## **CIONET** CIDO Networking Event

# Al in Manufacturing

Unleashing Germany's Data Treasures

01.10.2024 | 18:15 | IPAI Heilbronn



#### 24. Oktober 2024 | 18:00 Uhr | Zu Gast bei *eon* ünchen

# IT WORKFORCE TRANSFORMATION **Dem Technologiewandel Schritt halten**









21.11.2024 | 17:30 Uhr | München



# ALERZONS [UN]SUCCESSFUL STORIES

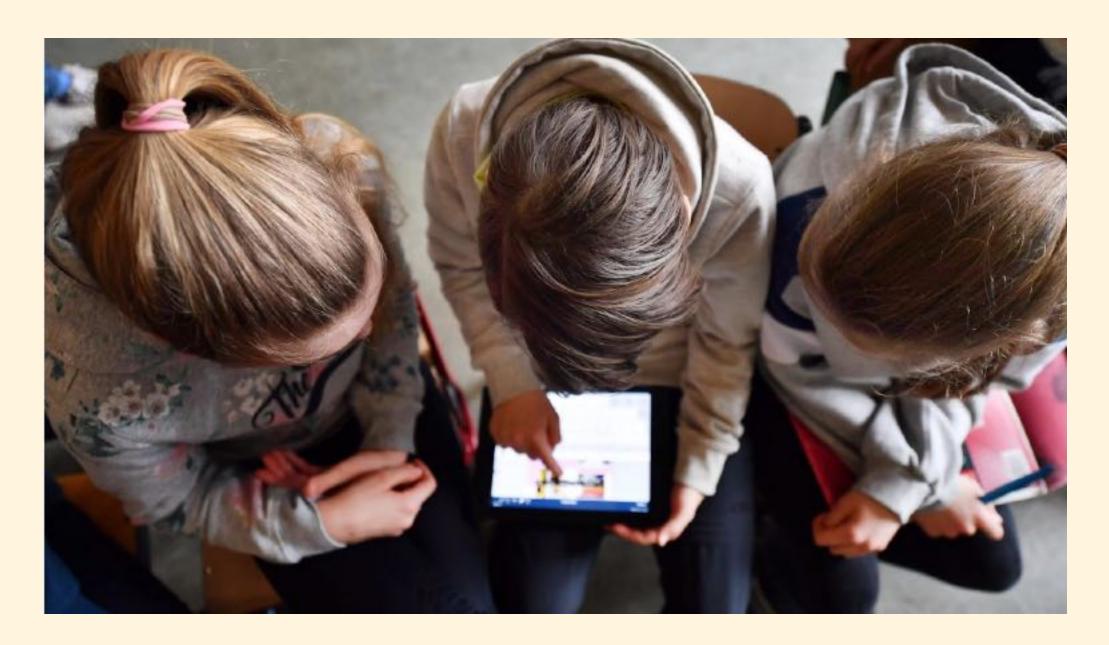
28. November 2024 | Frankfurt am Main

#### **Digitalisierung an NRW-Schulen**

#### Keiner kann sie einrichten, deshalb bleiben tausende Tablets ungenutzt

Von Alexandra Ringendahl 26.10.2023, 17:32 Uhr

Lesezeit 5 Minuten



Tablets einzurichten und zu warten bleibt oft an Lehrkräften hängen. Und jetzt läuft auch noch bald der Digitalpakt 1.0 aus. Land und Kommunen sehen die Gefahr, dass die Digitalisierung an den Schulen in NRW zum Stillstand kommt.

#### Umsetzung einer KI Implementierung & Lebenszyklusmanagement

#### 09:00 Uhr - 09:10 Uhr - Icebreaker | Format: Interaktive Gruppenarbeit

Ein lockerer Start in einen Vormittag intensiver Zusammenarbeit.

#### 09:10 Uhr - 09:25 Uhr - KI Use Case Ideation Format: Vortrag

Einführung in den Prozess der Ideation von KI-Anwendungen mit Schwerpunkt auf der Identifizierung potenzieller Anwendungen von KI.

#### 09:25 Uhr - 09:35 Uhr - Ausarbeitung KI-Use Cases | Format: Individuelle Arbeit

Die Teilnehmer konkretisieren den KI-Anwendungsfall, den sie vorbereitet haben, und wenden dabei die im Vortrag behandelten Konzepte an.

#### 09:35 Uhr - 09:50Uhr - KI-Use Cases | Format: Kollaboratives Gruppenfeedback

Präsentation der KI-Use Cases, danach interakives Peer-Feedback.

#### 09:50 Uhr - 10:00 Uhr - Bewertung von KI-Anwendungsfällen - Theorie | Format: Vortrag

Einführung "Wie KI-Anwendungsfälle anhand ihres wirtschaftlichen Wertbeitrags, der Machbarkeit und der zu erwarteten Ergebnisse priorisiert werden können.

#### 10:00 Uhr - 10:25 Uhr - Bewertung von KI-Anwendungsfällen - Praxis | Format: Interaktive Gruppenarbeit mit Canvas

Gruppen arbeiten an der Bewertung und Priorisierung ihrer Anwendungsfälle unter Verwendung des Priorisierungs-Canvas.

#### 10:25 Uhr - 10:30 Uhr - Use Case Pitches | Format: Präsentation im Plenum

#### 10:30 Uhr - 10:40 Uhr - Q&A Session | Format: Vortrag mit Q&A

Beantwortung von Fragen und Diskussion mit zusätzlichen Einblicke in den Prozess der Use Case Evaluation.

# How to implement Al

# FORBES.COM WHY DO MOST A PROJECTS FAIL?

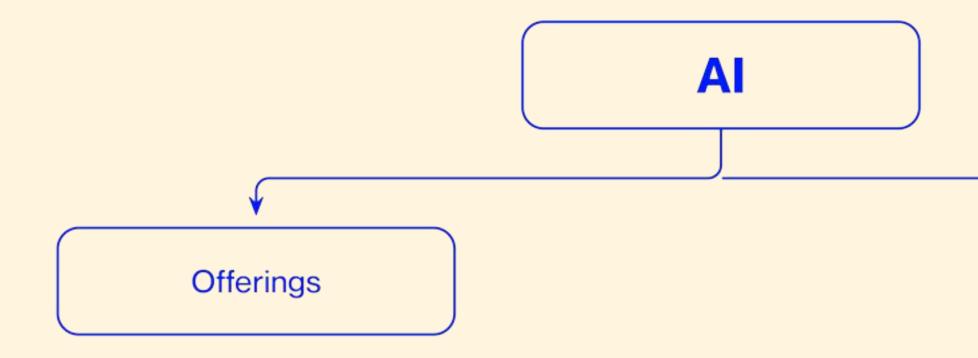
understand that the AI model top-notch AI system, but also is just as Important as the a good connection with the final integration of which it existing system. will be part.

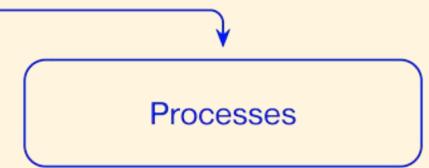
This failure occurs because Al integration into an already working system is an immensely difficult task.

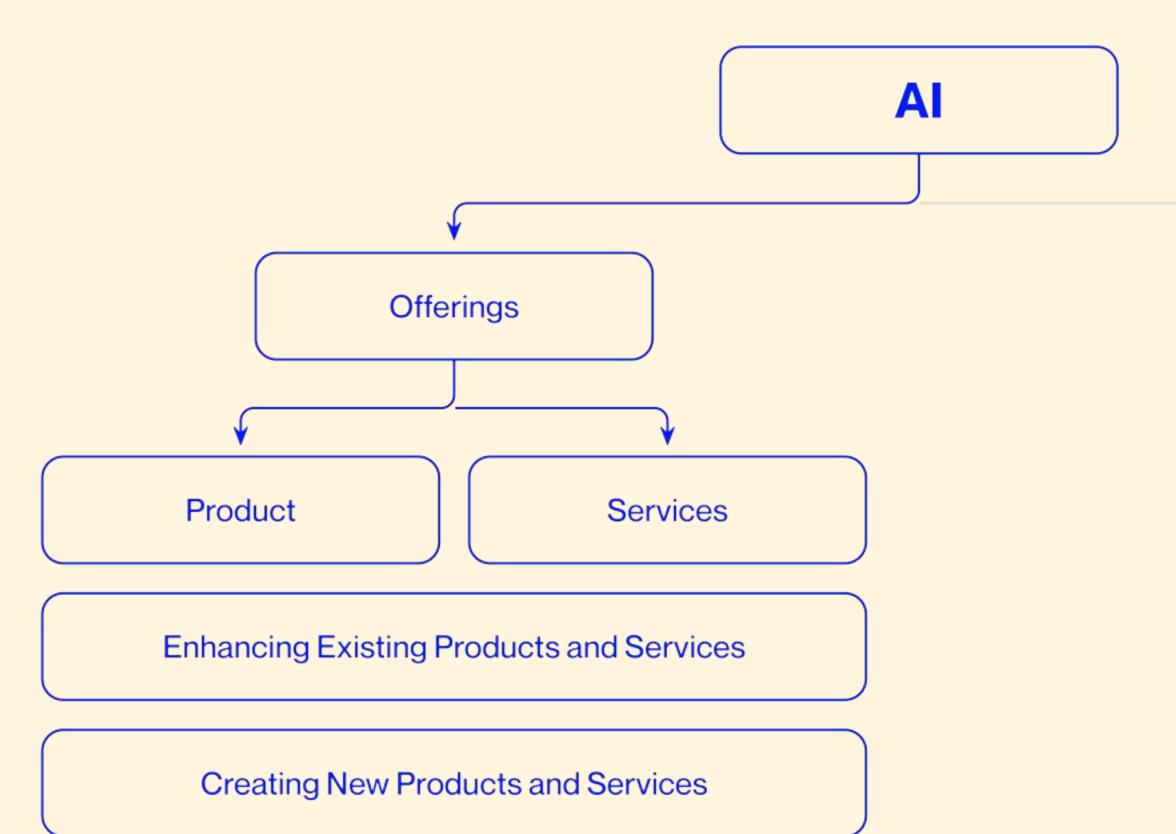
Many organizations fail to To do so requires not only a



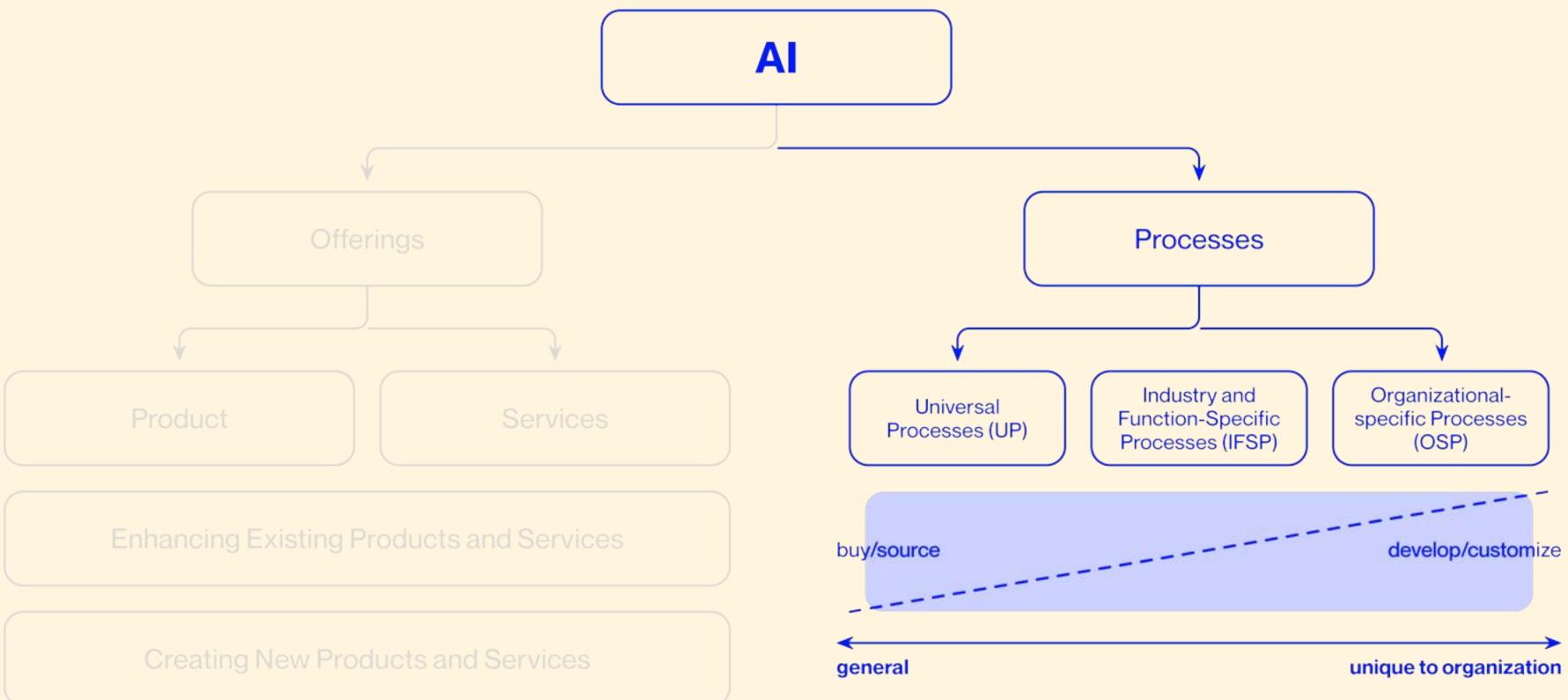








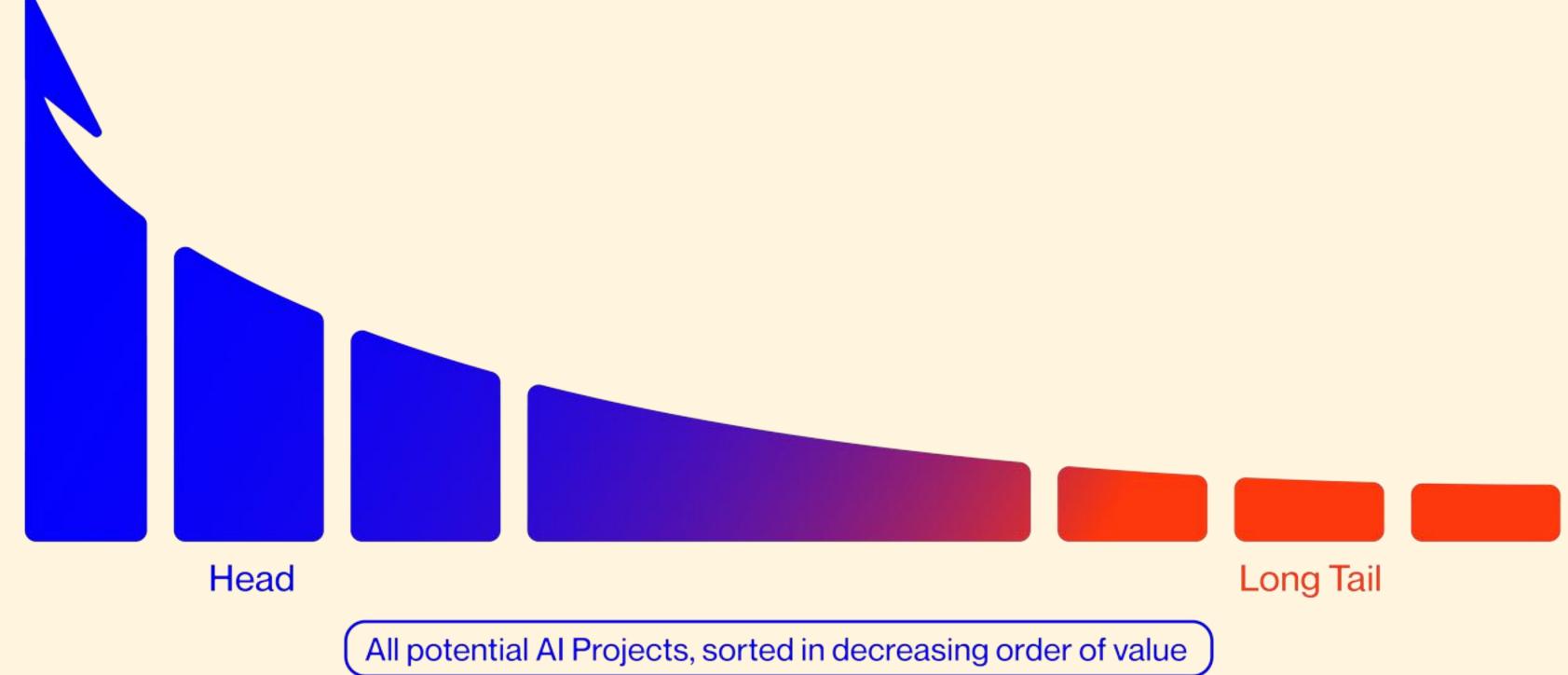




# Al Use Case Ideation

## **The Ideation Process**

Value

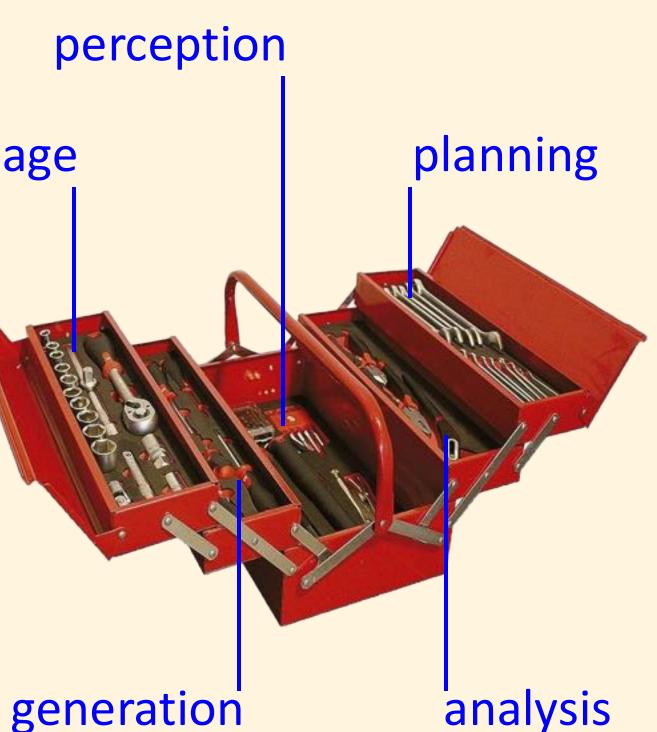


# AI Use Cases

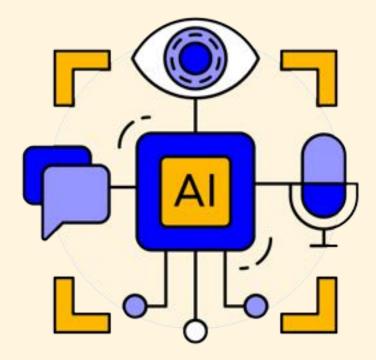
language

Clearly defined set of activities designed to reach a specific goal from a business or costumer perspective, in which one or more AI solution are involved in reaching the perspective goal

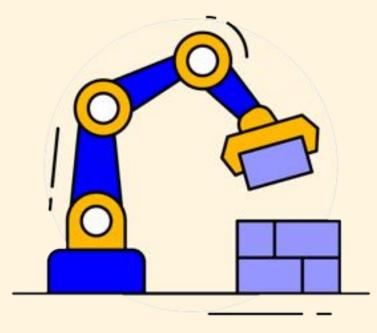
Use Cases use AI capabilities like tools in a toolbox



# Machine Capabilities







#### Perception **Capabilities**

- Comp. Vision
- Comp. Audition
- Comp. Linguistics

### Analytical Capabilities

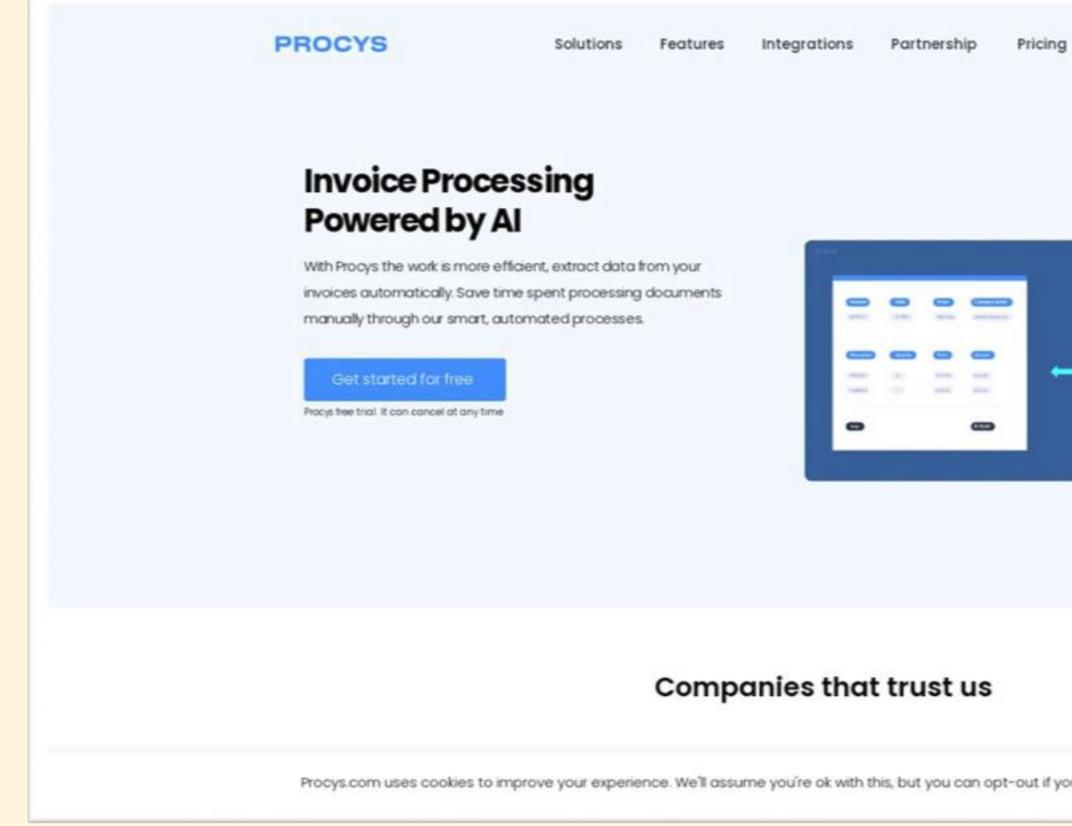
- Discovery
- Forecasting
- Planning & **Optimization**

- Motoric Capabilities
- Advanced **Robotics &** Control



### Generating **Capabilities**

Creation



Procys is an AI-powered invoice processing tool that helps businesses streamline their billing processes. It provides users with automated processes to extract data from invoices, label each fragment of the document correctly and export the processed data in a structured way.

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invoice	



FROM	INVOICE #	US-001
East Repair Inc.	INVOICE DATE	11/02/2019
1912 Harvest Lane New York, NY 12210	P.O.#	2312/2019
New FOR, NT 12210	DUE DATE	26/02/2019

#### BILL TO SHIP TO

John Smith 2 Court Square New York, NY 12210 John Smith

3787 Pineview Drive Cambridge, MA 12210

QTY	DESCRIPTION	UNIT PRICE	AMOUNT
1	Front and rear brake cables	100.00	100.00
2	New set of pedal arms	15.00	30.00
3	Labor 3hrs	5.00	15.00

#### Subtotal

Sales Tax 6.25%

TOTAL

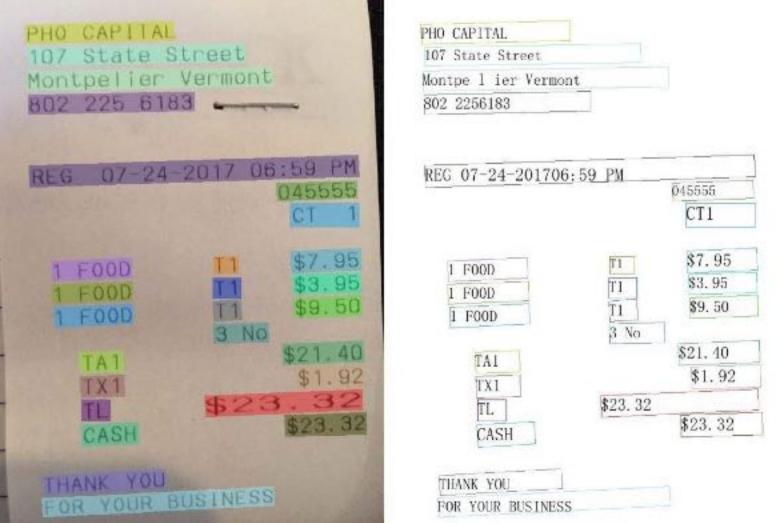
\$154.06

145.00

9.06

John Smith





TERMS & CONDITIONS

Payment is due within 15 days

Please make checks payable to: East Repair Inc.

#### **Breaking Down** a Complex Use Case

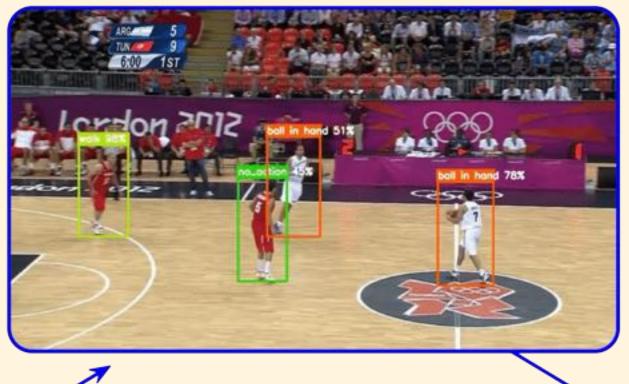




## **Pedestrian Detection** with histogram of Oriented Gradients (HOG)





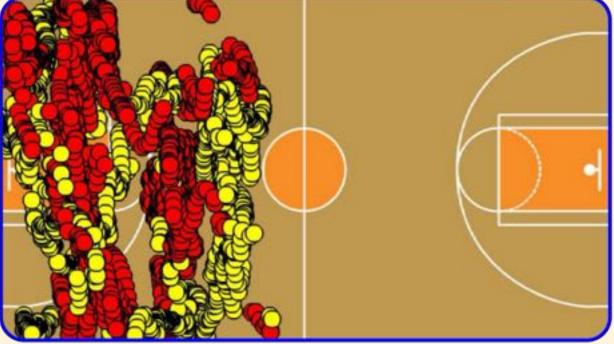


#### **Player Tracking**

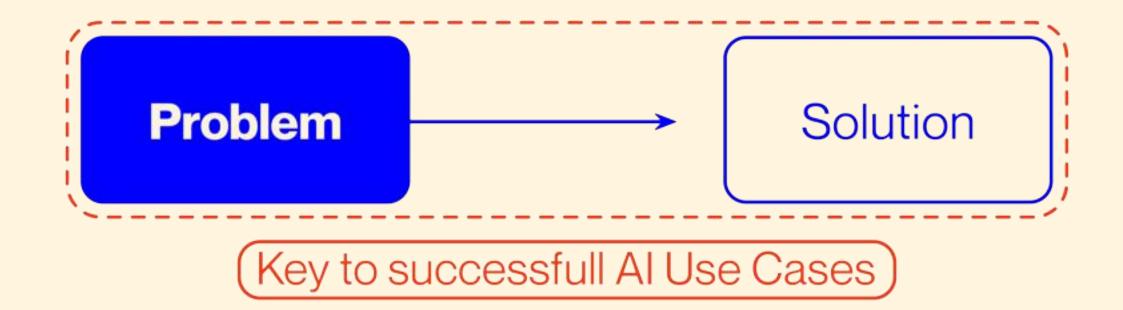
Mapping



Color-Based **Player Detection** and Classification



# **Conceptualising Use Cases**



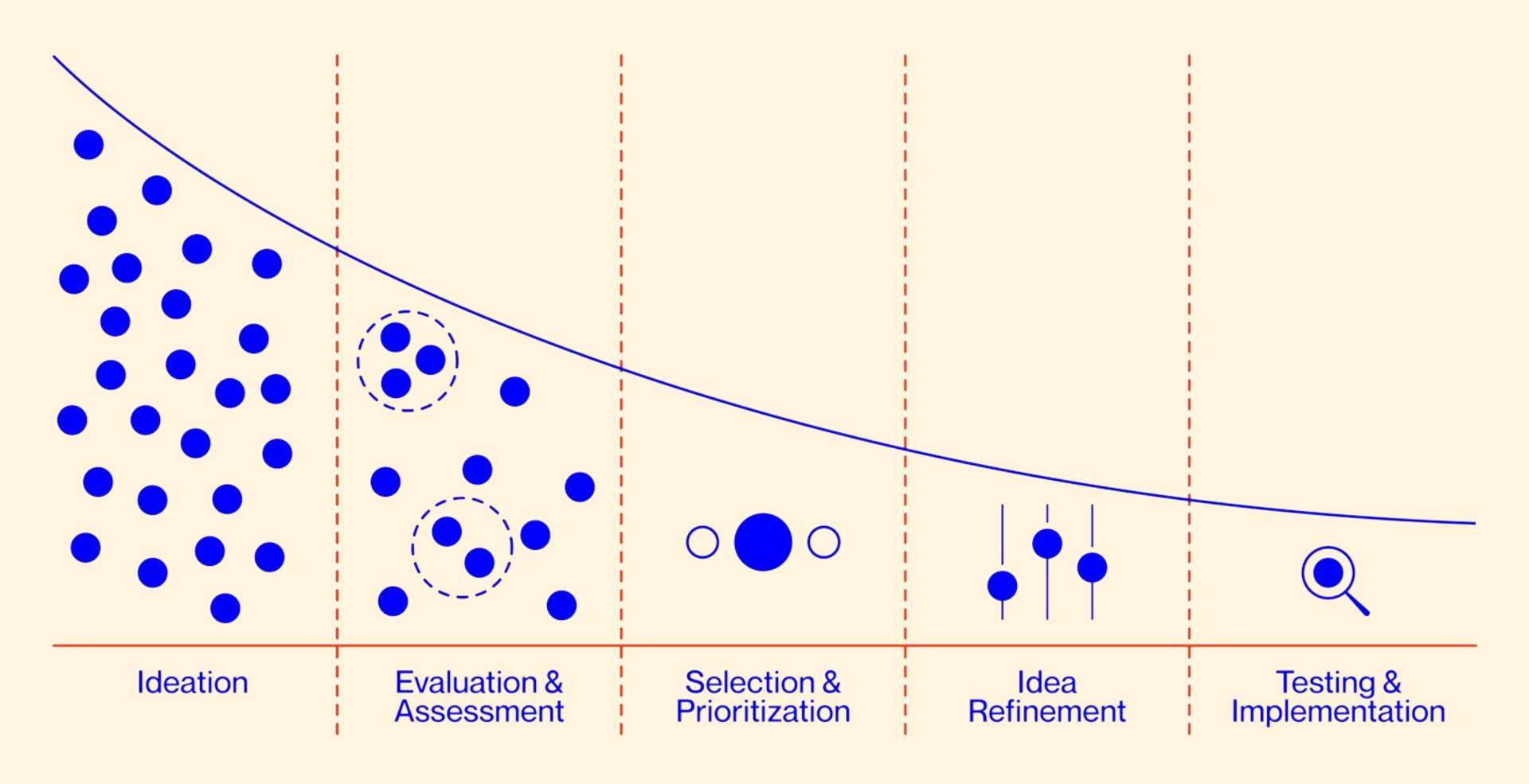
## Did you know this?





