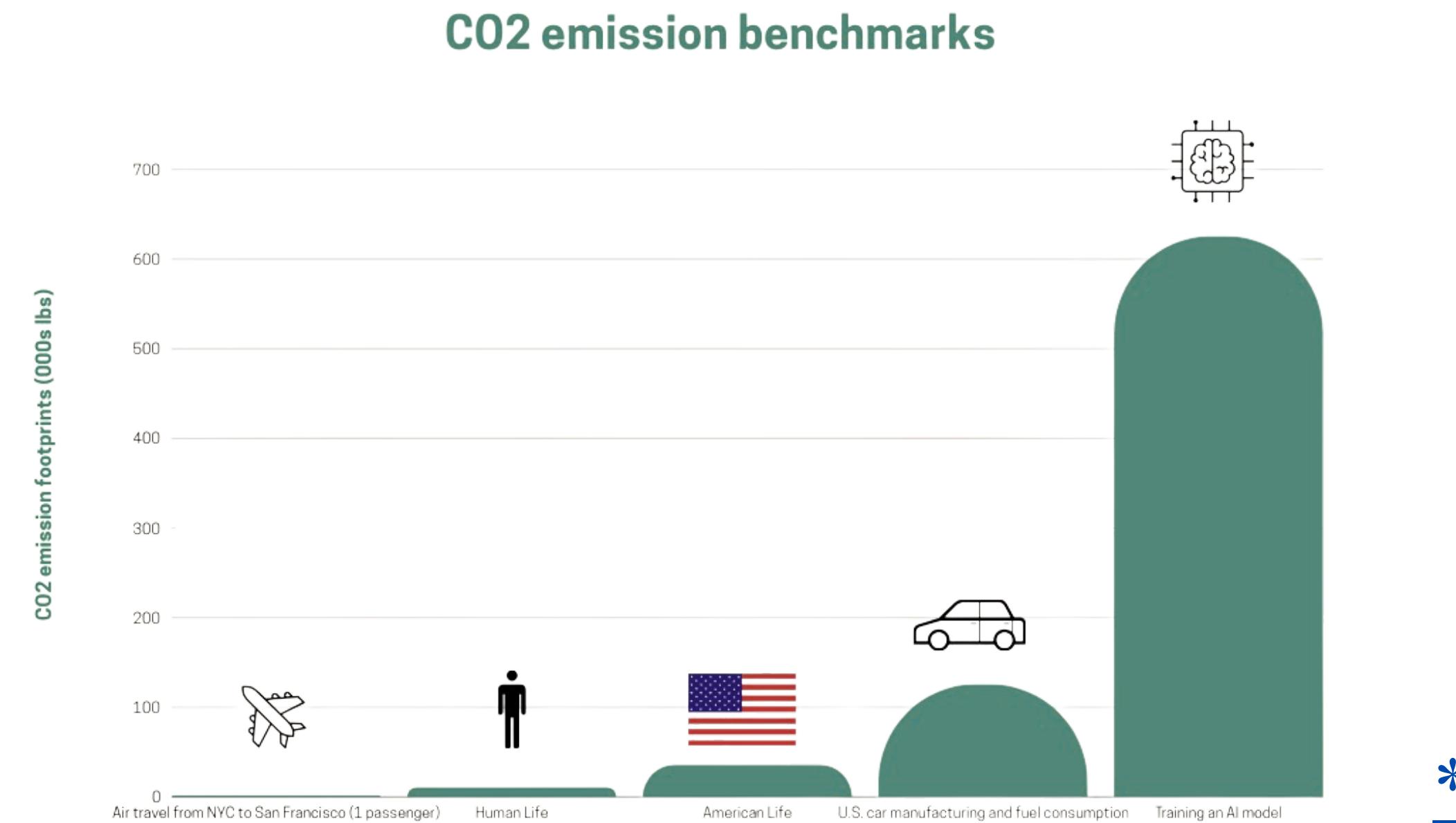
AI Ethics and Responsibility

- Principle 3 : Humanity



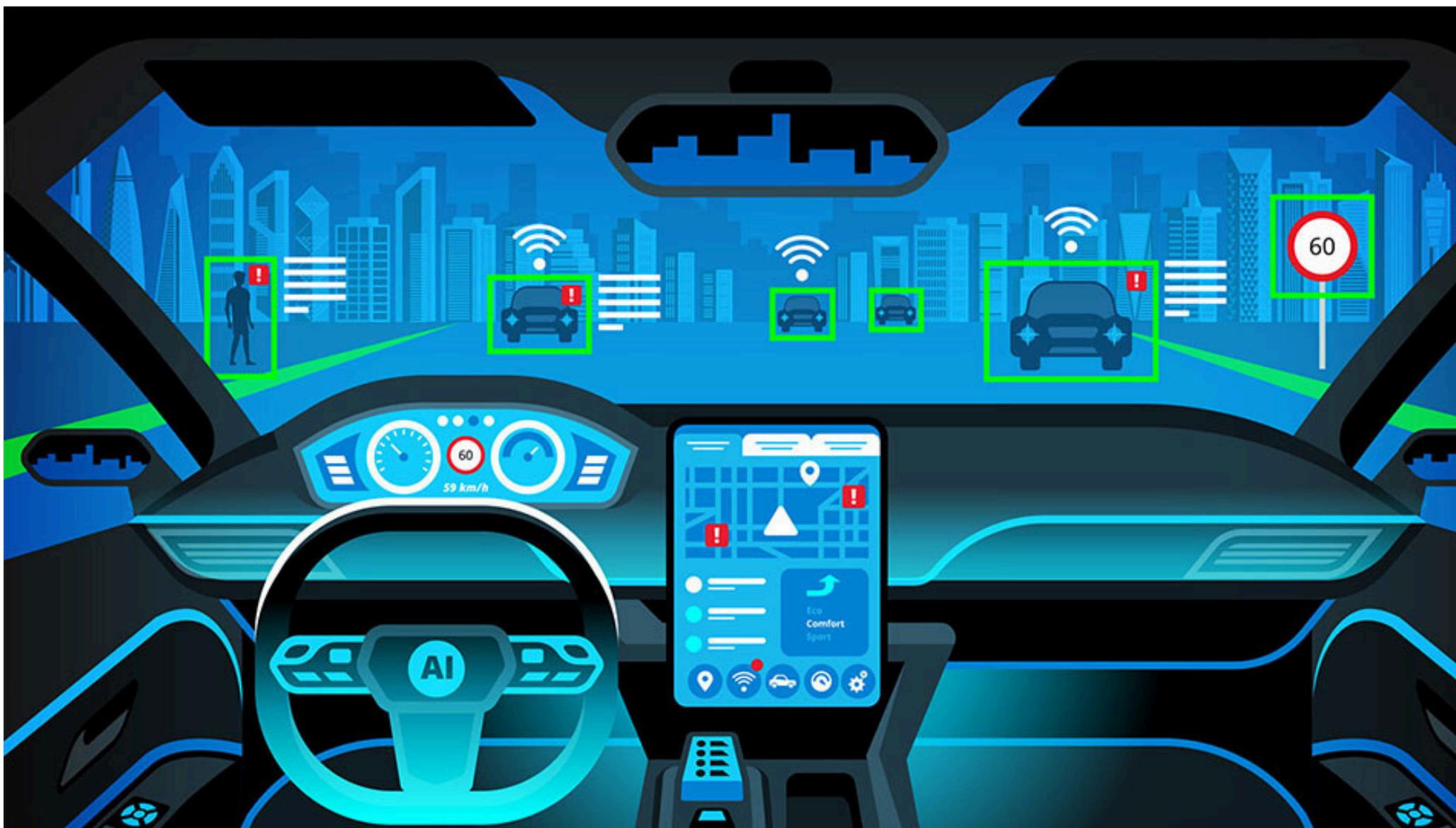
AI Ethics and Responsibility

- Principle 4 : Social and Environmental Benefits



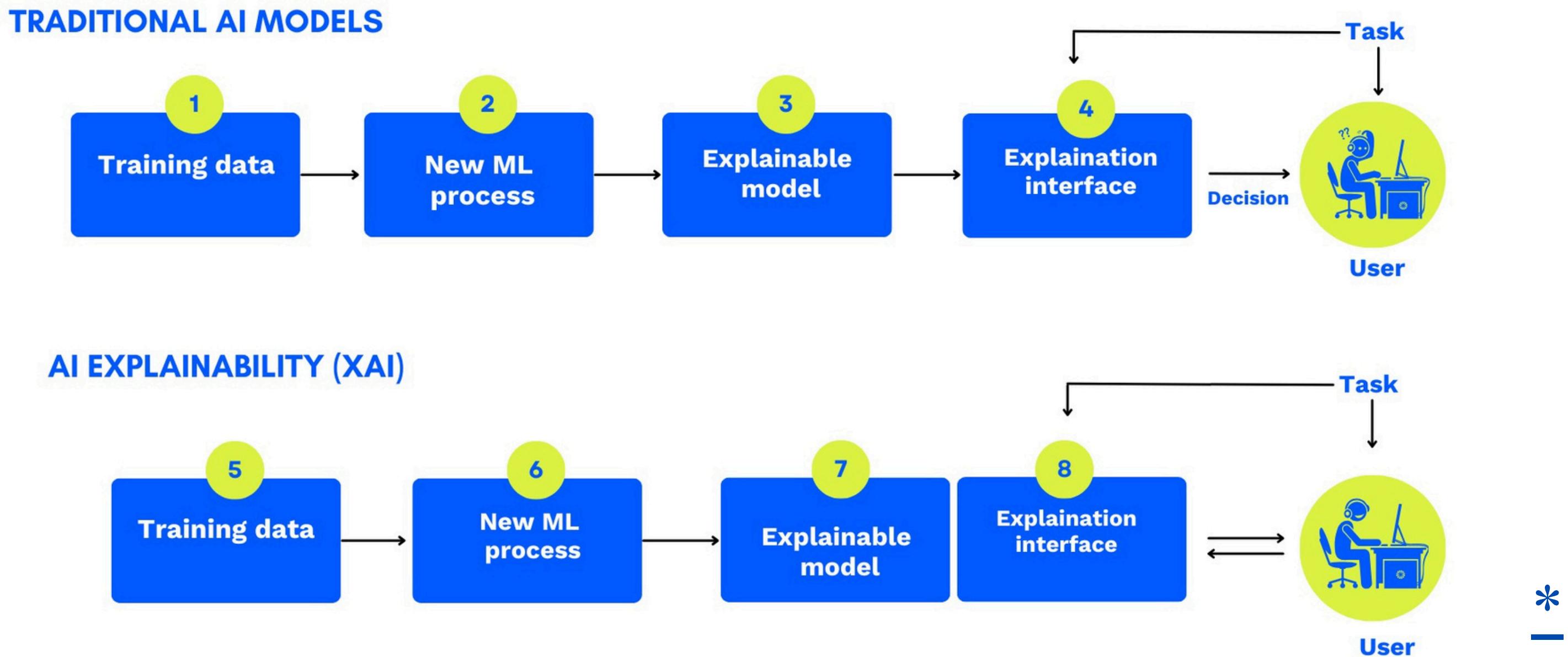
AI Ethics and Responsibility

- Principle 5 : Reliability and Safety



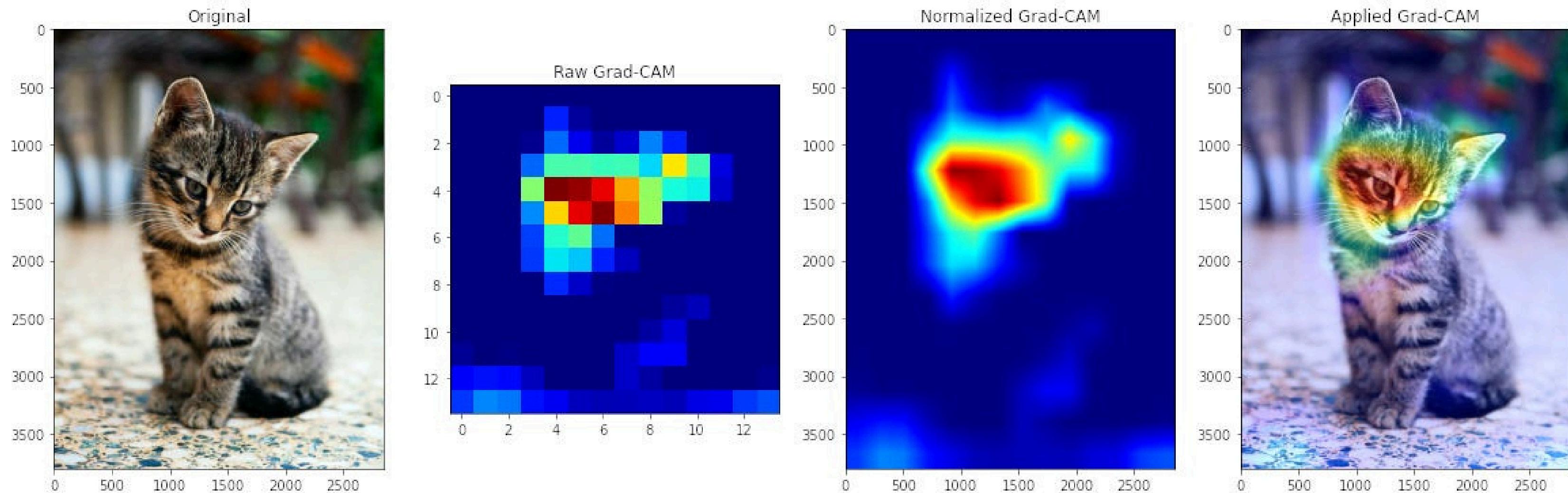
AI Ethics and Responsibility

- Principle 6 : Transparency & Explainability



AI Ethics and Responsibility

- Principle 6 : Transparency & Explainability



Prompt Engineering

