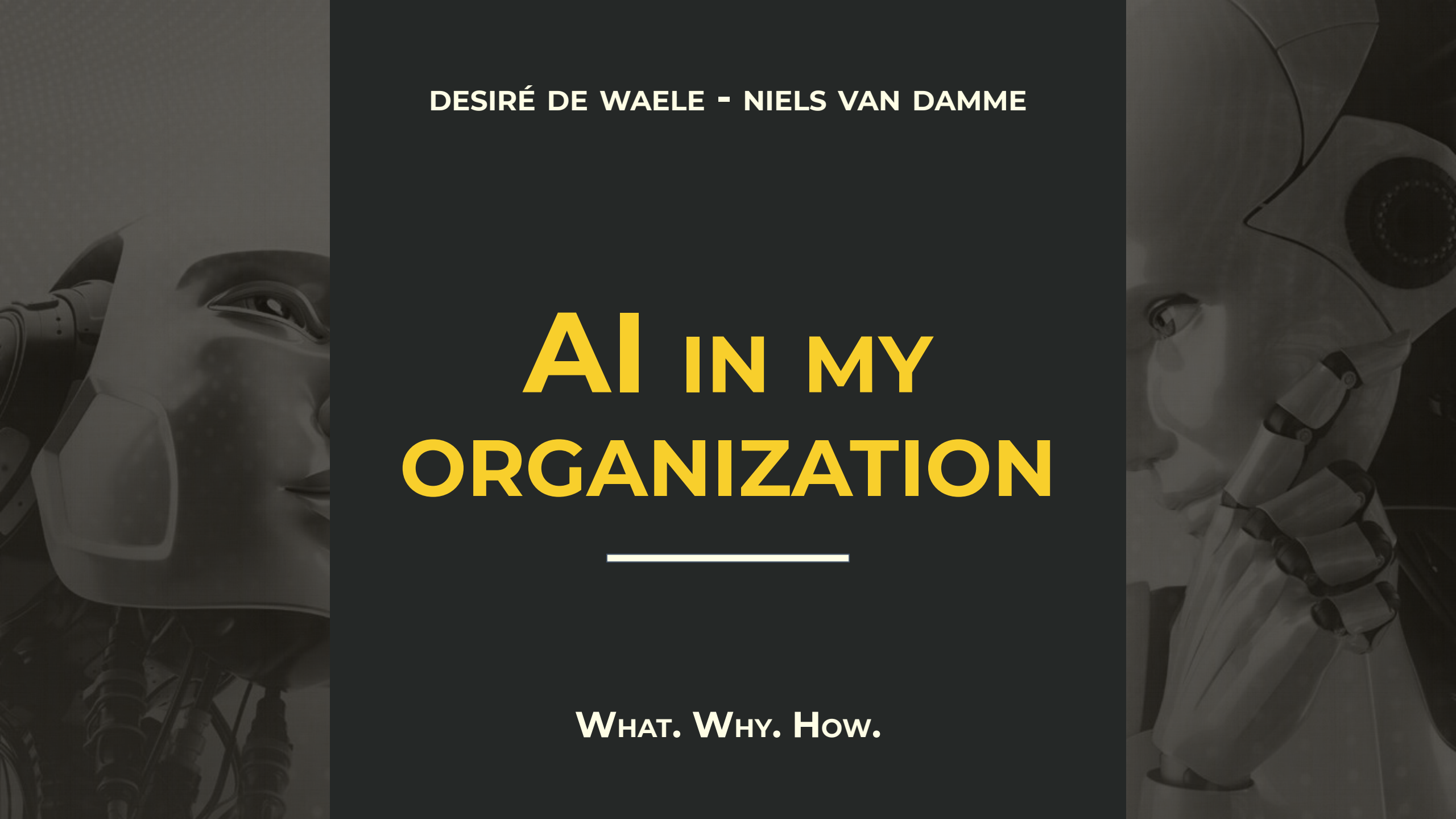


The background of the slide is a dark grey gradient. On the left and right sides, there are faint, semi-transparent images of robot faces. The robot on the left is looking upwards and to the right. The robot on the right is looking downwards and to the left. Both robots have a metallic, futuristic appearance with visible joints and sensors.