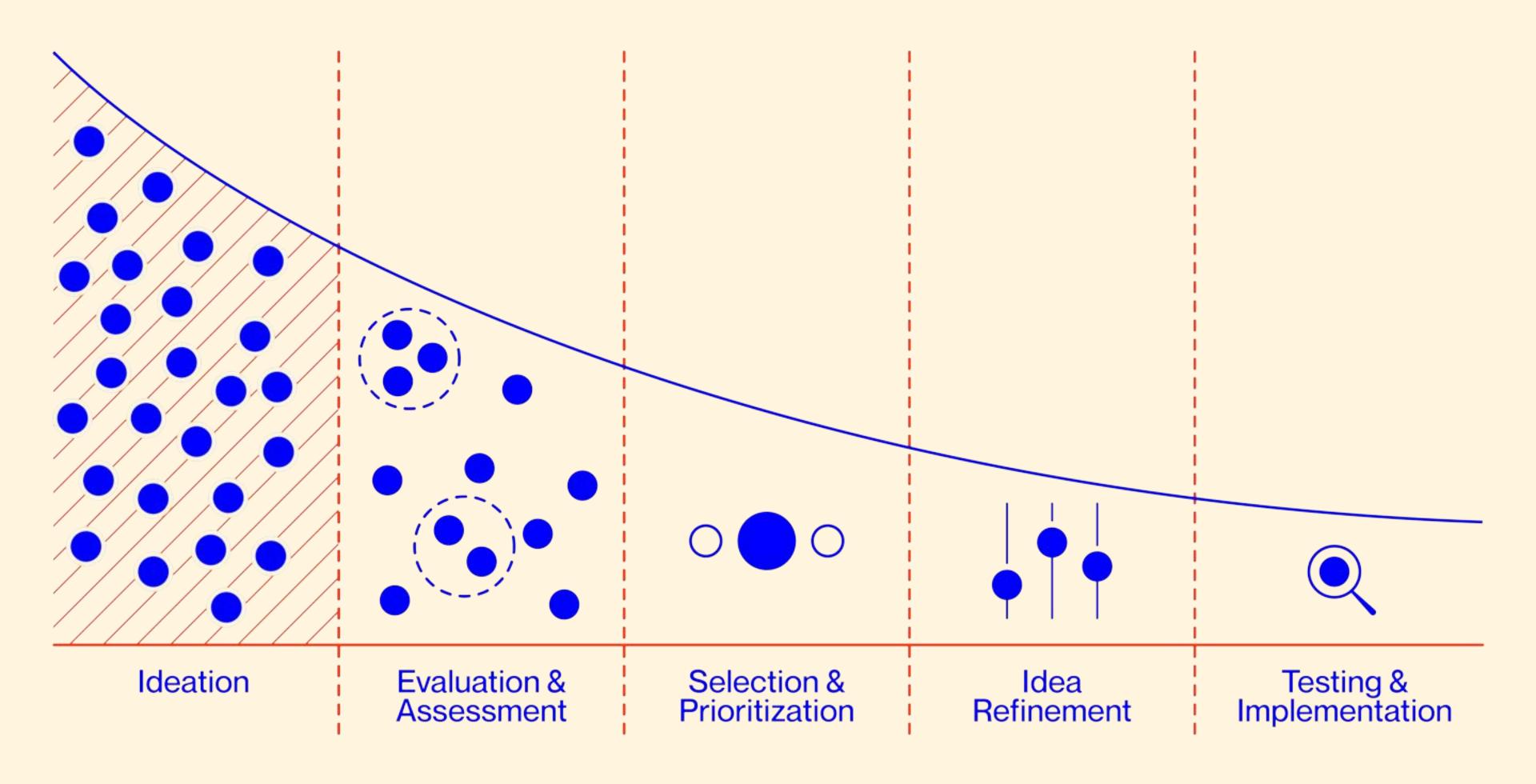
## The Ideation Process





## The Ideation Process



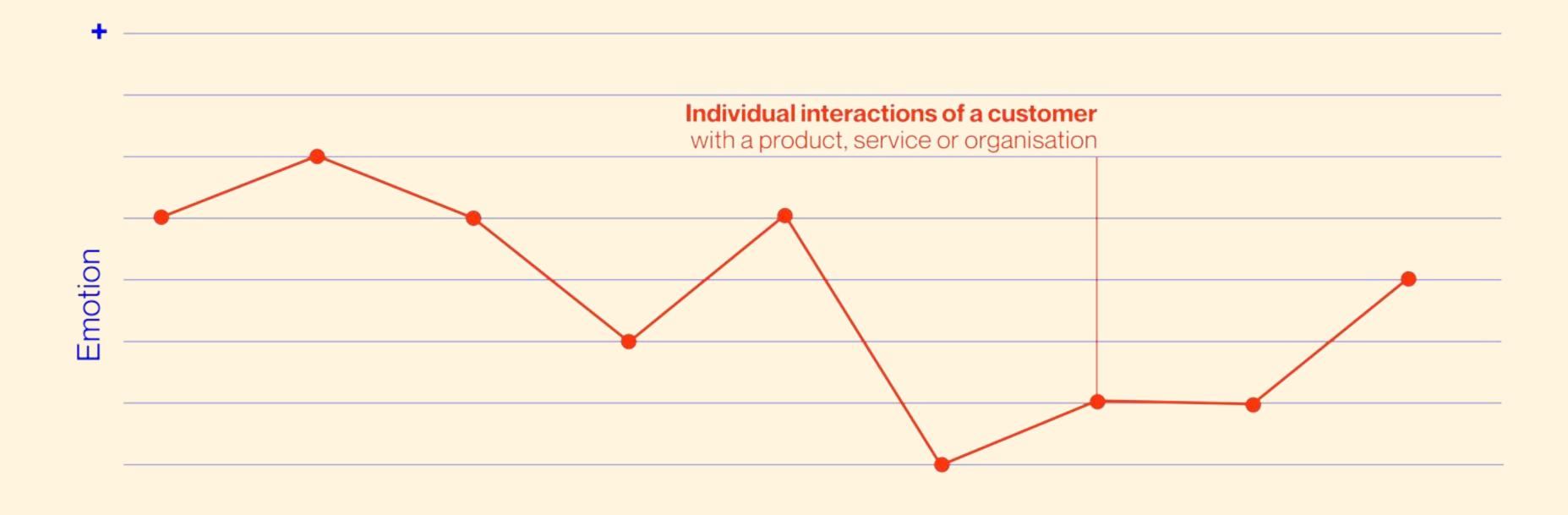


## **Ideating and Evaluating AI**

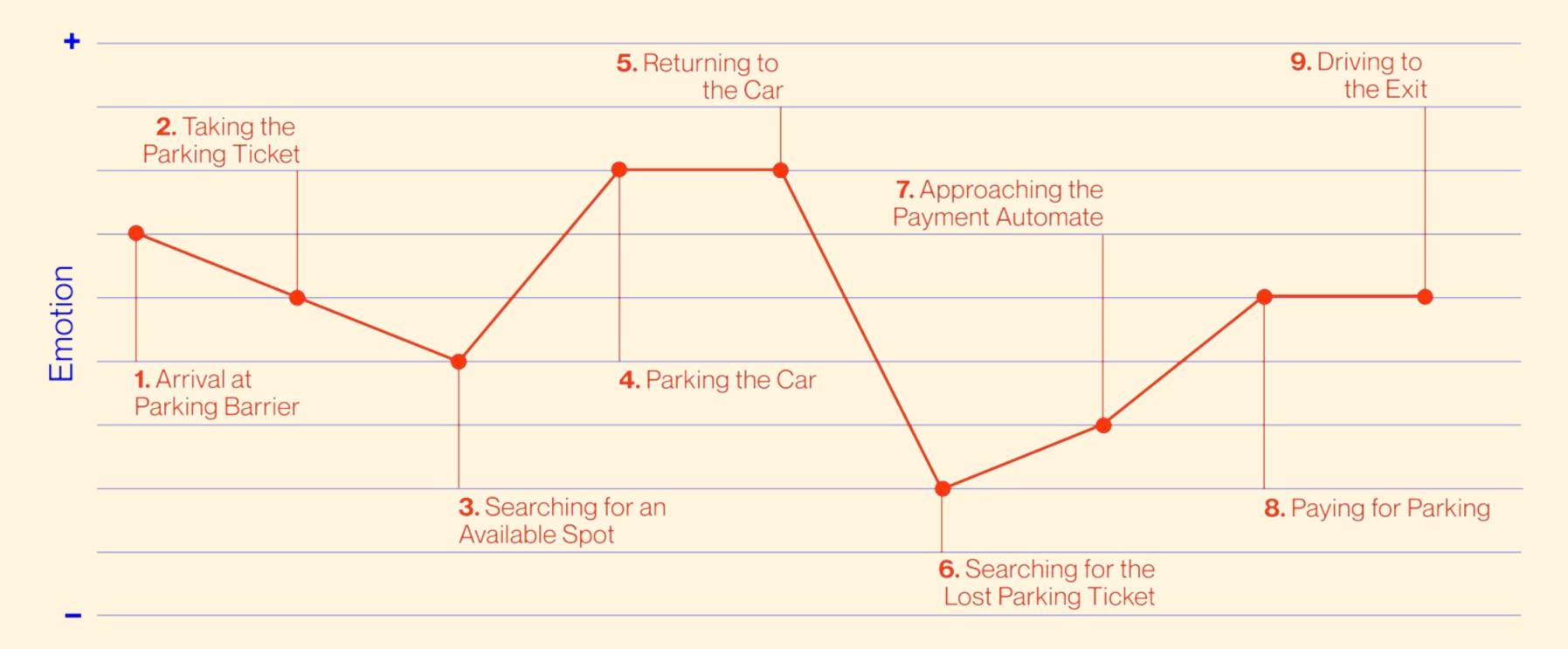
Firm Specific Capabilitites



# The Costumer Journey

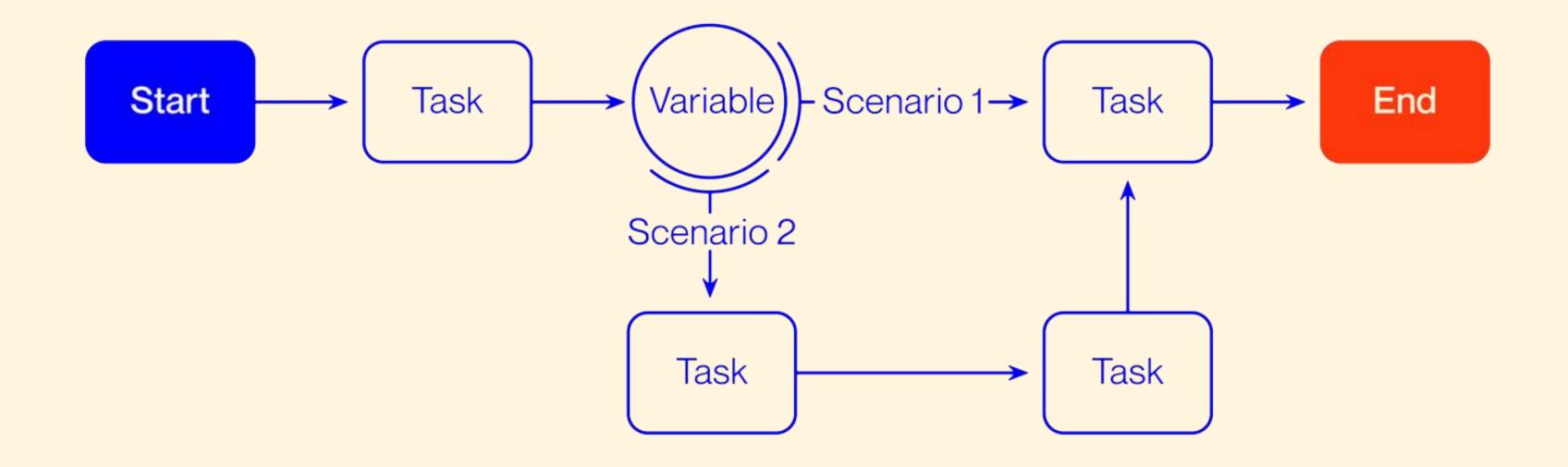


## Evaluate Action, Touchpoint and Emotion

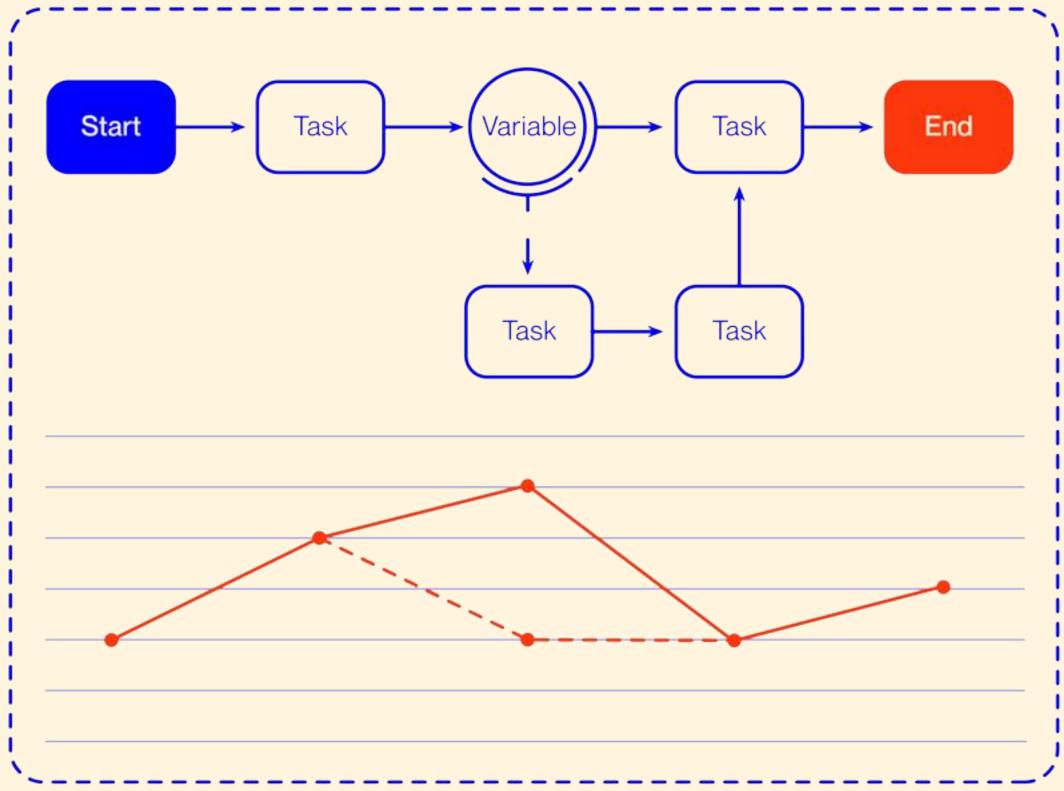




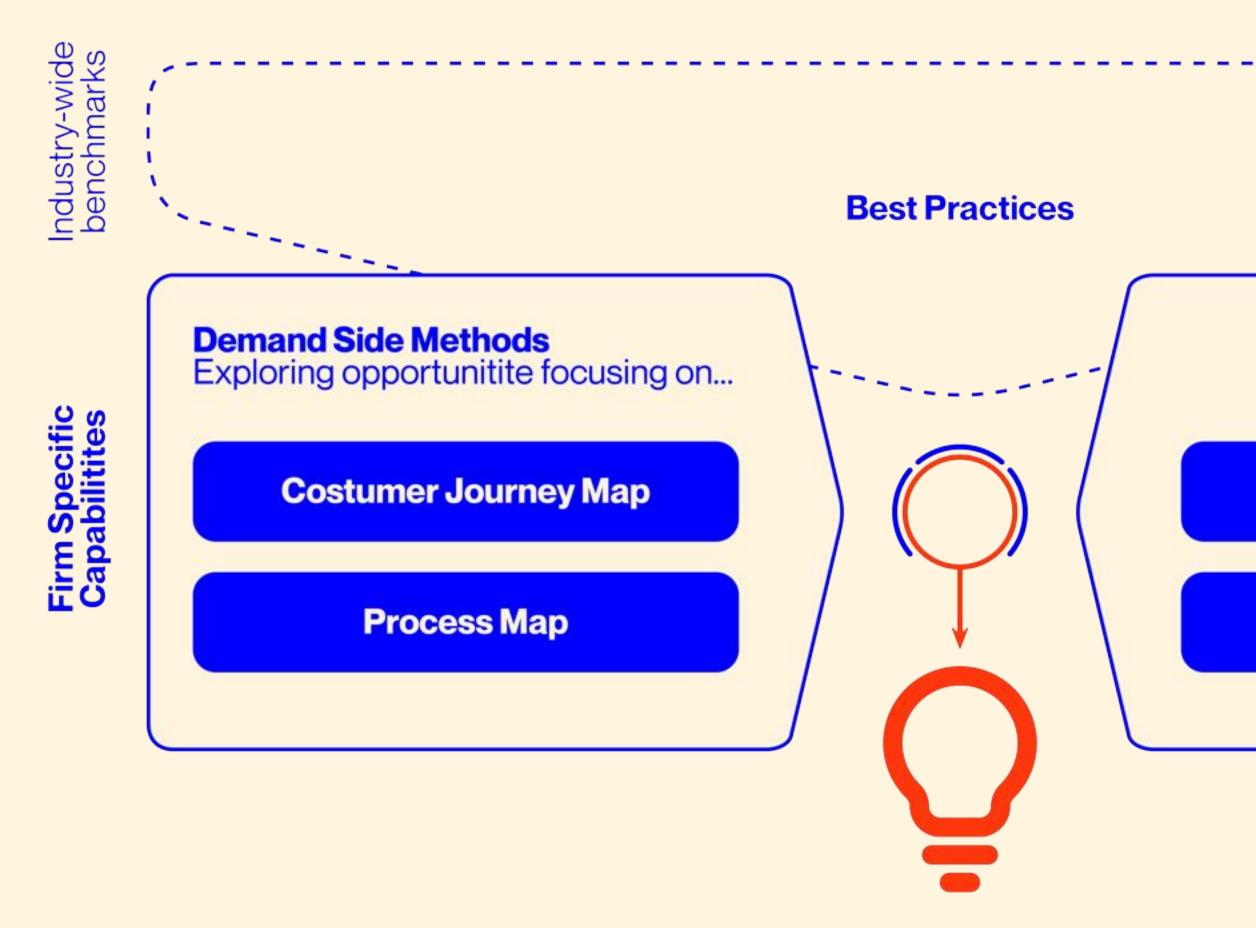
## The Process Map



### Combining both Customer Journey and Process maps ensures Al solutions are technically robust and user-centric, facilitating ideation and efficient problem-solving.



## **Ideating and Evaluating AI**



#### Supply Side Methods Finding UCs with support of...

**AI Capabilities** 

#### **Data Map**

#### **Interactive Intelligence**

#### **Computer Vision**

**Process visual data** and recognize objects

understand the semantics of images or video sequences

#### **Computer Audition**

Process and interpret audio signals

Natural language Proc.

Process, interpret and generate text and speech

## **Machine Capabilities Challenge Business Models**

Process large amounts of data and find patterns and 'logical' relationships

Discovery

Look for **optimal** solutions to problems with large solution space

Planning and Search

Make predictions about future course of time, series or likelihood of events

Forecasting

**Analytic Intelligence** 

#### Motion / Creative Int.

#### **Robotics and Control**

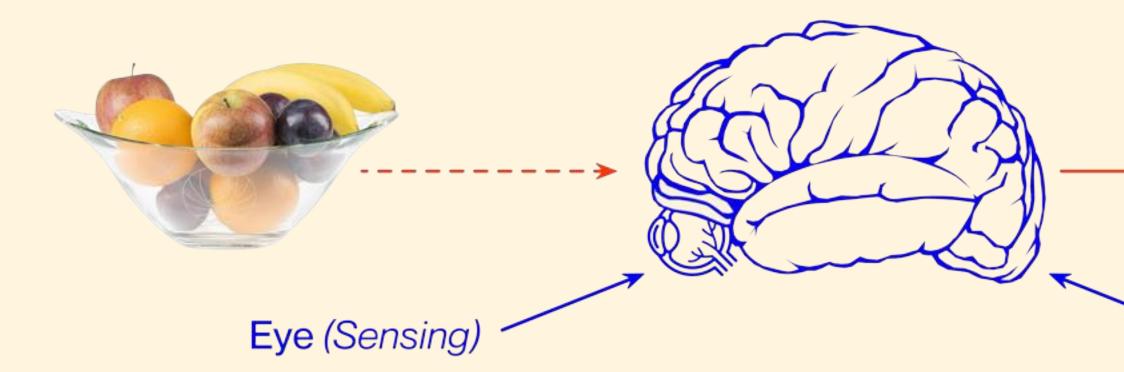
Analyze, interpret and learn from data representing physical systems (incl. IoT) and control its behavior

Generate images, music, speech and more based on sample creations

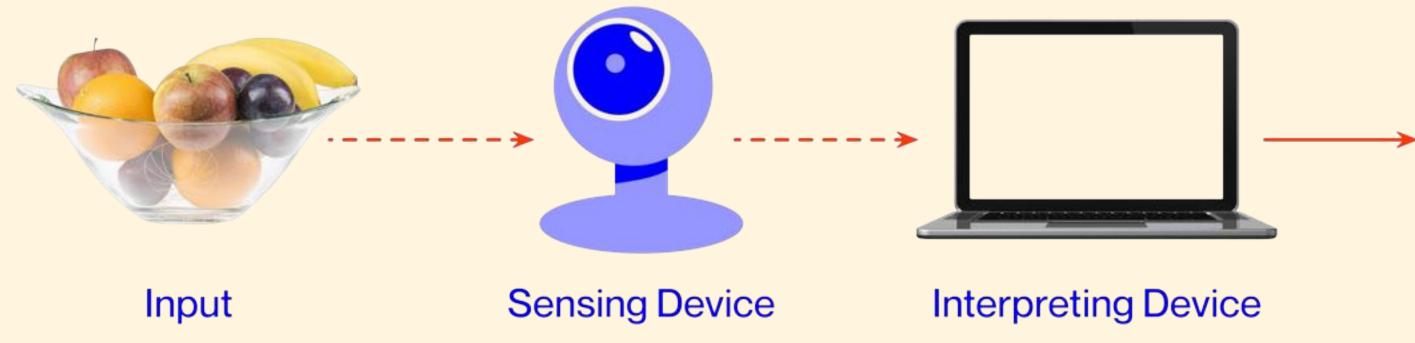
Creation

Motion / Creative Int.

#### **Human Vision System**



#### **Computer Vision System**



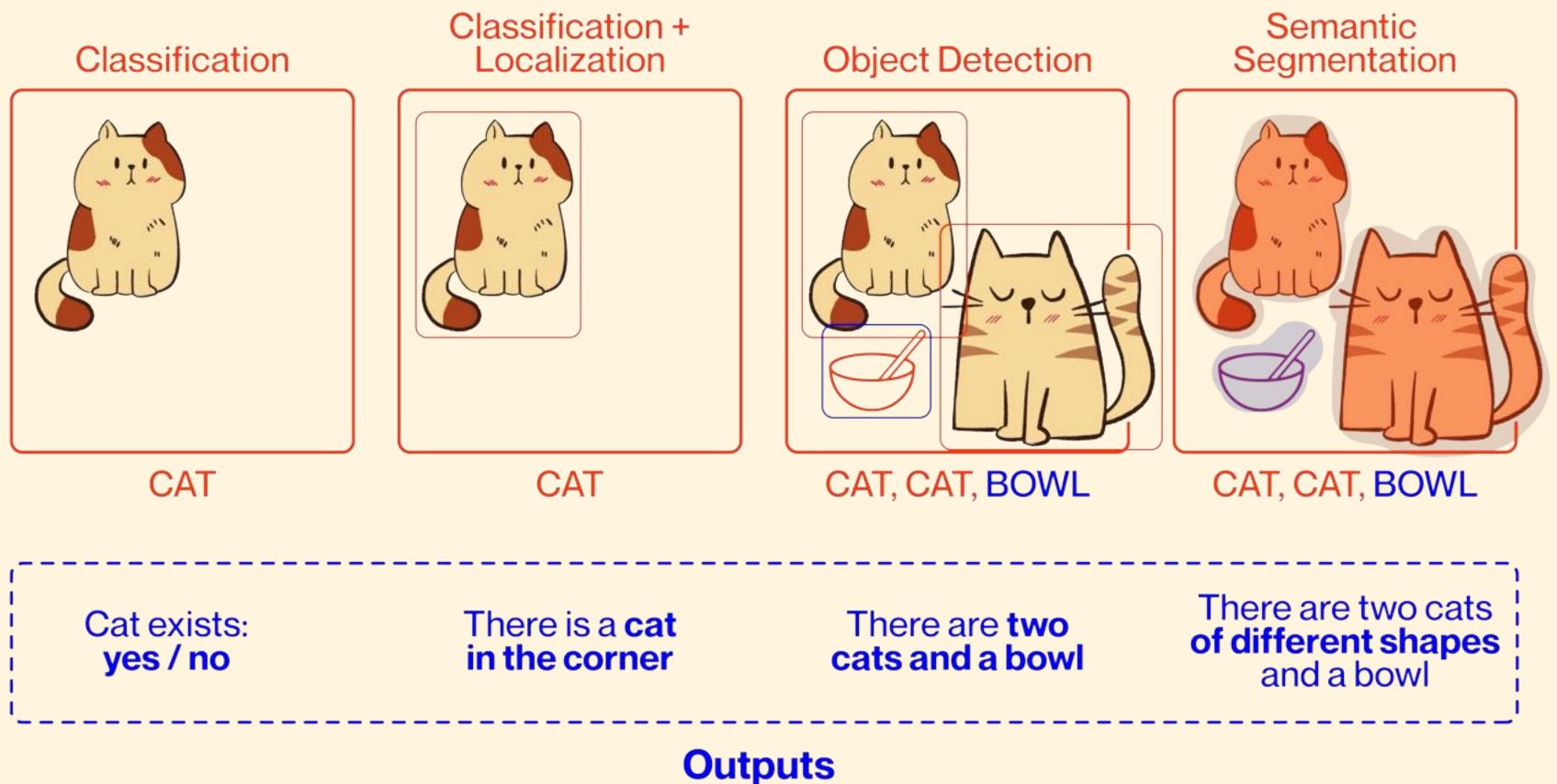
bowl, apples, oranges, bananas, plums

#### Brain (Interpreting)

bowl, apples, oranges, bananas, plums

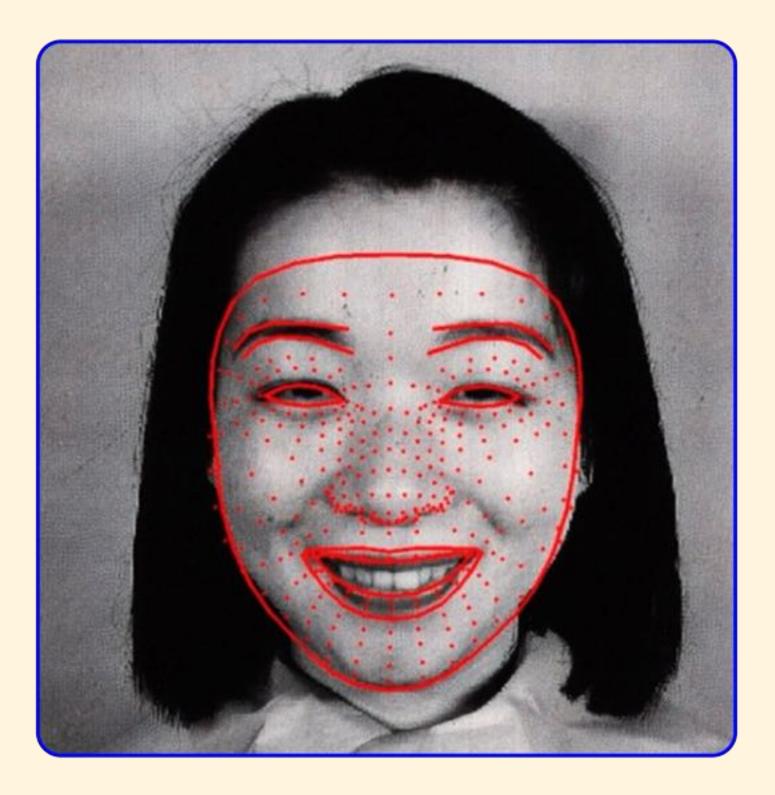
Output

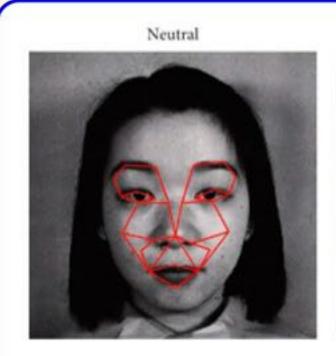
#### **Computer Vision Problem Types**



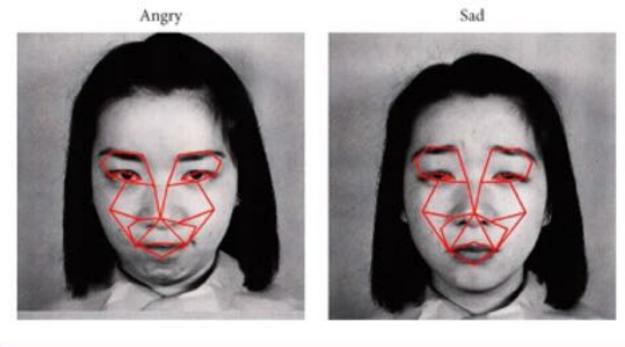


## **Emotion Recognition**





Angry

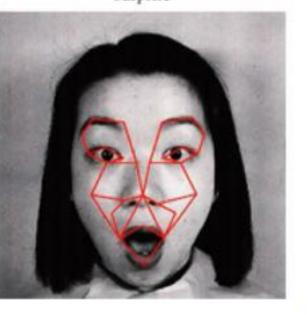


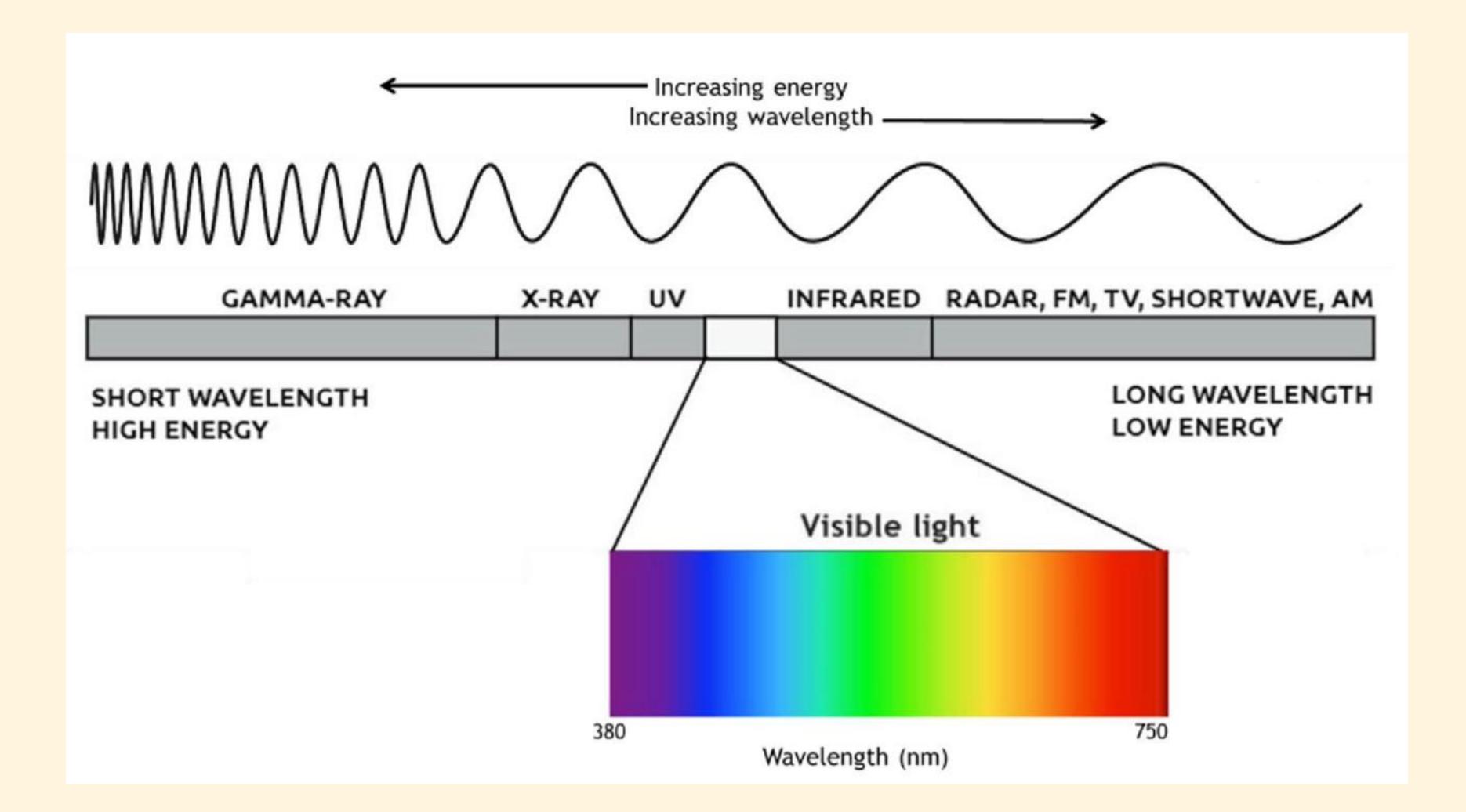
Fear



Нарру

Surprise

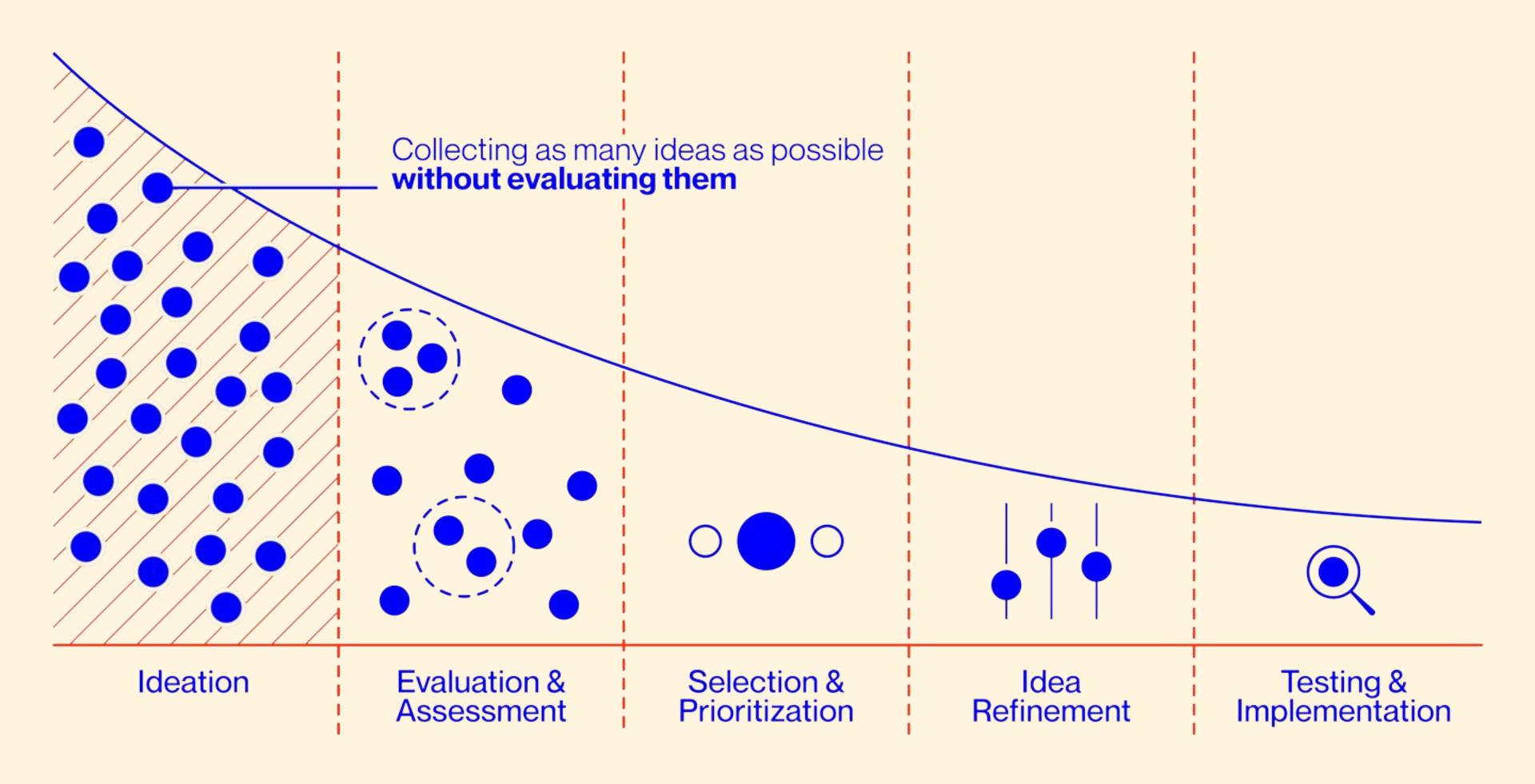


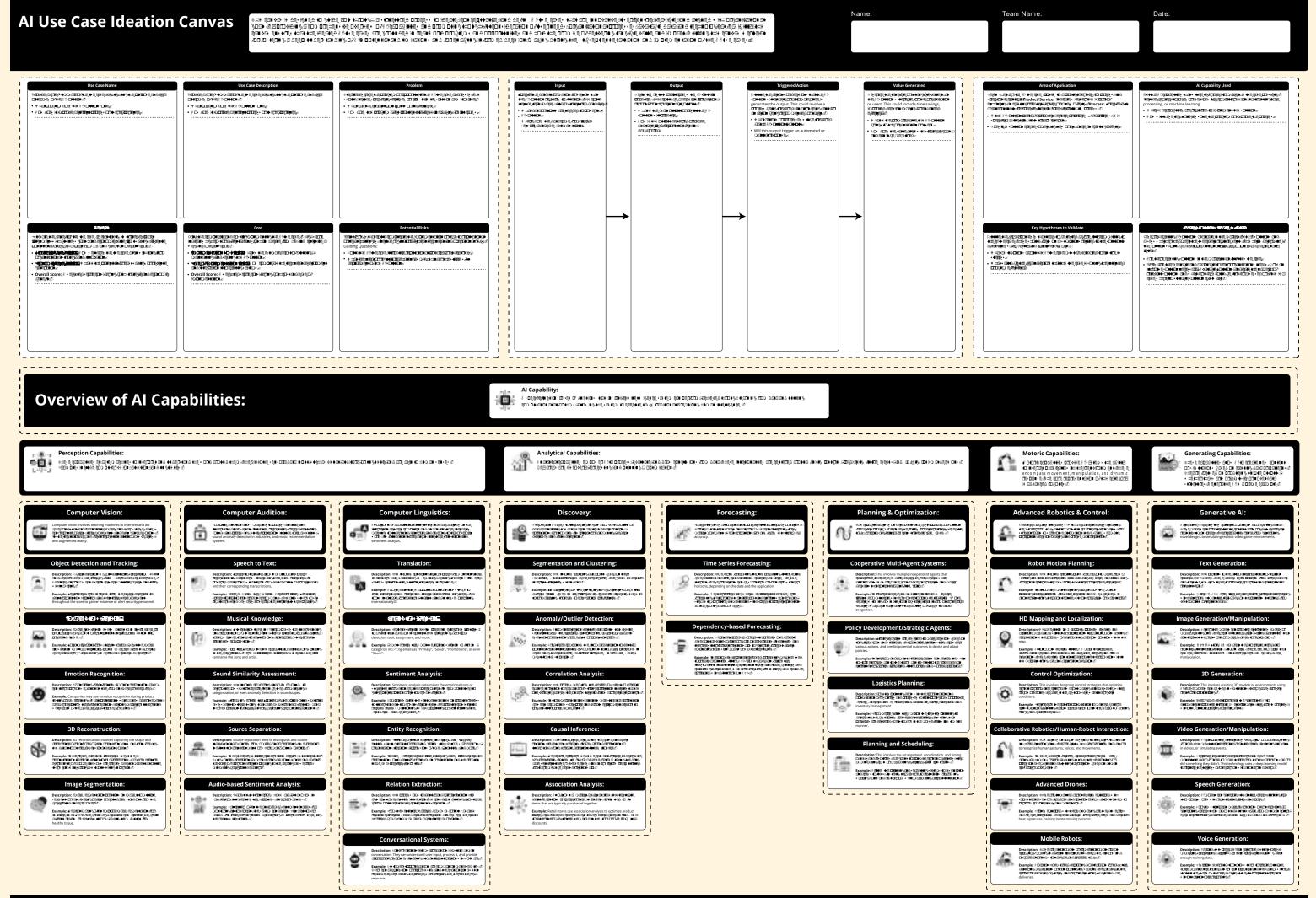




## 牛奶是只猫

16th century art...meet 21st century tech.

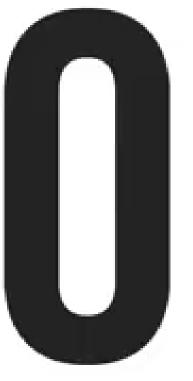




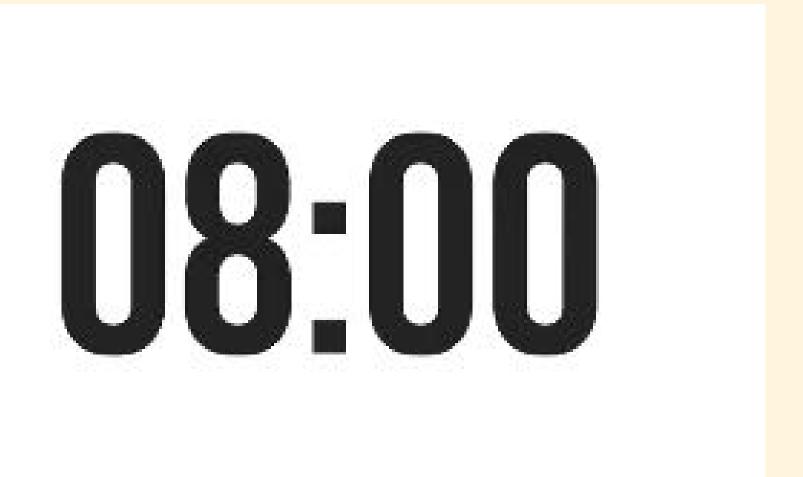
Al Strategy Institute

# **Use Case Description**





# Use Case Presentation in Group



## Umsetzung einer KI Implementierung & Lebenszyklusmanagement

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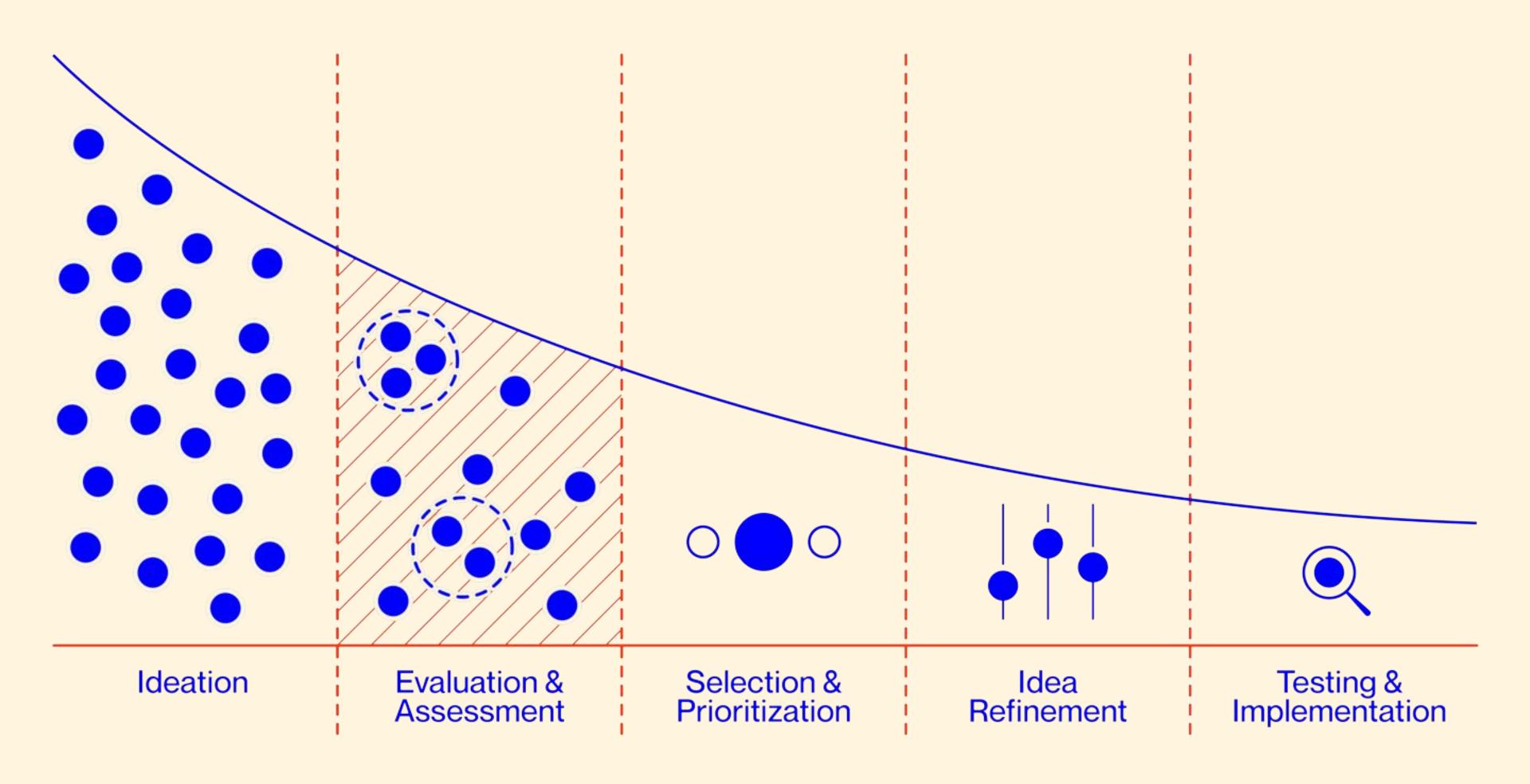
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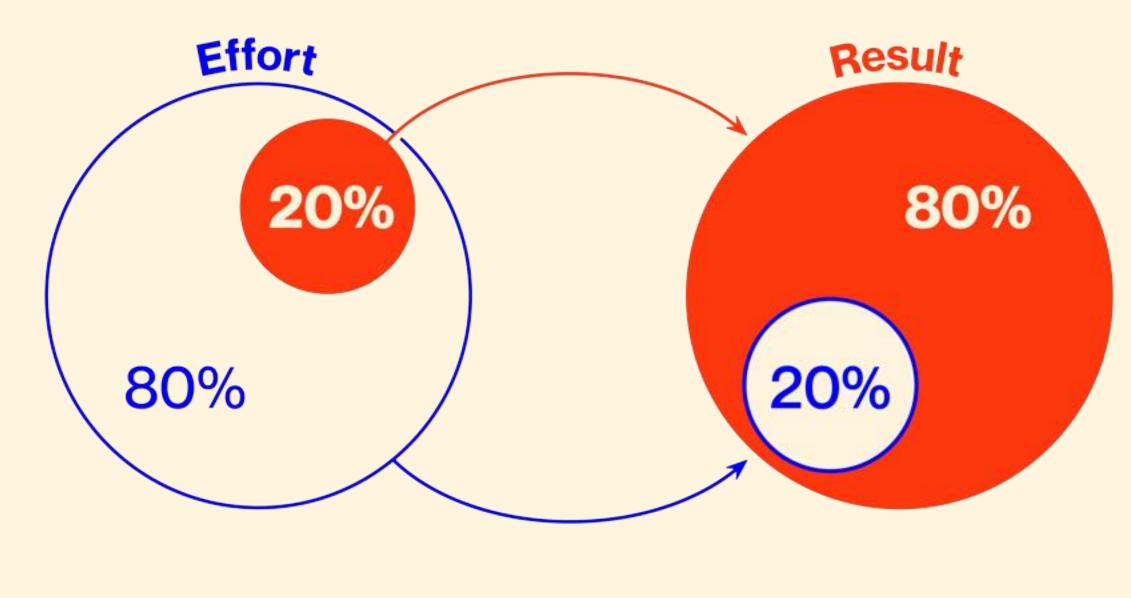
# Evaluation & Selection

# The Ideation Process





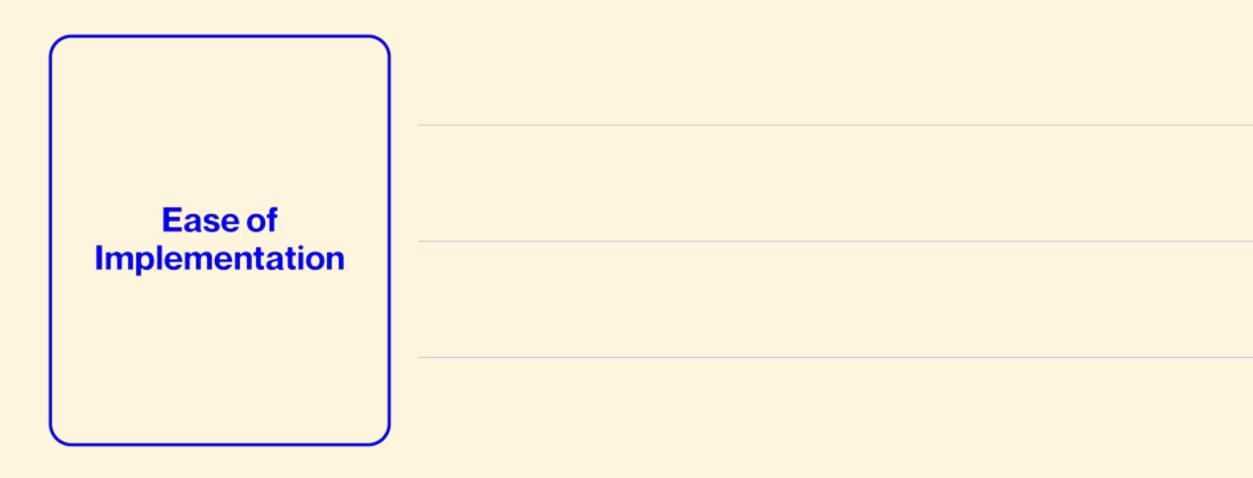
# The Pareto Principle







Dimension	<b>Specification</b>	Key Question
	Economic Value	What is the Economic potential (e.g. cost reduction, additional s
Value	Strategic Alignment	Does it contribute to the AI Stra



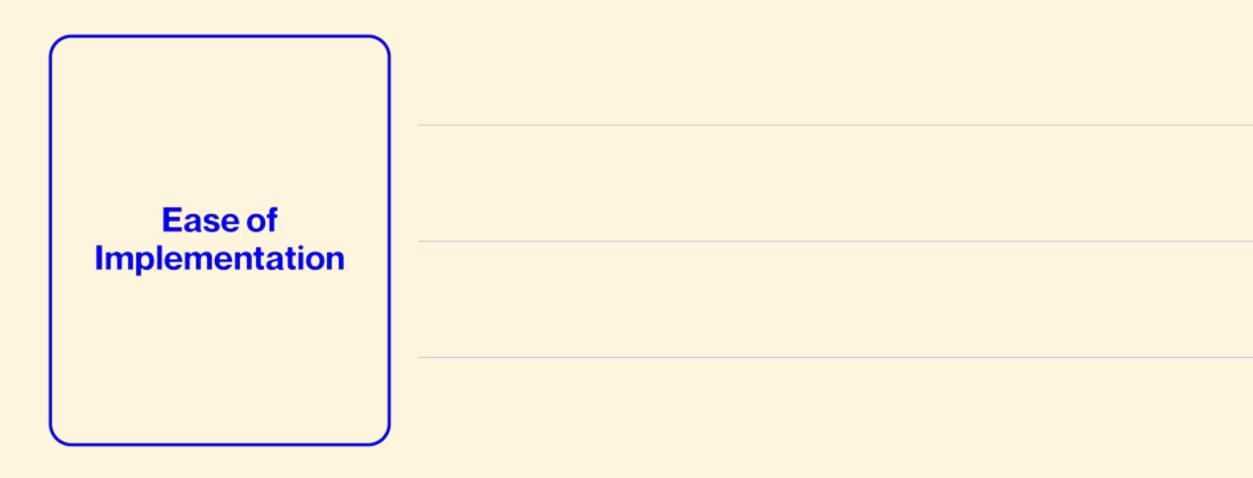
#### Value Score

l of the UC sales...)?

(low value = 0)high value = 5)

ategy?

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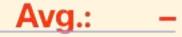


#### Value Score

I of the UC sales...)?