Introduction

Prompt Engineering

- A prompt is the input or instruction given to an AI model to guide its output.



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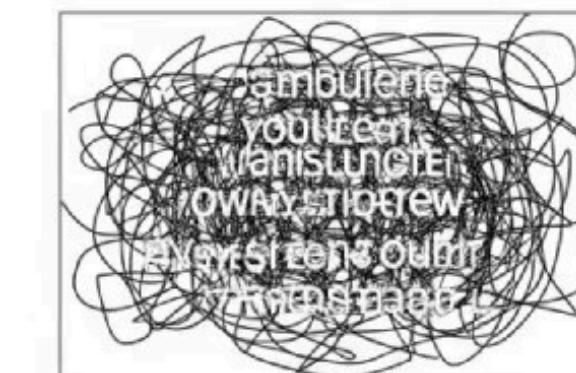
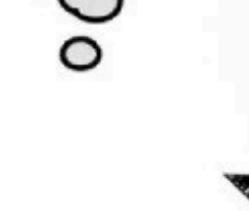
—

Prompt Engineering

- Prompting Large Language Models (LLMs)

- Clarity and specificity matter

Vague Input



Unpredictable Output

Specific Input

Summarize the article into a 3-bullet point list. Each bullet point should be a complete sentence and capture a key insight for a busy tech executive.