DESIRÉ DE WAELE - NIELS VAN DAMME

AI IN MY ORGANIZATION

WHAT. WHY. HOW.

INTRO



OBJECTIVE

- ❖ To fill the gap between hype and reality about AI.
 - ❖ To offer concrete steps to introduce AI.
-

WHO ARE WE

Two AI enthusiasts and autodidacts.

OUTLINE

I. WHAT IS AI?

Definition - Self-learning Component - AI framework

II. WHY INTRODUCE AI?

Added Value - End-to-end Automation - Accessibility

III. HOW TO INTRODUCE AI?

Identify Use Cases - Talent resources - Project roadmap

WHAT MATERIALS DO WE OFFER?



PLAYBOOK

Written version of the contents, in 20-paged document.



WEBSITE

Landing page with all necessary information.

learnfromdata.ai/workshop



CURRICULUM

Technical material to teach your very own AI resources.

PART ONE. WHAT IS AI?

FUNCTIONAL DEFINITION

SELF-LEARNING COMPONENT

AI FRAMEWORK

TWO THINGS ARE CONSIDERED AI

ARTIFICIAL **GENERAL** INTELLIGENCE

Machines that resemble human intelligence or have a consciousness

ARTIFICIAL **NARROW** INTELLIGENCE

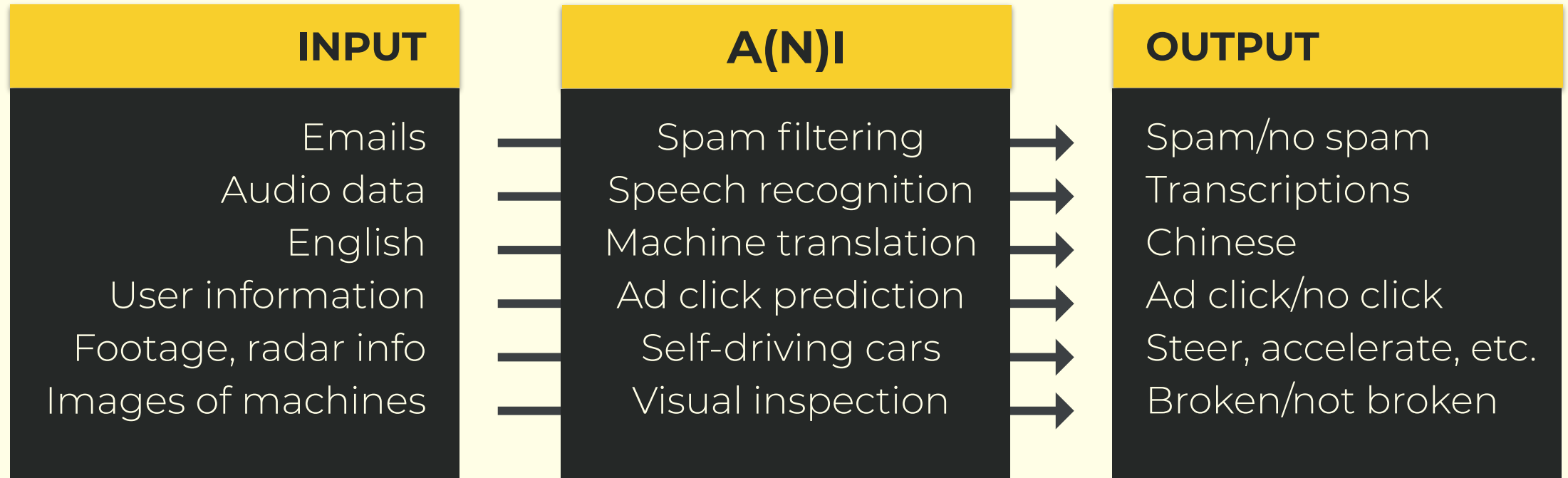
Machines that are capable to perform one complex task well

Machines can be robots, computers, software, etc.

“AGI is science-fiction, ANI is changing the world.”