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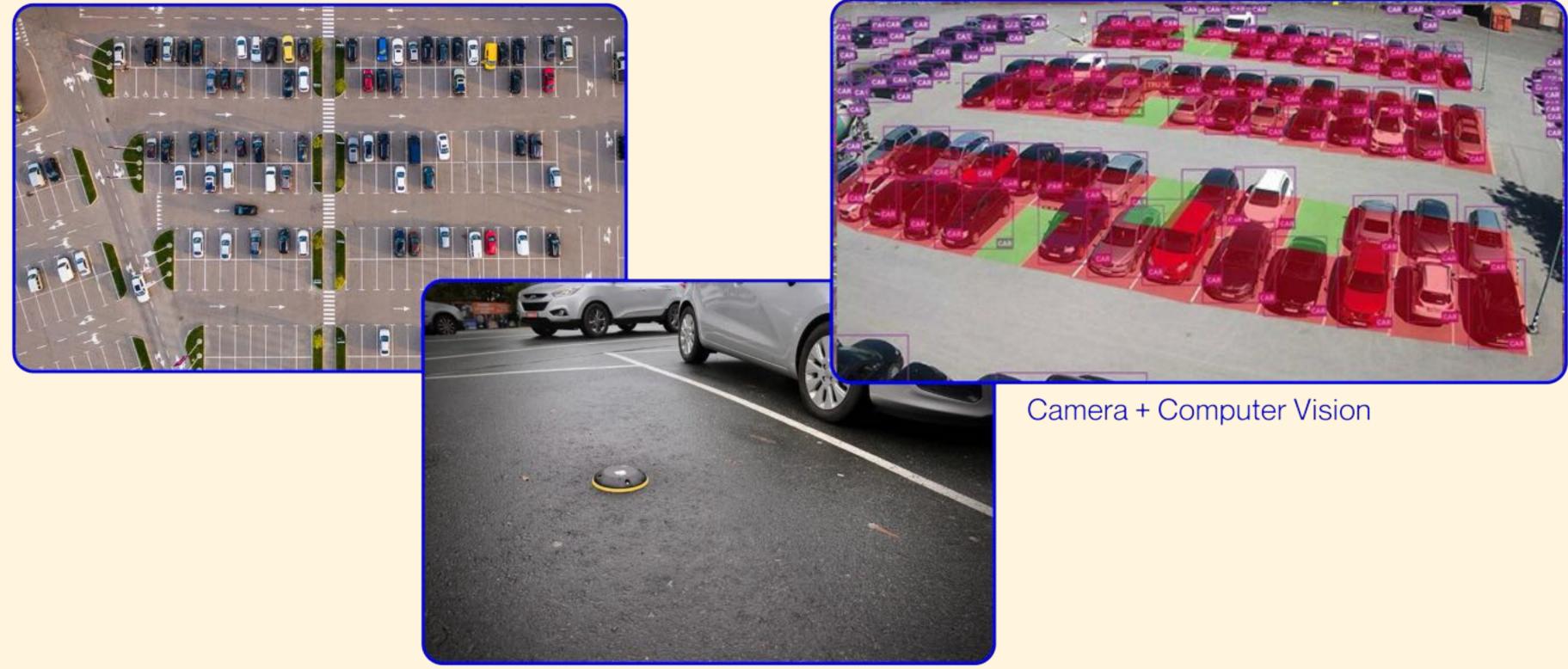
(low value = 0)high value = 5)



Dimension	<b>Specification</b>	Key Question	Value
	Data	Do we have the necessary data?	(difficult to implement = 0 high ease = 5)
Ease of	Algorithm	Is there a known implementation of the UC? In our industry or in anouther industry/domain?	
Implementation	Process / Systems	Which processes and systems are affected	
	Required Know-How	Do we have the required technical and domain know-how?	_

Dimension	<b>Specification</b>	Key Question	Value Score
	Economic Value	What is the Economic potential of the UC (e.g. cost reduction, additional sales)?	(low value = 0 high value = 5)
Value	Strategic Alignment	Does it contribute to the AI Strategy?	
	Data	Do we have the necessary data?	(difficult to implement = 0 high ease = 5)
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# Example: Smart Parking



Ground Sensor

Dimension	<b>Specification</b>	Key Factors
Value	Economic Value	Benefits: Improved Customer E Enhanced Security, Accurate D Costs: High Cost of Installation,
	Strategic Alignment	Efficient Ressource Manageme Customer Loyalty, Scalability ar
Ease of Implementation	Data	Availability, Difficulty in Procure
	Solution Blueprint	Prior Implementations, Pre-exis
	Process, Systems Tools, People	Processes Affected, Systems a
	Required Know-How	Technical Expertise, Domain-sp Difficulty in Acquisition

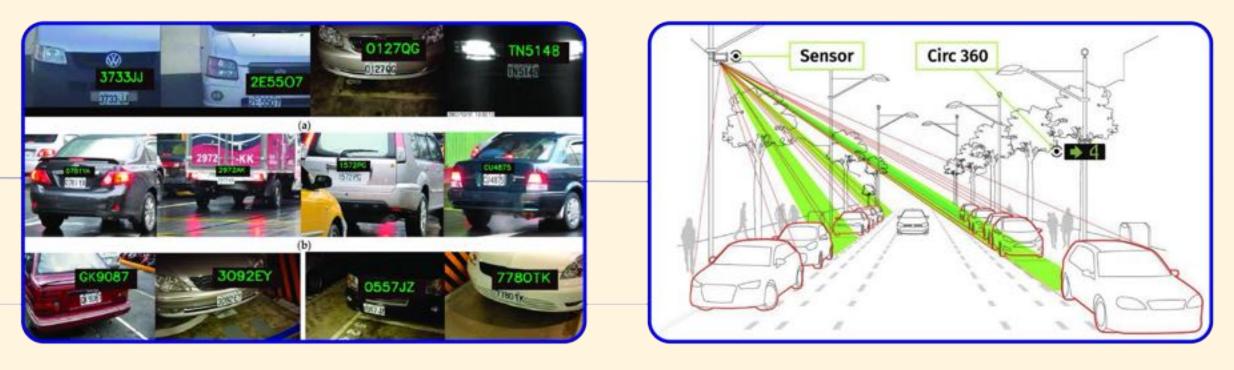
### Value Score

Experience, Reduced Traffic Congestion Data Analytics, Revenue Generation I, Regular Maintenance Requirements	n, 4.5
ent, Environmental Benefits,	4.5
nd Adaptability <b>Avg.</b> :	4.5
ement, Importance	4
sting Templates	4.5
and Tools, People Affected	3.5
pecific Knowledge,	4
Avg.:	4

**Specification** 



**Dimension** 



	Data	Availability, Difficulty in Procurement, Importance		4
Ease of	Solution Blueprint	Prior Implementations, Pre-existing Templates		4.5
Implementation	Process, Systems Tools, People	Processes Affected, Systems and Tools, People Affected		3.5
	Required	Technical Expertise, Domain-specific Knowledge,		4
	Know-How	Difficulty in Acquisition	Avg.:	4

**Key Question** 

### Value Score

Dimension	Specification	Key Factors
Value	Economic Value	Benefits: Improved Customer E Enhanced Security, Accurate D Costs: High Cost of Installation,
	Strategic Alignment	Efficient Ressource Manageme Customer Loyalty, Scalability ar
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	Avg.:	4.5
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pecific Knowledge,		4
	Ava.:	4

# Al Red Flags

Al red flags are critical issues such as regulatory compliance, ethical dilemmas, cybersecurity vulnerabilities, and human-centric challenges that can significantly impede the successful implementation of AI systems.

## **Regulations / Ethics**

Navigating complex and evolving regulatory frameworks and ethical considerations presents significant challenges in AI implementation.

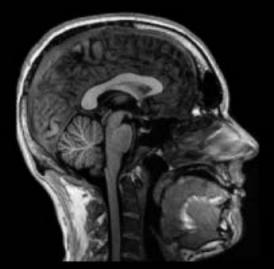
## Cybersecurity

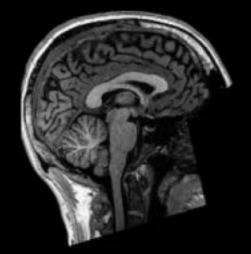
Ensuring robust cybersecurity measures is critical, as Al systems are increasingly targeted by sophisticated cyber threats.

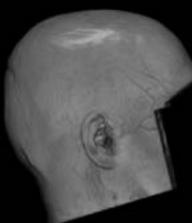
## **Human Aspect**

**Addressing the human** factor, including workforce adaptation and public perception, is essential for successful AI integration and acceptance.

#### Raw Data Defaced

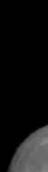




















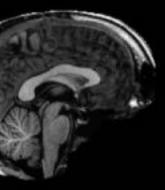


# **Sagittal** (cut middle)



# **Rendering** (frontal)

## **Brain Mask**





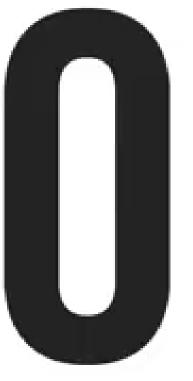


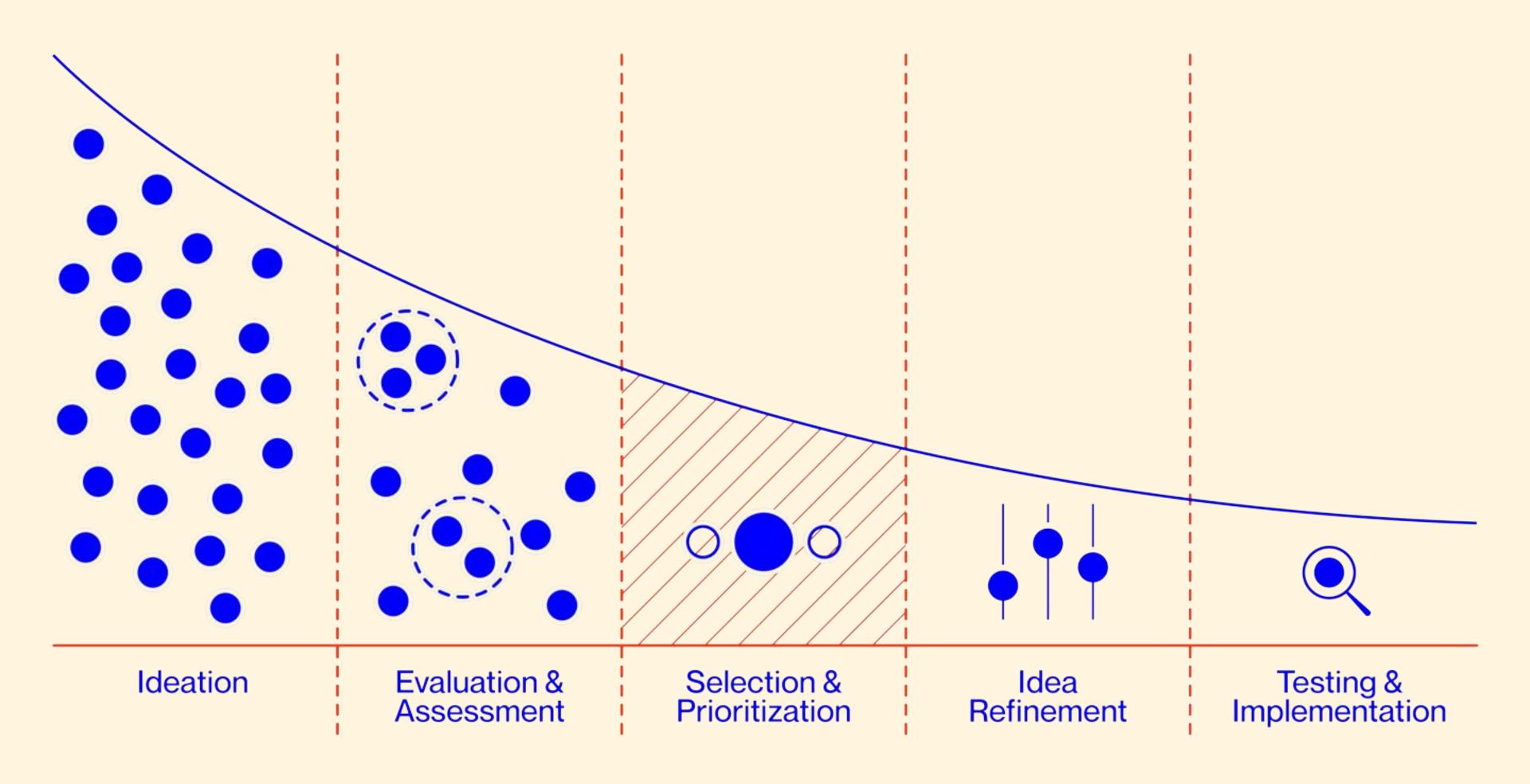
# The Ideation Process

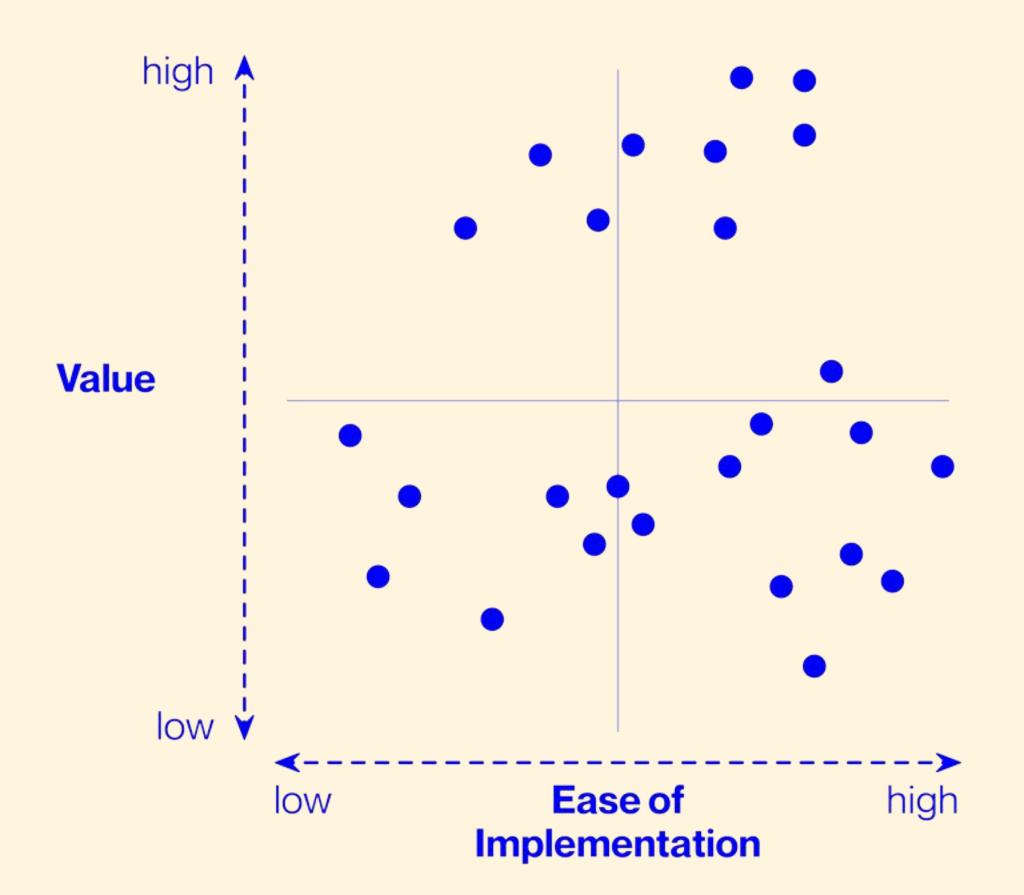


# Use Case Evaluation

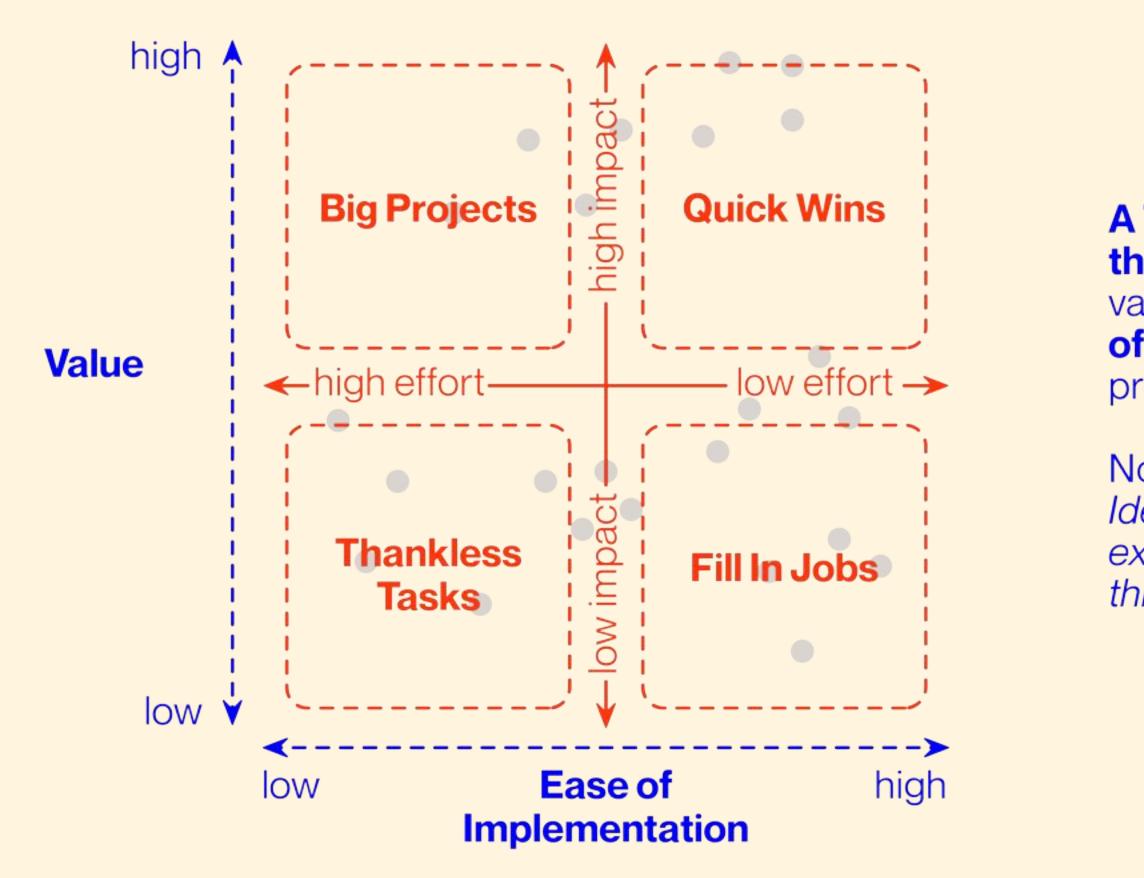






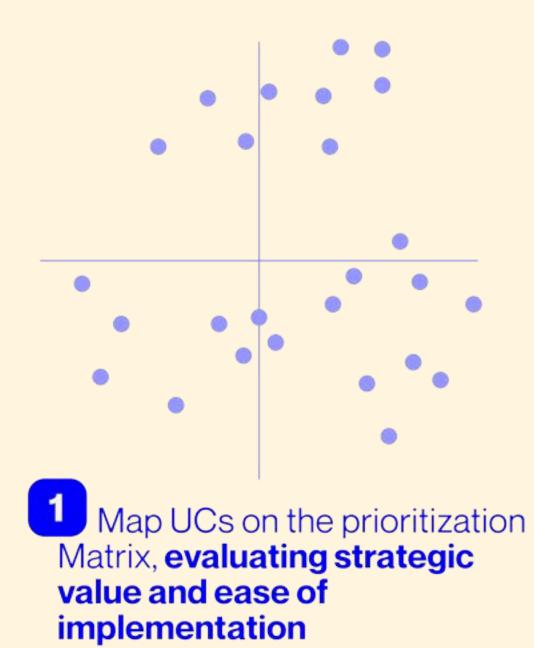


A Tool to rank projects based on their value and ease of implementation.



A Tool to rank projects based on their value (business & customer value, strategic alignment) and ease of implementation (data, algorithm, process/system, required expertise).

Note: Ideally both business domain and AI expertise should be in the room for this excersice



1 Map UCs on the prioritization Matrix, evaluating strategic value and ease of implementation

2 Cluster UCs by

- Input data
- Al capability
- Product / process

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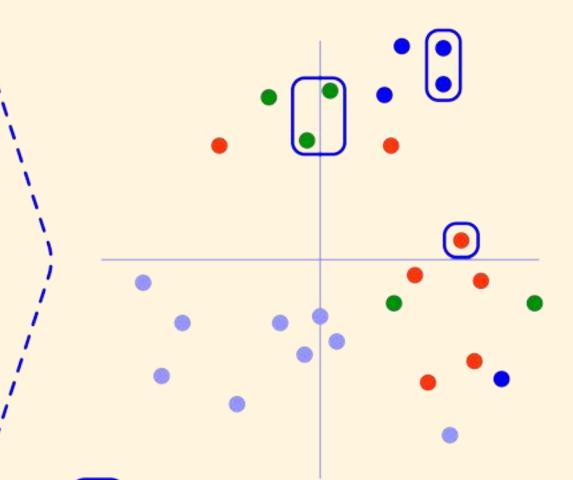
**3** Prioritize 2-3 clusters

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**3** Prioritize 2-3 clusters

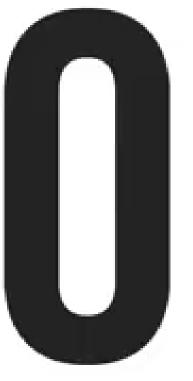


4 Within prioritized clusters, pick 1-2 UCs (so 3-6 cases overall) for validation – good candidates can have different characteristics, e.g.

- quick wins
- High strategic relevance
- High marketing relevance

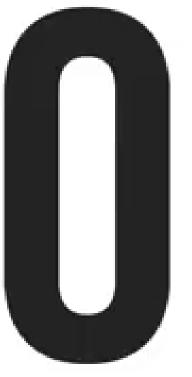
# Use Case Prioritization





# **Presentation of Prioritization**





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#### 09:50 Uhr - 10:00 Uhr - Bewertung von KI-Anwendungsfällen - Theorie | Format: Vortrag

Einführung "Wie KI-Anwendungsfälle anhand ihres wirtschaftlichen Wertbeitrags, der Machbarkeit und der zu erwarteten Ergebnisse priorisiert werden können.

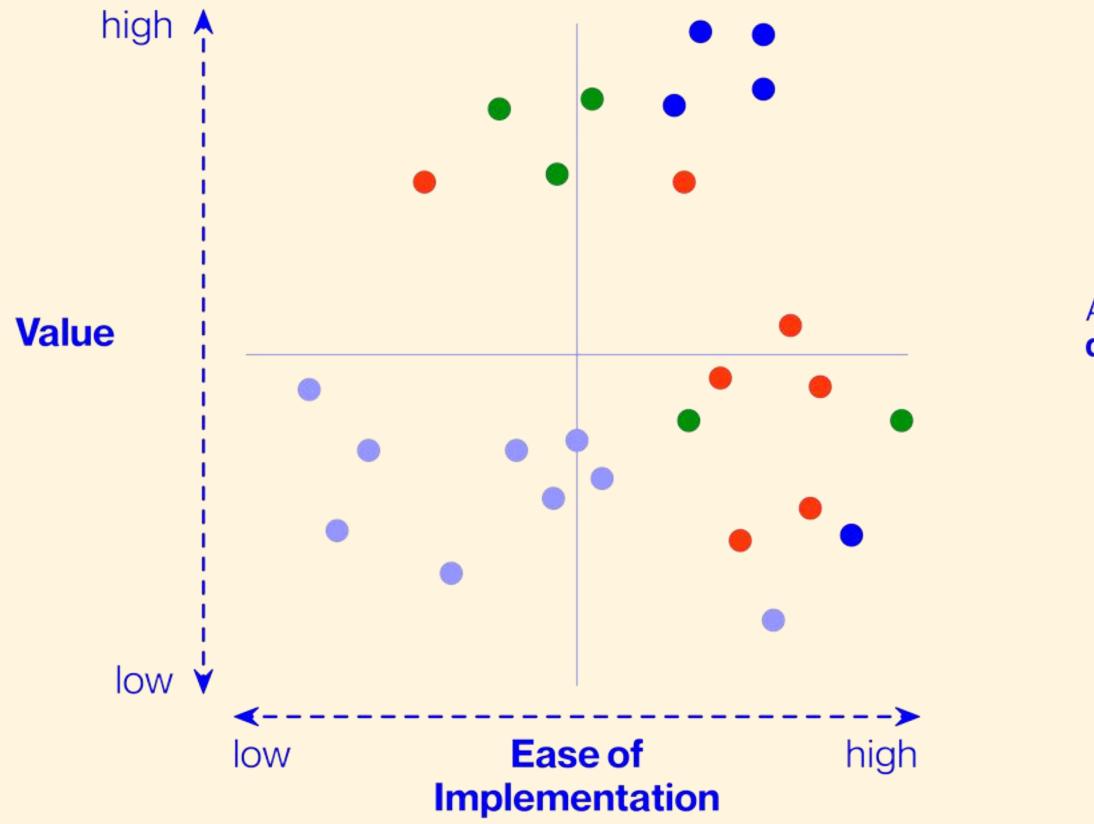
#### 10:00 Uhr - 10:25 Uhr - Bewertung von KI-Anwendungsfällen - Praxis | Format: Interaktive Gruppenarbeit mit Canvas

Gruppen arbeiten an der Bewertung und Priorisierung ihrer Anwendungsfälle unter Verwendung des Priorisierungs-Canvas.

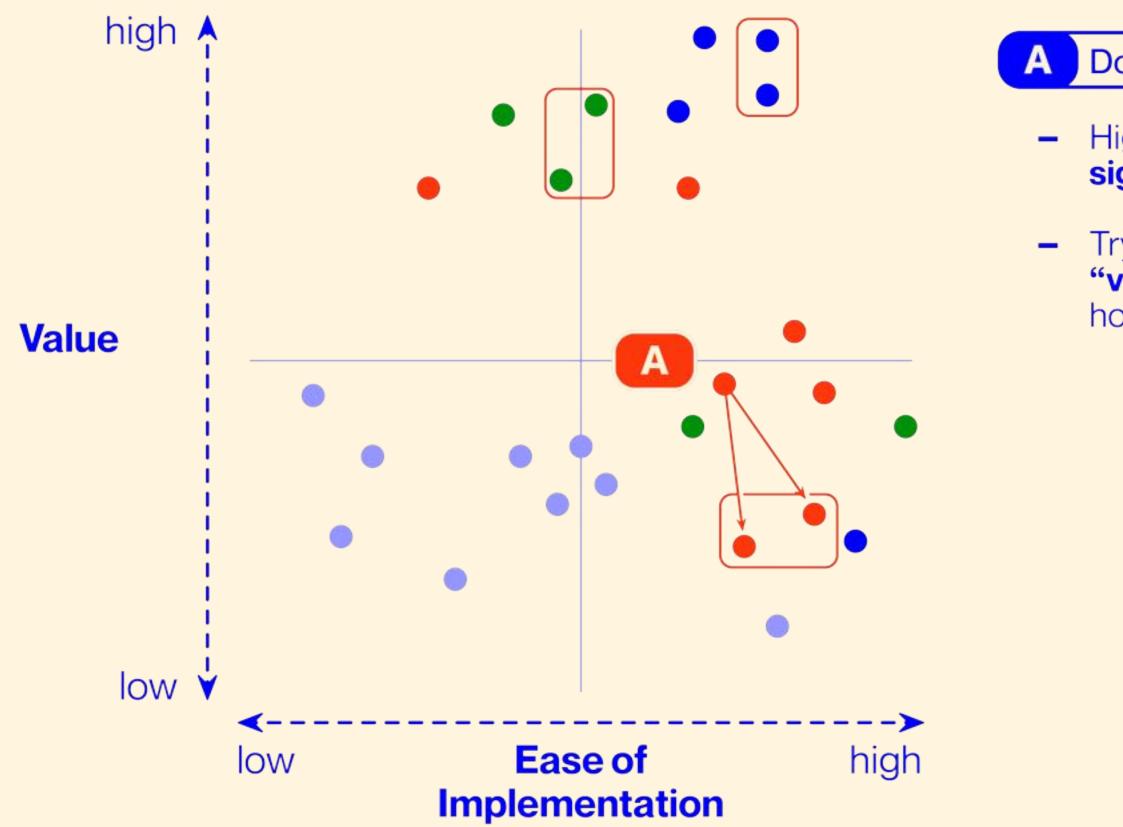
#### 10:25 Uhr - 10:30 Uhr - Use Case Pitches | Format: Präsentation im Plenum

#### 10:30 Uhr - 10:40 Uhr - Q&A Session | Format: Vortrag mit Q&A

Beantwortung von Fragen und Diskussion mit zusätzlichen Einblicke in den Prozess der Use Case Evaluation.



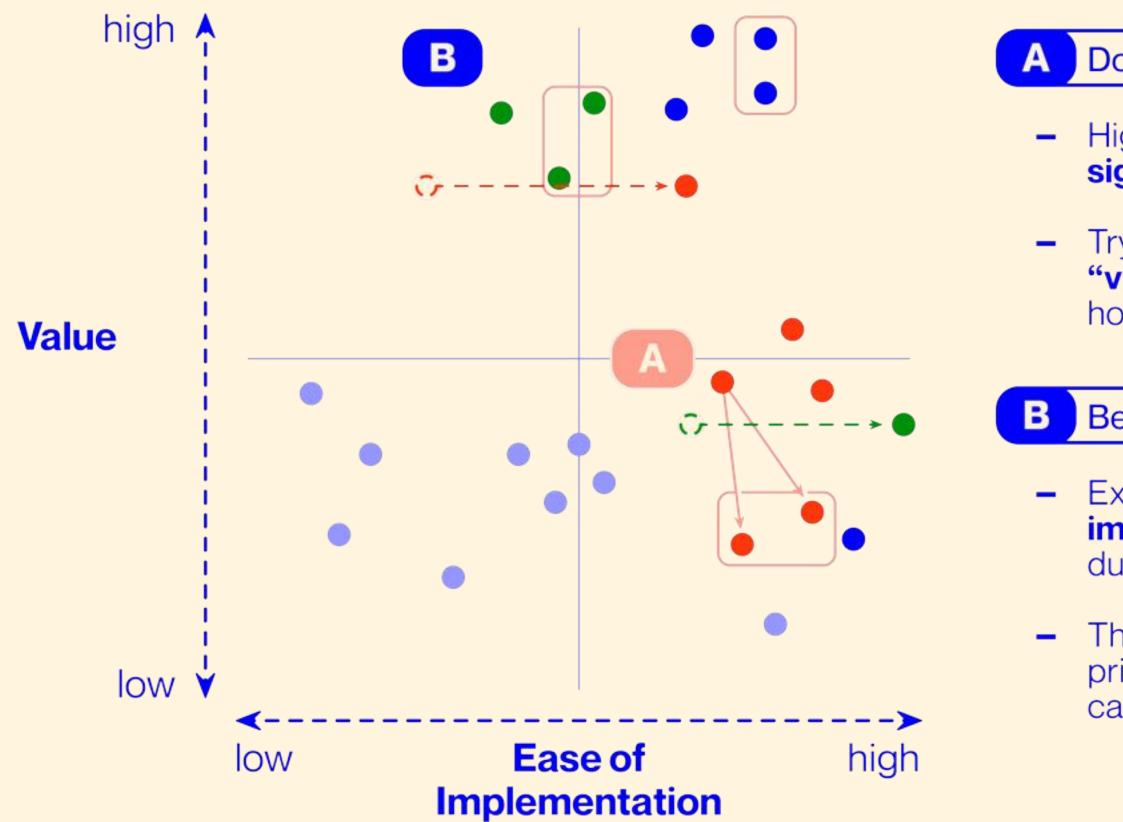
Al Use Cases can be clustered by data source, AI capability, domain etc.



Do not discard complex UCs immediatly

High Value UCs might be significantly complex

Try to **decompose them into intermediate "viable products"** and develop a **roadmap** how to pursue implementation step by step



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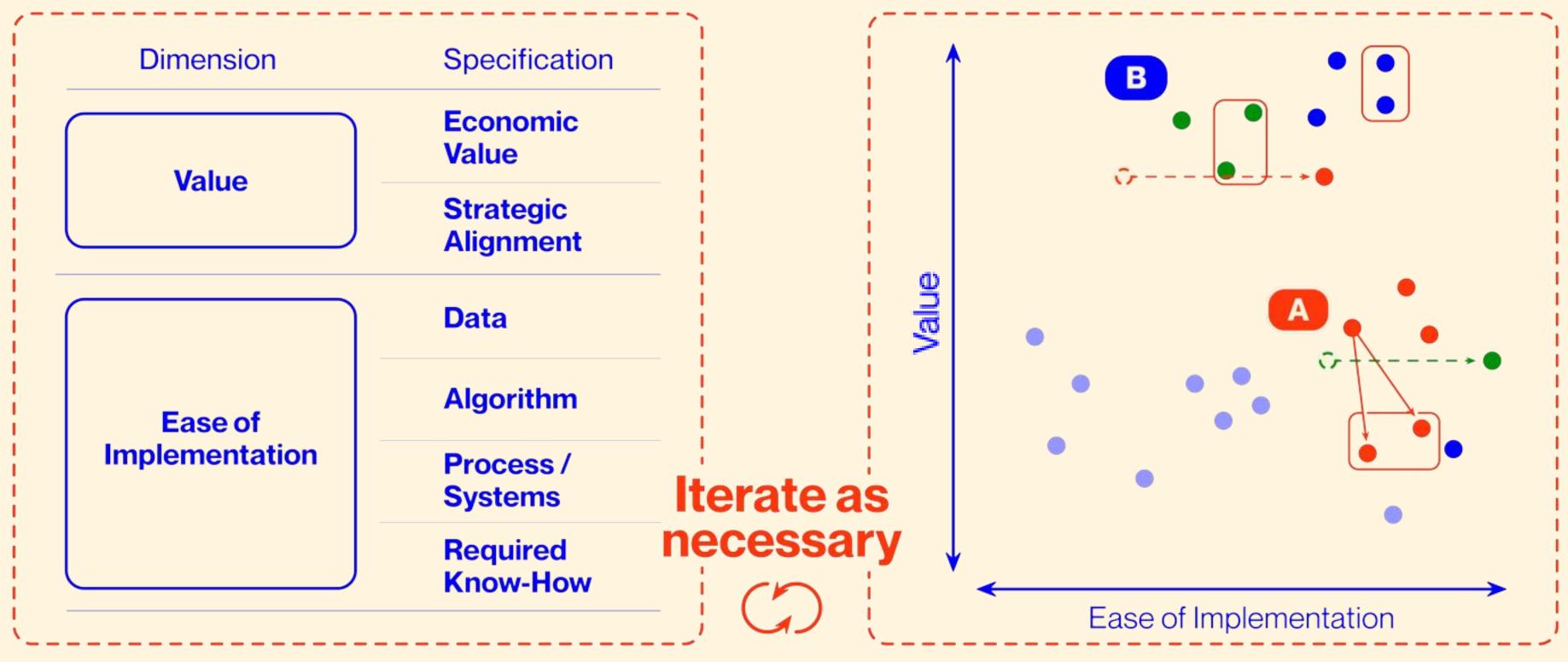
Be aware of technological interdependencies

Executing one UC can have **positive implementation benefits for other UCs** due to re-use of same data set, etc.

This can **change the dynamic** in the prioritization/selection and clustering those can **speed up collective implementation** 

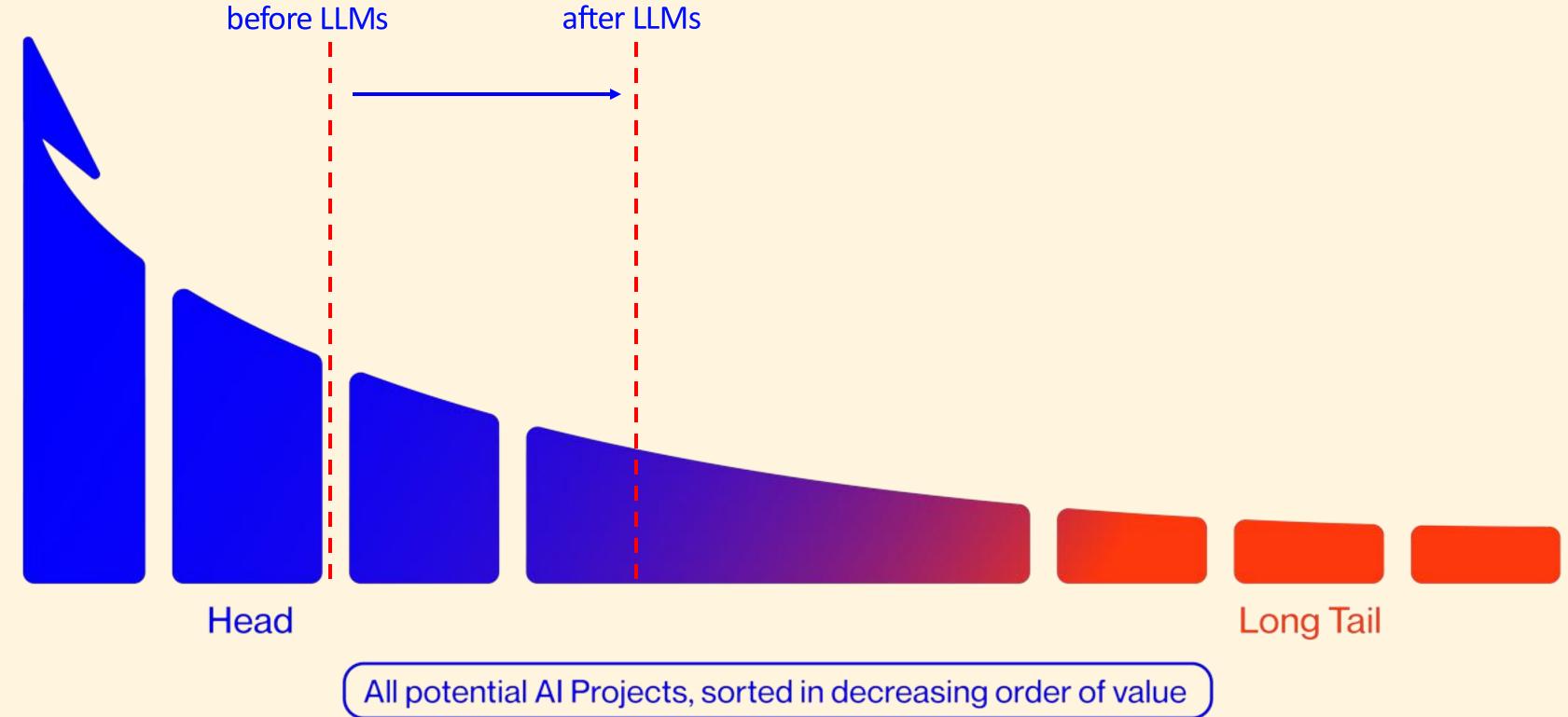
## **An Iterative Process**

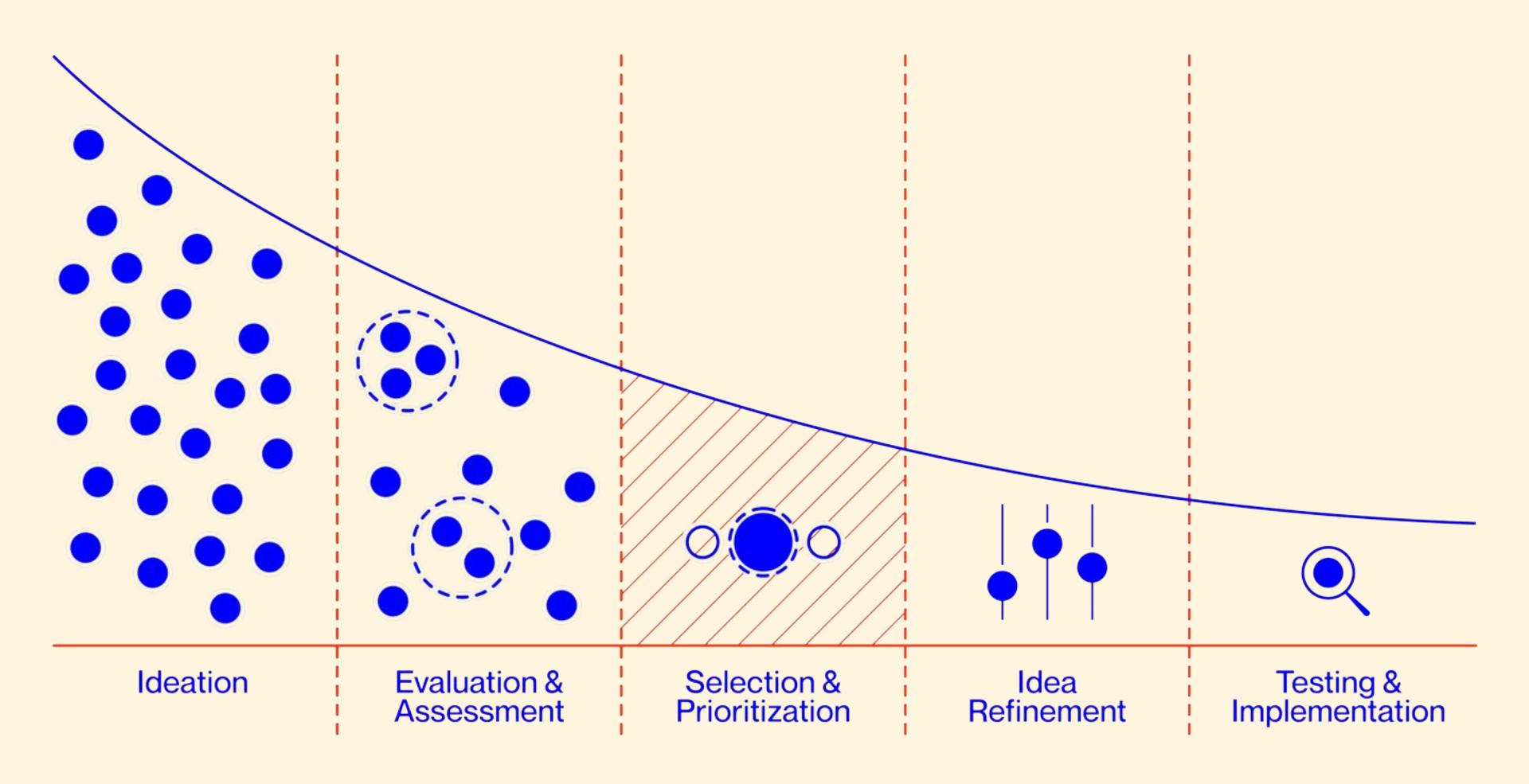
#### Assessment of UC Ideas



#### Prioritization of UC Ideas

Value





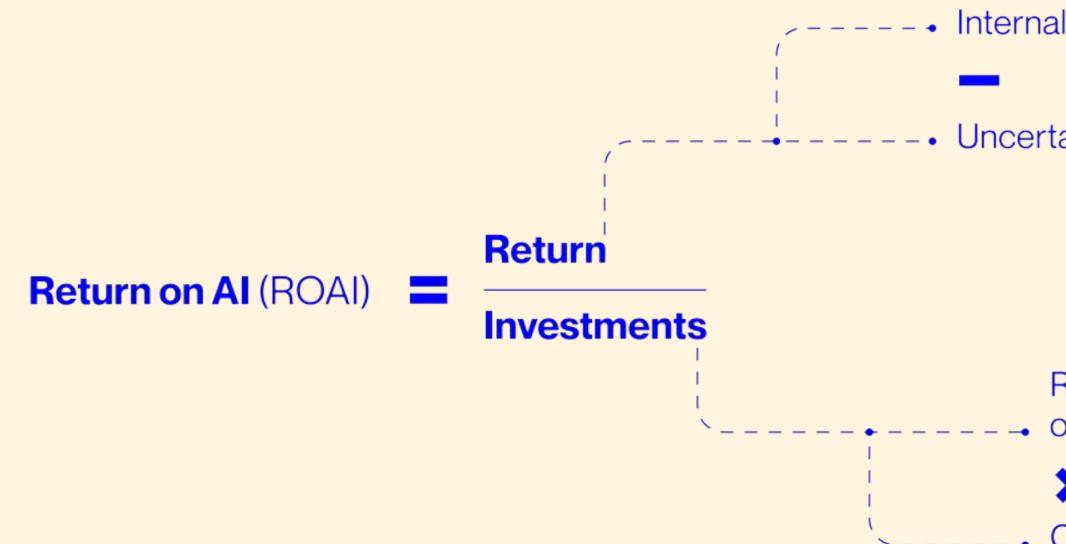
# The Ideation Process



# Idea Refinement & Testing



## Return on Al



Internal and external value generation

Uncertainty of benefits

Resources for model development, operation and maintainance

Cost per resource

# Saving Time with AI

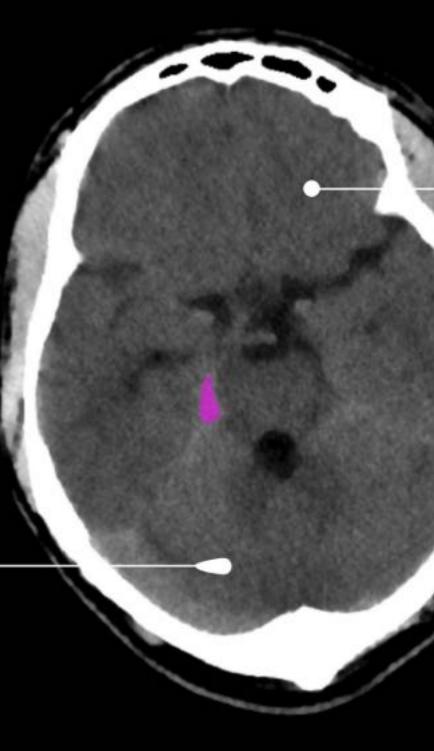
Original time taken: 30 min

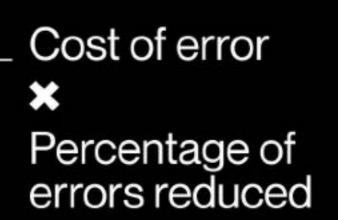
Time taken with AI Assistance:

15 min

Time saved per scan:

15 min





### = saving

Ideation & Scoping

#### Exploration

#### Development, validation and testing

#### Ideated, prioritized use case

Structured use case ideation; initial (qualitative) value assessment aease of implementation evaluation; connection of model perf. metrics to business KPIs

€ (cumulative)

#### Go/no-g decision for further development

Data acquisition; exploratory data analysis and insight generation; initial modeling and testing; (re-)eveluation of value and technical feasibility hypotheses

#### **Technically &** commercially validated, deployment-ready model

Data analysis and preparation; feature engineering; model training, validation and testing; (automated) model selection: model versioning (exp. tracking)

Review for deploy; testing (QA / staging); inference pipeline design; model serving (deployment to appropriate runtime engine)

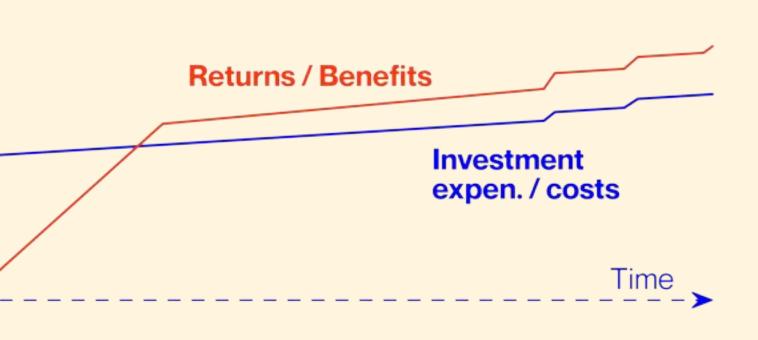
#### Deployment

#### Operation, monitoring, maintenence, scaling

#### Integrated, productive application/service

#### **Operational self-learning**, maintenance and scaling

Model monitoring mainten. (incl [automated] retraining); reporting; infrastructure mgmt.; further roll-out/scaling across processes, regions, sites, etc.