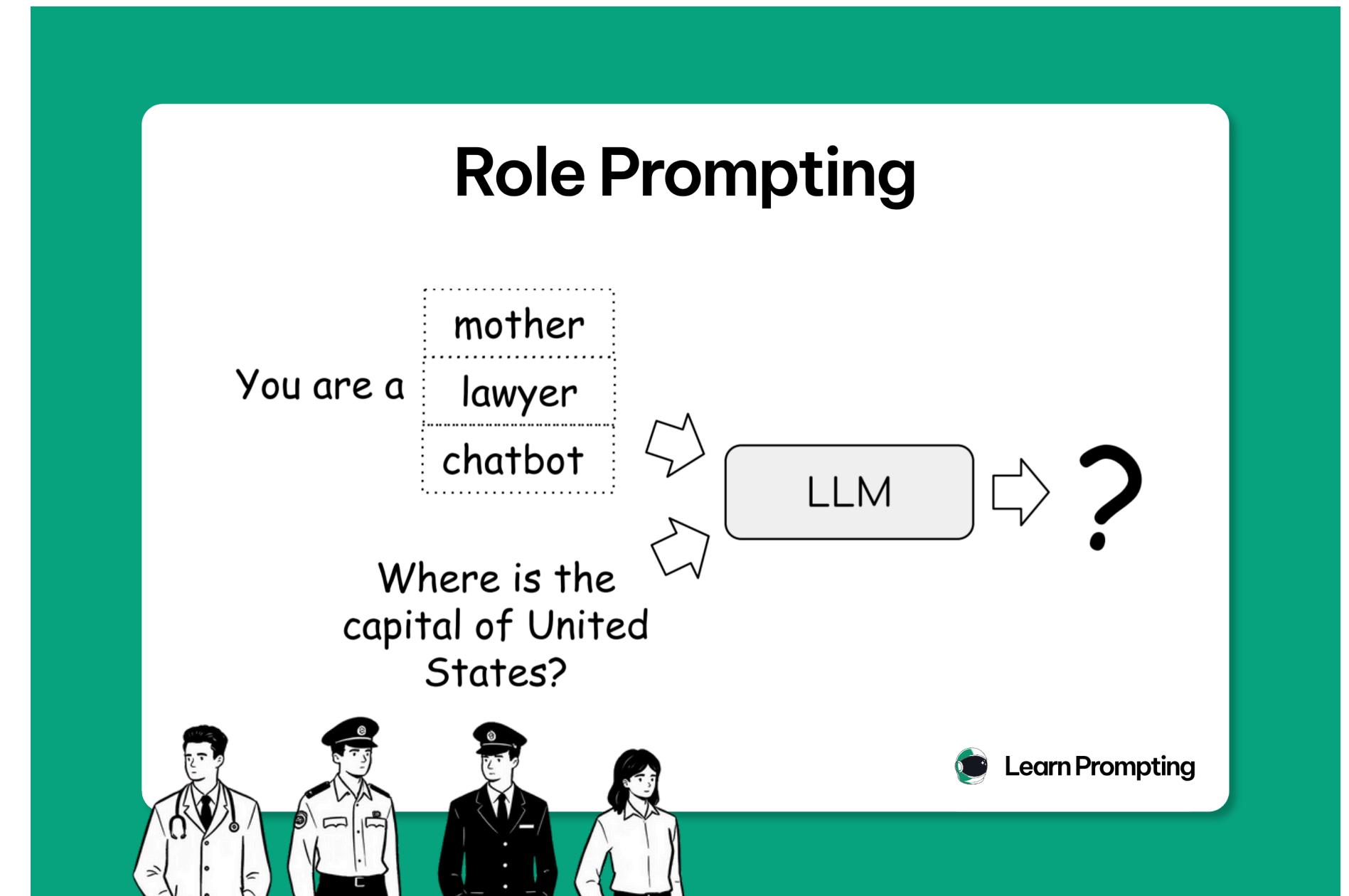
- The core argument supports a new market strategy.
- Emerging data indicates a shift in consumer behavior.
- Key findings suggest a need for technological adaptation.

Predictable Output

*

Prompt Engineering

- Prompting Large Language Models (LLMs)
- Role Assignment



Prompt Engineering

- Prompting Large Language Models (LLMs)
 - Example-based prompting

Zero-shot

Translate
“Good morning”
to French

One-shot

“Hello” →
“Bonjour”
Now translate:
“Goodbye” →

Few-shot

“Hello” → “Bonjour”
“Yes” → “Oui”
“No” → “Non”
“Thank you” →

Prompt Engineering

- Prompting Large Language Models (LLMs)

- Chain of Thought



Prompt Engineering

- Image generation



Image 1



Image 2

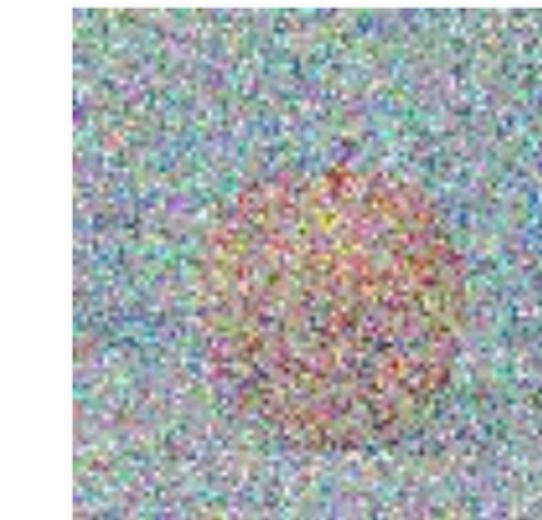


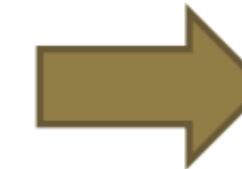
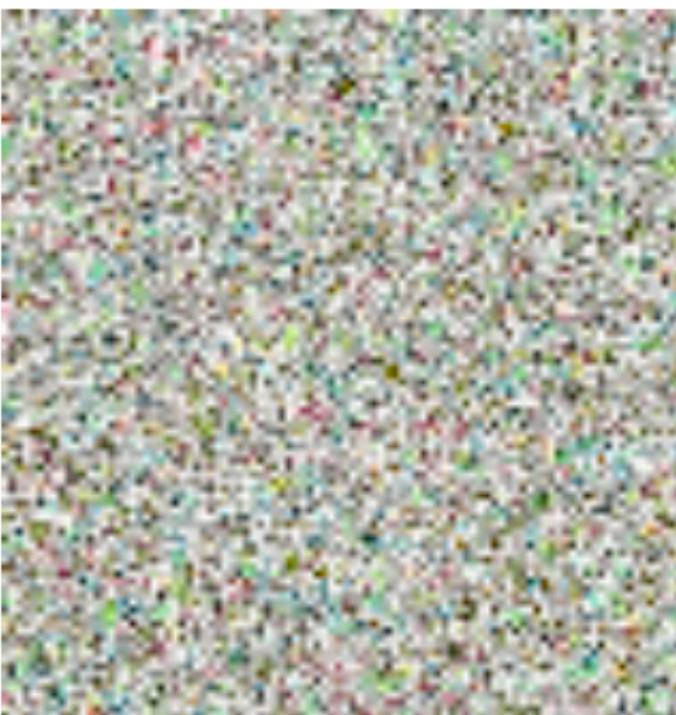
Image 3