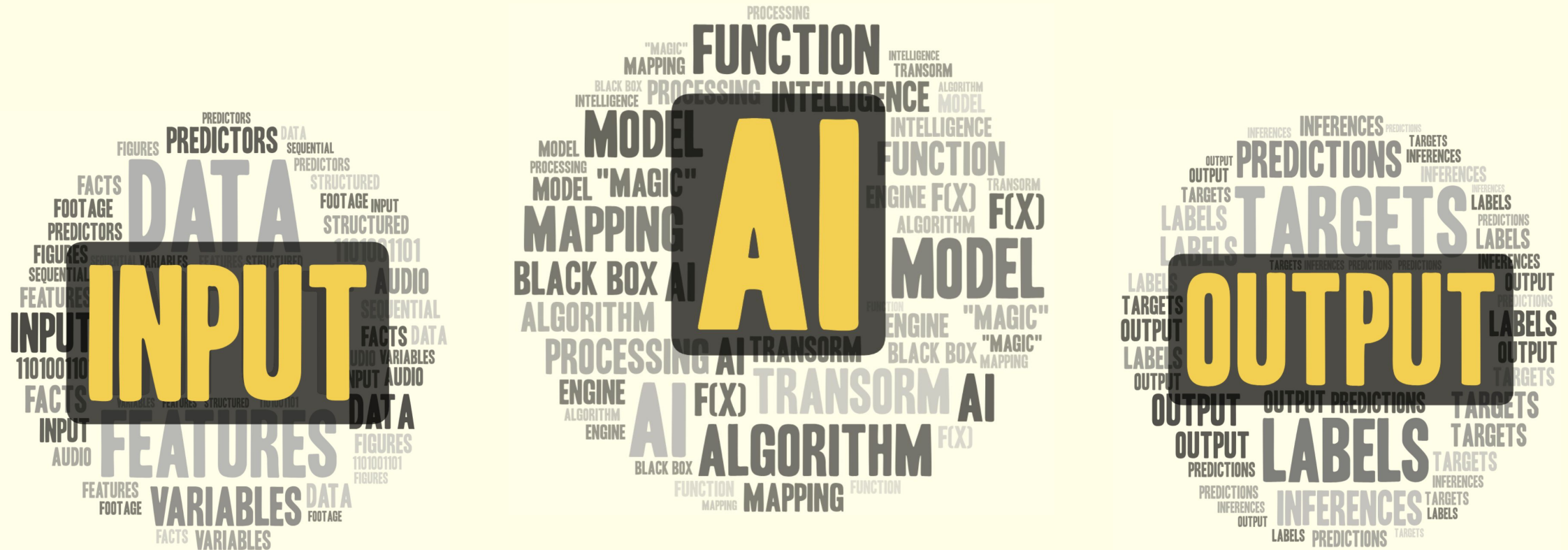
ANI performs tasks by transforming an input to an output.