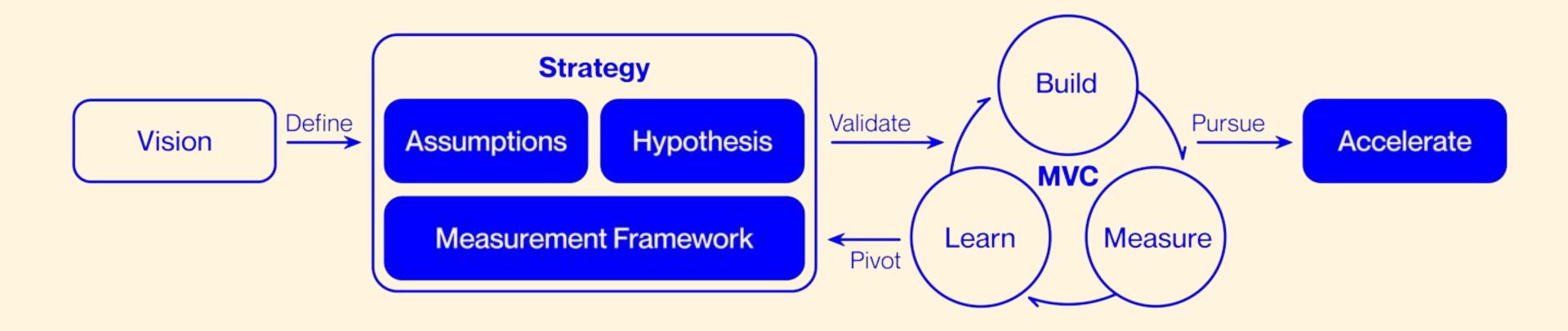
# Al Value Assessment

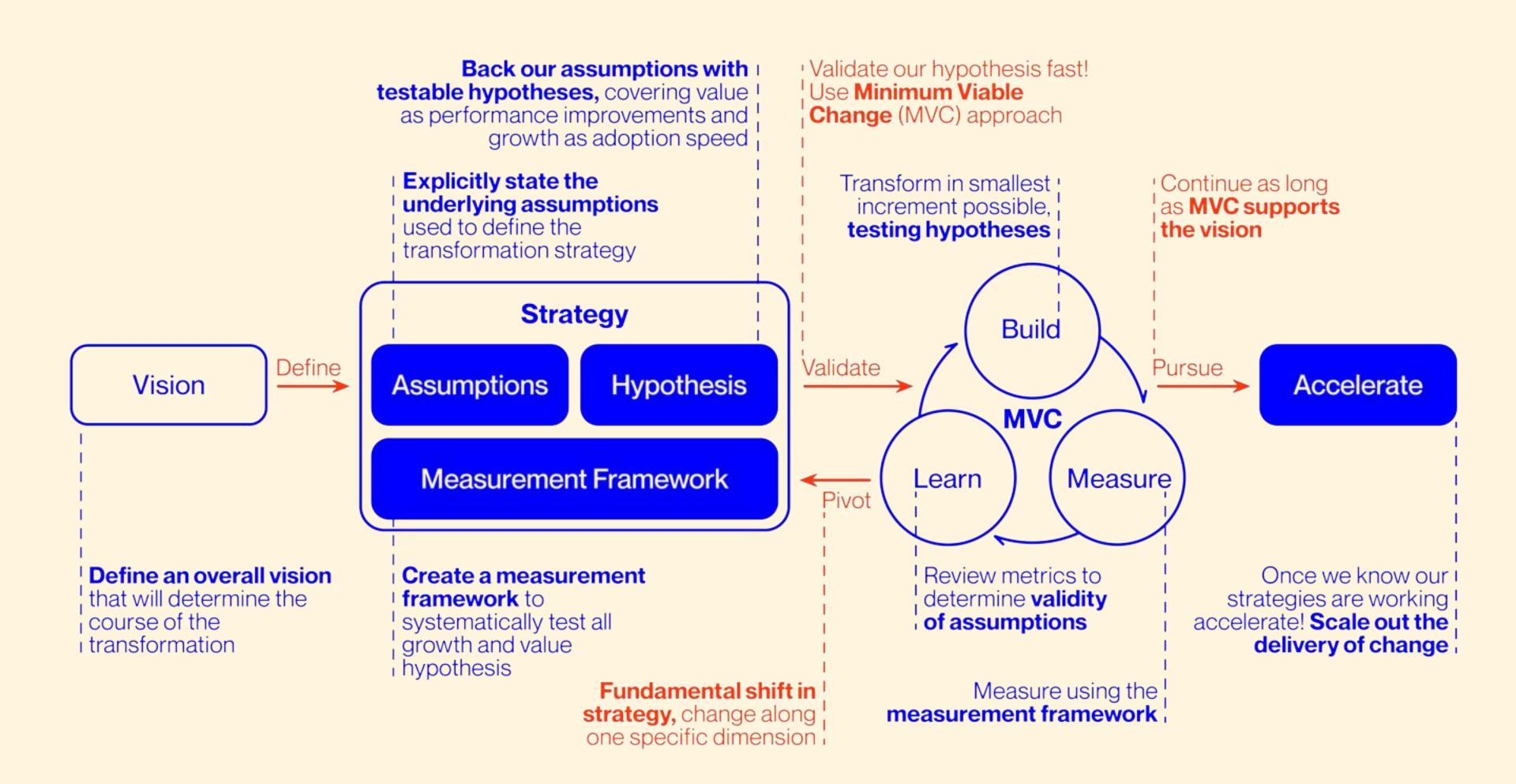




Essential for formulating **a product pricing strategy** 

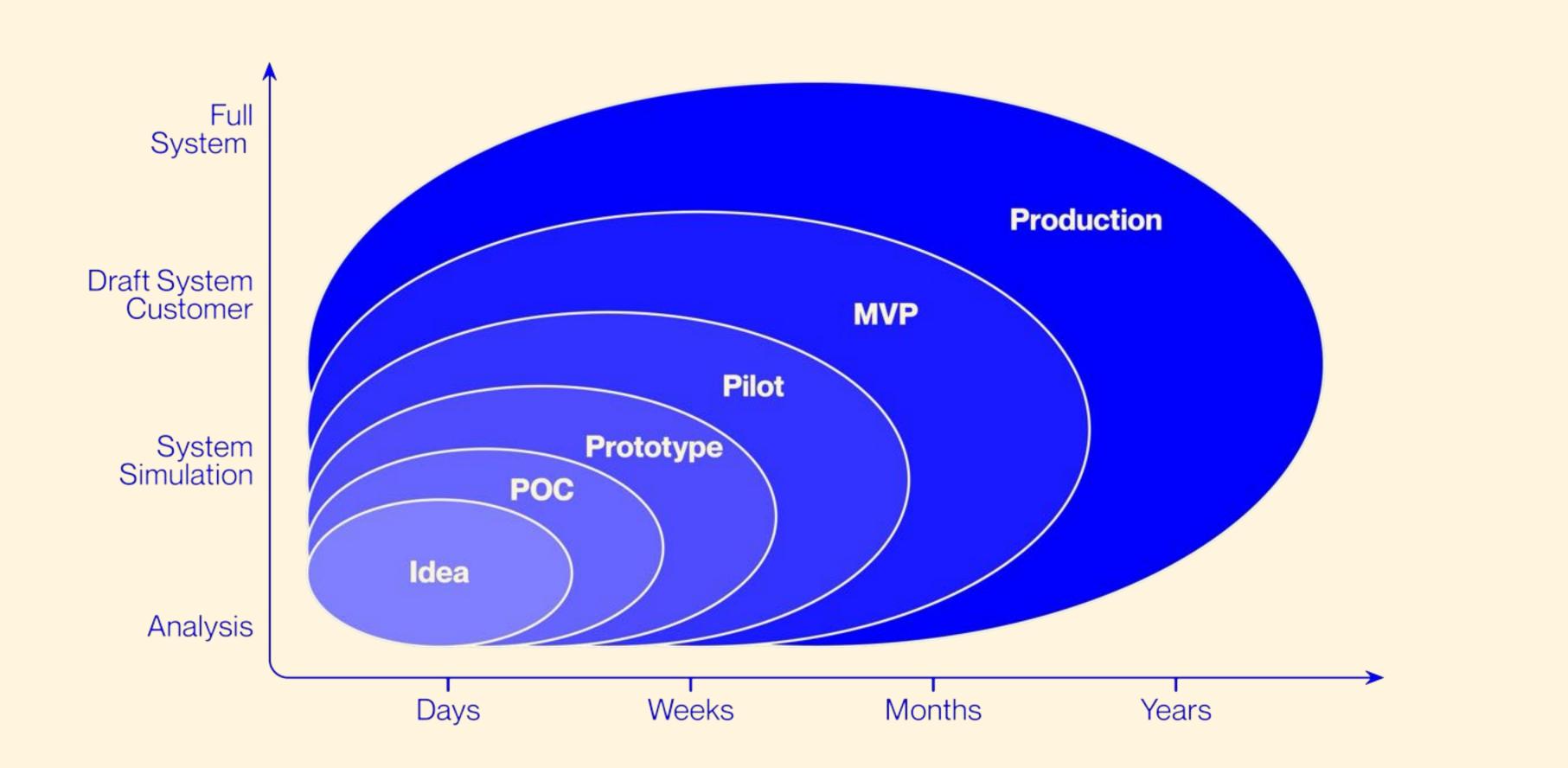


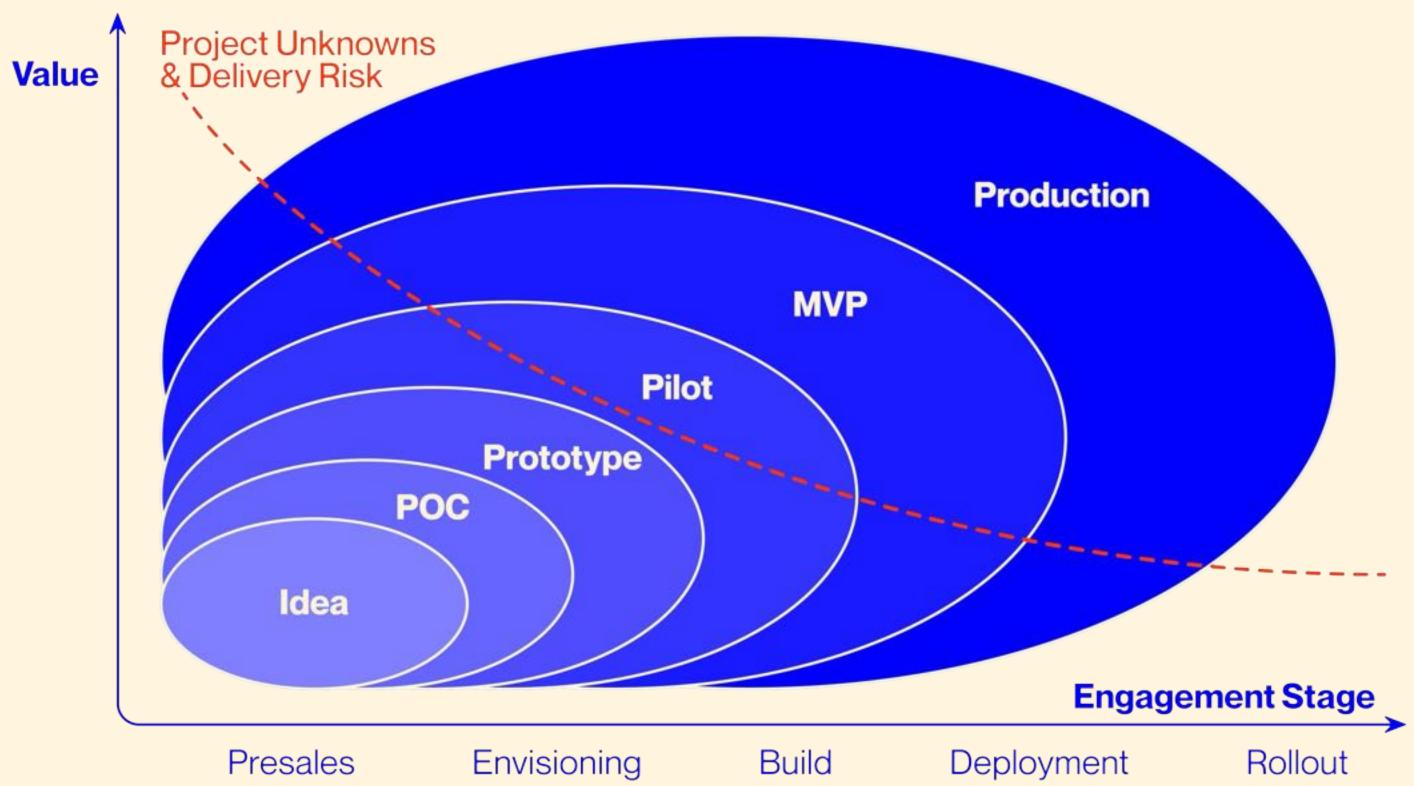




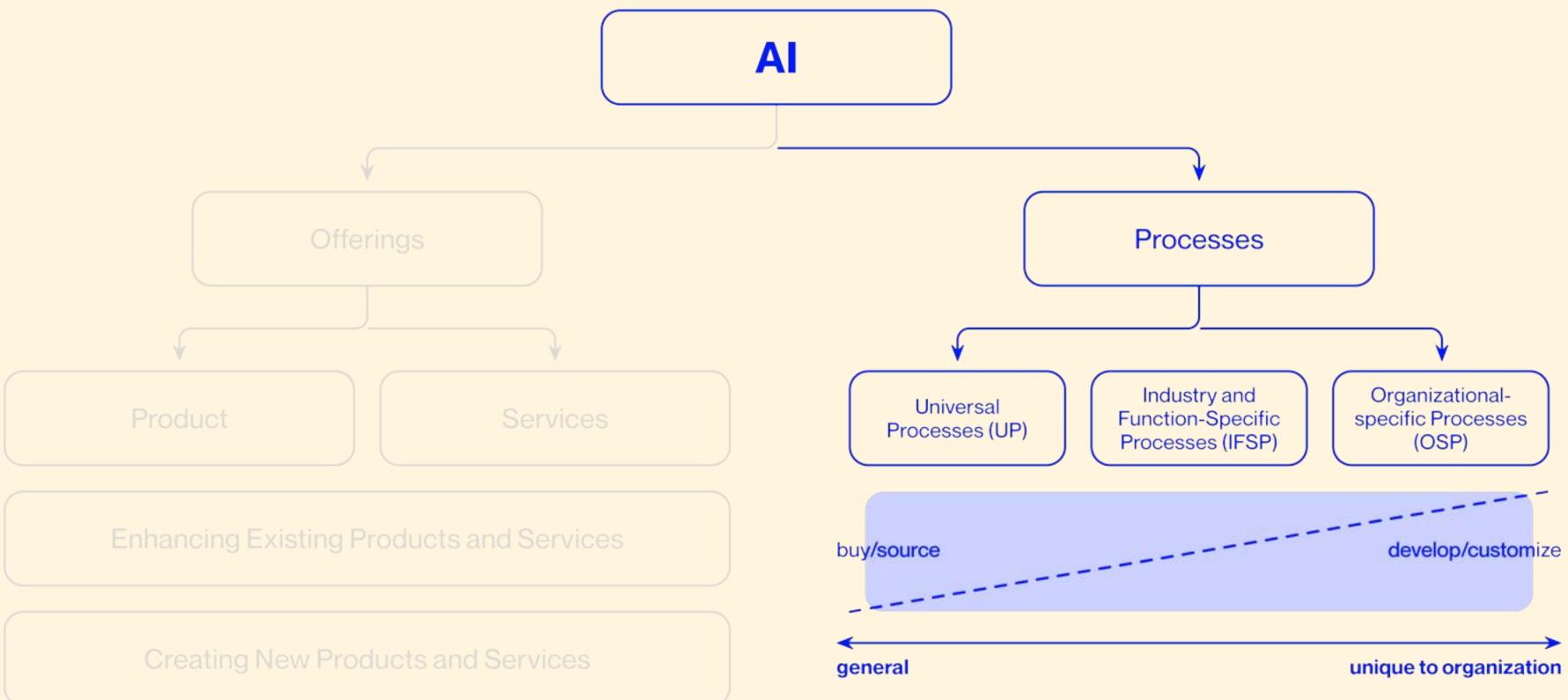
# **Development Process**



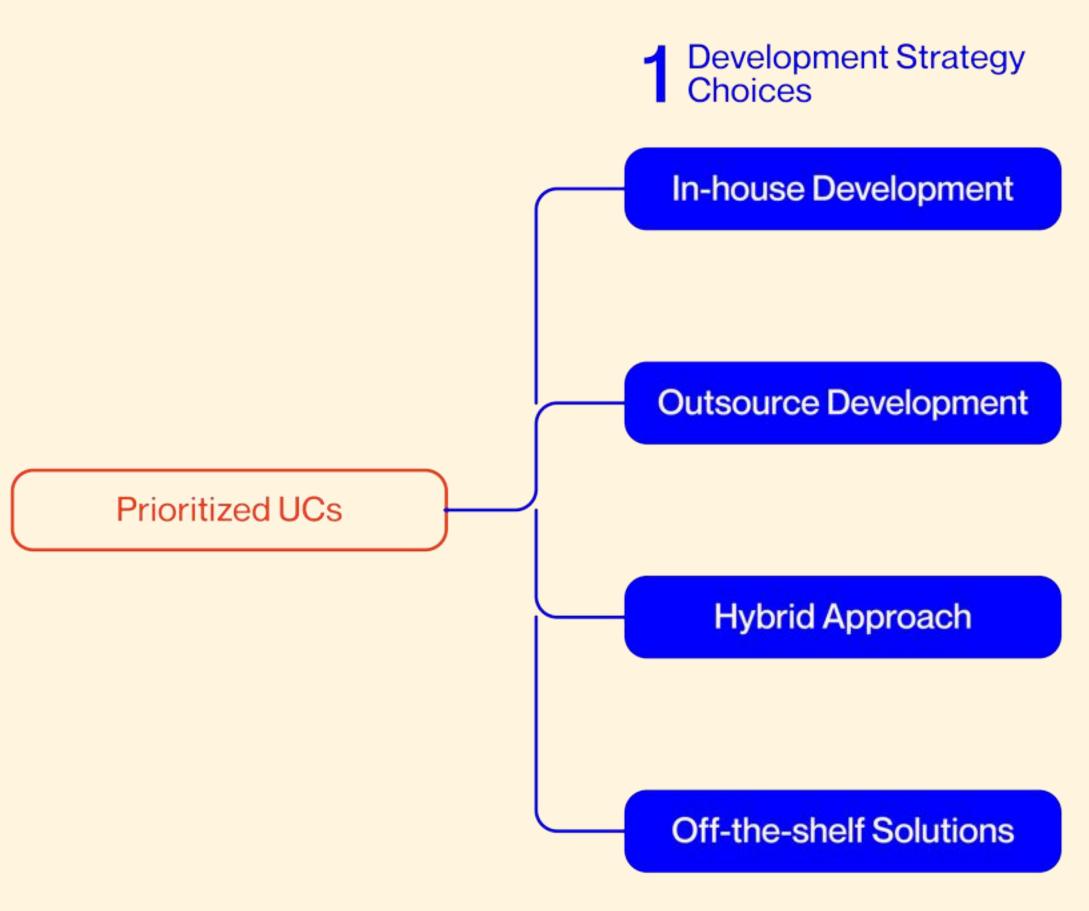




# Make or Buy



## **Development Choices**





**Internal AI Team** 

**Startups** 

Academia

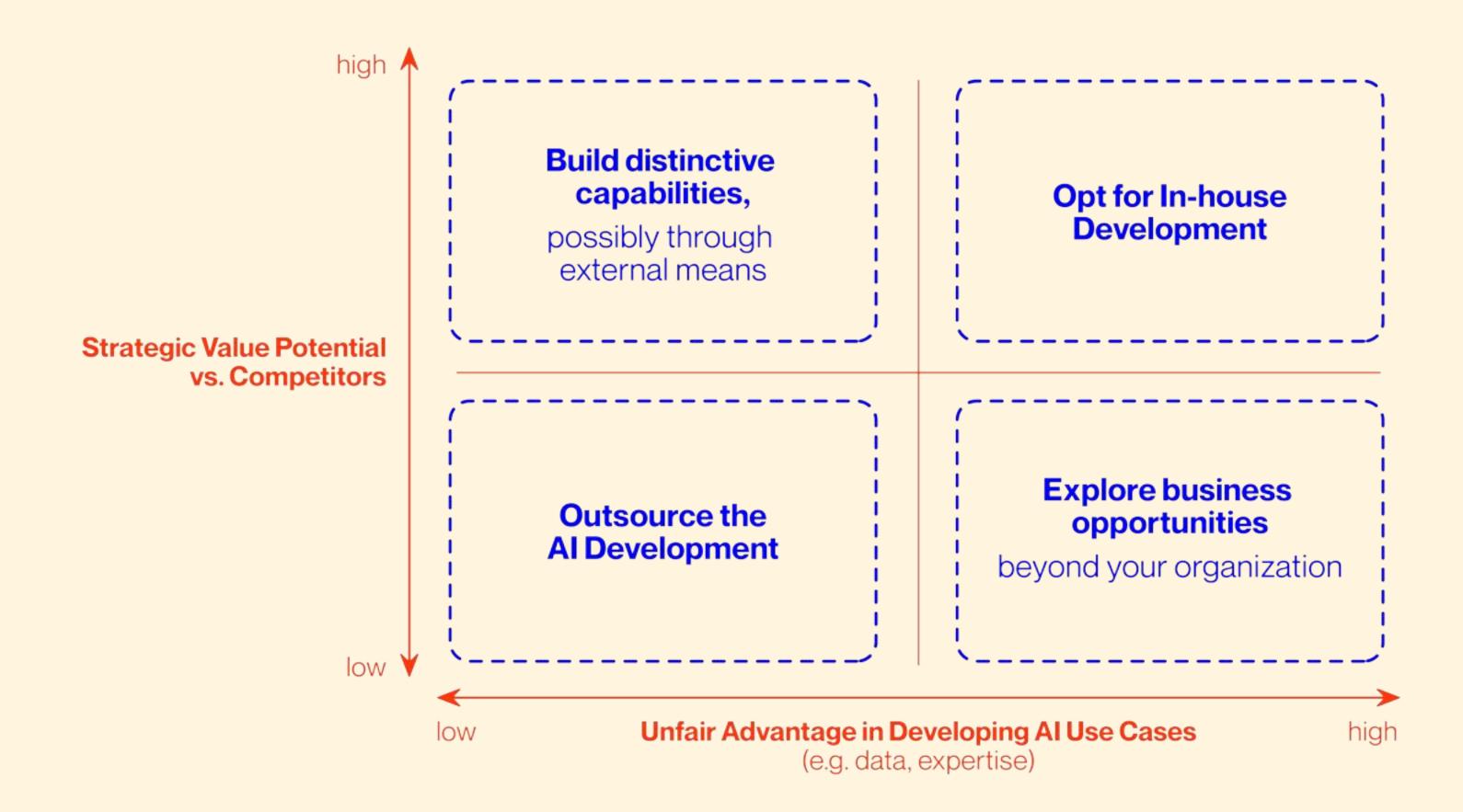
**Consultancy Firms** 

**Research Institutions** 

**Innovation Awards** 

**Established Vendors** 

## Make or Buy Decision



### Umsetzung einer KI Implementierung & Lebenszyklusmanagement

#### 09:00 Uhr - 09:10 Uhr - Icebreaker | Format: Interaktive Gruppenarbeit

Ein lockerer Start in einen Vormittag intensiver Zusammenarbeit.

#### 09:10 Uhr - 09:25 Uhr - KI Use Case Ideation Format: Vortrag

Einführung in den Prozess der Ideation von KI-Anwendungen mit Schwerpunkt auf der Identifizierung potenzieller Anwendungen von KI.

#### 09:25 Uhr - 09:35 Uhr - Ausarbeitung KI-Use Cases | Format: Individuelle Arbeit

Die Teilnehmer konkretisieren den KI-Anwendungsfall, den sie vorbereitet haben, und wenden dabei die im Vortrag behandelten Konzepte an.

#### 09:35 Uhr - 09:50Uhr - KI-Use Cases | Format: Kollaboratives Gruppenfeedback

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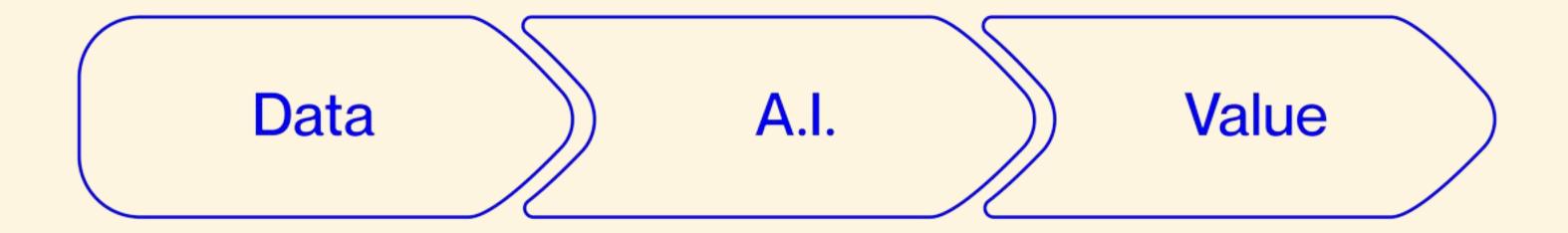
# ML Lifecycle Management



# From Output









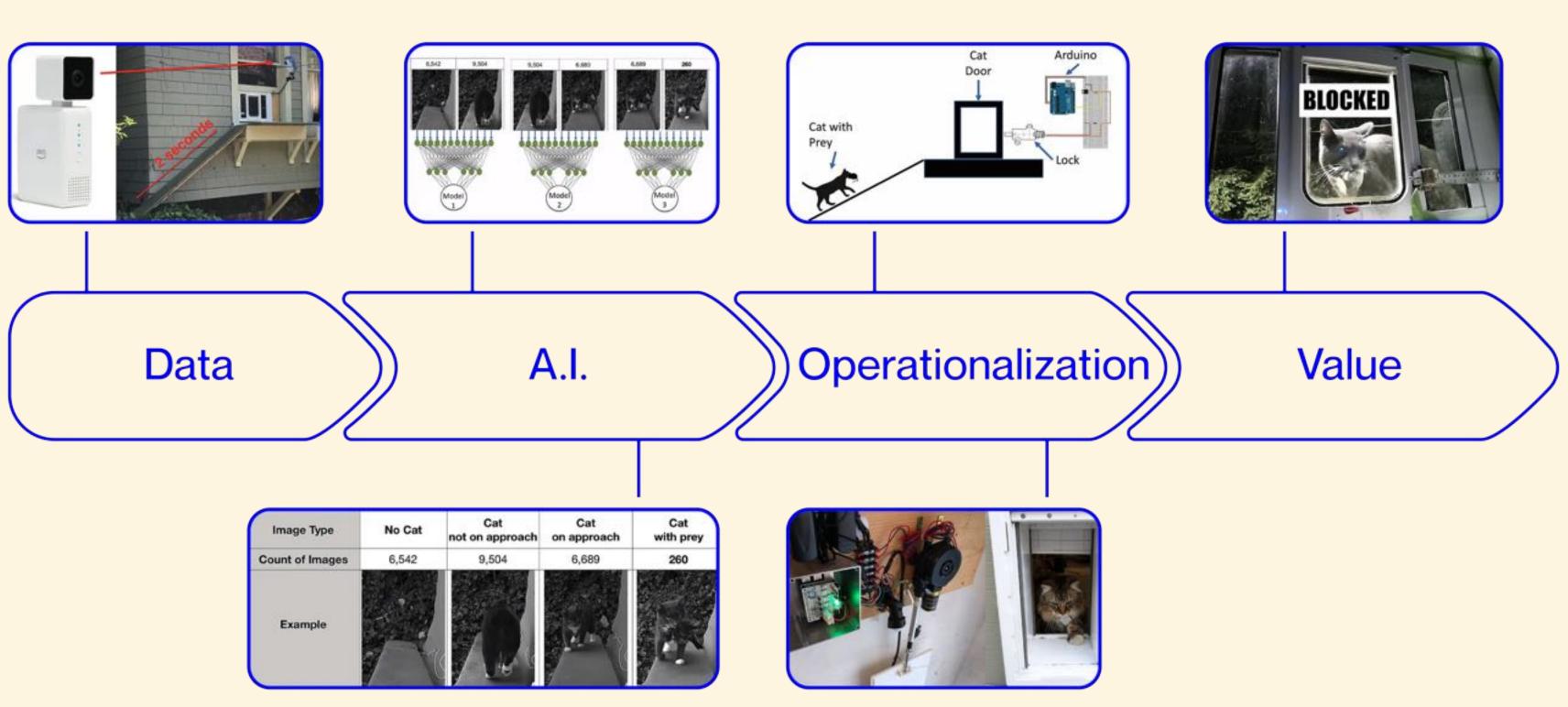
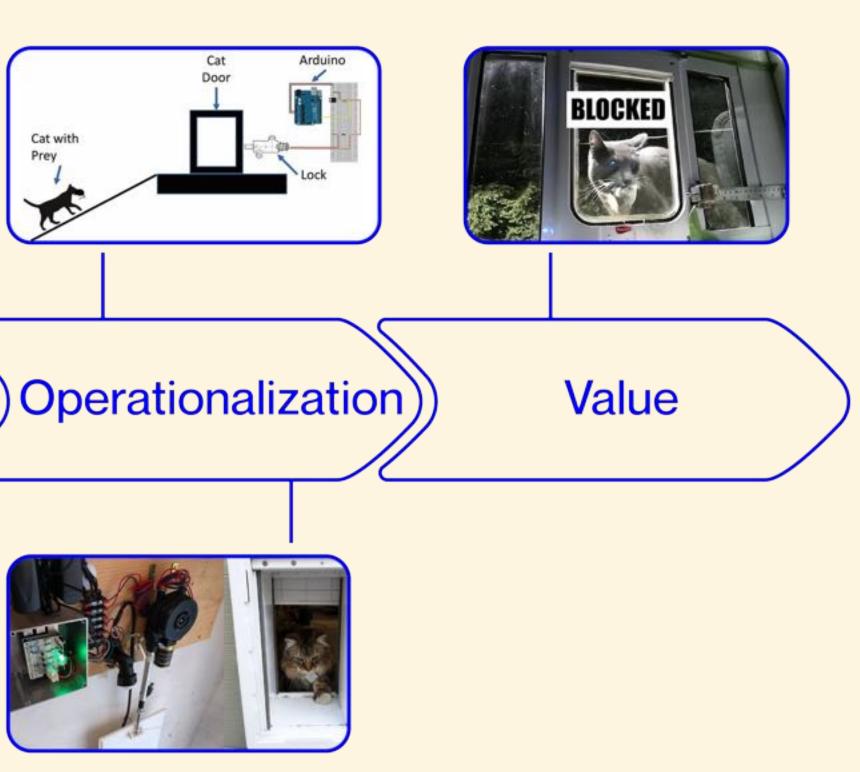
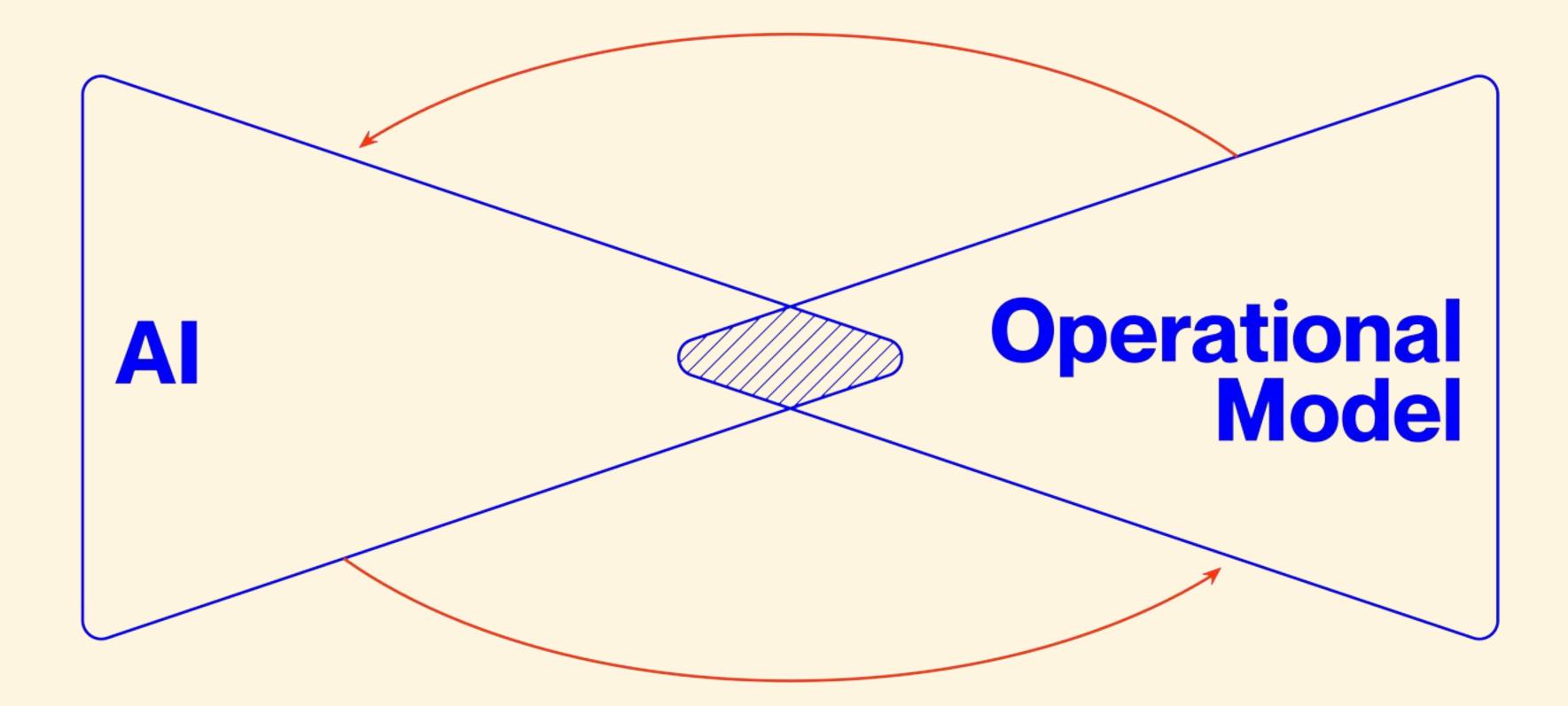


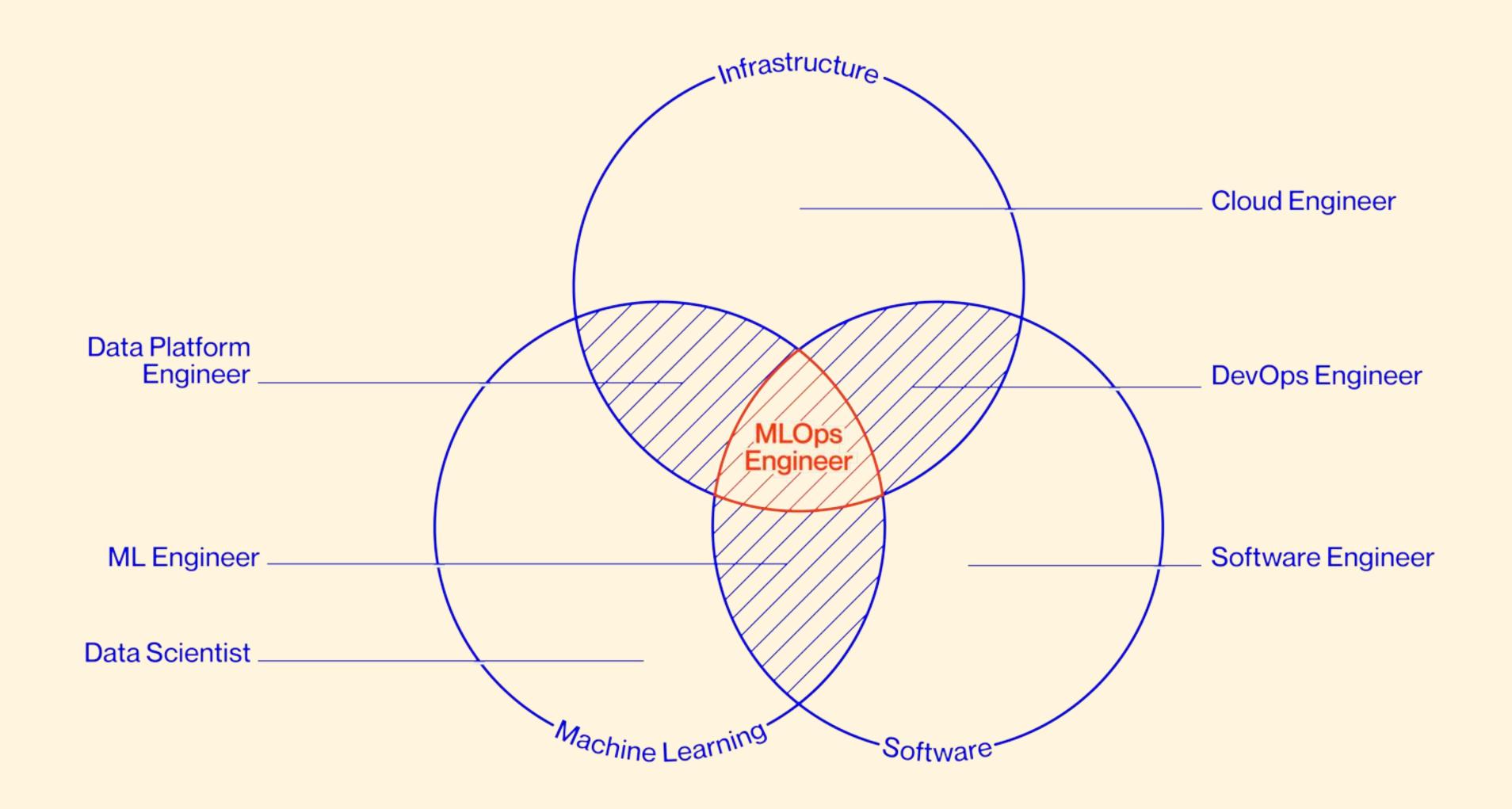
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Count of Images	6,542	9,504	6,689	260
Example	R			



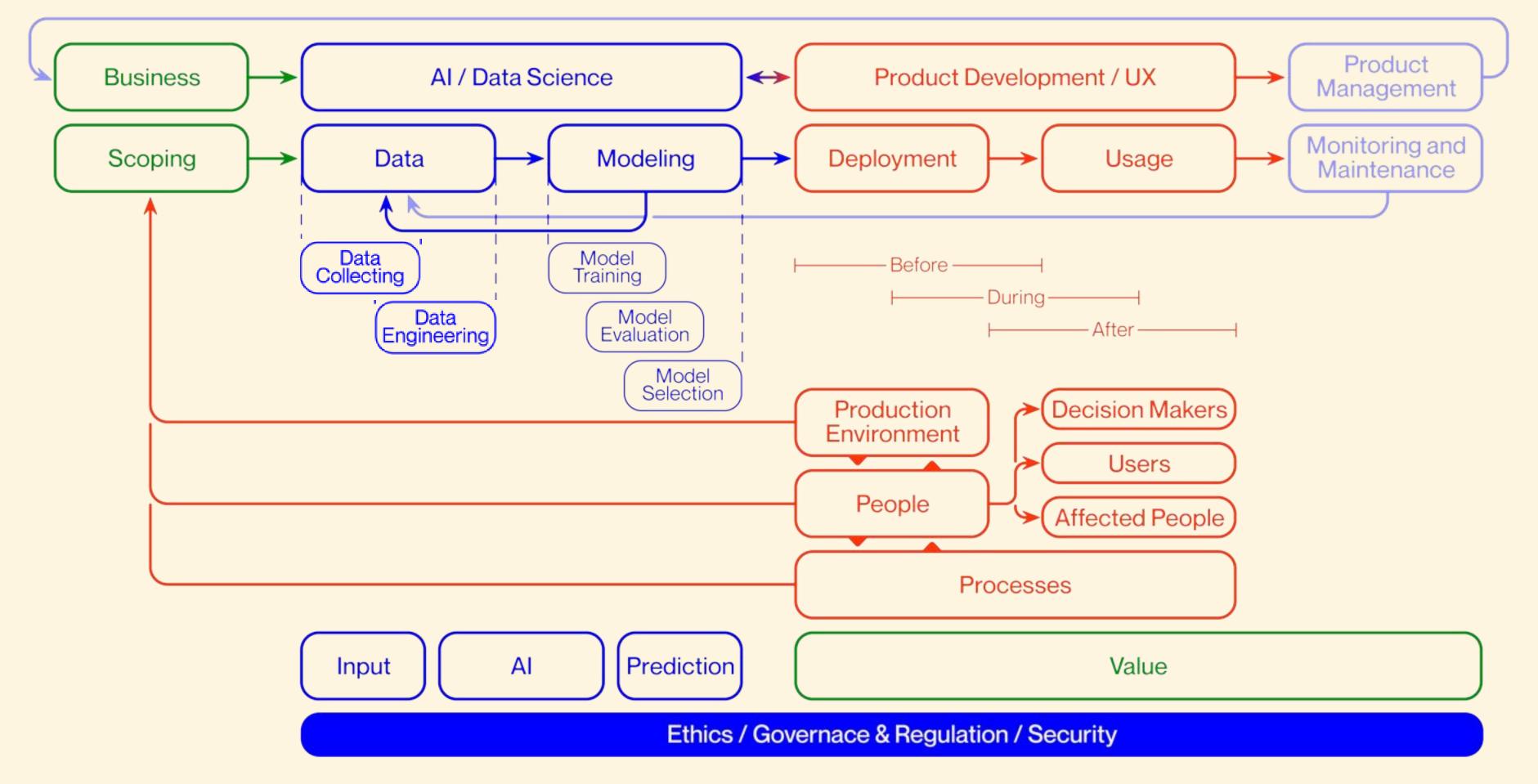


# MLOps

MLOps unifies machine learning development and operations, emphasizing seamless integration and deployment of ML models in production environments.