Image 4

Prompt Engineering

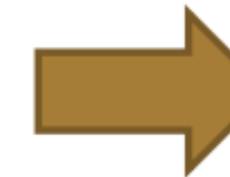
- Image generation



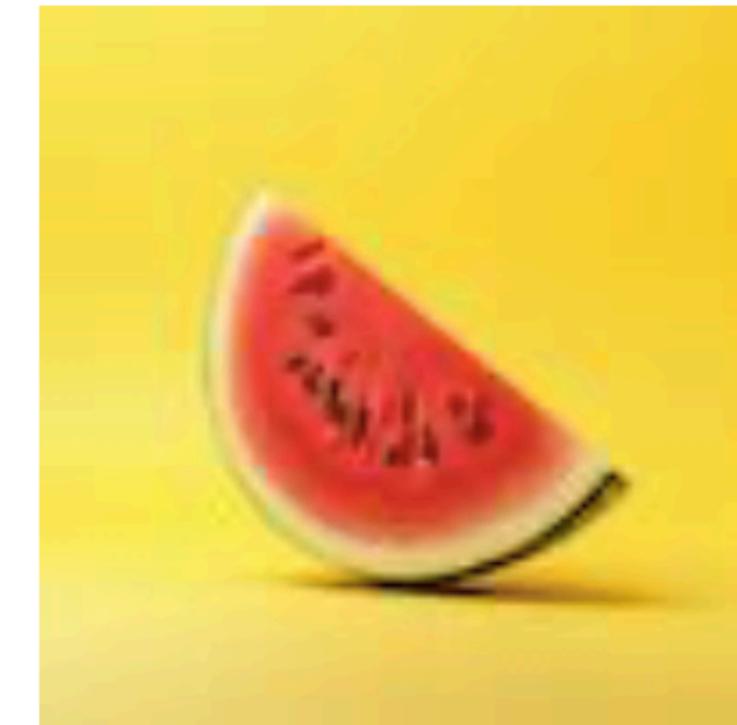
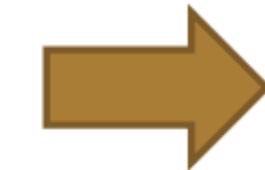
Noisy image → Slightly less noisy image

Prompt Engineering

- Image generation



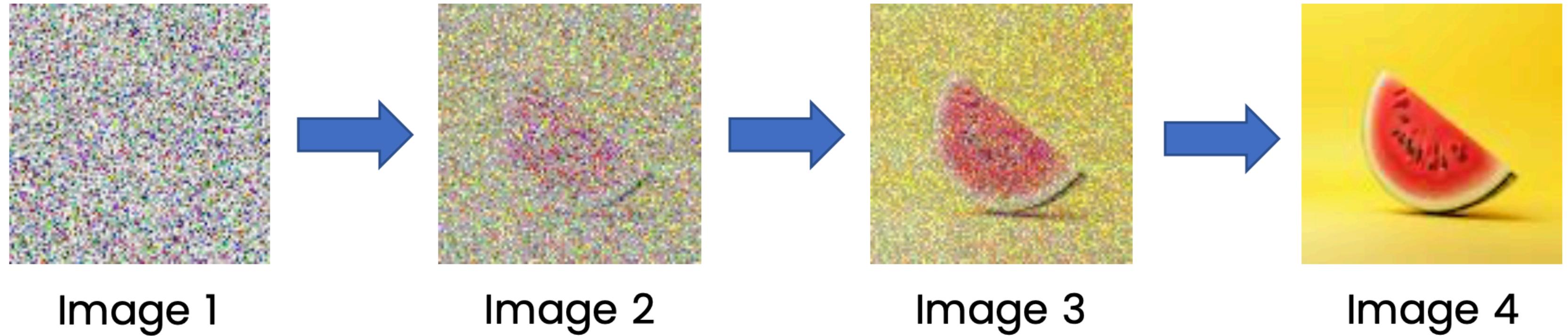
Then, Slightly less noisy image



Then, Slightly less noisy image

Prompt Engineering

- Image generation



Typically ~ 100 steps for diffusion model

Prompt Engineering

- Image generation



Image 1,
“red apple”



Image 2

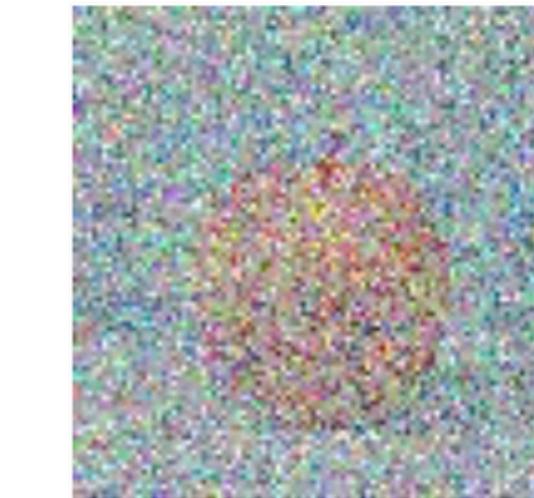


Image 3

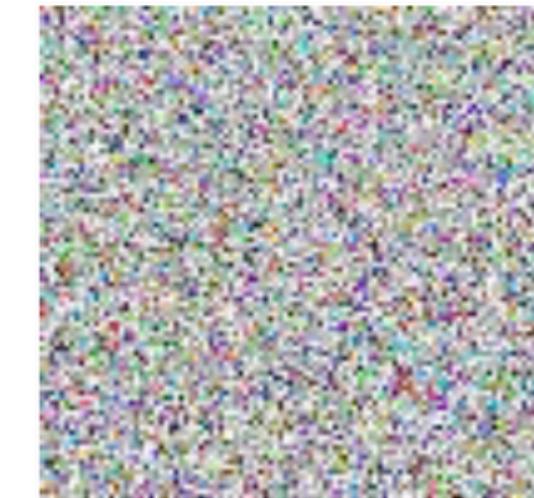


Image 4

Noisy image and caption



Slightly less noisy image

AI Workflow Automation for Organizations

AI Workflow Automation for Organizations



35%

of businesses
worldwide use AI
in 2022



9/10

leading businesses
have ongoing
investments in AI

61%

of employees say
AI helps to improve
their productivity



54%

of organizations have
reported cost-savings
and efficiencies as the
result of AI implementation

IBM, 2022; NewVantage, 2022; SnapLogic, 2021

What Is AI
Adoption?



AI Workflow Automation for Organizations

» AI Adoption

- Integrating AI into core operations to create measurable business value.



AI Workflow Automation for Organizations

»» AI Adoption

- Changing how work gets done



AI Workflow Automation for Organizations

»» AI Adoption

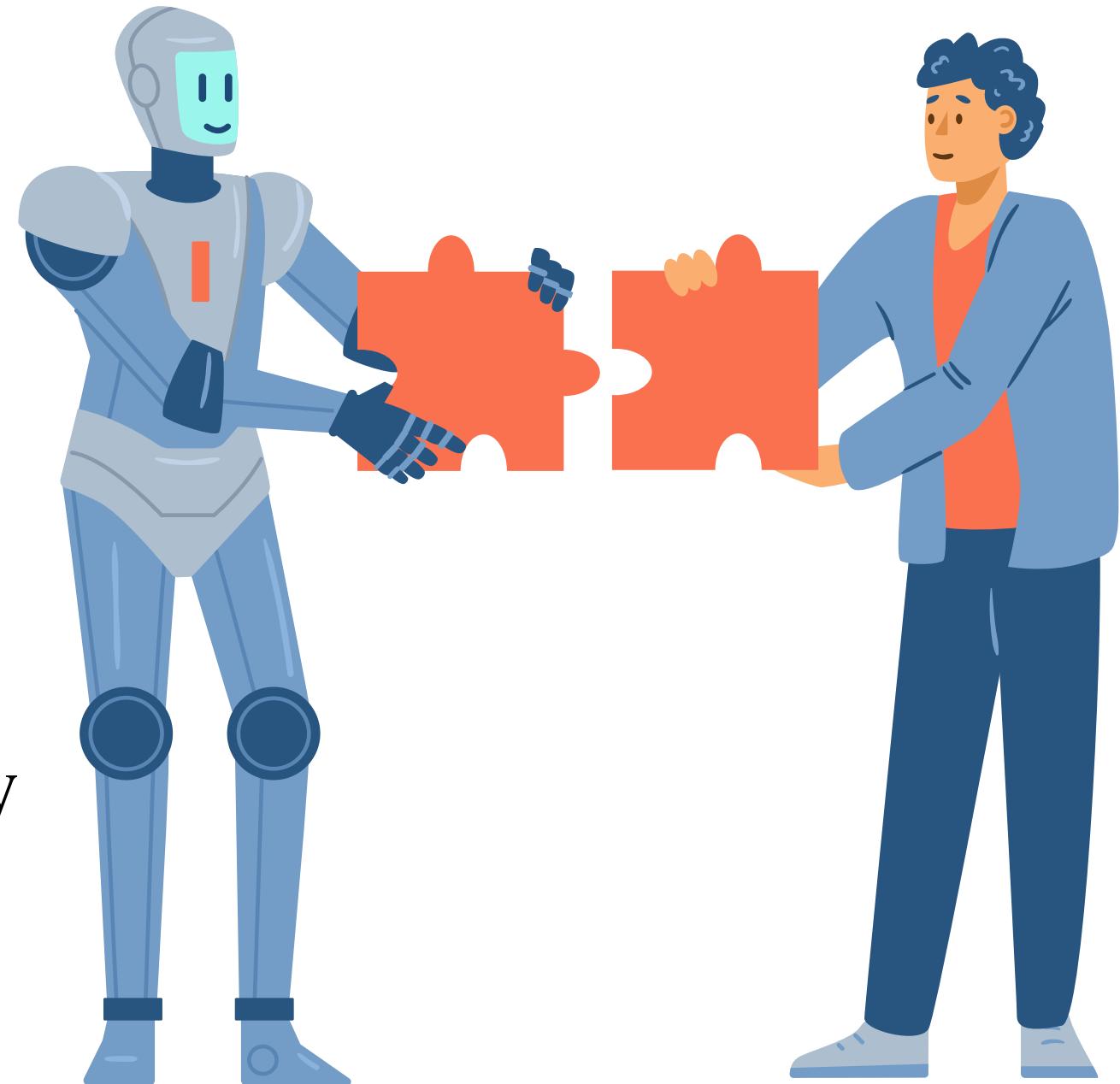
- Changing how work gets done
- Changing how decisions are made



AI Workflow Automation for Organizations

»» AI Adoption

- Changing how work gets done
- Changing how decisions are made
- Changing how employees interact with technology



AI Workflow Automation for Organizations

AI Adoption in
organizations

True AI Adoption

- Employees use AI daily
- Workflows redesigned to maximize AI
- Clear measurable outcomes (cost, speed, customer experience)

AI Workflow Automation for Organizations

AI Adoption in organizations

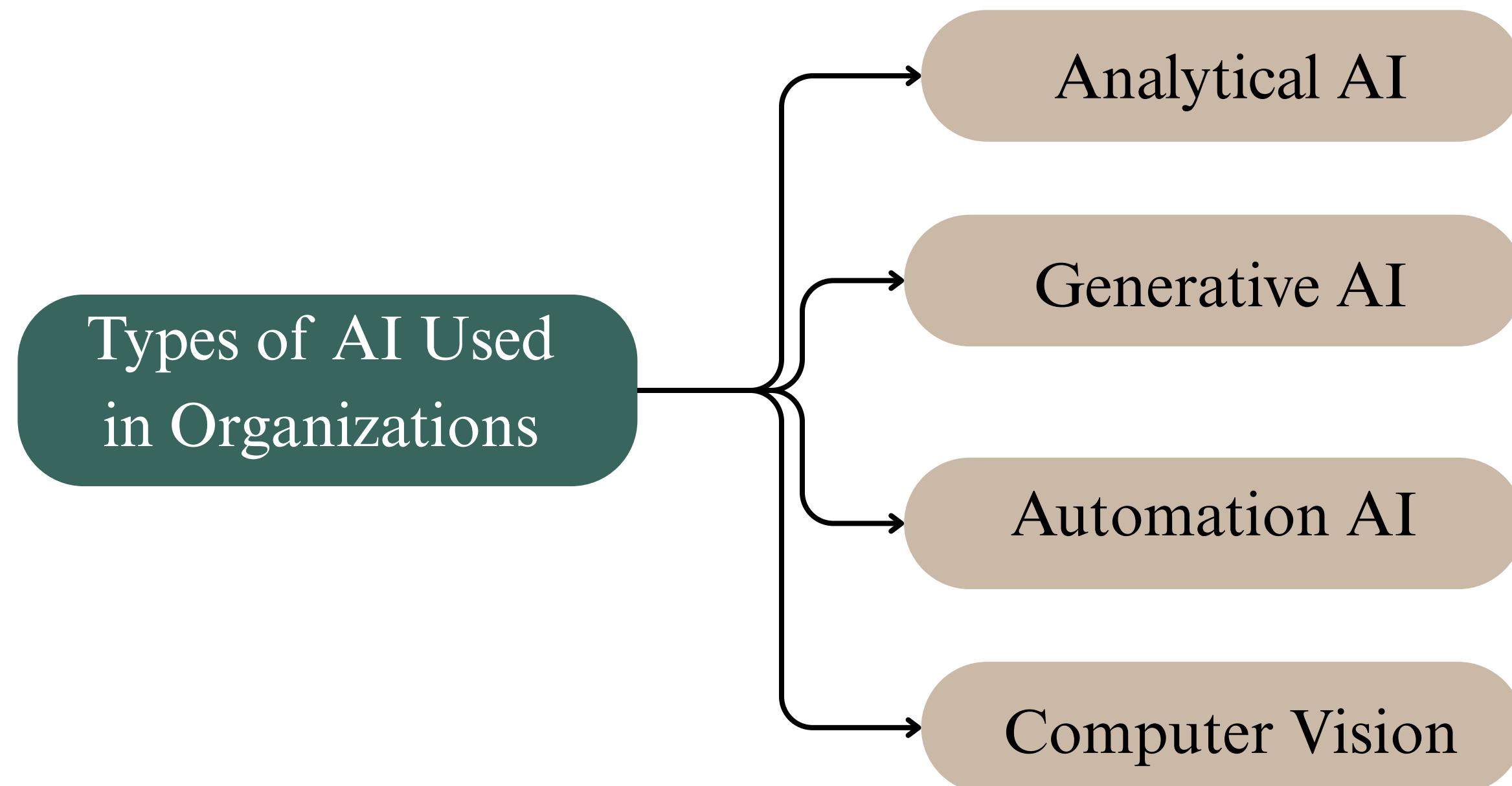
True AI Adoption

- Employees use AI daily
- Workflows redesigned to maximize AI
- Clear measurable outcomes (cost, speed, customer experience)