## Human- and Process Centric MLOps

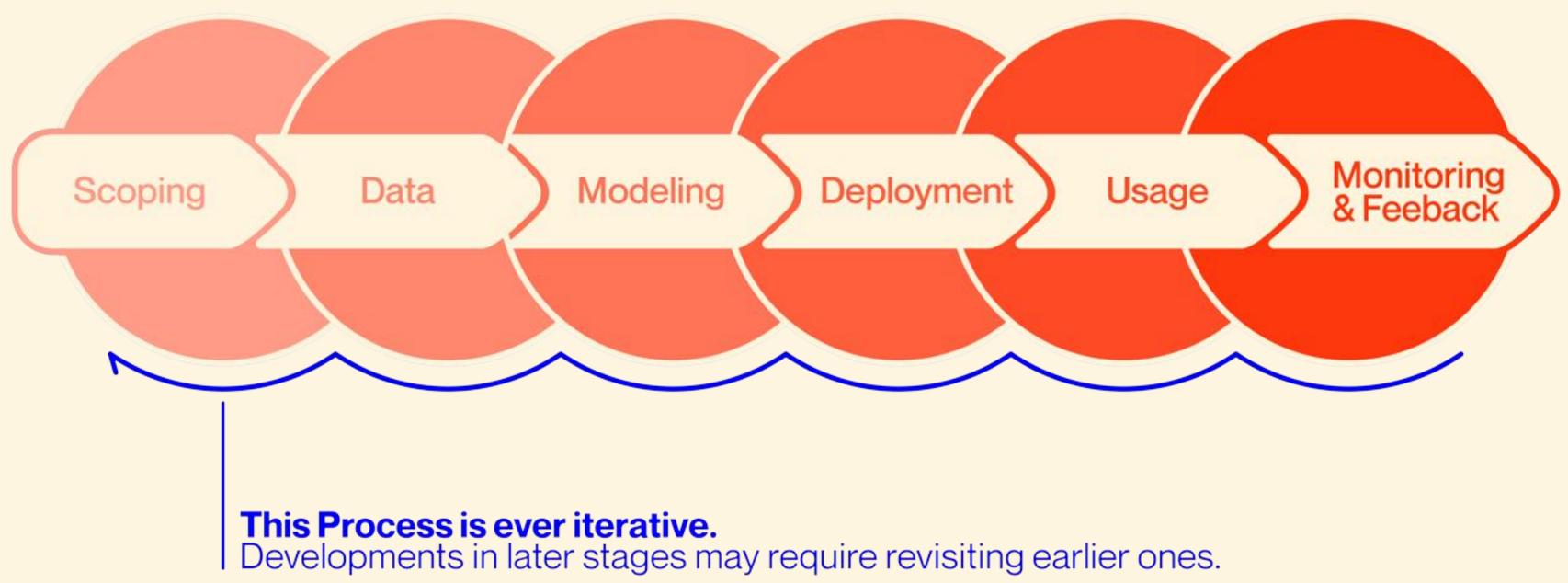


Human Centric ML Ops C	anvas		User Name:	Use Case Name		Case Description	
MLOps: MLOps unifies machine learning development and operations, empha Human-Centric MLOps: Human-Centric MLOps emphasizes how AI fits into human workflows Comment on the Main Difference:	sizing seamless integration and deployment of ML models in production env and behaviors, ensuring models align with organizational needs and are ado Ops ensures Al integrates well with human needs and organizational process	ptable by users.	Team Name:	Canvas Date:			
Scoping           This is the phase where we clearly define what problem we want to solve using AI. Think of It like choosing the destination for a journey. We need to ensure that the goal is achievable, beneficial to the organization, and well-understood by everyone involved.           Why it's important:         Winvit's dear destination for media.           Winvit's dear destination, we might end up building an AI system that doesn't address any real-world problem or need.           Problem Definition:           • What specific challenge or opportunity align with our broader organizational goals or	Data           In the world of AL data is like the fuel for our car. Before we start our journey (or build our Al model), we need to ensure we have the right kind of fuel and enough of it. This phase involves collecting relevant data and preparing it for use. <b>Why it's important:</b> Just as a car can't run without fuel, AI models can't function without data. The better the quality of our data, the more efficient and currate our AI system will be. <b>Acquiring Data:</b> • What kind of data to we need to address our defined problem or opportunity?           • What kind of data sources are currently available internally within our organization? Who are	Modelling           This is where the magic happens. We take our prepared data and use it to to model. Think of it like choosing the best car for our journey, based on the te destination.           Why it's important:           Just as you'd choose a rugged SUV for a mountain trip and not a sports car, se building the right Al model ensures we effectively address the problem we solve.           Requirements & Expectitations:           • What specific requirements do we have for our model? For instance, do we be building keyalahable for regulatory on vert rust reasons?	train an Al errrain and Why its important Network is the state. We have the dyse Why its important Network is seen to be a cor here Network is seen to be a correct Network is seen to be a correct seen to be a	Ioyment           In in the rad windt. This phase is like driving our car out of the intervent our outsing spectrations, ensuing it's accessable to users.           In the our outsing spectrations, ensuing it's accessable to users.           Intervent it's a wated resource. Deployment ensures out           In the Interraction:           to our existing systems or platforms? Are there existing systems is a type:           Vin are the decision-makers?	Usage et o ensare pupel are using i effectively. Its like ensuing driven asizes training and adaptation. Rek don't use it correctly or understand its benefits.	- and passengers know how to use the car's features and	Monitoring           Be regularly services our car, we need to leave an eye on our A lystem to ensure it runs smoothly. This phase involves inciding as performance, ensuring that ladvage to produce methods, and maning messary adjustments.           Why of is important: Why of the important is a start of the involve of the involve our All system remains relevant, accurate, and beneficial just as an origin ensure our car remains reladvortly.           Responsibility and Management Which is time or department will own the responsibility for managing and monitoring the All product observed relationship.
needs? • What existing solutions or processes are in place, and how does Al offer a unique or improved approach?	the stakeholders or departments responsible for this data? If internal data is insufficient, what external data sources can we consider? Are there third-party providers or public datasets that could be relevant? Are there any ethical or regulatory considerations we should be aware of when acquiring external data? How can we ensure that data acquisition respects privacy and has proper consent?	How accurate does our model need to be? Is there a minimum performance to that is should meet?     Are there specific considerations regarding false positives or false negation critical would it be if the model makes a mistake, and what could be the repercussions?	ives? How	ervices will the deployed model interact? Are erations or technical constraints to address? What is the wison for this Al solution in V What site wison for this Al solution in a chirve? V What is the allocated budget for deployment, including hidden costs?	g to Owner the major milestones in the deployment roadmap?	After Opployment: - Is the solution achieving its intended - How does the maintenance cost compare to the forecasted budget?	Product part-deployment?     A re there specific roles, like AI product managers or MLOps engineers, within the team to     oversee this?     Communication:     How will the responsible team communicate findings and updates related to the AI product to     other stakholders in the organization?     What is the process for escalating any critical issues that arise during monitoring?
Objective Setting:           • What are the specific, measurable outcomes we aim to achieve with our Al solution?           • How will we measure the success or impact of the Al implementation?           • Are these objectives both short-term and long-term, and how might they evolve over time?			How will end-users interact with the d mobile app, or some other interface?	Visers:     What does the users?       What does the current workflow look       • What does the current workflow look       • What does store of the current system pain paints?		After Deployment: • How insultive is the AI solution for end-uter? • Are there any emerging challenges or pain points post-deploymen?	Feedback Collection           Data-Driven Feedback:           • How will changes in data distribution (data drift) be detected and managed?           • It there a mechanism in glace to automatically retrain or flag the model if it starts performing below a certain threshold?
Feasibility Analysis:           • Do we have access to the necessary data to train and validate an AI model for this objective?           • Does our current technical infrastructure support the development, training, and development of an Alsolution?	Preparing Data: • Once we've identified our data sources, how will we collate and consolidate this data into a usable format? • Are there any immediate quality issues with the data, such as missing values, duplicates, or inconsistencies, that need addressing? • Do we have a clear understanding of what each data field or feature represents? If not, who in the organization can provide darity or context?	Internal Capabilities:  Do we have internal teams or departments with the expertise to build and model?  If not, do we need to consider extending contractors or consultants? How evaluate and choose the right extending anothers?  Does our organization have the necessary infrastructure and tools to support events and testing?  Does our organization have the necessary infrastructure and tools to support events the training and testing?	w will we	People Affected: Who are the people affected? Biology and the most impacted by introduction of the A solution? A re there any concerns on apprehens among the affected parties?	the Ouring Opplayment: • How will we maintain transparent communication with affected parties? • What metchnisms will be in place to capture feedback?	Atter Deployment: Have roles been positively or negatively impacted post-deployment? Were Initial concerns effectively addressed?	User Feedback: • How will user feedback be captured post-deployment? • Is there a structured way for users to report any anomalies, errors, or challenges they face while interacting with the Al system?
What are the anticipated benefits of pursuing an AI approach compared to other potential solutions?	who in the organization can provide dany of context? • How will we divide the data to evaluate our Al solution's performance effectively, considering we might want a portion of the data as a reference for its success?	Research & Existing Solutions:   Are there existing models or solutions available, either within our organi externally, that address similar problems? Can these be adapted or fine-tune use case?	What technical skills are needed for di Are there specific programming langu- proficient in?     Do we have the necessary expertise in collaborate with external partners?	Kills & Resources: ployment? House? If not, do we need to hire new talent or House? If not, do we need to hire new talent or	Adöttend Szakehdéers:		Process Impact: • How will the system's impact on existing workflows and processes be assessed continuously? Are there any KPB (Key Performance Indicators) set up to measure the tangble benefits of the • A system on organizational processes?
Stakeholder Engagement: • Who are the critical stakeholders for this Al project, both internal and external? • How can we ensure consistent communication and collaboration among these stakeholders throughout the Al lfecycle' • What concerns or input might these stakeholders have, and how can we address or integrate their feedback?	General Data Availability and Management:  • Do we have a centralized system or platform within our organization where data is stored and managed? If so, is this system accessible for our Al project?	<ul> <li>Isas someone documented building a similar model in research papers, case or online platforms?</li> <li>Gan we leverage insights or findings from these existing works to expedite o development or to set performance benchmarks?</li> </ul>	bur model HardWare & So • Is the deployment purely software-bas (e.g., IoT devices, sensors, edge device	it be sourced, installed, and maintained? Are	temporarily adjusted or halted during	solution in place?     Are there any unforeseen process	System Monitoring Dbjectives of System Monitoring: • How will we mesure and ensure the reliability of the AI system over time? • What safeguards are in place to mantain the security of the AI solution, especially concerning user data and proprietally information? • What benchmarks are set up to ensure the AI system is performing optimally?
Expectation Management: How are we communicating the potential outcomes and limitations of the AI project to all stakeholders? What is our estimated timeline for each phase of the AI lifecyde, from scoping to monitoring? How will we manage and address potential shifts in expectations or project objectives as we progress?	<ul> <li>Who are the gatekeepers or stakeholders responsible for data management within our organization? Do we need to get permissions or collaborate with them for our Al initiative?</li> <li>Are there established data management practices or protocols within our organization 1 that we should be aware of or align with?</li> <li>If external data is being considered, how will it be integrated with our internal data? Are there compatibility or format issues we should be mindful of?</li> </ul>	Model Selection & Evaluation:     Based on our problem definition and requirements, what types of machine     models might be appropriate? (e.g., regression, classification, clustering)     Which metrics will we use to evaluate our model's performance? (e.g.,     precision, real, F1 society of instance, if achieving higher accuracy com     model explanability, how will we prioritize?	accuracy, promises Value or impact our broader business or organizationa	E& Impact:     of the deployed model? How does it align with     lobjectives?     What metrics or KPIs will be     What metrics are the ideal candidates to be     first test pilots for the A solution?     What metrics make them suitable for     initial phase?	phases?	Feedback Mechanisms How will we capture feedback during the initial role-out What mechanisms are in place to quickly act upon the feedback received?	Hey Areas to Monitor:           • Individual Gitches:           • How will we monitor for hardware and software glitches that could impair the AI system's functioning?           • Is there an alet system in place for immediate notification of any technical issues?           • User Behavior:           • What metrics and tools will we use to understand how users are interacting with the AI system?           • How will user feedback be used to enhance and refine the AI system over time?           • Security:           • How will potential security breaches be detected?           • What mechanisms are in place to ensure data integrity and prevent unauthorized access?
							Continuous Improvement:  Based on the findings from monitoring, how often will the AI system be updated or refined?  I there a pipelme in place for continuous integration and continuous deployment (CL/CD) for the AI solution?
· · · · · · · · · · · · · · · · · · ·							

# Human- and Process Centric MLOps

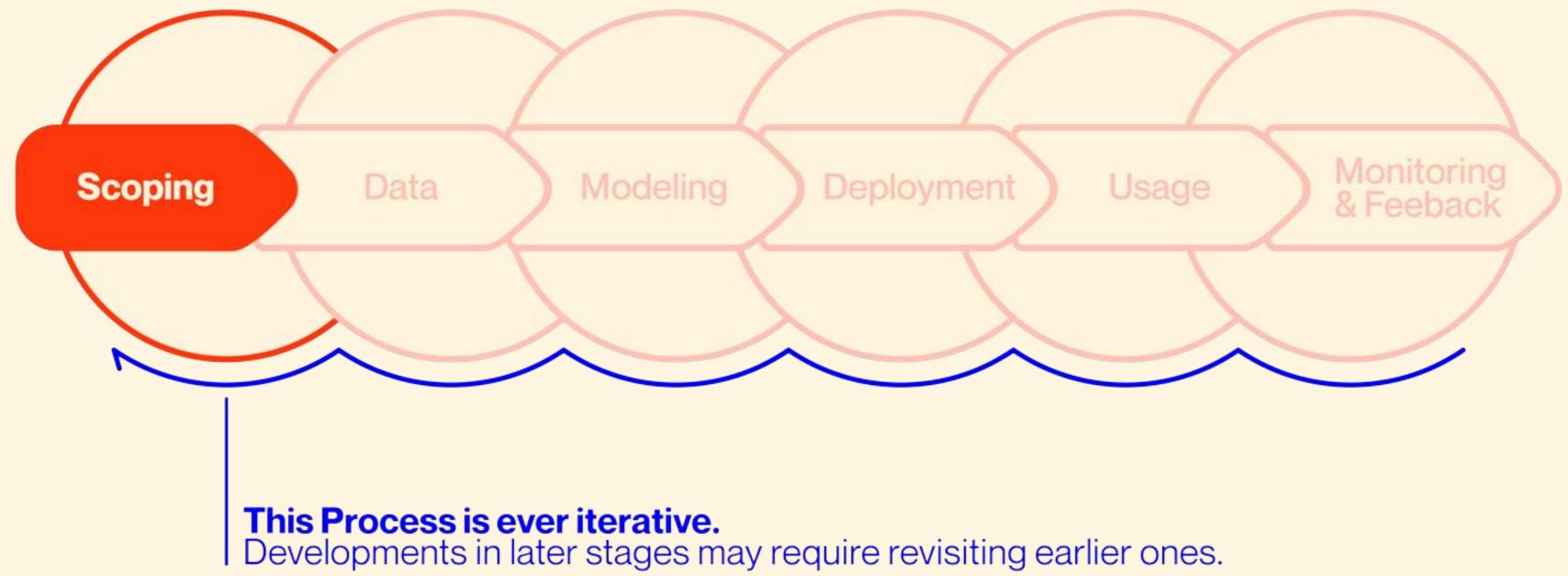
Human-and Process Centric MLOps emphasizes how AI fits into (human) workflows and behaviors, ensuring models align with organizational needs and are adoptable by users.

## Human Centric ML Lifecycle



# Scoping

## Human Centric ML Lifecycle



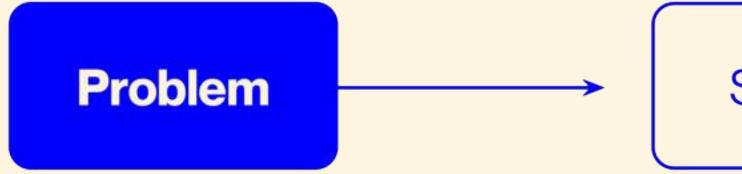
# Starting From a Real Need

**Problem** 



### **Solution**

# **Starting From a Real Need**

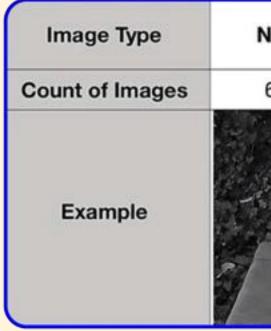


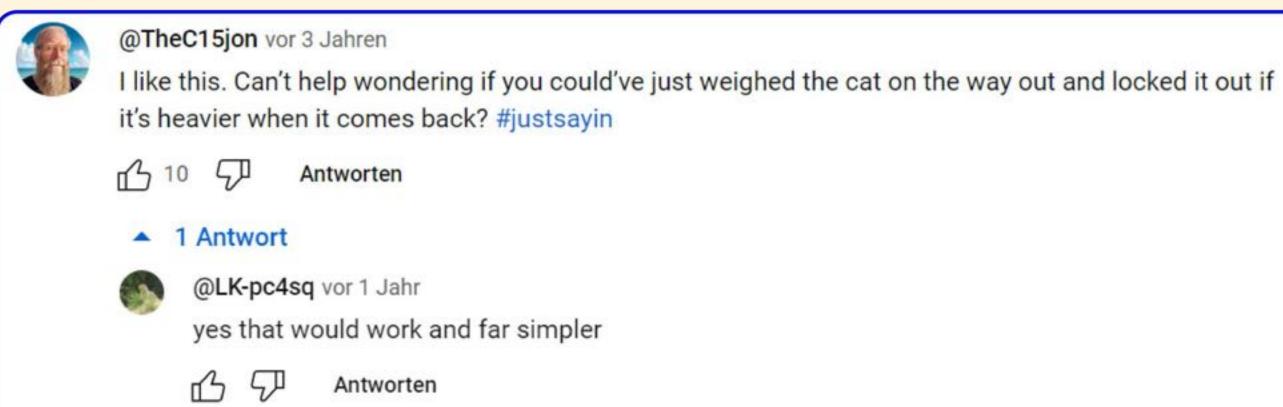
"a clearly defined set of activities designed to reach a specific goal from a business or costumer perspective, inwhich one or more Al solutions are involved Use Case: in reaching the respective goal"



### Solution

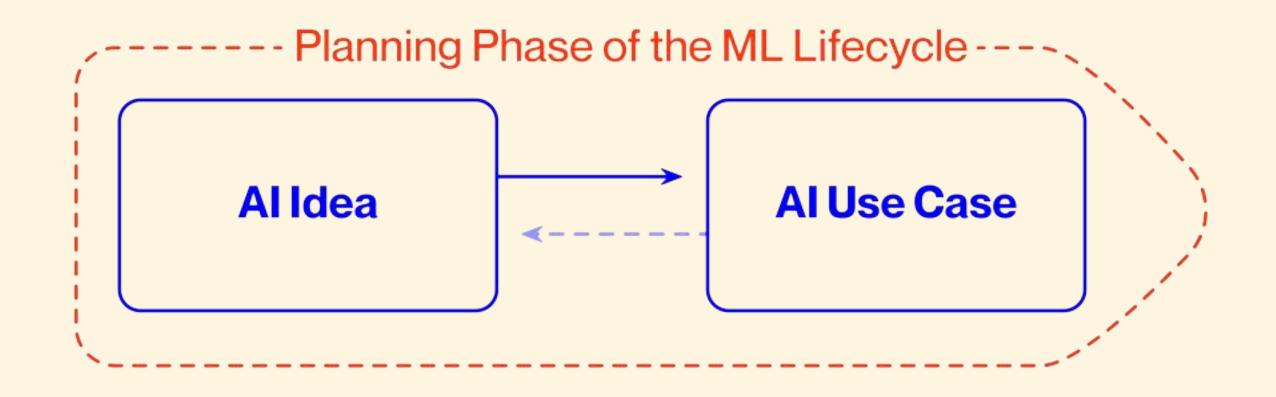
### Always ask: what is the right tool for the job?





No Cat	Cat not on approach	Cat on approach	Cat with prey
6,542	9,504	6,689	260
	146		

## From Idea to Reality

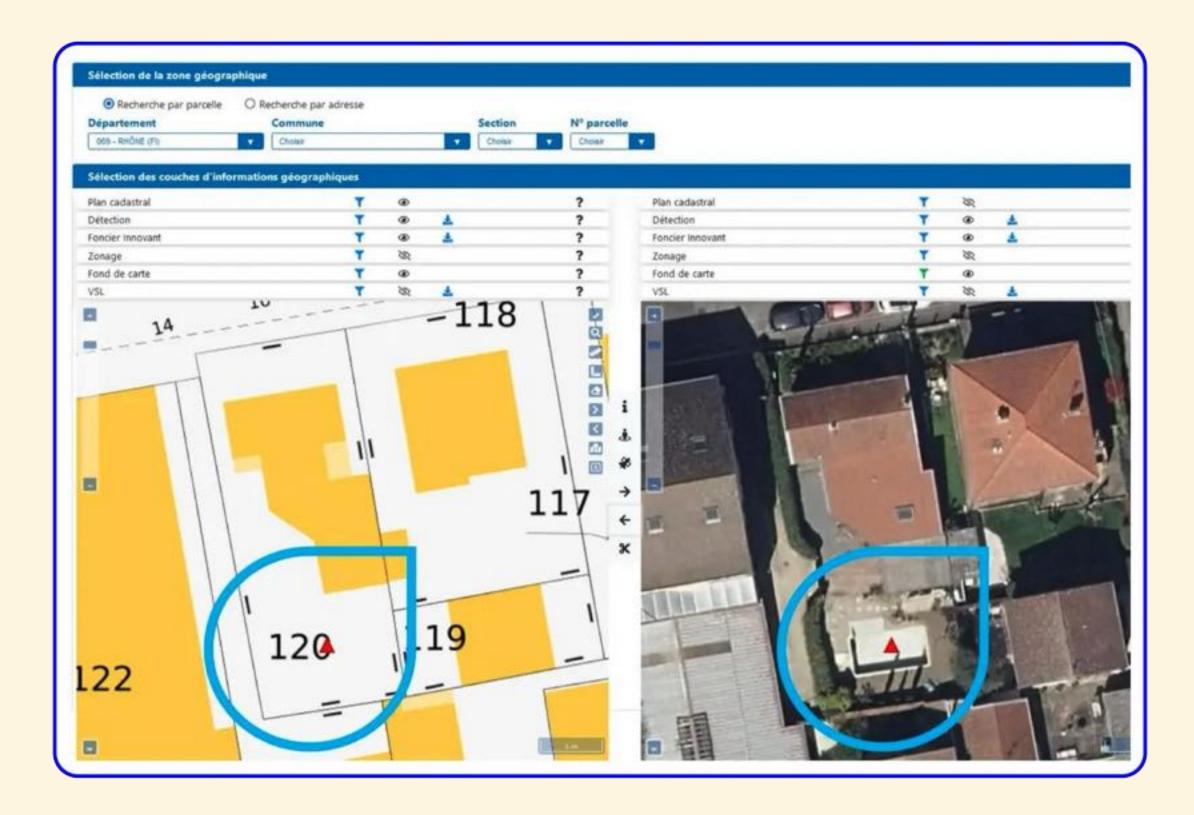


### To begin with the end in mind means to start with a clear understanding of your destination. It means to know where you're going so that you better understand where you are now and so that the steps you take are always in the right direction

**Stephen Covey** Author



#### euronews.



How can the French tax authorities efficiently detect

these undeclared swimming pools to ensure proper taxation?



#### **Detection and Classification of Rice Plant Diseases for the World Food Organization**

Develop an AI system to help farmers in India detect and treat rice plant diseases using smartphone images. This solution will aid in improving crop yields and tracking disease outbreaks in rural areas.



#### Pneumonia Detection in Pediatric Chest X-rays for Doctors Without Borders

Create an AI-based diagnostic tool to detect pneumonia in children from chest X-rays, assisting healthcare workers in remote areas of Africa. This system will ensure timely treatment and help monitor the spread of the disease.



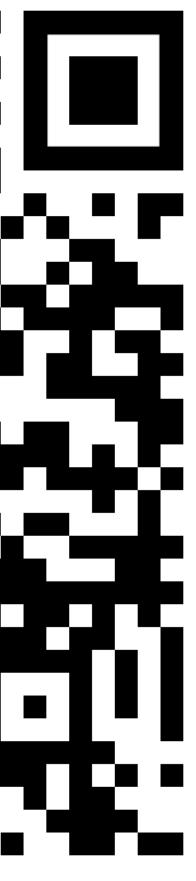


#### **Quality Control for Potato Chips at Frito-Lay**

Implement a deep learning model to automate the detection of defective potato chips, focusing on burnt or damaged areas. This solution will maintain product quality and prevent the closure of a Frito-Lay factory in Spain.

# 

https://shorturl.at/lbbCX



# Scoping

- What is the problem that you are trying to tackle?
- How could the problem be solved using AI?
- What is the role AI plays?
- What will be the output of the AI model?
- How will the solution change the status quo?

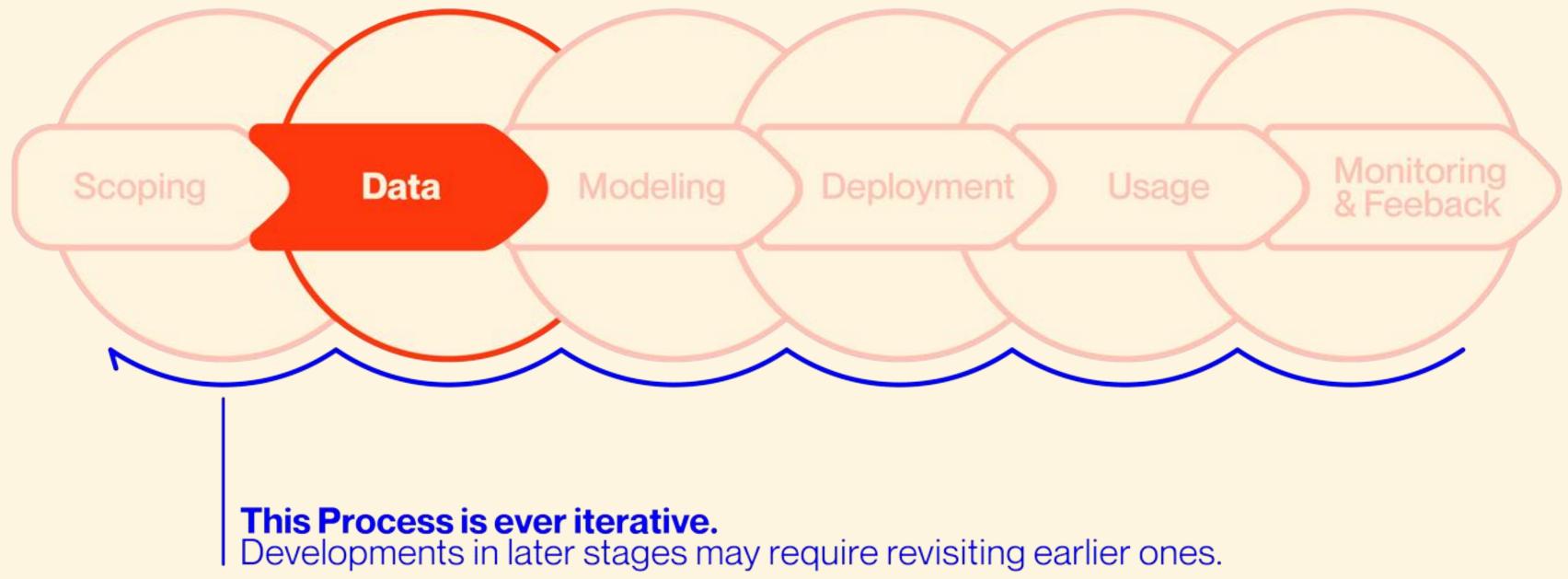
to tackle? AI?

? quo?

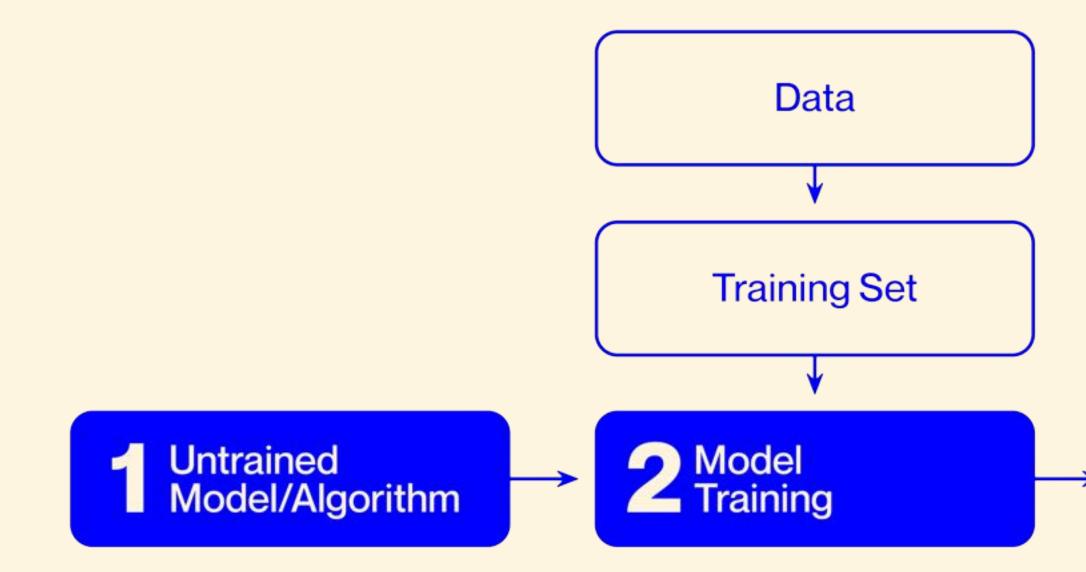
# 08:00

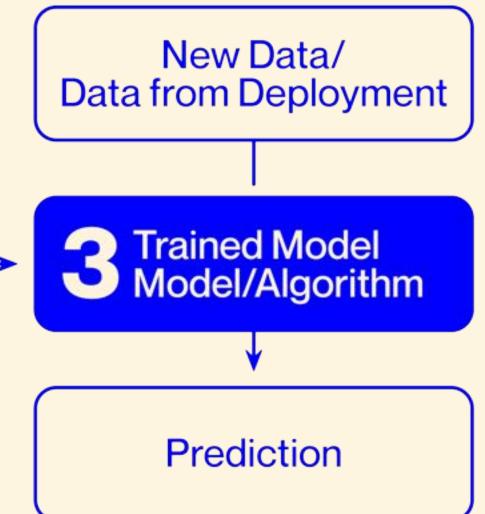
# Data

#### Human Centric ML Lifecycle

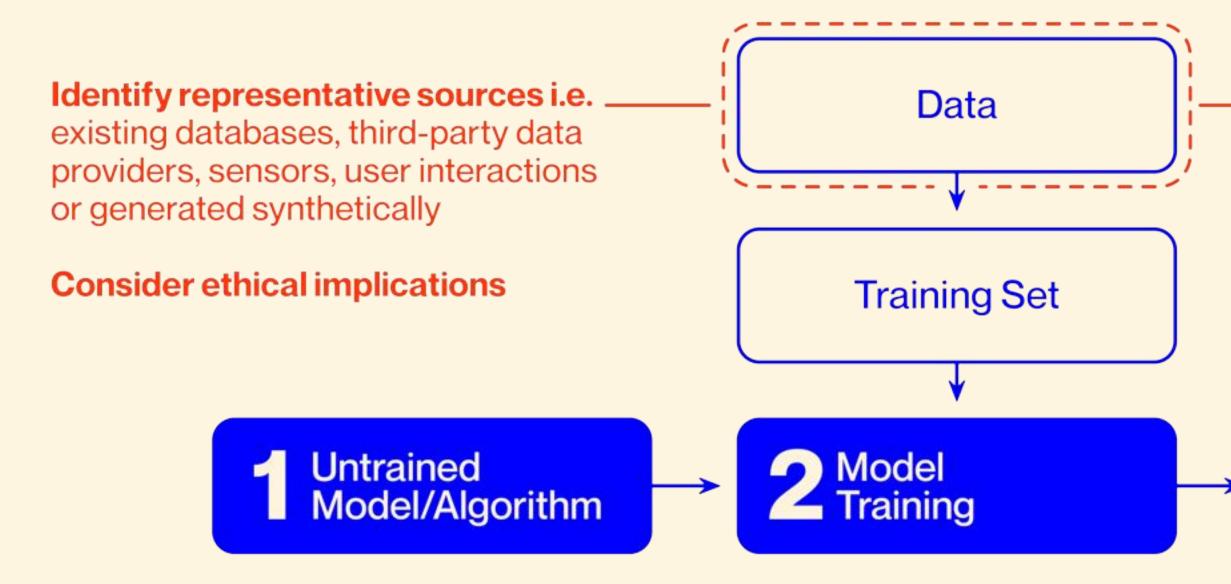


#### Acquiring and Preparing Representative Data

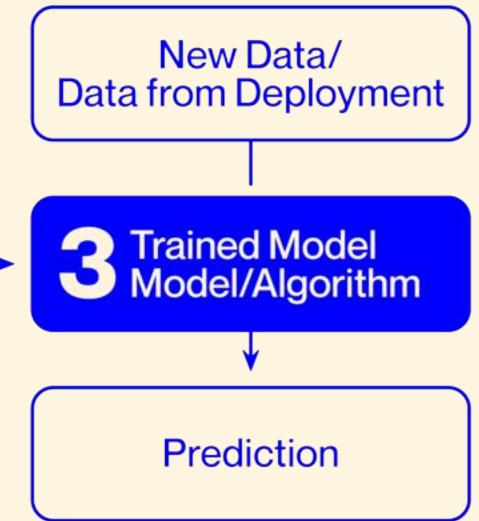




### **Acquiring Representative Data**

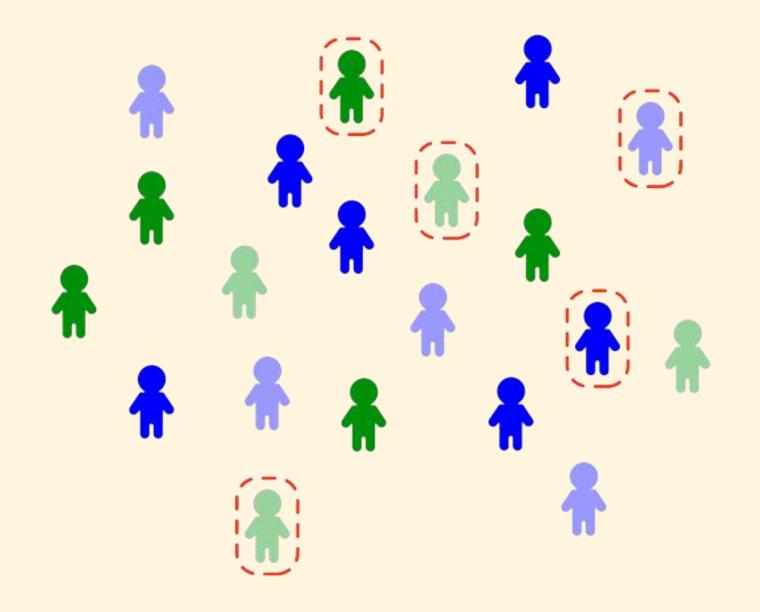


Gathering representative data is crucial for model generalisation, avoiding bias, robustness and trust and adoption by users.