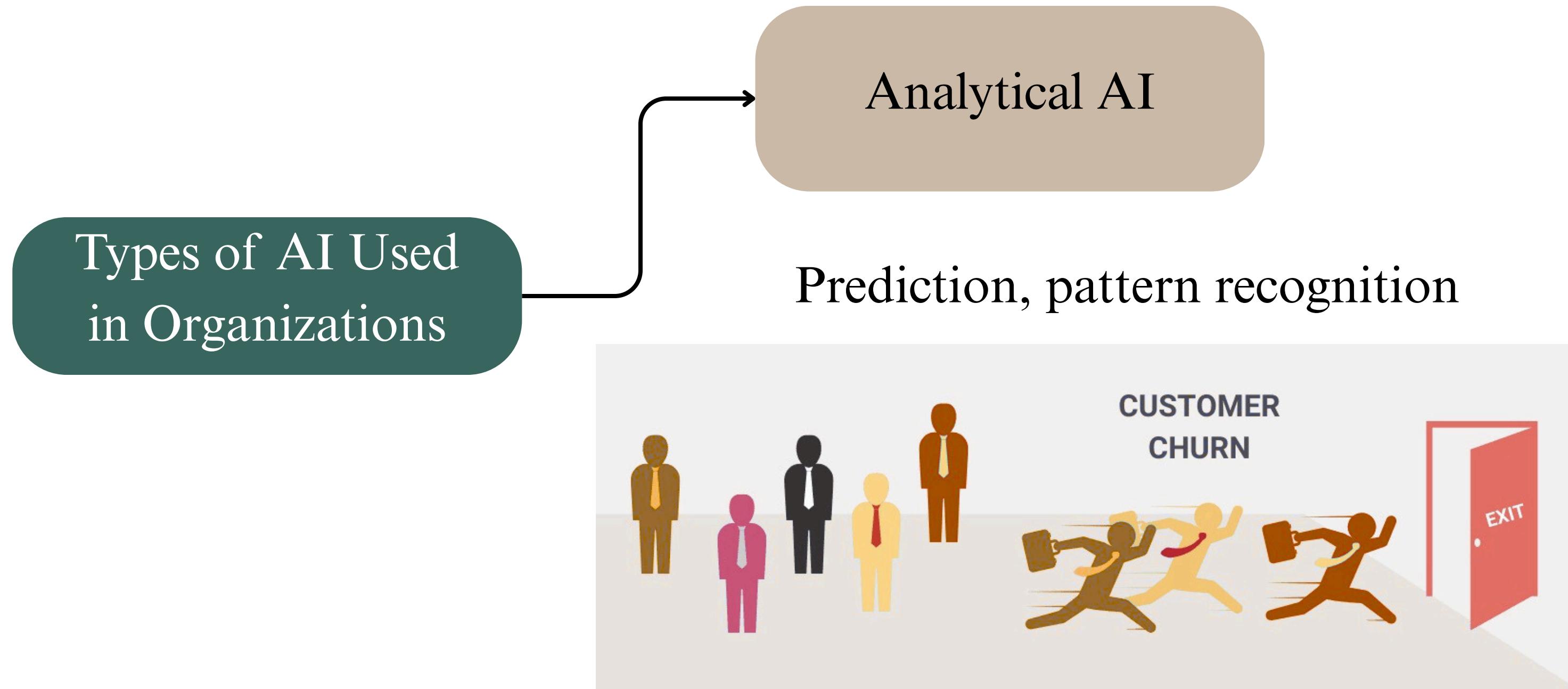
Still experimenting

- Small pilots in isolated teams
- No integration into real workflows
- No cultural acceptance

AI Workflow Automation for Organizations



AI Workflow Automation for Organizations

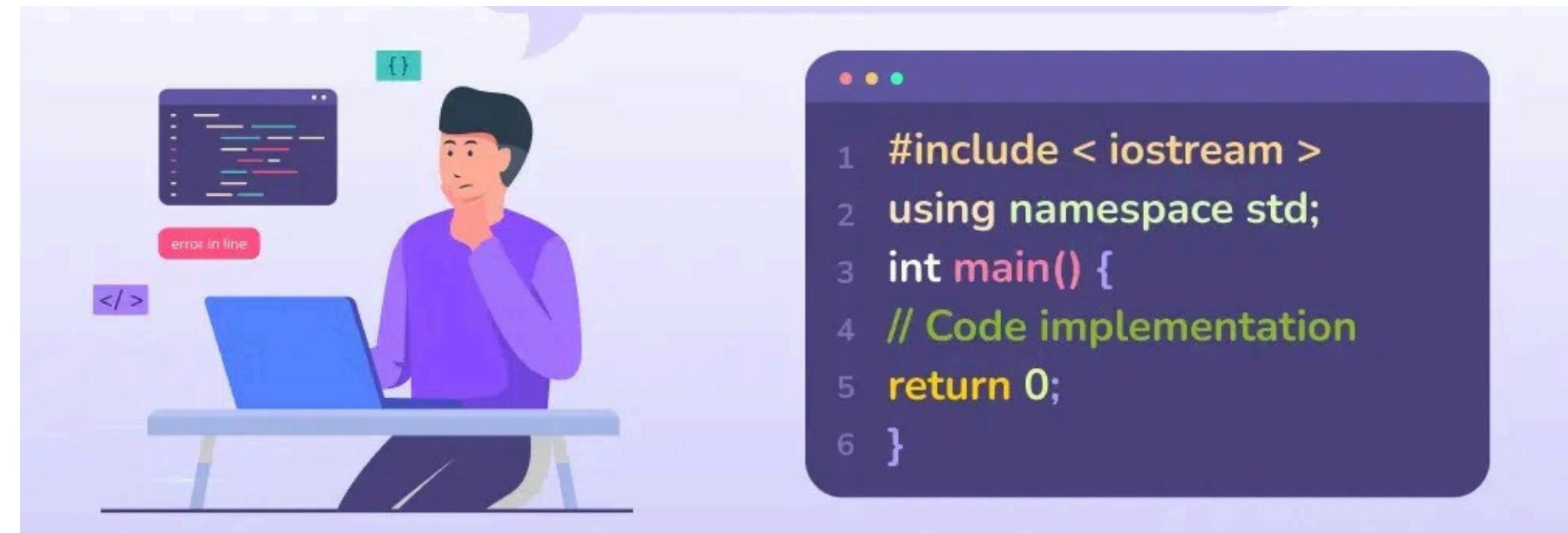


AI Workflow Automation for Organizations

Types of AI Used
in Organizations

Generative AI

Writing, coding, summarizing

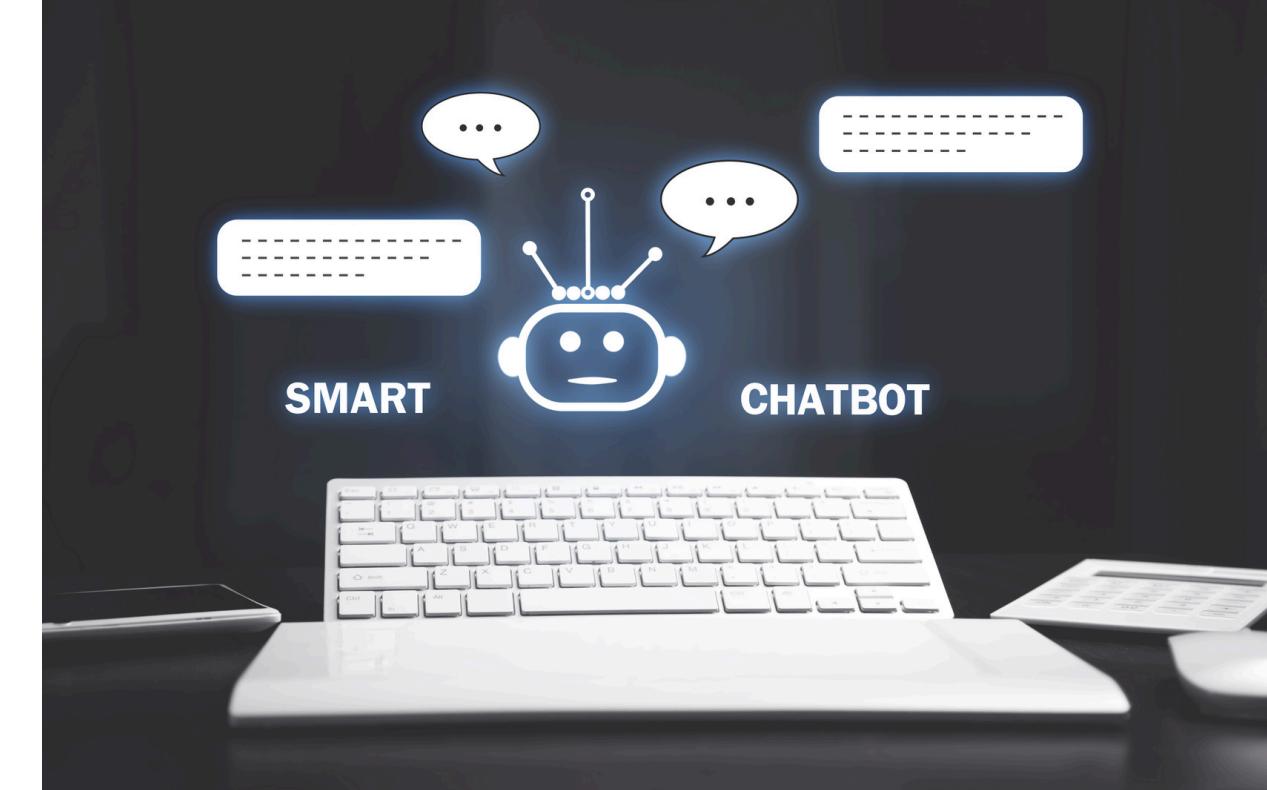


AI Workflow Automation for Organizations

Types of AI Used
in Organizations

Automation AI

Repetitive work, workflow automation

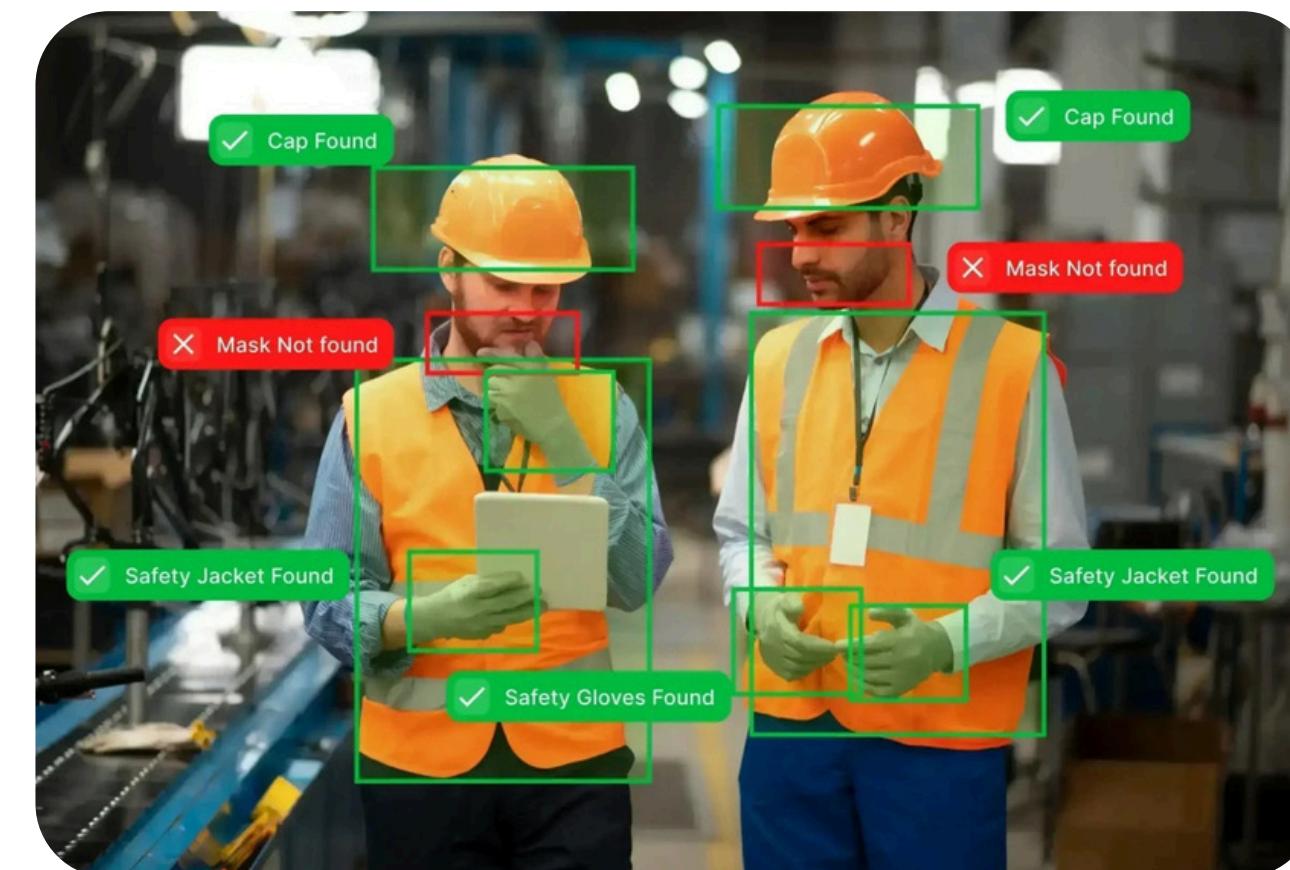


AI Workflow Automation for Organizations

Types of AI Used
in Organizations

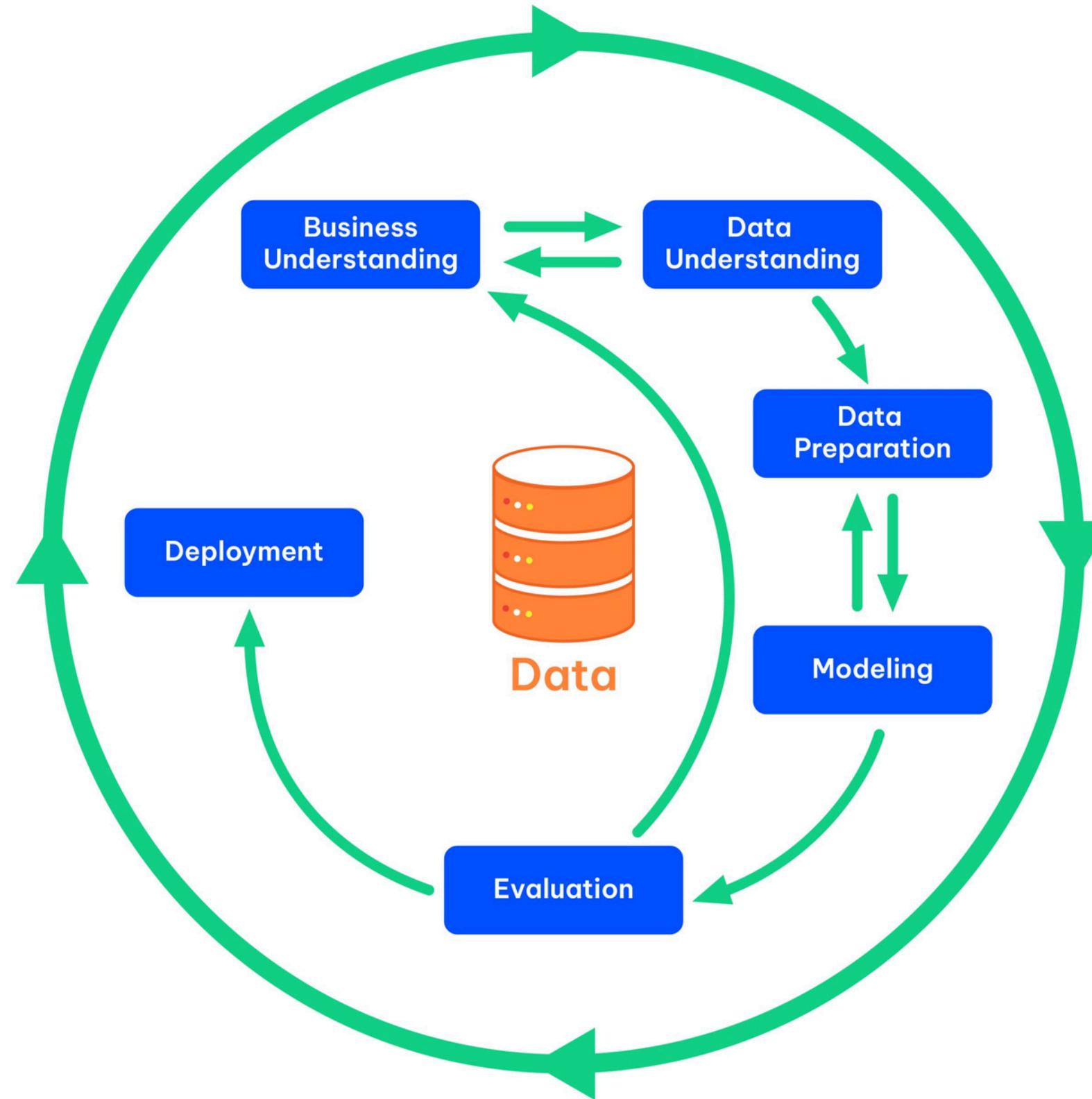
Computer Vision

Manufacturing quality, diagnostics



AI Project Implementation

AI Project Implementation



AI Project Implementation

» Stage 1:

- Problem Understanding

1. What are we trying to achieve?

AI Project Implementation

» Stage 1:

- Problem Understanding

1. What are we trying to achieve?

- What problem does the customer want to solve?
- What does success look like for the business?



AI Project Implementation

» Stage 1:

- Problem Understanding

2. Are we ready to do it?

AI Project Implementation

» Stage 1:

- Problem Understanding

2. Are we ready to do it?

- Do we have the required resources and data?
- What are the risks, constraints, and dependencies?
- Is the project worth the cost (cost–benefit)?



AI Project Implementation

3. How will we execute the project?

» Stage 1:

- Problem Understanding



AI Project Implementation

» Stage 1:

- Problem Understanding

3. How will we execute the project?

- What are the AI/LLMs goals?
- What phases will the project follow?
- What tools and techniques are needed?



AI Project Implementation

» Stage 2:

- Data understanding

1. Is there existing data available?

AI Project Implementation

» Stage 2:

- Data understanding

1. Is there existing data available?

- Where is it stored?
- How much data do we have?
- Does it cover all scenarios?



AI Project Implementation

» Stage 2:

- Data understanding

2. Is the data labeled ?

AI Project Implementation

» Stage 2:

- Data understanding

2. Is the data labeled ?

- Do labels exist (classification/regression) to give to LLM for tuning?
- Who created the labels? Are they accurate?
- If unlabeled, how much labeling effort is required?



AI Project Implementation

» Stage 2:

- Data understanding

3. Does the data represent the real world?

AI Project Implementation

» Stage 2:

- Data understanding

3. Does the data represent the real world?

- Is the data balanced across categories?
- Does the data contain major biases?
- Does the data have sufficient variation?
- Is the data up to date and relevant?



AI Project Implementation

» Stage 2:

- Data understanding

5-Does the data align with the problem?

AI Project Implementation

» Stage 2:

- Data understanding