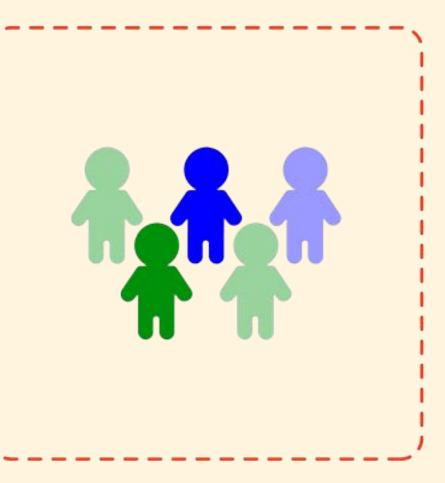


### The Right Data

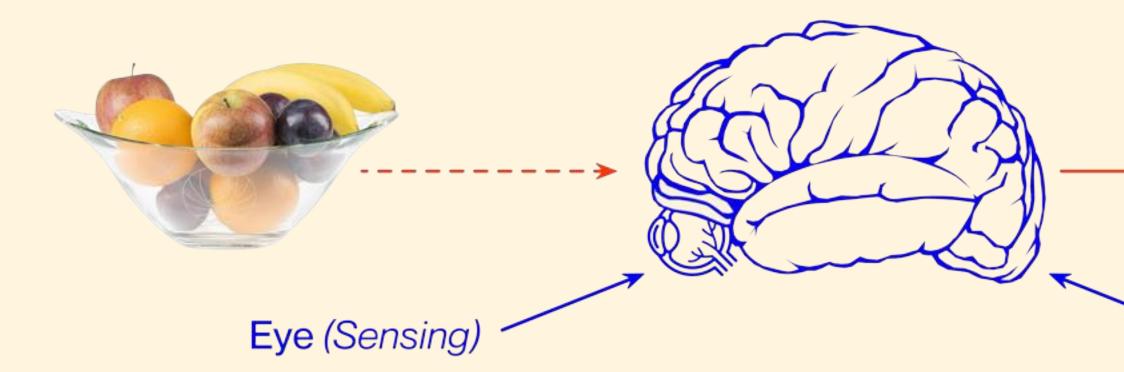
**Real World Data** 



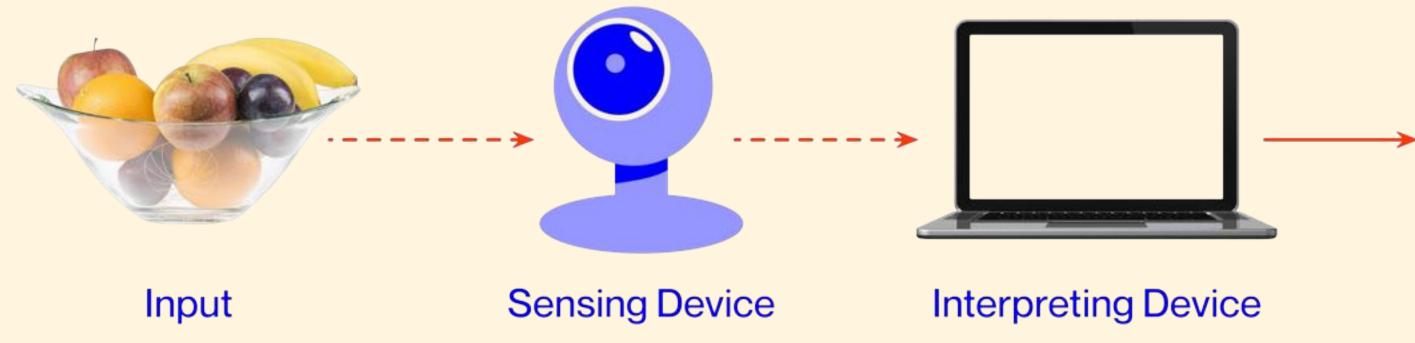
### Representative **Data**



#### **Human Vision System**



#### **Computer Vision System**



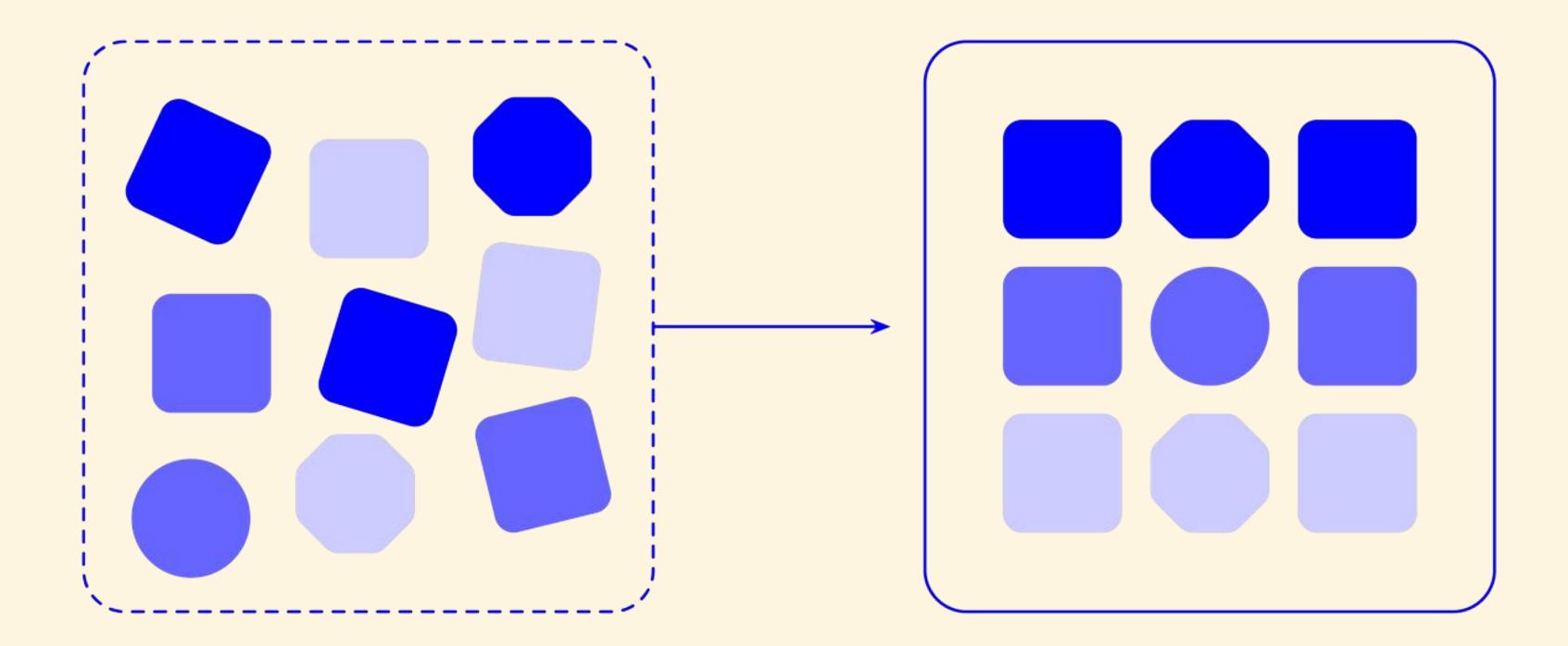
bowl, apples, oranges, bananas, plums

#### Brain (Interpreting)

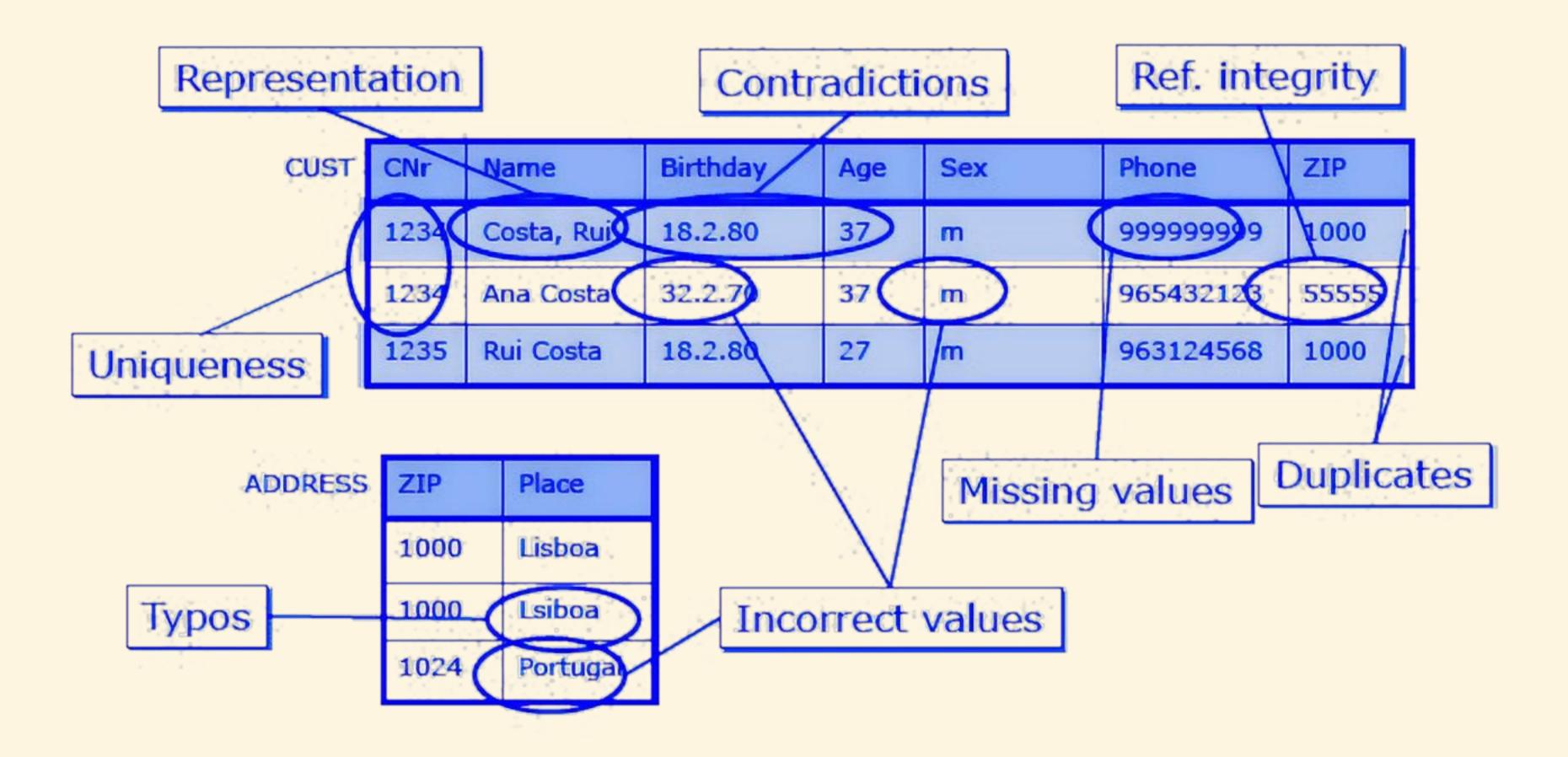
bowl, apples, oranges, bananas, plums

Output

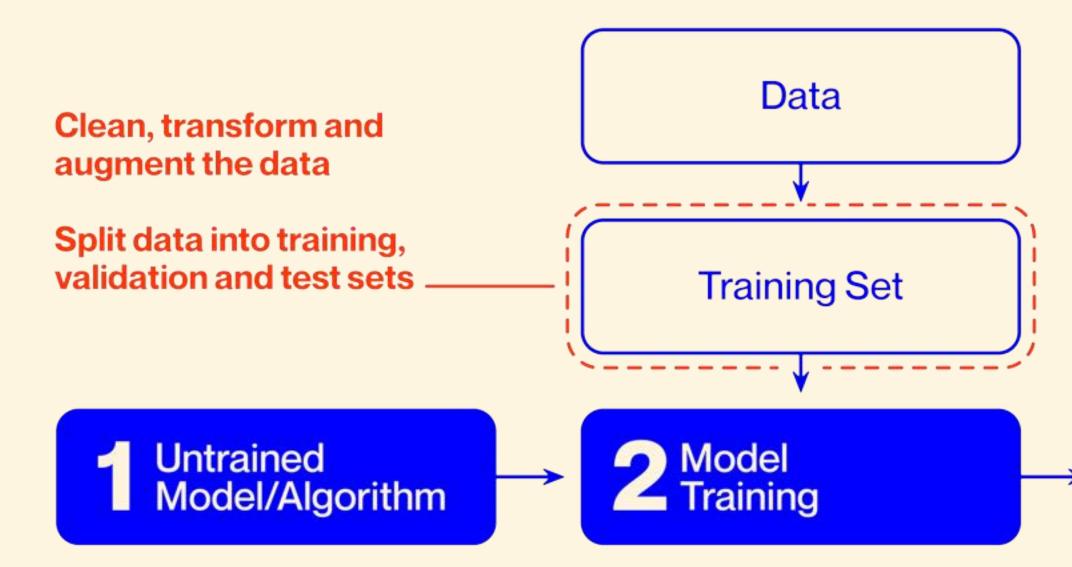
#### **Acquiring Representative Data**

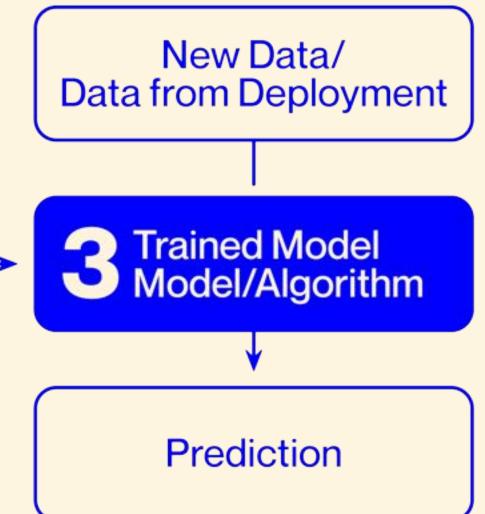


#### **Deep Dive: Data Cleaning**



#### **Preparing Representative Data**







r 🛛		
science	for a chan	iging world

#### EarthExplorer

patience.

Search Criteria	Data Sets	Additional Criteria	Results	Search Criteria Summa	ry (Show)
	earch area: ty	eria ype in an address or map to define your s	A REAL PROPERTY OF THE RE		Official -
	ools, view the nge.	help documentation		St Helio	Par

V

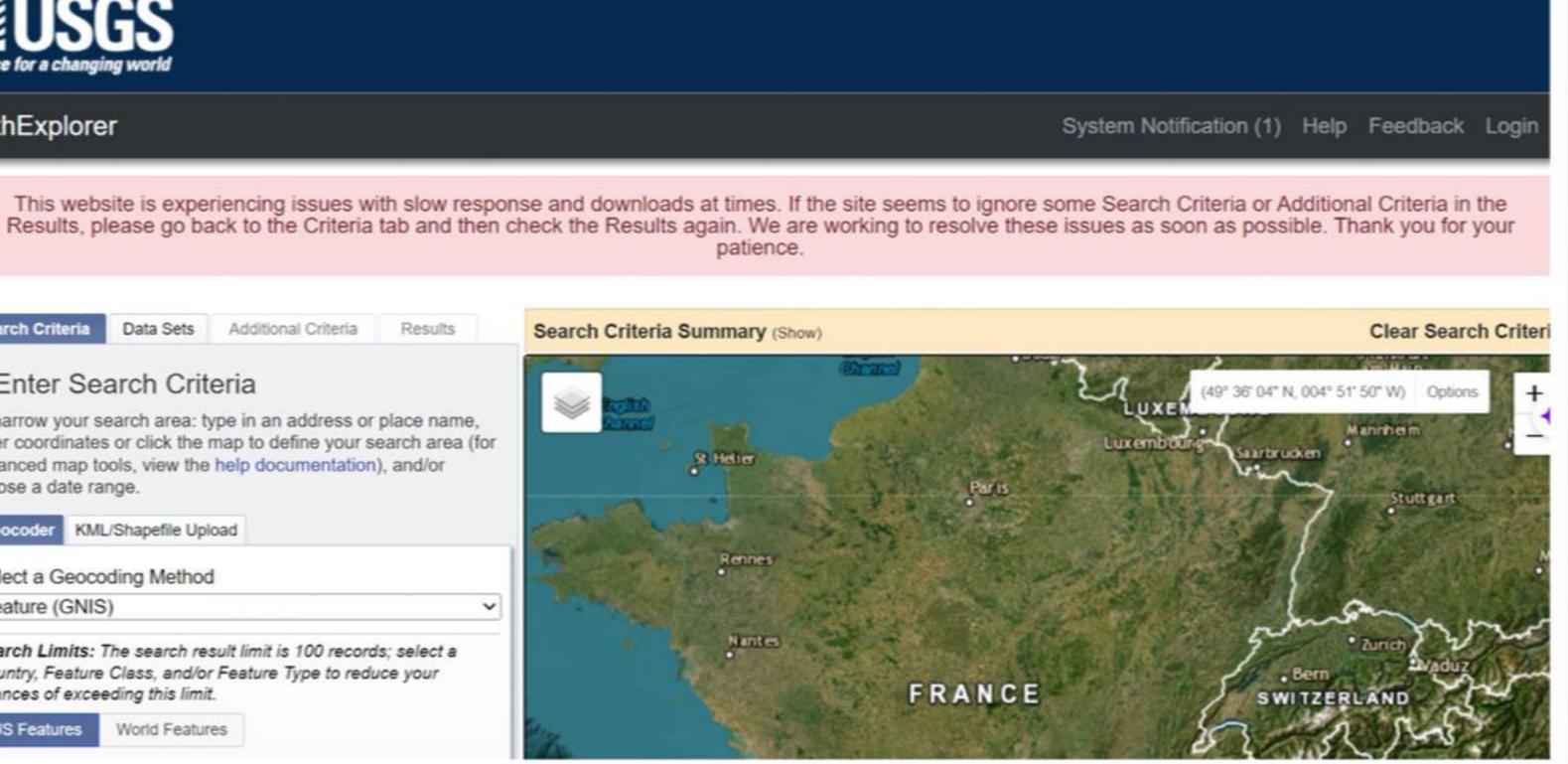
Select a Geocoding Method

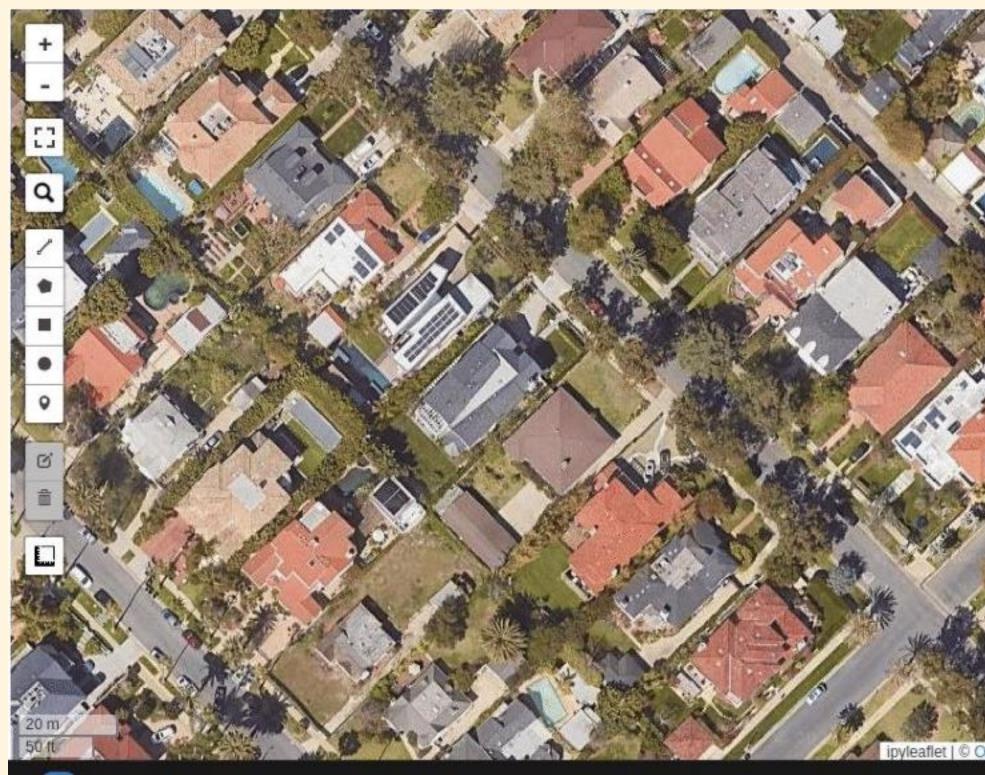
Feature (GNIS)

Search Limits: The search result limit is 100 records; select a Country, Feature Class, and/or Feature Type to reduce your chances of exceeding this limit.

US Features

World Features





Text prompt: I   Box threshold: 0.25   Text threshold: 0.25   Palette: viridis   Opacity: 0.50   Regularize Color   #ff0000 Segment   Save Reset		× \$		
Text threshold:       0.25         Palette:       viridis         Opacity:       0.50         Regularize       Color       #ff0000	C.P	Text prompt:	l	
Palette: viridis Opacity:	M	Box threshold: -	0	0.25
Opacity: 0.50		Text threshold: -	0	0.25
Regularize Color #ff0000	28	Palette: viridis		•
	X	Opacity:	-0	0.50
Segment Save Reset		🗆 Regularize	Color #	±ff0000
		and the second sec		
		Segment	Save	Reset
		Segment	Save	Reset
			Save	Reset

ipyleaflet | © OpenStreetMap contributors, Google, Raster file served by localtileserver.





### **Testing Set**

- presence of a lake and a blue tag, 433 × 340 pixels \_\_\_\_\_
- 4. very small and high zoom image, 100 × 118 pixels \_\_\_\_\_
- 5. unusual swimming pool body, 366 × 270 pixels \_\_\_\_\_
- 7. the same court as in image 6 and a green swimming pool, 1099 × 1333 pixels, \_\_\_\_\_













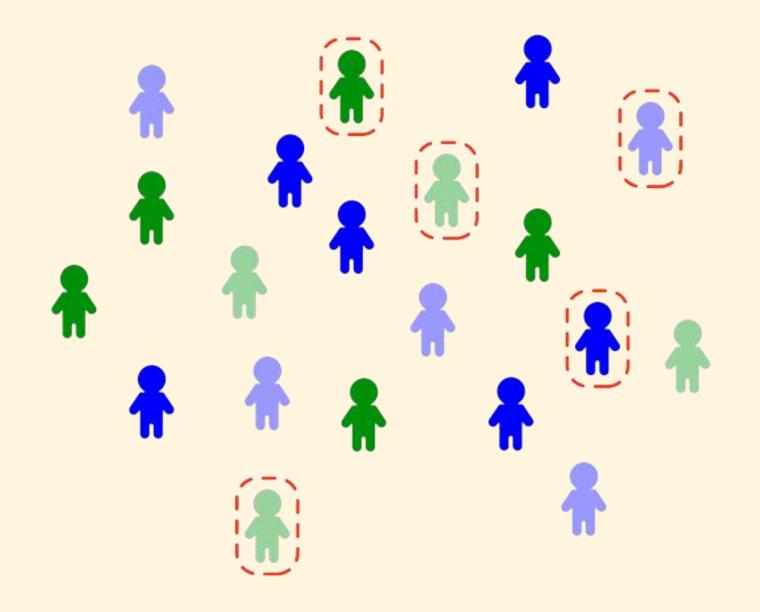


- 2. encloses two swimming pools and a pool look-alike glassstructure, 442×258 pixels
- З. a pool without one of the most common characteristics, the blue colour, 298 × 241 pixels
- 6. very high-quality 3-dimensional picture with two pools and a basketball court, 1351 × 1364 pixels

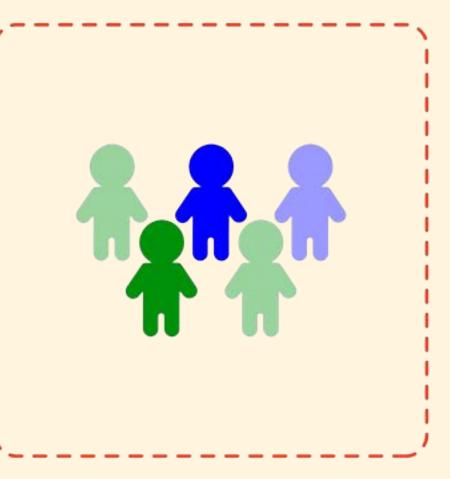


### The Right Data

**Real World Data** 



#### Representative Test Data (≠ Training Data)



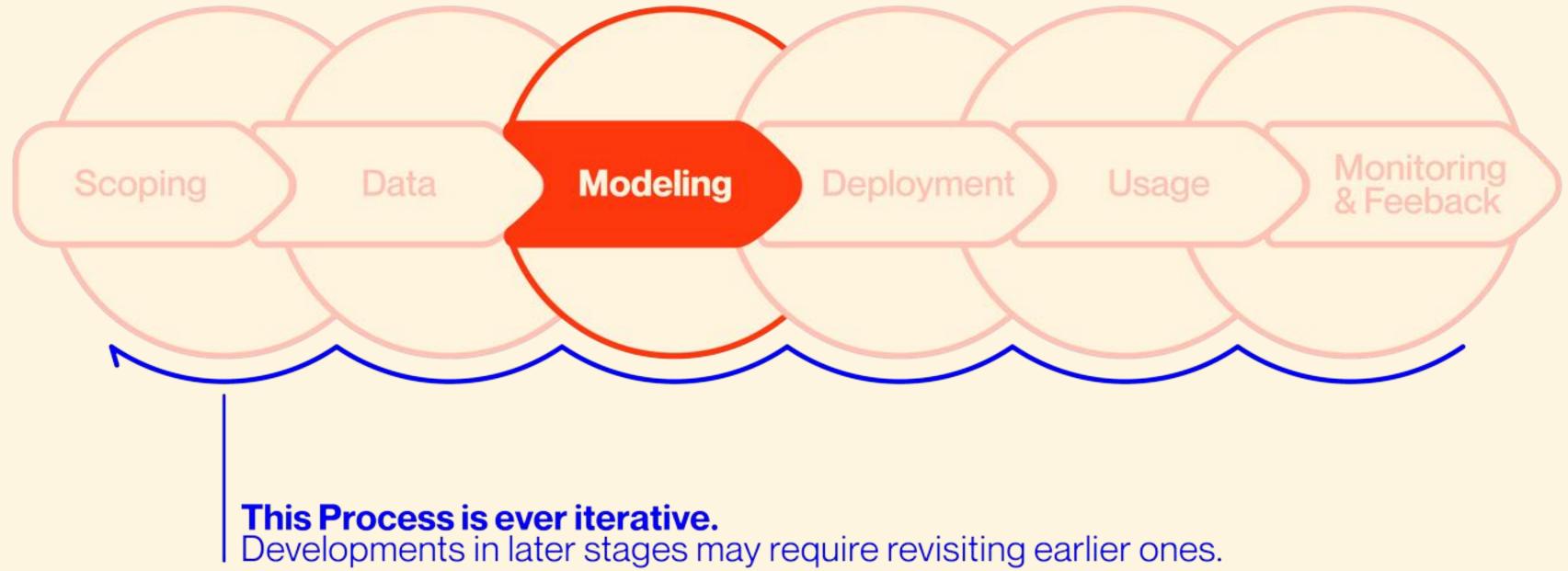
# Data

- What data do you need?
- How would you get/collect the data?
- How can you make sure the data is correct?
- What might be challenges?

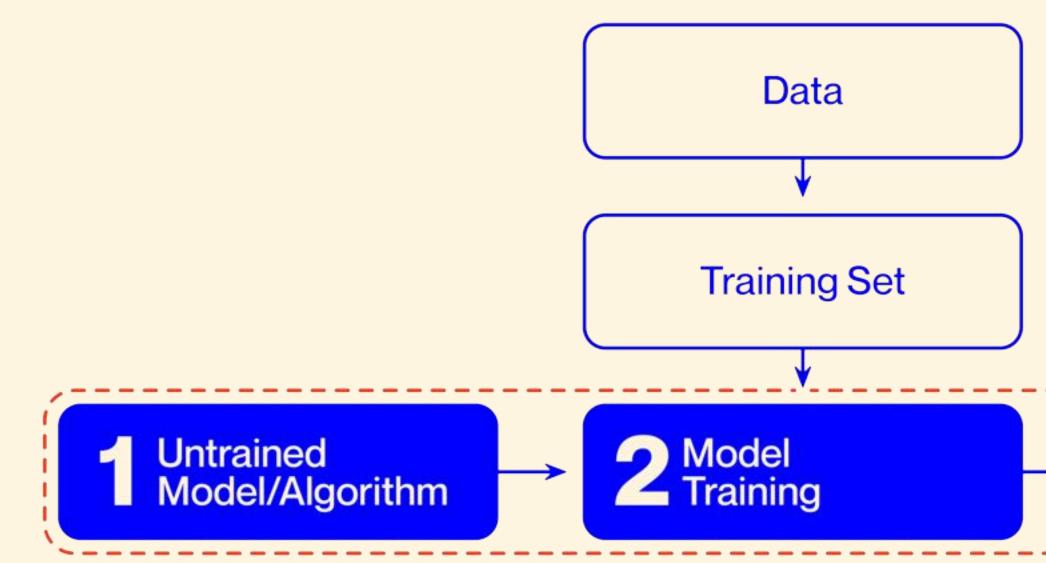
# 08:00

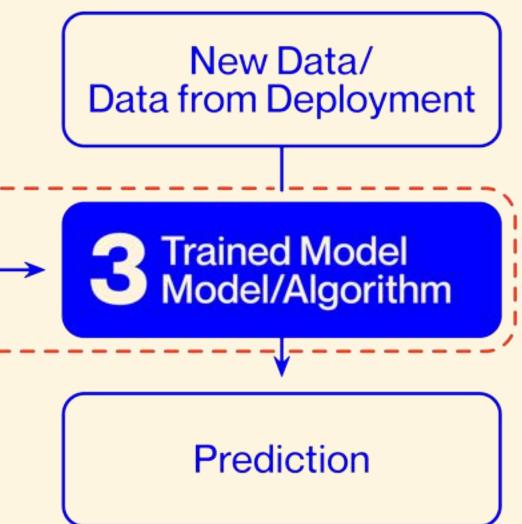
# Modeling

#### Human Centric ML Lifecycle

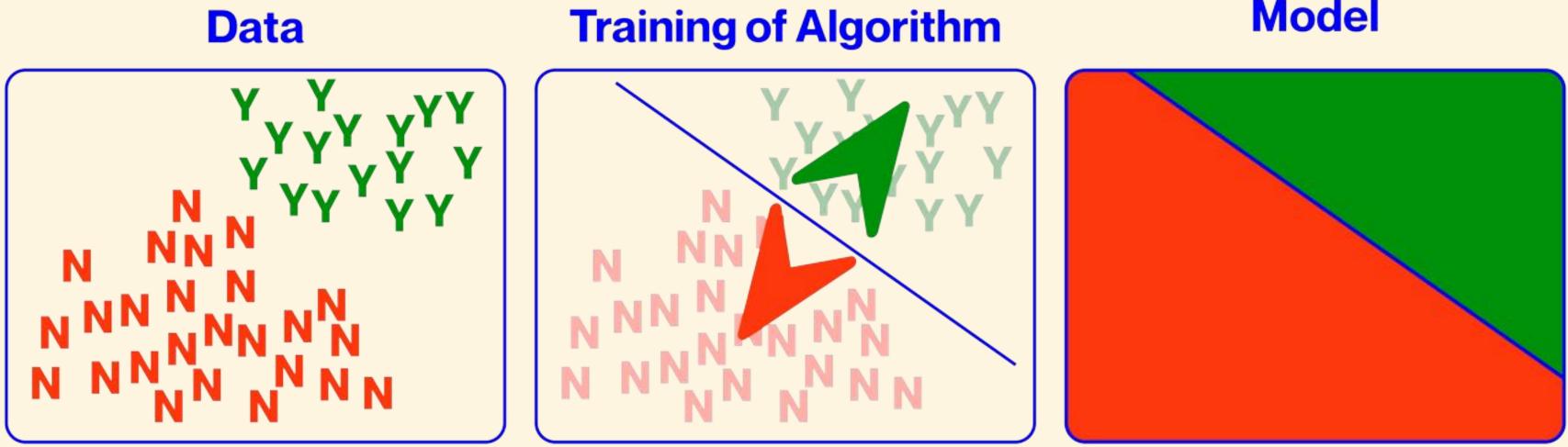


### Algorithm Selection and Model Evaluation



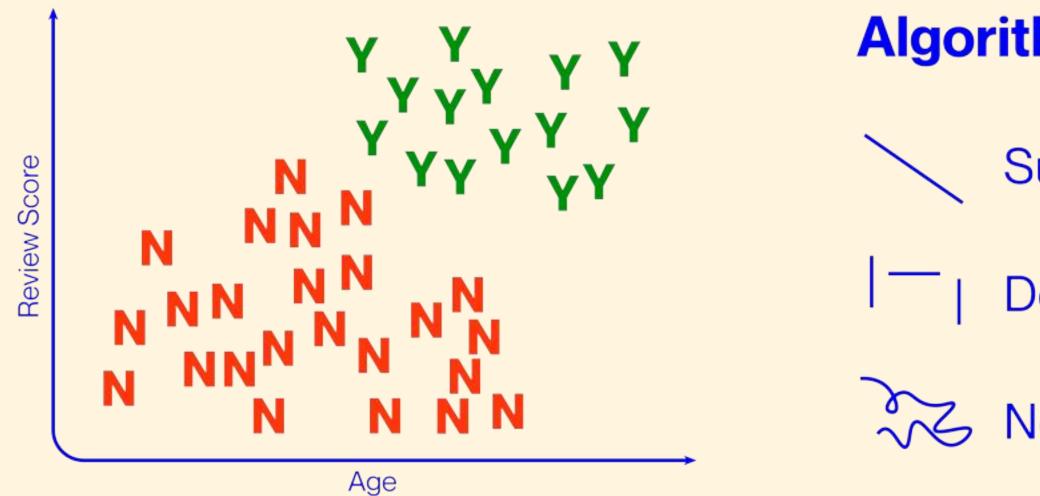


### Data to Trained Model



#### Model

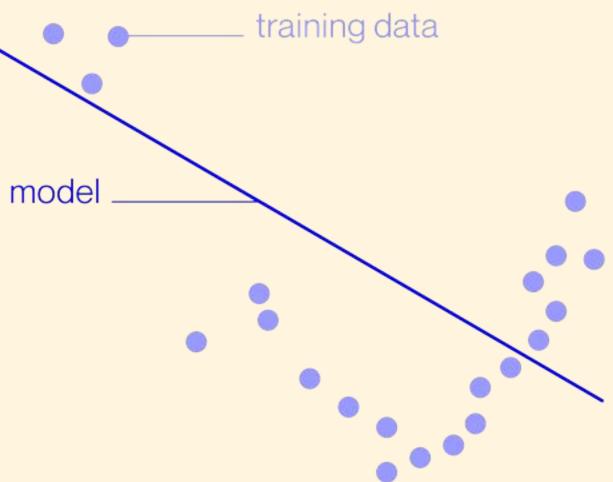
### Choosing the Right Algorithm



#### **Algorithm selection:**

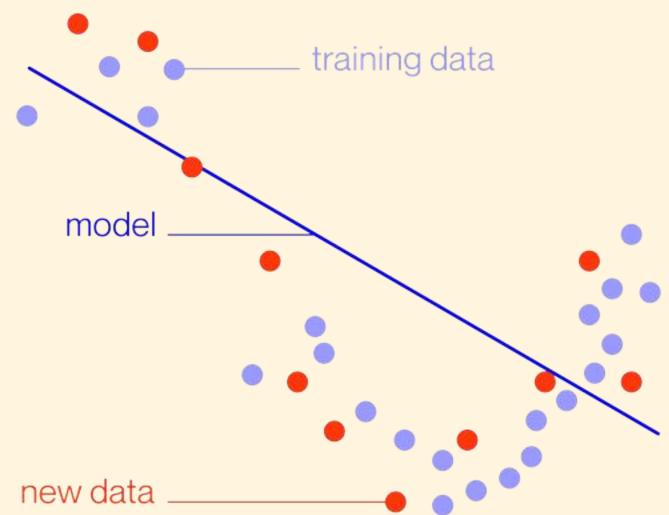
- Support Vector Classifier
- **Decision Tree**
- Neural Network

### Underfitting



#### underfitting

#### Underfitting



#### the underfitted model lacks the depth and complexity needed to make accurate predictions.

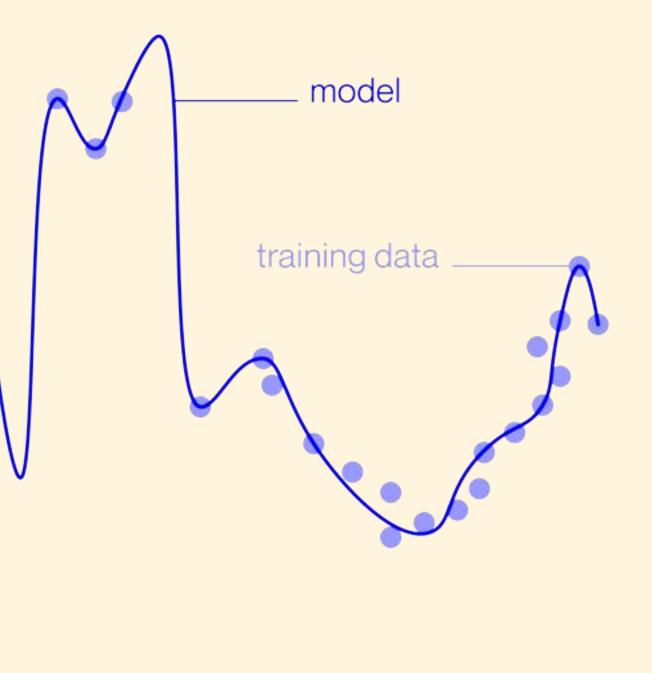
#### underfitting

# **tt** Half knowledge is worse than ignorance

**Thomas B. Macaulay** 

### Historian

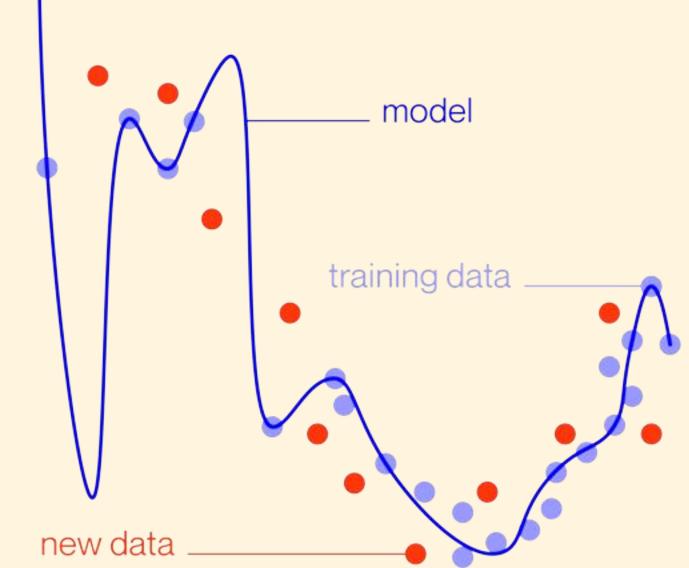
### Overfitting



#### overfitting

#### Overfitting

#### The overfitted model is so tailored to the training data that it fails to generalize to new scenarios.

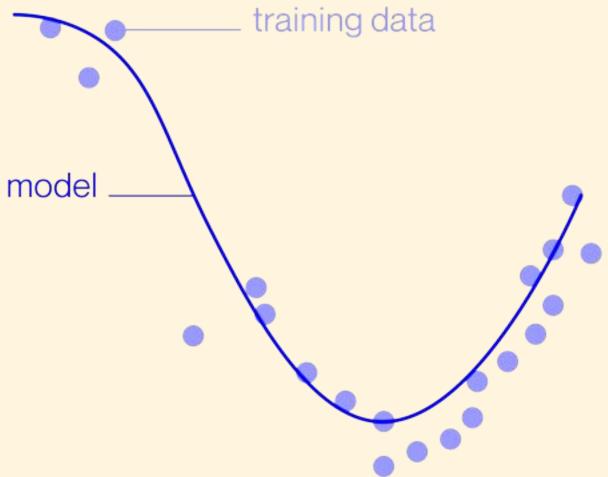


#### overfitting

## **Proper Generalization**

•

## proper generalization



## **Proper Generalization**

To ensure our model generalizes well, we aim for a **balance** between the extremes of underfitting and overfitting.

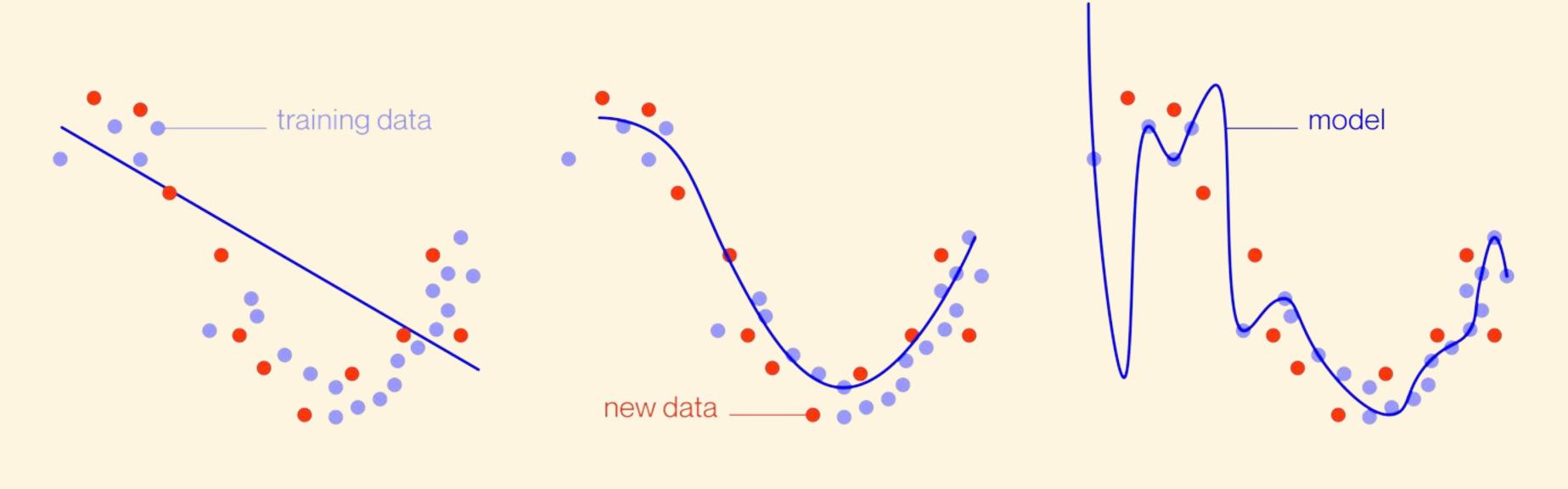
We want a model that learns the essential patterns from the training data without getting bogged down by its intricacies, ensuring it performs well in real-world



# training data model new data

### proper generalization

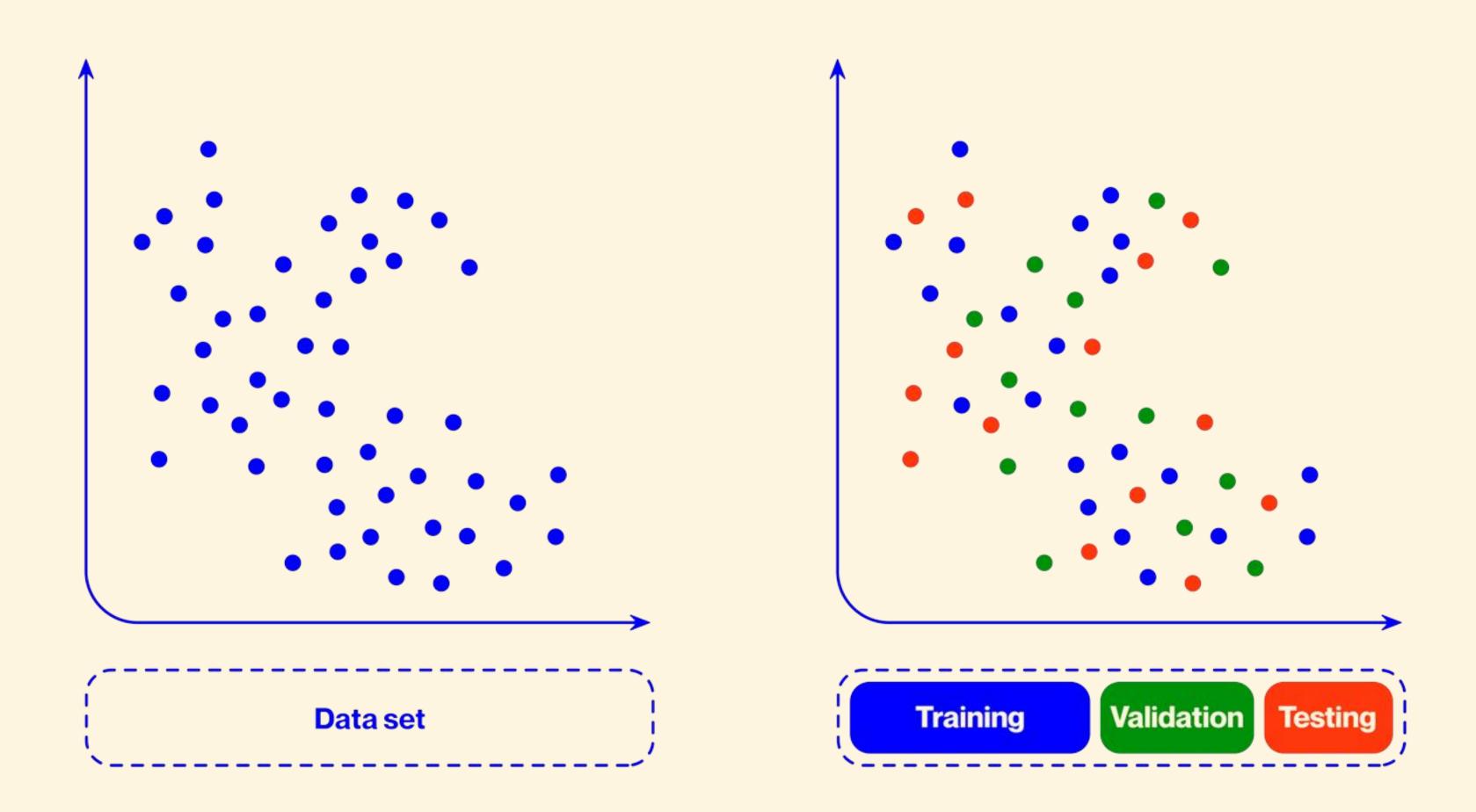
## **Model Valuation Generalisation**



#### proper generalization

#### underfitting

overfitting



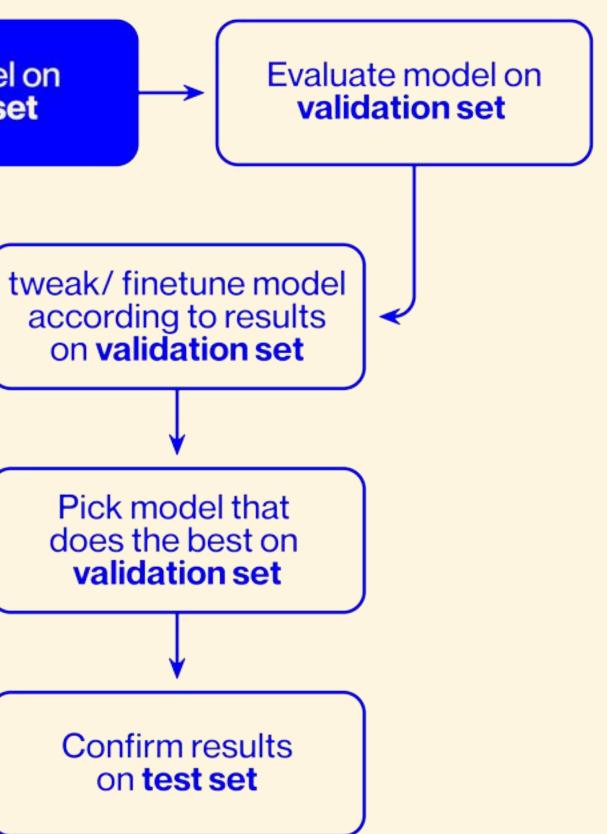
## How to pick the right model

#### Model Validation refers to the process of confirming that the model actually achieves its intended purpose.

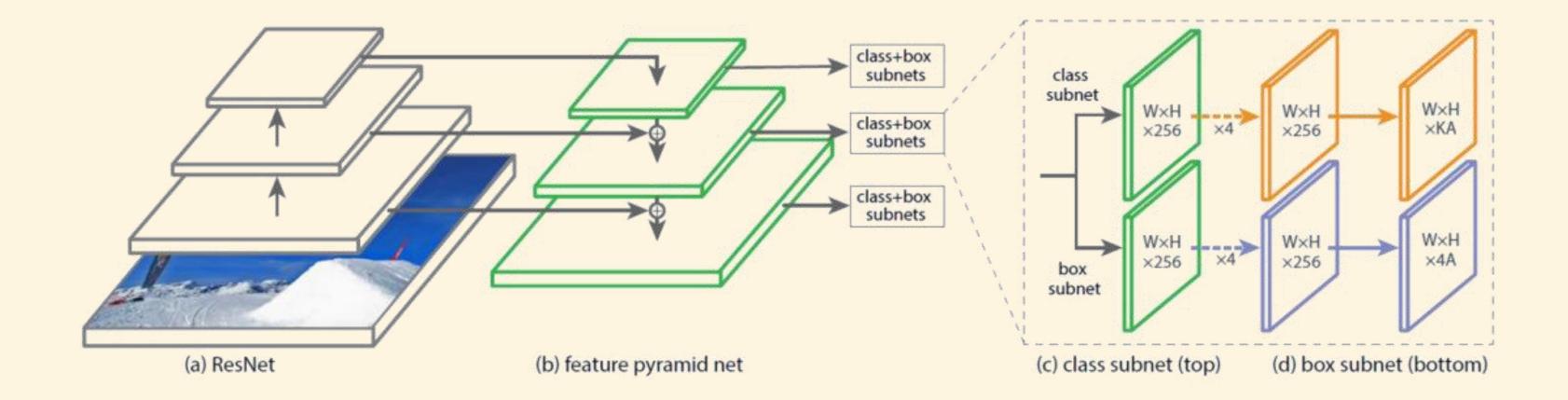
In most situations, this will involve confirmation that the model is predictive under the conditions of its intended use.

this type of validation occurs by comparing model simulations to an independant experimental data set. Data used in estimation of model parameter values cannot be included in the external data set.

#### Train model on training set



## The Model



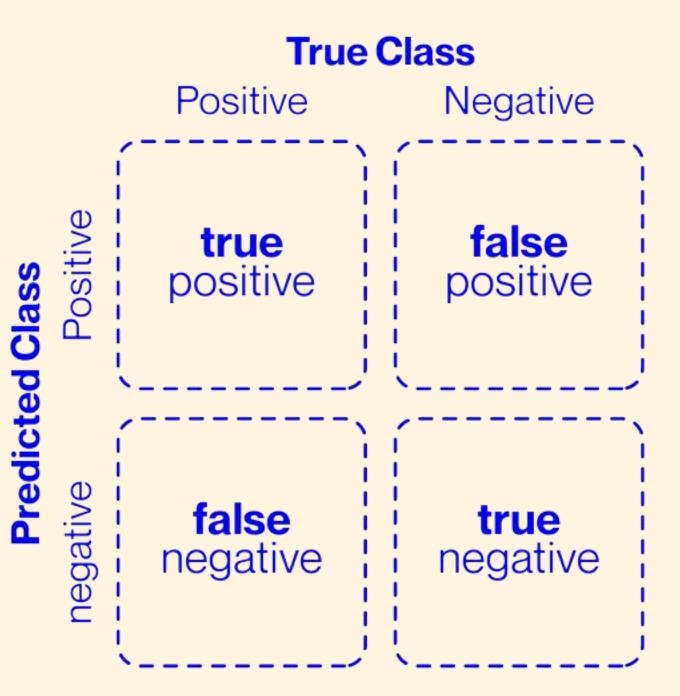
RetinaNet network architecture composed of four main components: a) Bottom-up pathway; b) top-down pathway; c) classification subnetwork; d) regression subnetwork

## The Model

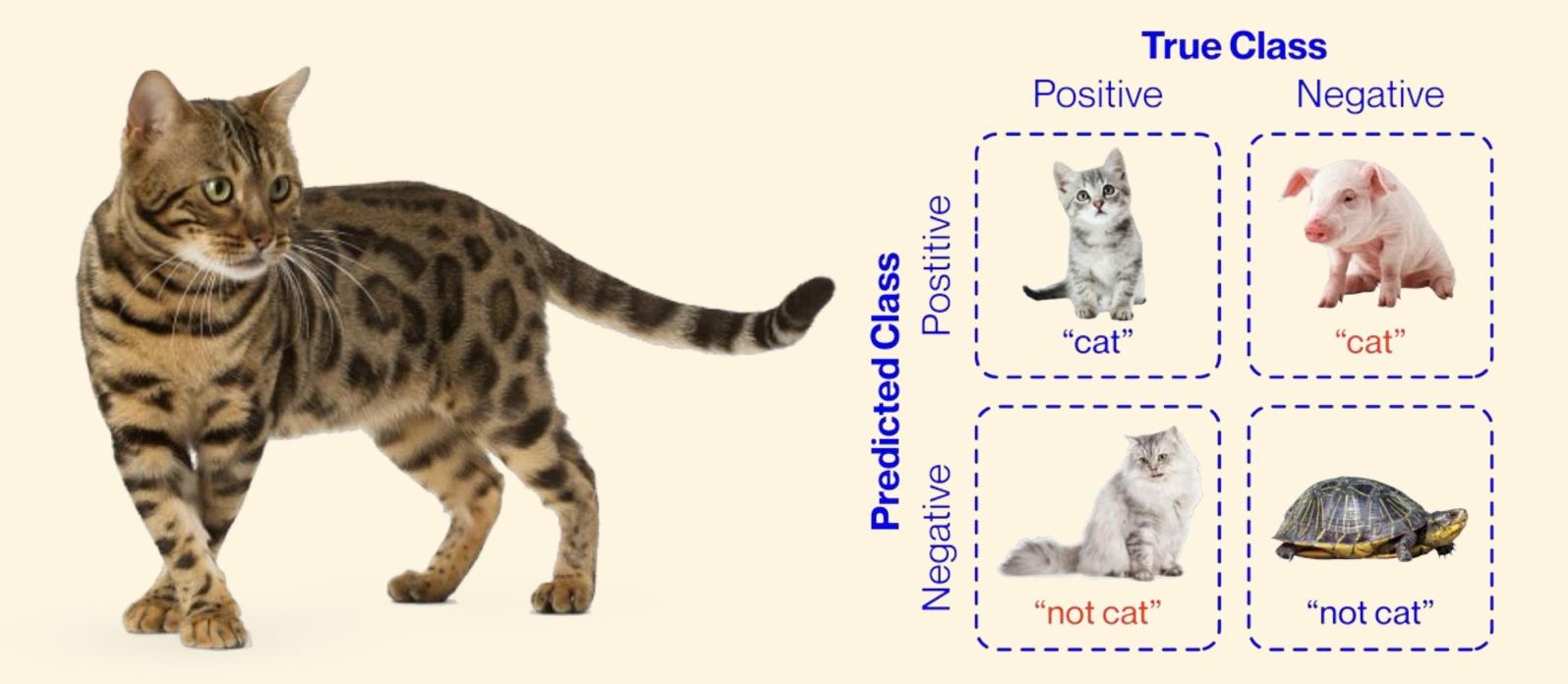
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer			
conv1	112×112			7×7, 64, stride 2					
				3×3 max pool, stride 2					
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64\\ 3\times3, 64 \end{bmatrix} \times 2$	$\left[\begin{array}{c}3\times3,64\\3\times3,64\end{array}\right]\times3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$			
conv3_x	28×28	$\left[\begin{array}{c}3\times3,128\\3\times3,128\end{array}\right]\times2$	$\left[\begin{array}{c}3\times3,128\\3\times3,128\end{array}\right]\times4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$			
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256\\ 3\times3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$			
conv5_x	7×7	$\begin{bmatrix} 3\times3,512\\ 3\times3,512 \end{bmatrix} \times 2$	$\left[\begin{array}{c}3\times3,512\\3\times3,512\end{array}\right]\times3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$			
	1×1	average pool, 1000-d fc, softmax							
FLOPs		$1.8 \times 10^{9}$	3.6×10 <sup>9</sup>	3.8×10 <sup>9</sup>	7.6×10 <sup>9</sup>	11.3×10 <sup>9</sup>			

## **Classification Confusion Matrix**

#### A confusion matrix is a summary of prediction results on a classification problem



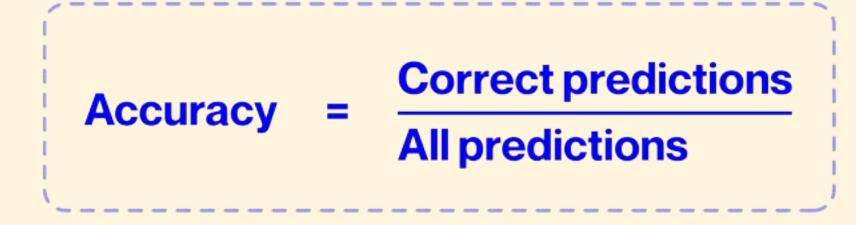
## **Classification Confusion Matrix**



## **Classification Accuracy**

## Accuracy is defined as the percentage of correct predicitions for the test data.

It can be calculated by deviding the number of correct predictions by the number of total predictions.



## **Classification Accuracy**

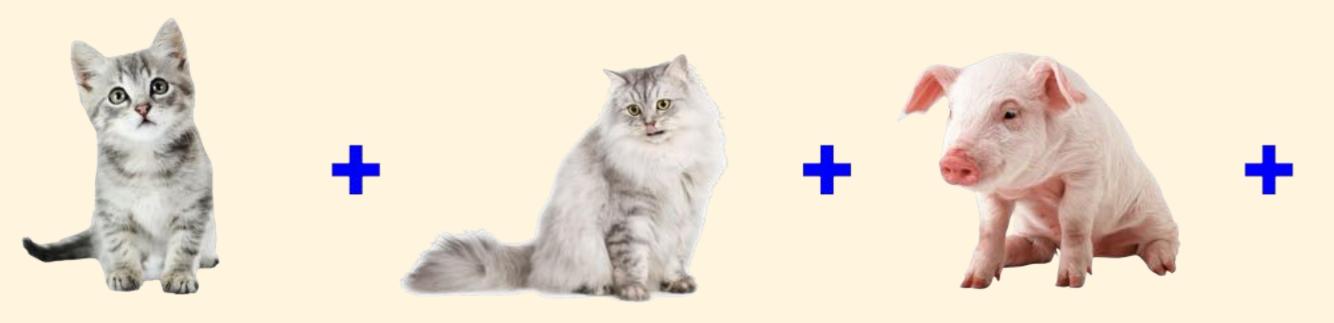




"cat"

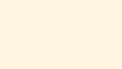
"not cat"

"not cat"



"cat"

"cat"











## **Classification Precision**

Precision is defined as a fraction of relevant examples (true positives) among all off the examples which were predictied alto belong in a certain class.

Or: Out of all examples that are predicted as positive, how many are actually positive?

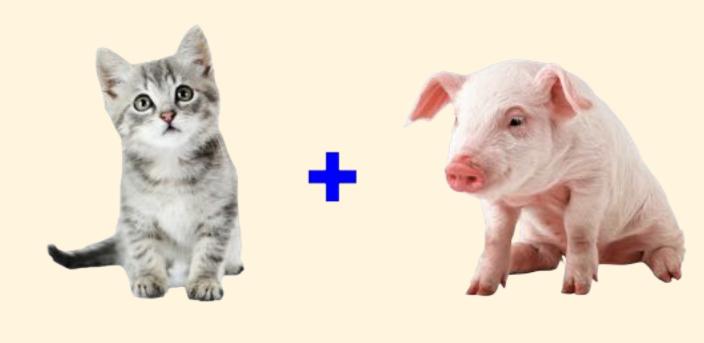




## **Classification Precision**



"cat"



"cat"



## **Classification Recall**

Recall is defined as the fraction of examples which were predicted to belong to a class with respect to all of the examples truly belonging to said class.

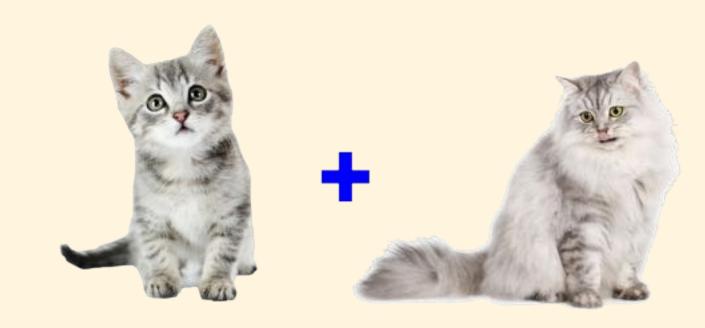
Or: Out of all positive examples, how many are really predicted as positive.



## **Classification Recall**

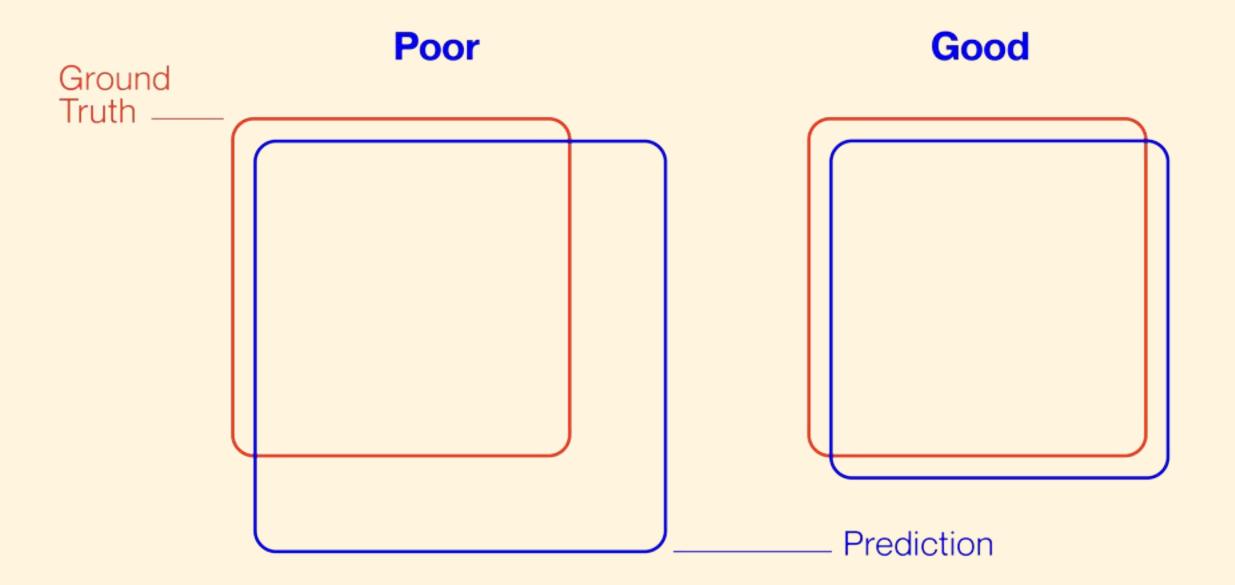


"cat"



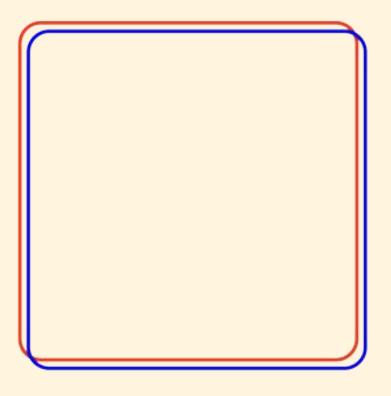
"cat"

"not cat"

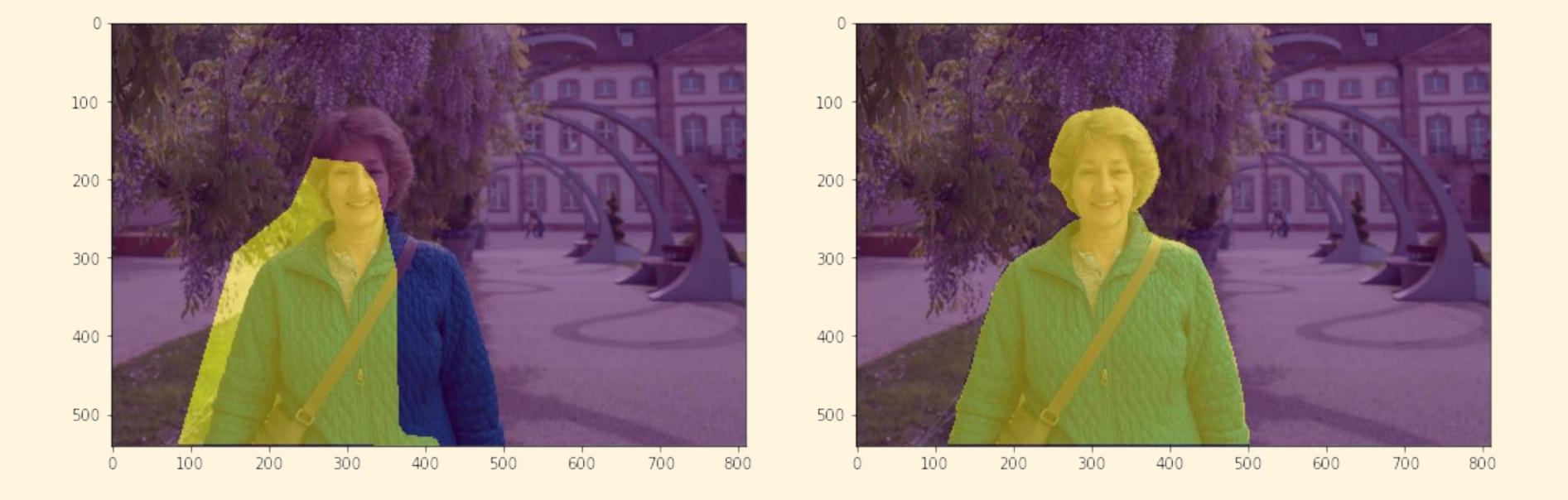


#### Ground truth refers to information that is known to be real or true, obtained through direct observation and measurement rather than inference.





## Ground Truth vs. Prediciton



## **Testing Set**

- presence of a lake and a blue tag, 433 × 340 pixels \_\_\_\_\_
- 4. very small and high zoom image, 100 × 118 pixels \_\_\_\_\_
- 5. unusual swimming pool body, 366 × 270 pixels \_\_\_\_\_

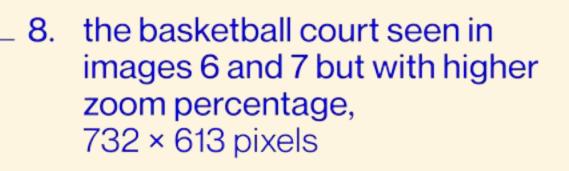




7. the same court as in image 6 and a green swimming pool, 1099 × 1333 pixels, \_\_\_\_\_

Eight test images taken from *Google Maps* with different sizes and resolutions.

- 2. encloses two swimming pools and a pool look-alike glassstructure, 442×258 pixels
- З. a pool without one of the most common characteristics, the blue colour, 298 × 241 pixels
- 6. very high-quality 3-dimensional picture with two pools and a basketball court, 1351 × 1364 pixels



## **Model Selection**



#### **RetinaNet + ResNet50**

The models with ResNet50 and ResNet101 are not able to detect unusually coloured pools, green as in the tested examples.

The results show that the model with ResNet50 is sensitive to the zoom of the image, indicating a wrong classification of objects when the zoom percentage is high



#### **RetinaNet + ResNet101**

The models with ResNet50 and ResNet101 are not able to detect unusually coloured pools, green as in the tested examples.



#### **RetinaNet + ResNet152**

Classification of exceptionally small images is difficult for the model with ResNet152.

## **Model Selection**

	TP	TN	FP	FN	Accuracy	Precision	Sensitivity	Specificity	Type I	Type II
ResNet50	471	2200	18	149	0.9412	0.9632	0.7600	0.9919	0.0081	0.2400
ResNet101	480	2285	7	140	0.9495	0.9856	0.7742	0.9969	0.0031	0.2258
ResNet152	503	2241	6	117	0.9571	0.9882	0.8113	0.9973	0.0027	0.1887

## **Model Selection**

	TP	TN	FP	FN	Accuracy	Precision	Sensitivity	Specificity	Type I	Type II
ResNet50	<b>47</b> 1	2200	18	149	0.9412	0.9632	0.7600	0.9919	0.0081	0.2400
ResNet101	480	2285	7	140	0.9495	0.9856	0.7742	0.9969	0.0031	0.2258
ResNet152	503	2241	6	117	0.9571	0.9882	0.8113	0.9973	0.0027	0.1887

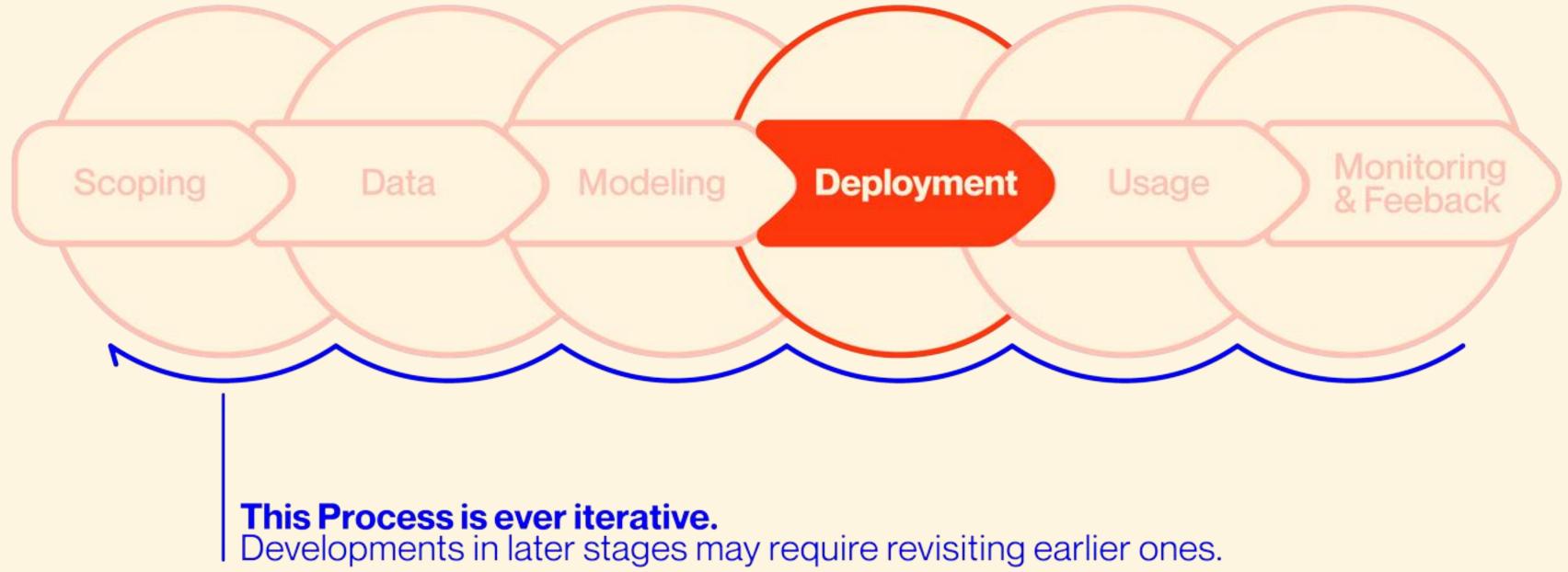
# Modelling

- Use the provided data set from Google drive to gather and group images into classes
- Use Google Teachable Machine to train your model on these classes
- Test the model model to ensure it can correctly classify new examples
- Save the model later for the presentation

## 08:00

## Deployment

## Human Centric ML Lifecycle



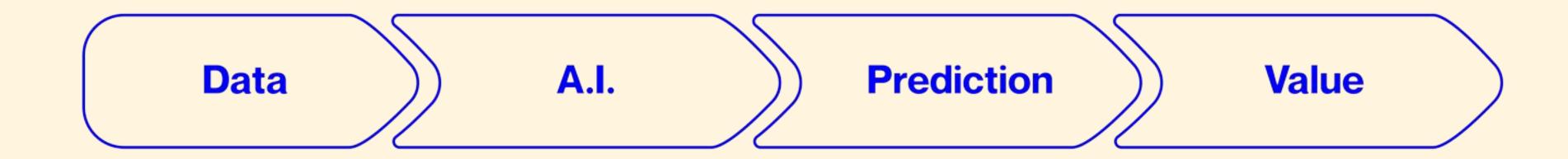




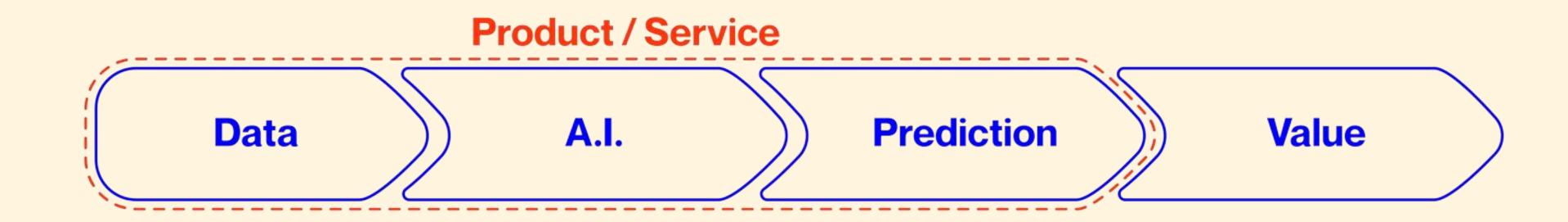


## Who cares?

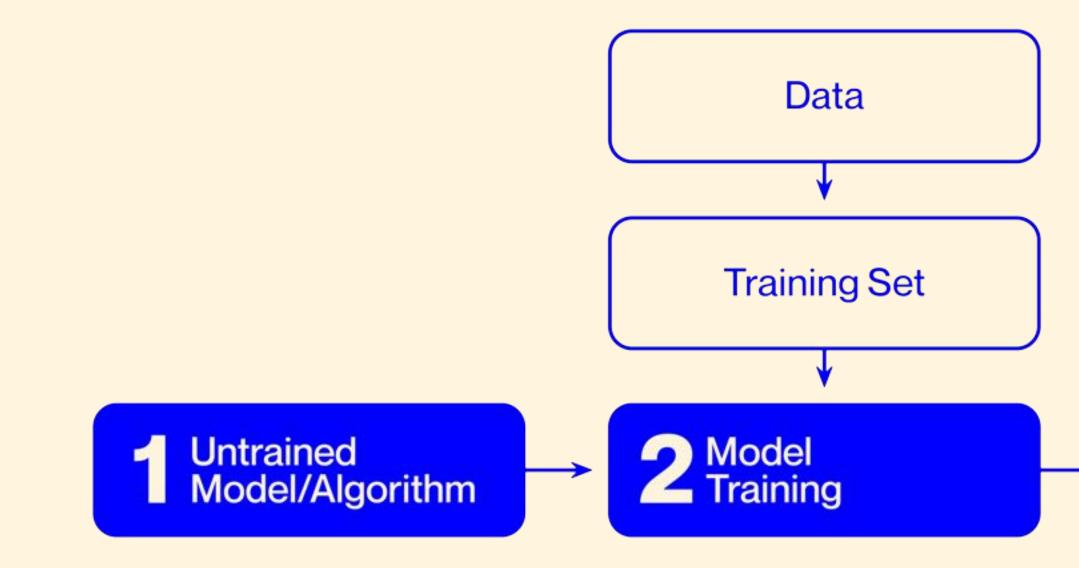
## **Creating Value**

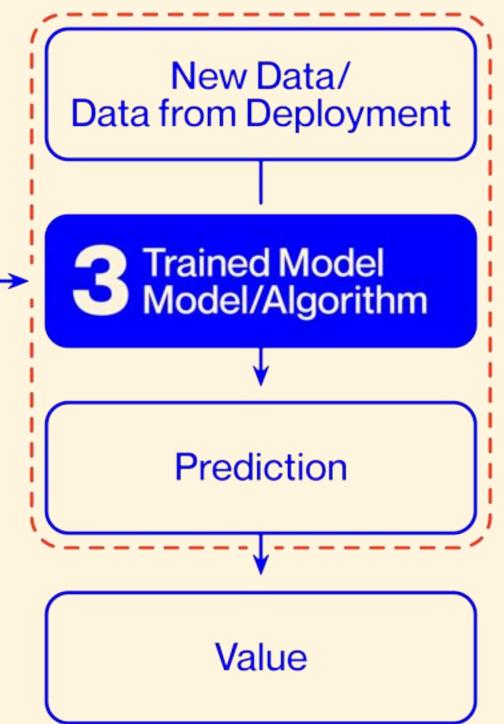


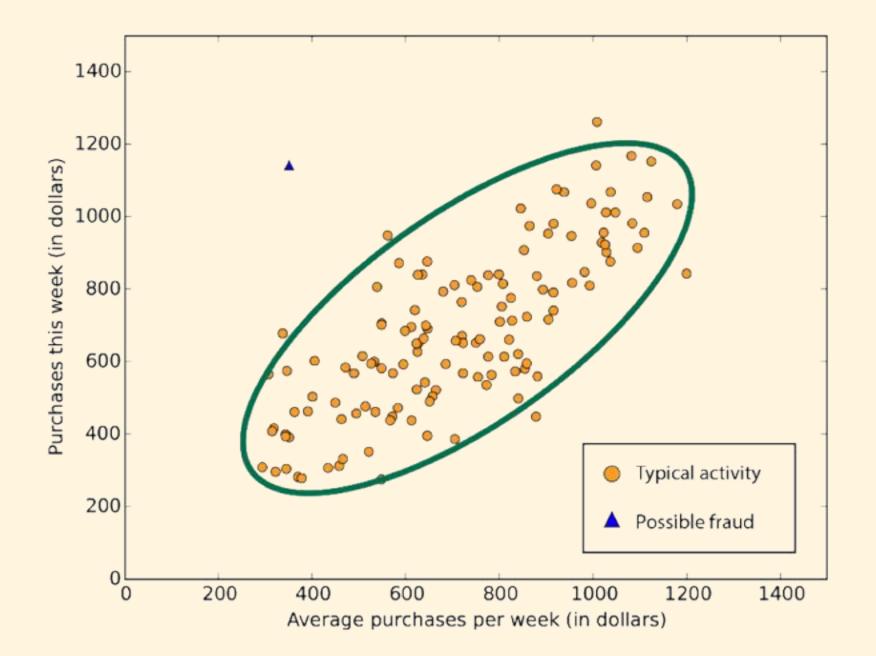
## **Creating Value**



## **Creating Value**



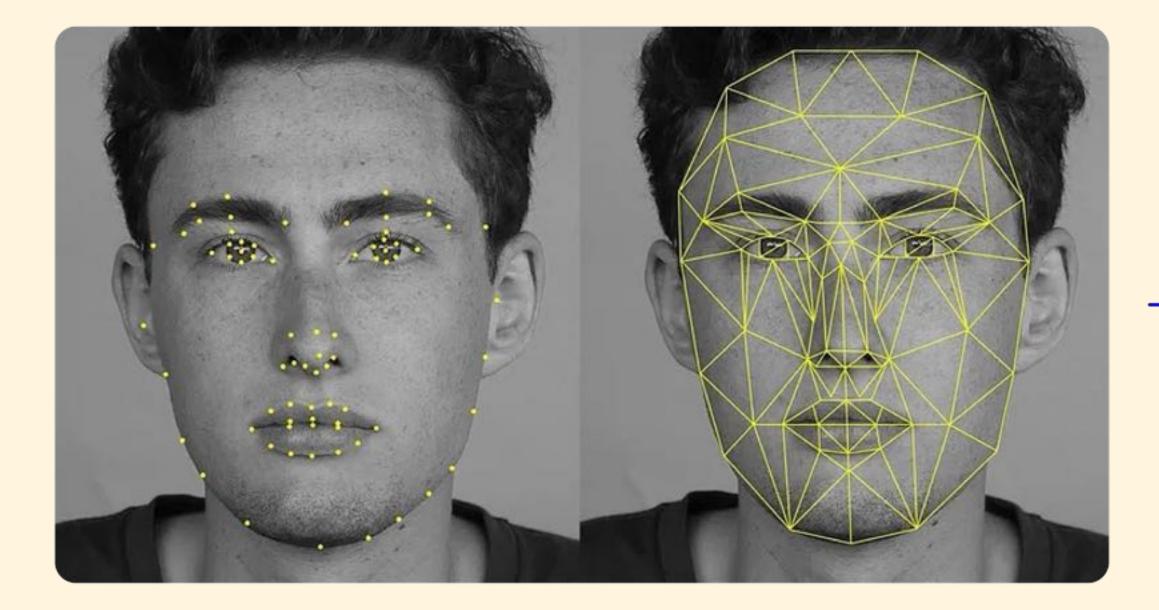




Model that predicts wther a transaction is fraudulent or not



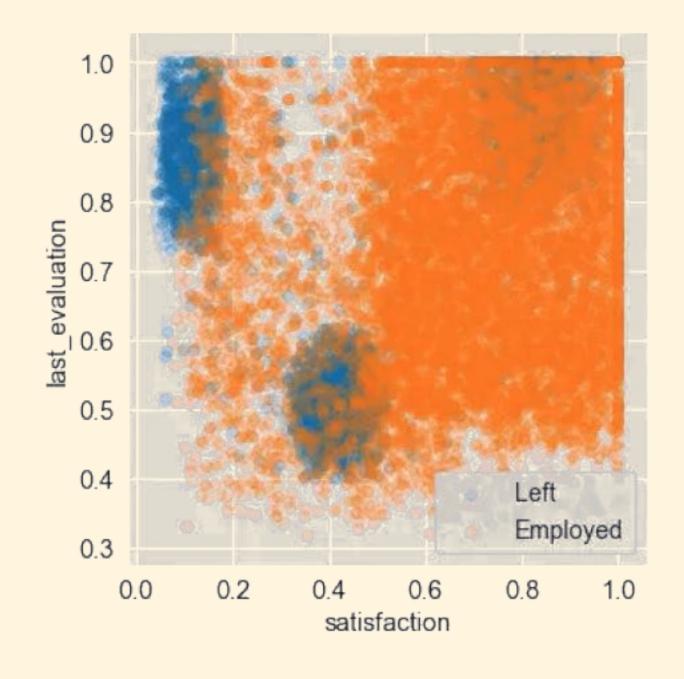
#### **Inform Customer**



Model that predicts wether the face in the image is you



#### **Unlock iPhone**





Model that predicts employer churn

- Invite employees, that are high performers and have high churn rate to HR

- Inform Managers about model output

### **Operational Environment**

## **Technical Environment**

hardware, software, and network infrastructure that support the AI model

### **AI Model**

#### the processes and people that will interact with

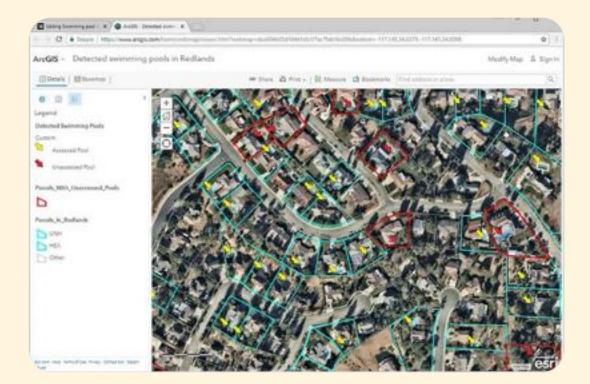
that will interact with the Al system

## **Creating Value in Production**

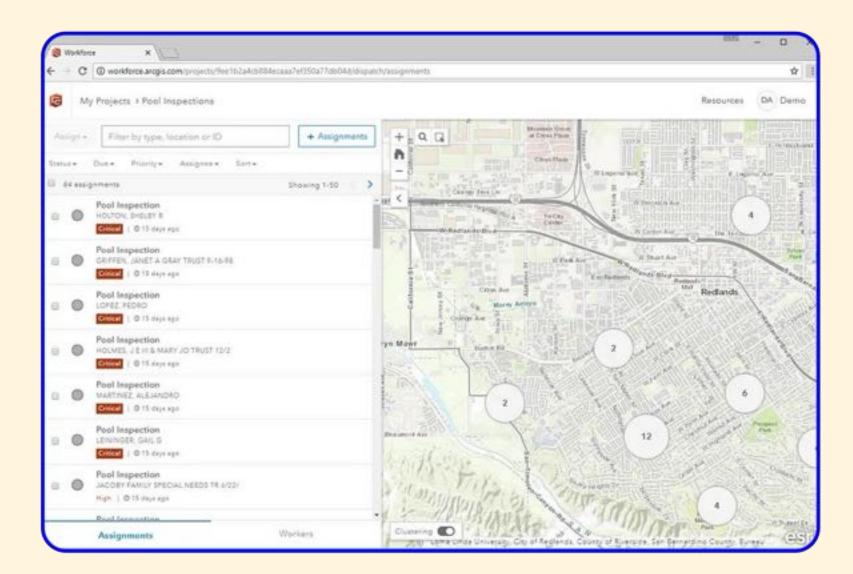




### Prediction \_\_\_\_\_



### System Creating Value

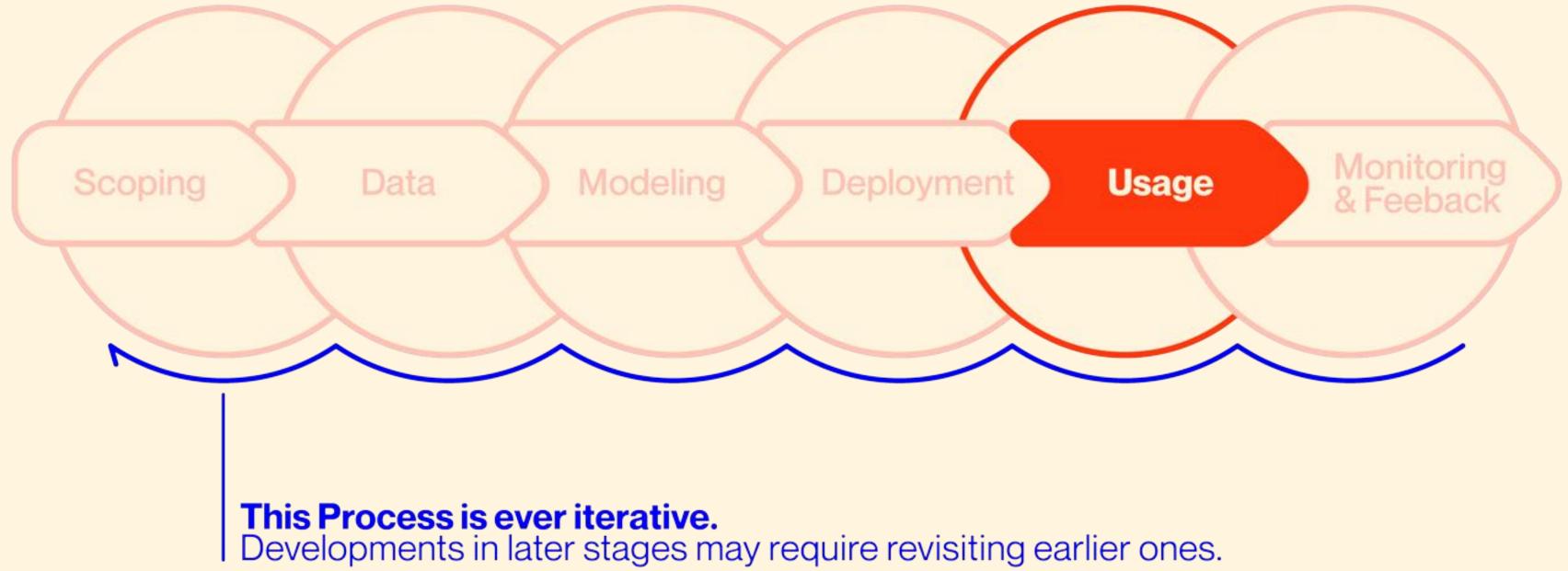




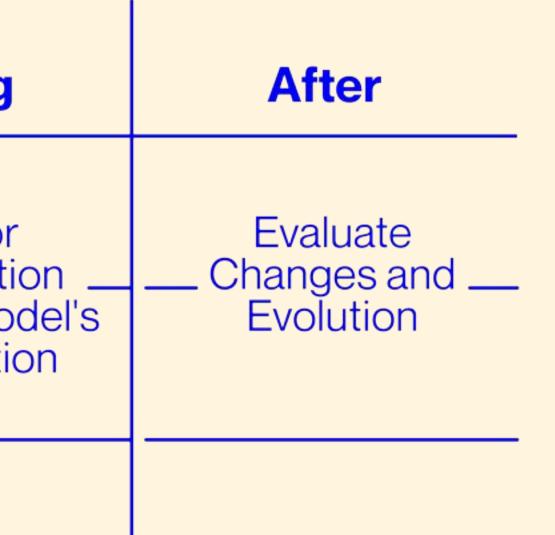
## Governmental Inspection



## Human Centric ML Lifecycle



	Before	During
People	Assess Current State	Monitor the Adapti to the Al Mo Introductio
Processes		