5-Does the data align with the Problem?

- Are the right variables present?
- Do we need additional data sources?
- Can we actually answer the problem with this dataset?



AI Project Implementation

» Stage 3:

- Data Preparation

- Is the data clean, complete, and usable?
- Is the data balanced, unbiased, and representative?
- Is the data properly formatted and ready for modeling?



AI Project Implementation

» Stage 4:

- Modeling/LLM Choice

Which modeling techniques are appropriate for this problem?

*

AI Project Implementation

» Stage 4:

- Modeling/LLM Choice

Which modeling techniques are appropriate for this problem?

- Which algorithms should be tested (such as , regression, decision trees, neural networks)?



AI Project Implementation

» Stage 4:

- Modeling/LLM Choice

How should the data be split into training, validation, and testing sets?



AI Project Implementation

» Stage 4:

- Modeling/LLM Choice

How should the data be split into training, validation, and testing sets?

- What split strategy best fits the chosen modeling technique?



AI Project Implementation

» Stage 4:

- Modeling/LLM Choice

- Which models should we try and compare?

AI Project Implementation

» Stage 4:

- Modeling/LLM Choice

- Which models should we try and compare?



- How do the models perform against the defined success criteria?
- Which model best fits the domain requirements and test design?

AI Project Implementation

» Stage 5:

- Evaluation

Do the models meet requirements?

AI Project Implementation

» Stage 5:

- Evaluation

Do the models meet requirements?

- Which model best aligns technical performance with business success?



AI Project Implementation

» Stage 5:

- Evaluation

Was the project executed correctly?

AI Project Implementation

» Stage 5:

- Evaluation

Was the project executed correctly?

- Is the project complete and technically correct?
- Are the results reliable and ready for decision-making?



AI Project Implementation

» Stage 6:

- Deployment

How will the model be delivered into real organizational use?

AI Project Implementation

» Stage 6:

- Deployment

How will the model be delivered into real organizational use?

- Will the output be delivered as a report or dashboard?
- Does the solution require full system integration across the organization?



AI Project Implementation

» Stage 6:

- Deployment

How should the model be deployed for real-world use?



AI Project Implementation

» Stage 6:

- Deployment

How should the model be deployed for real-world use?

- Where will the model run (platform, system, workflow)?
- Who will use the model (teams, departments)?
- How will outputs reach end users (API, dashboard, automation)?
- What technical resources are required?
- How will security and access be controlled?