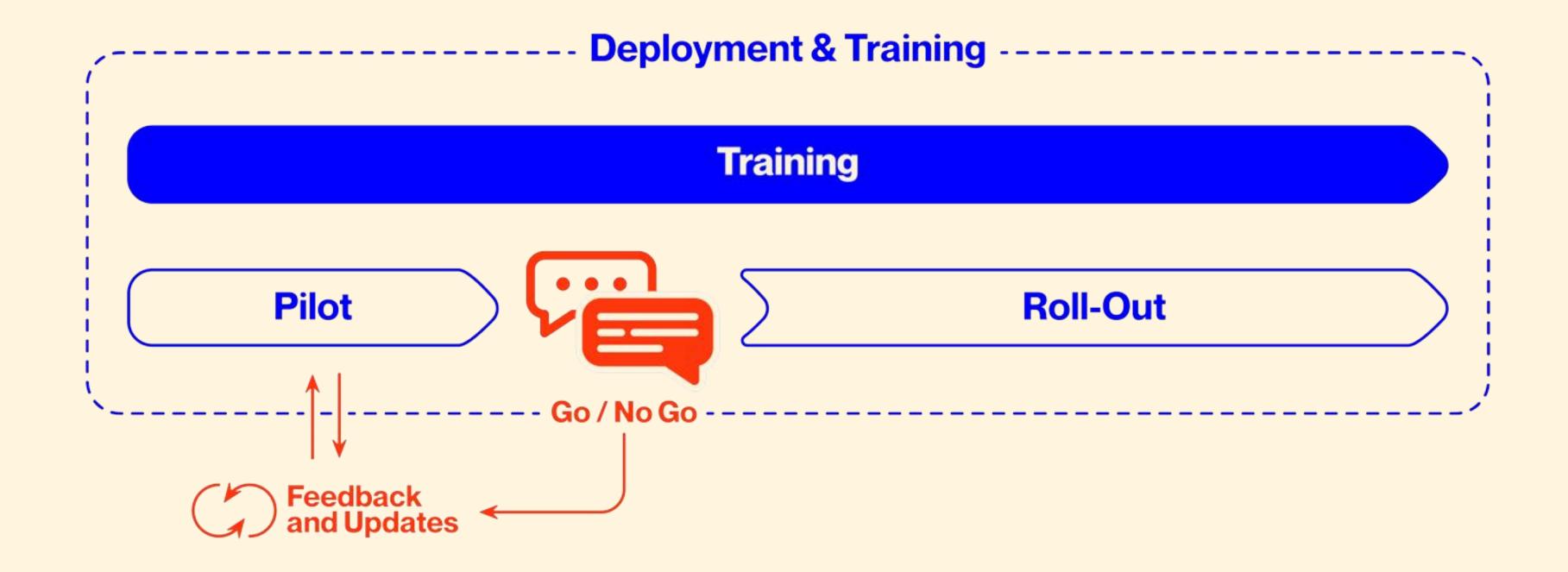
	Status Quo (Before Deployment)	During Deployment
Decision- Makers		
Users		
People Affected		

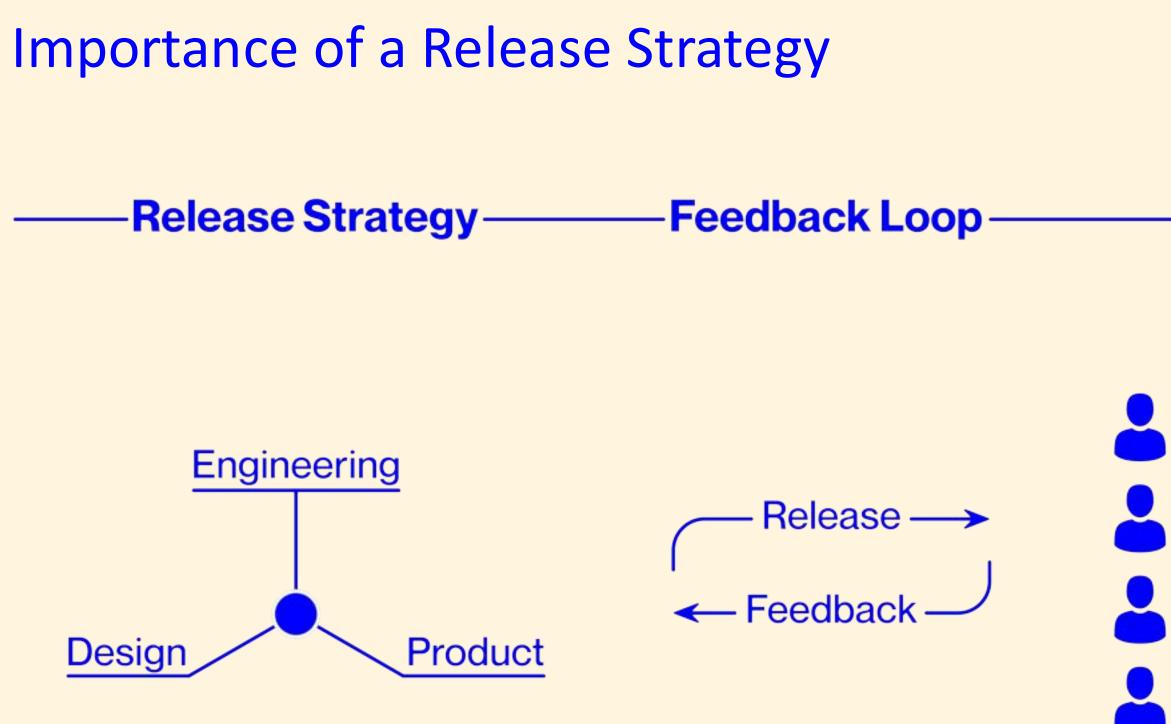
After Deployment

	Status Quo (Before Deployment)	During Deployment	After Deployment
Decision- Makers	What are the key objectives?	How will ROI be managed during this phase?	Is the solution meeting its objective?
	What is the budget?	What are the milestones?	What are the maintenance costs?
Users	What is the current workflow	What training is needed?	Is the solution user-friendly?
	What are the pain points?	How will the transition be managed?	Are there any new pain points?
People Affected	How will this change current roles?	What communication is needed?	How has the role changed?
	What are the concerns?	How will feeback be collected?	Are the initial concerns adressed?

	Status Quo (Before Deployment)	During Deployment	After Deployment
Decision- Makers	What are the key objectives?	How will ROI be managed during this phase?	Is the solution meeting its objective?
	What is the budget?	What are the milestones?	What are the maintenance costs?
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People Affected	How will this change current roles?	What communication is needed?	How has the role changed?
	What are the concerns?	How will feeback be collected?	Are the initial concerns adressed?

# Starting with a Pilot





#### Engineering, Product and Design teams continuously collaborate

on release and roll-out strategy, assessing user and performance feedback along the way

### **Roll-Out**

() ()U

Test / **Pilot User** Limited **Roll-Out** Gradual **Roll-Out** Full **Roll-Out** 

# Rollout







#### euronews.

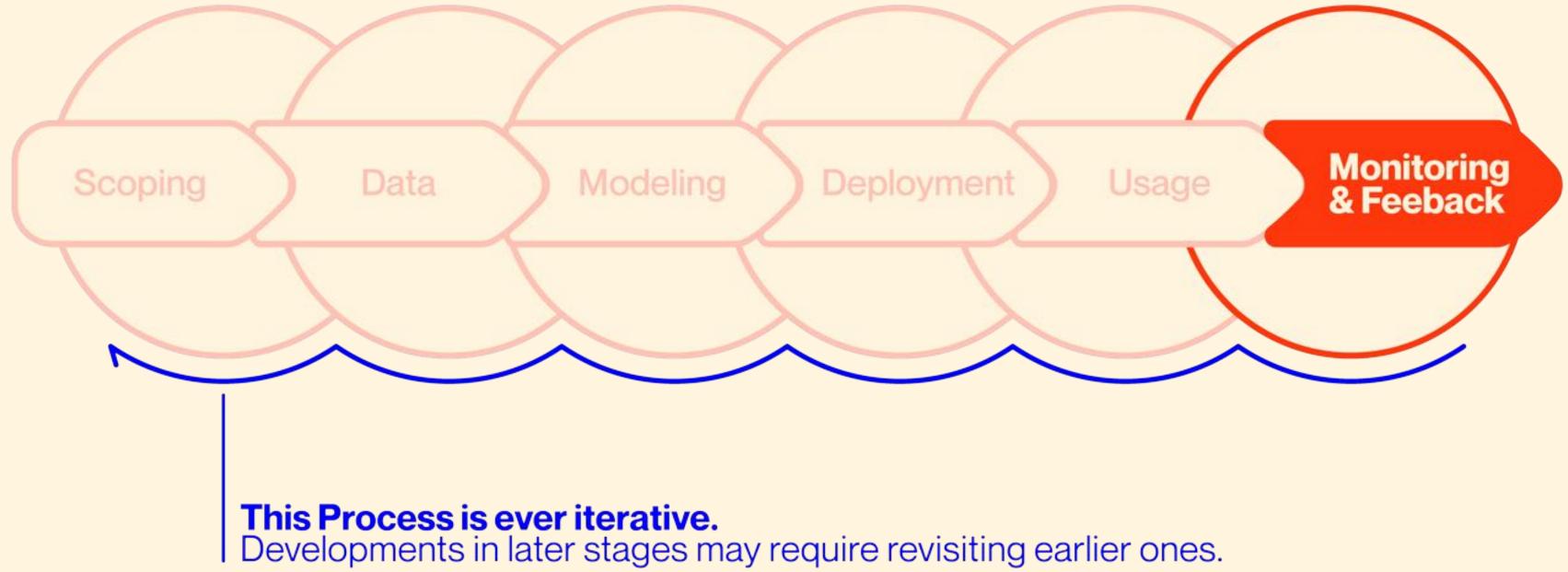
# Deployment/Usage

- Describe the final product
- Who are the different stakeholders?
- How are stakeholders affected differently by the solution?
- How would the process look like where the solution is used?
- How would you measure success?

# 08:00

# Monitoring

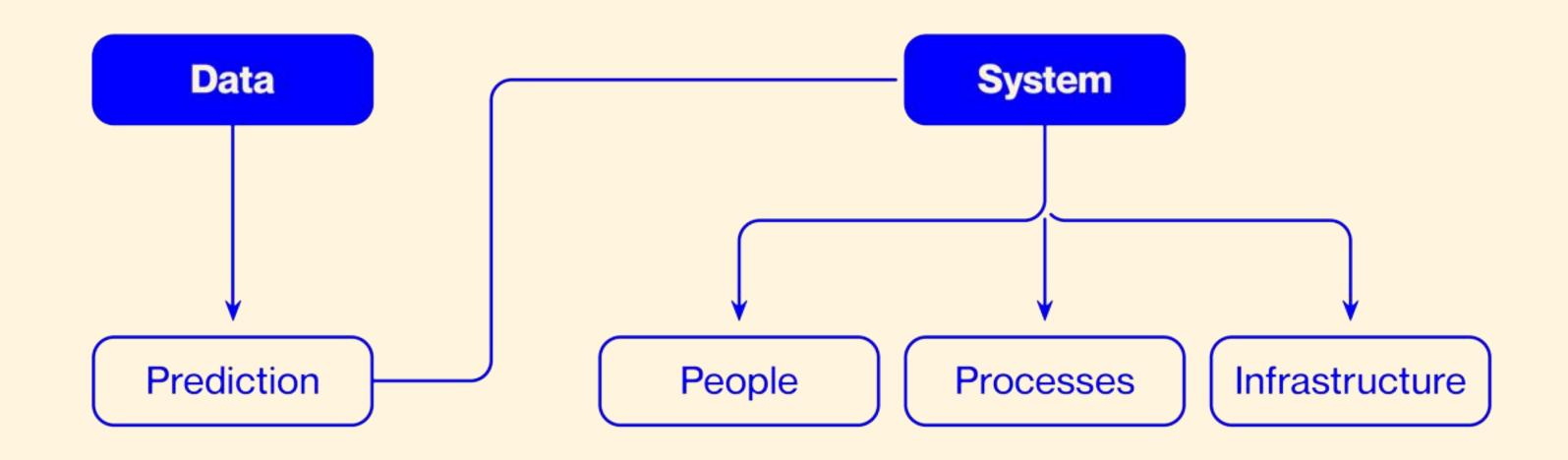
# Human Centric ML Lifecycle



## Monitoring







### **System Monitoring**

## Data Drift

Data Distribution

Sudden Drift: A new Concept Occurs within a short Time

### **Gradual Drift:**

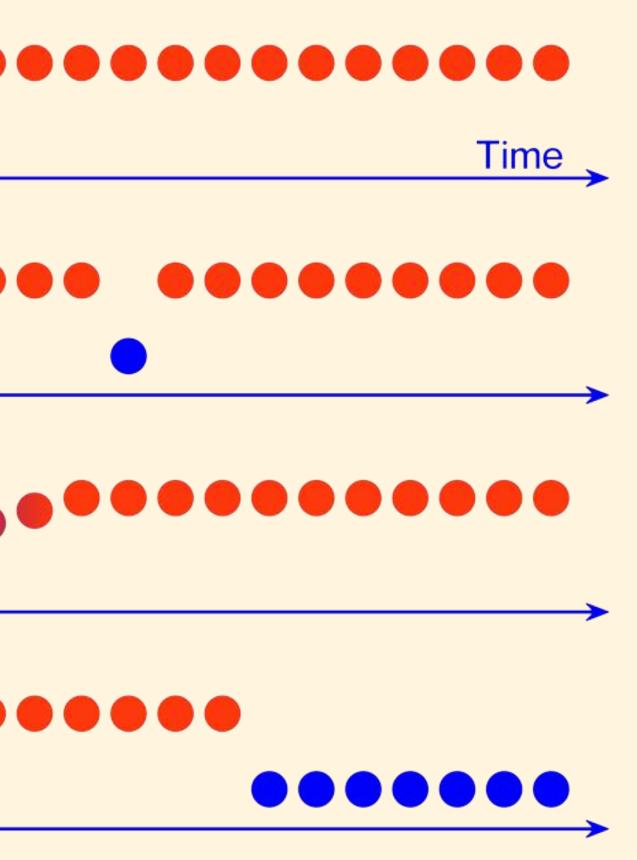
A new concept gradually replaces an old one over a period of time

### **Incremental Drift:**

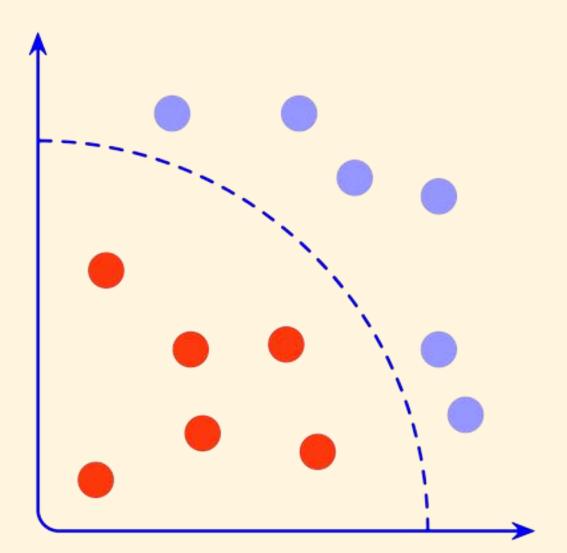
An old concept incrementally changes to a new concept over a period of time

### **Reoccurring Drift:**

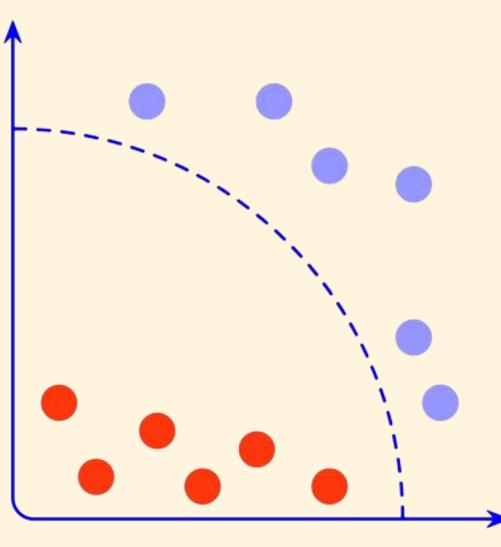
An old concept may reoccur after some time



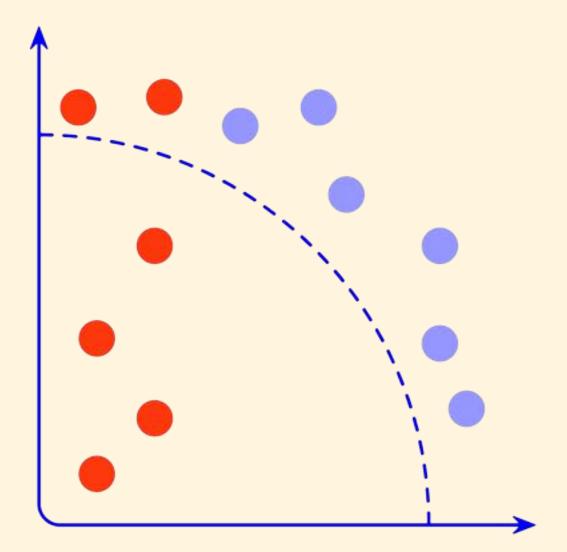
## Data Drift



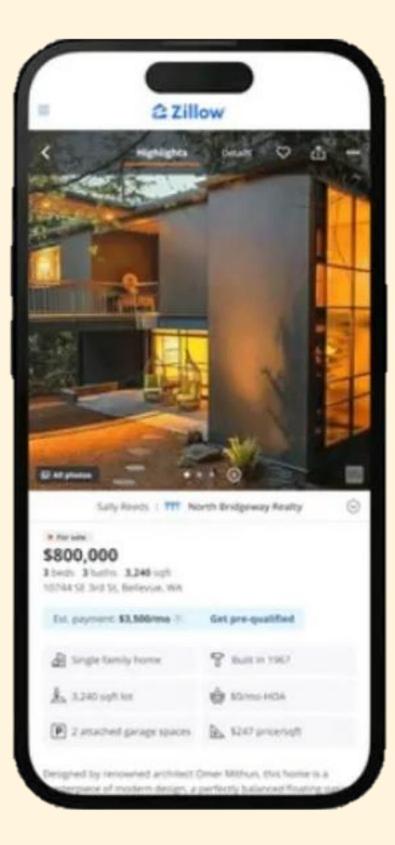
Decision boundary fit to training data



Data drift in orange class, but the decision boundary still holds



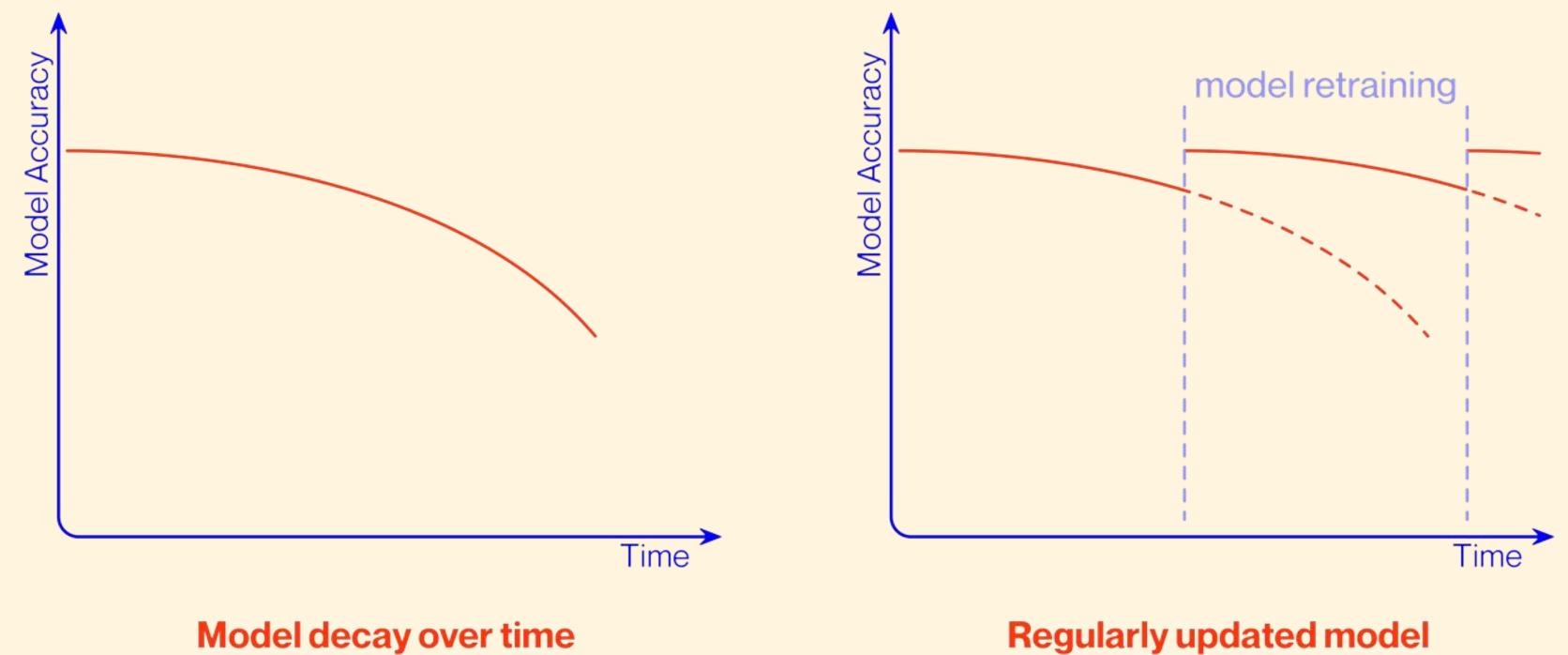
#### Data drift in orange class, detrimental empact on performance



# The dangers of AI model drift: lessons to be learned from the case of Zillow Offers

In the past three years, Zillow invested hundreds of millions of dollars into Zillow Offers, its Alenabled home-flipping program. The company intended to use ML models to buy up thousands of houses per month, whereupon the homes would be renovated and sold for a profit. Unfortunately, things didn't go to plan. Recently, news came out that the company is <u>shutting down its iBuying</u> program that overpaid thousands of houses this summer, along with laying off 25 percent of its staff. Zillow CEO Rich Barton said the company <u>failed to predict</u> house price appreciation accurately: "We've determined the unpredictability in forecasting home prices far exceeds what we anticipated."

# Retraining



### **Regularly updated model**

# System Monitoring in MLOps

- 1. Objectives of System Monitoring
- Ensure Reliability
- Maintain Security
- Optimize Performance

- 2. Key Areas to Monitor

- Technical Glitches: Hardware & Software

- User Behavior: Usage Patterns & Feedback

- Security: Breach Detection & Data Integrity

# System Monitoring in MLOps

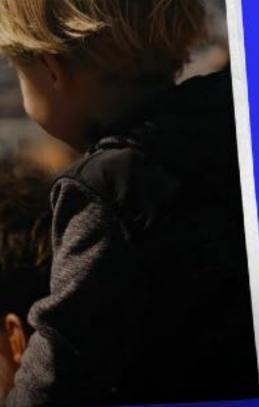
- 1. Objectives of System Monitoring - Ensure Reliability - Maintain Security - Optimize Performance 2. Key Areas to Monitor - Technical Glitches: Hardware & Software - User Behavior: Usage Patterns & Feedback - Security: Breach Detection & Data Integrity 3. Tools for Monitoring\*\*
- Application Performance Monitoring (APM)
- Security Information and Event Management (SIEM)
- User Activity Logs

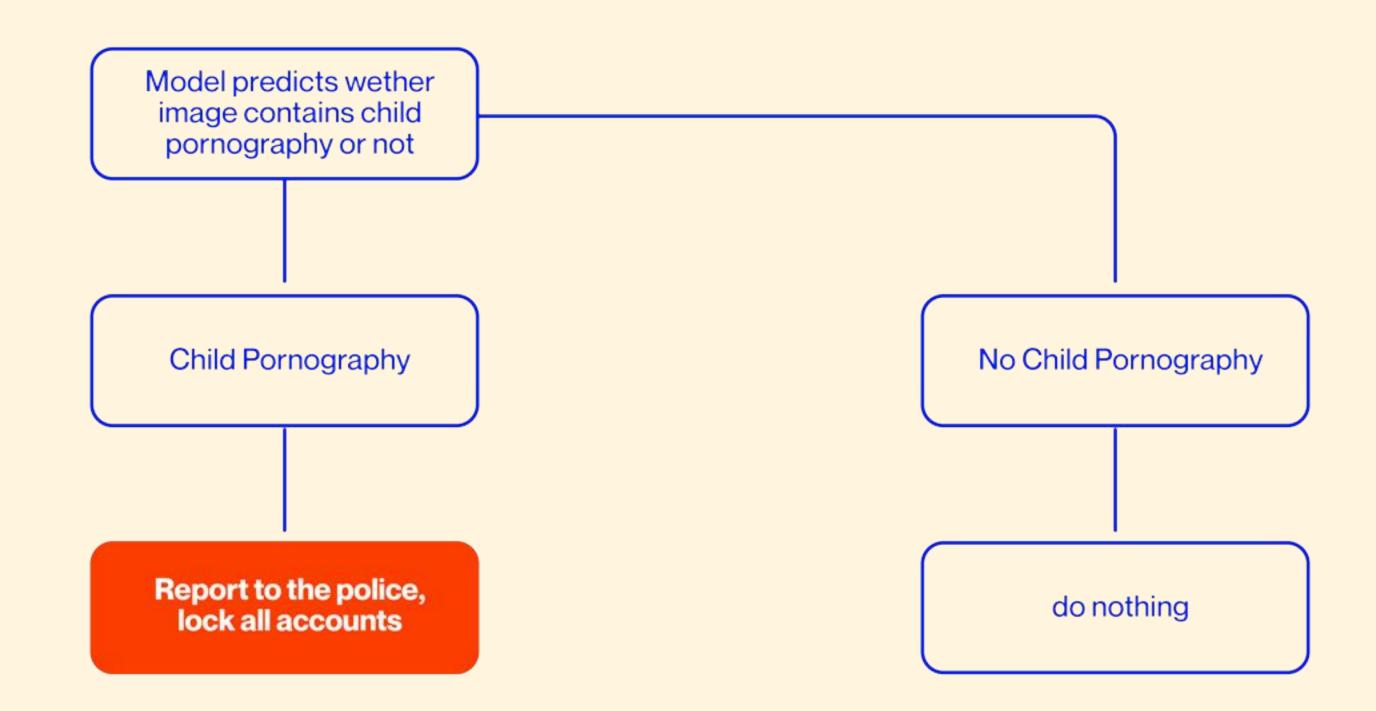
- 4. Why It's Crucial
- Quick Issue Identification
- Timely Fixes & Updates
- Adapt to Changing Conditions
- 5. Next Steps
- Regular Audits
- Periodic Reporting
- Stakeholder Communication

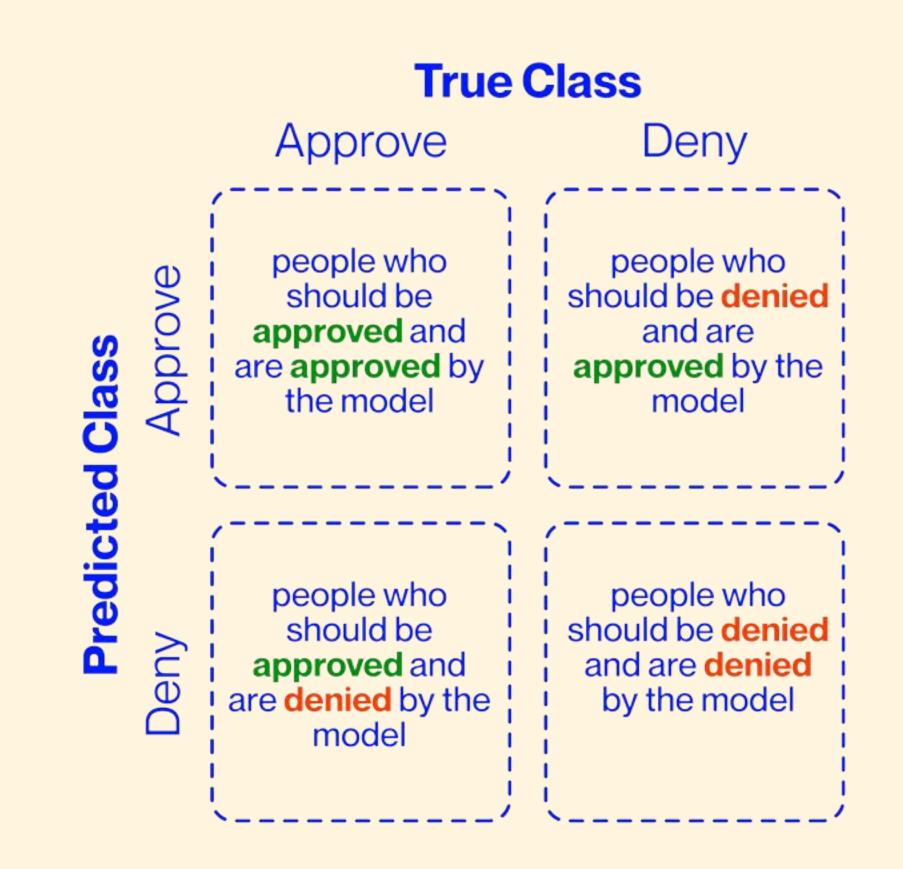
# BUSINESS INSIDER AUGUST 21 2022 A DAD TOOK PHOTOS OF HIS NAKED TODDLER FOR THE DOCTOR. GOOGLE HIM AS A CRIMINAL.

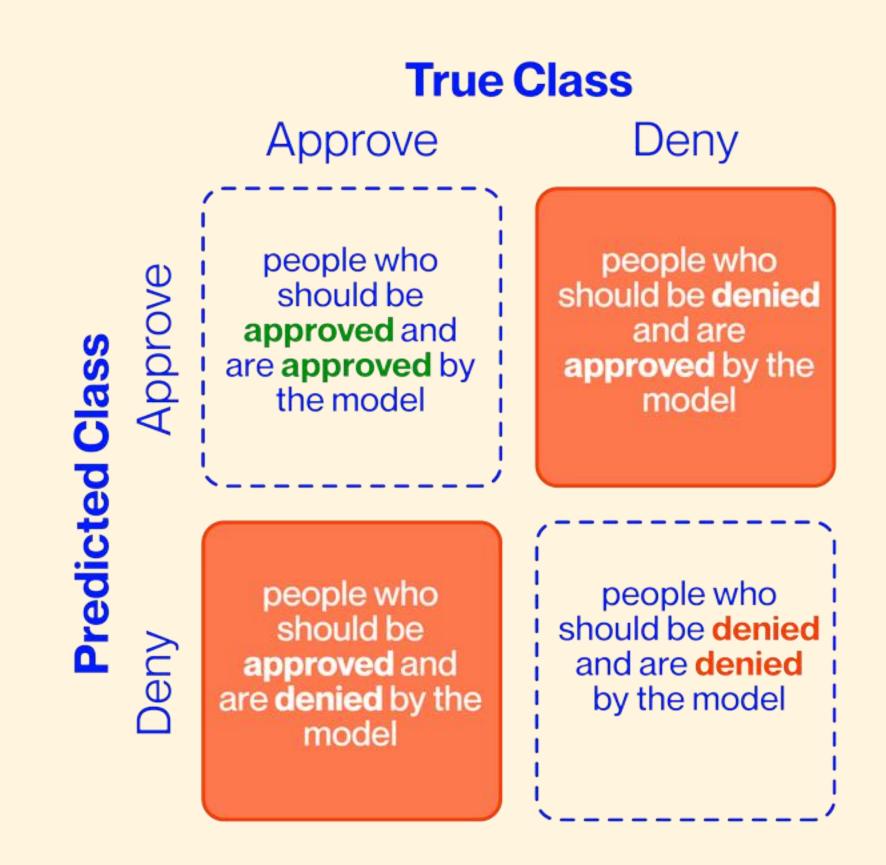
Google has an automated tool to detect abusive images of children. But the system can get it wrong, and the consequences are serious.

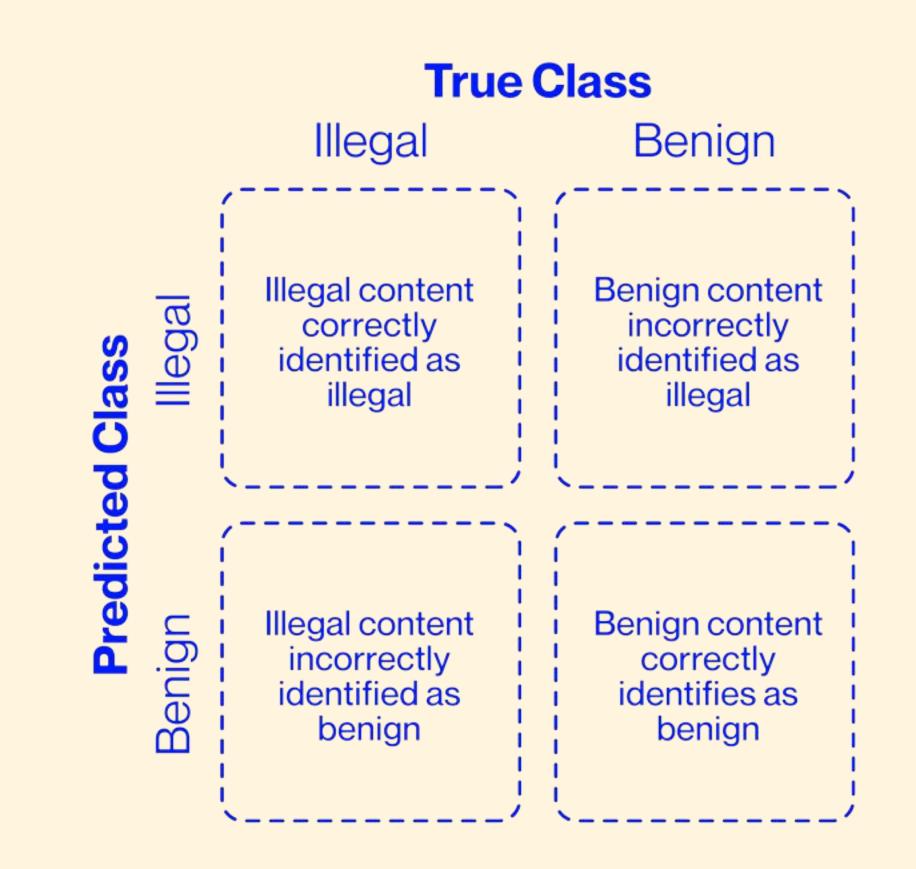
Mark noticed something amiss with his toddler. His son's penis looked swollen and was hurting him. Mark, a stay-at-home dad in San Francisco, grabbed his Android smartphone and took

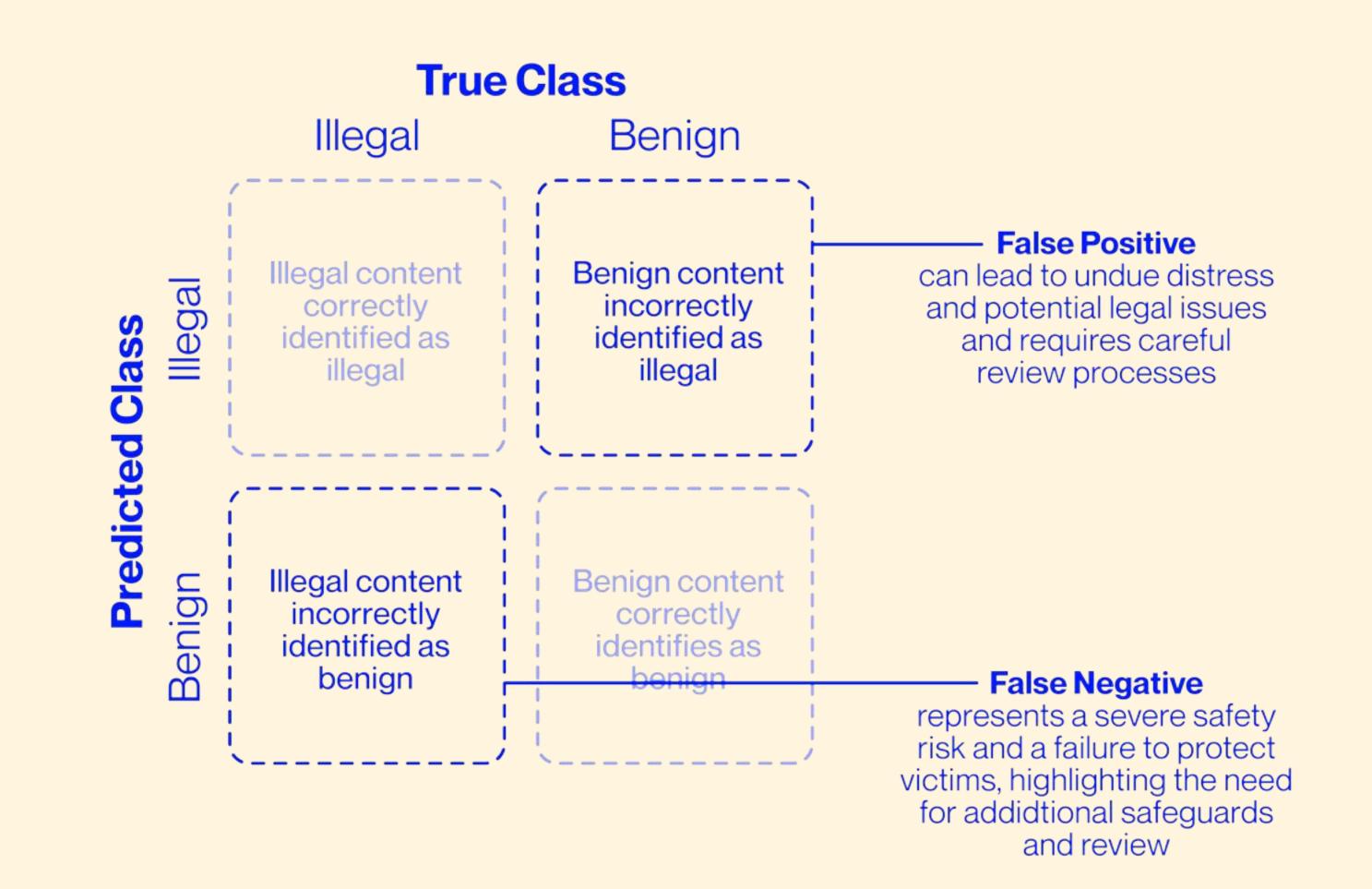




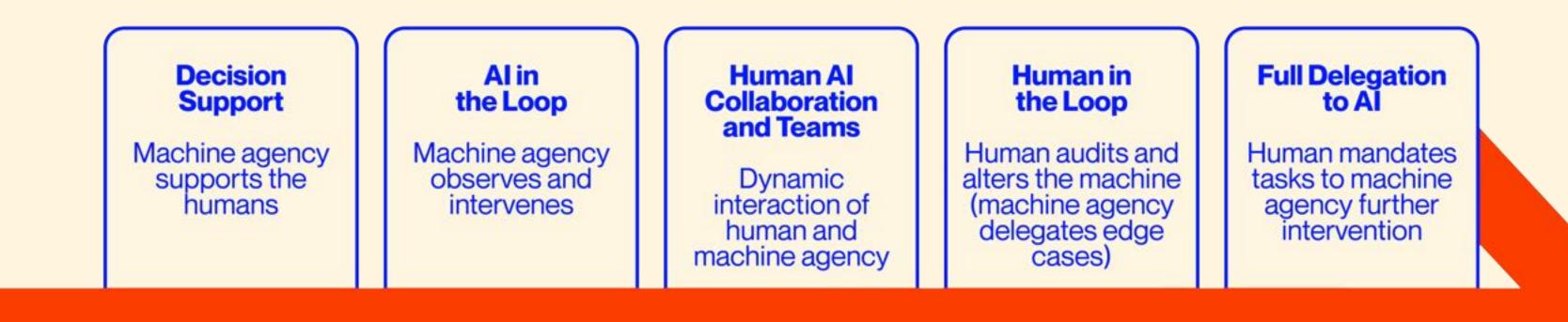








# **Increasing Degree of Automation**



The spectrum from human- and machine augmentation to full automation

# Monitoring

- What could go wrong?
- Who might suffer from errors?
- What could you do to avoid errors and improve the product over time?
- How could you make sure to reverse or mitigate harm once it has happened?

product over time?
m once it has happened?

# 08:00