EXAMPLES OF ANI SYSTEMS



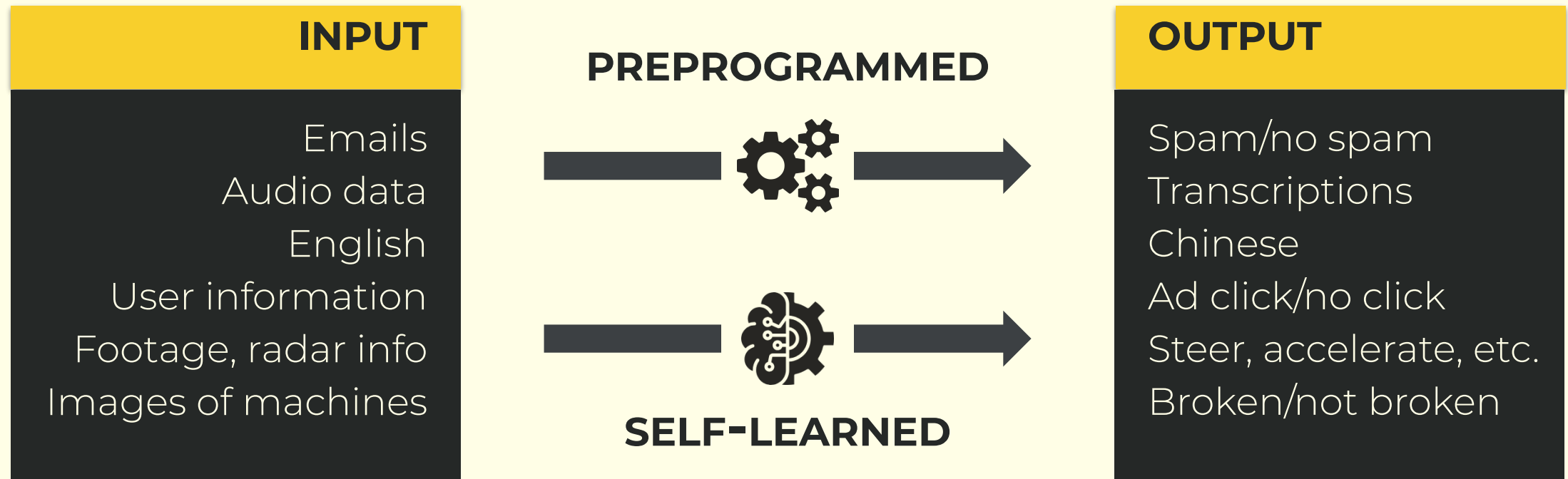
TRANSFORMING INPUT TO OUTPUT

Varying domain terminology boils down to...



TWO WAYS TO TRANSFORM INPUT

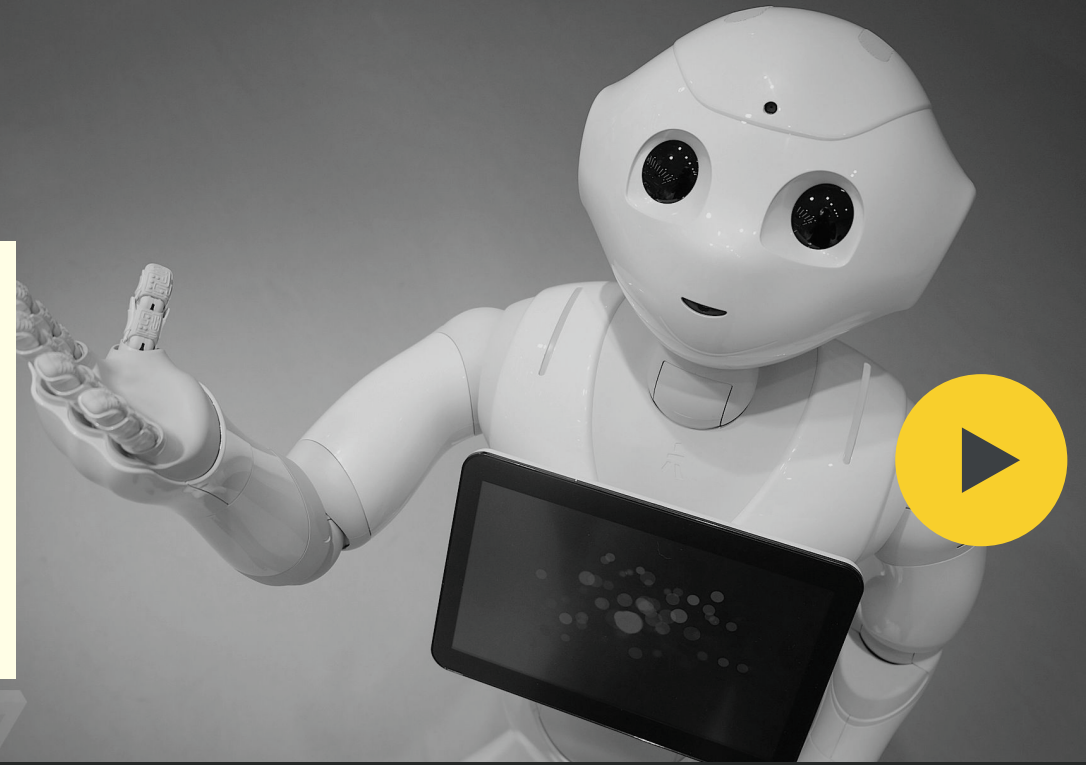
Self learning component is arguably inherent to AI



PREPROGRAMMED AI?

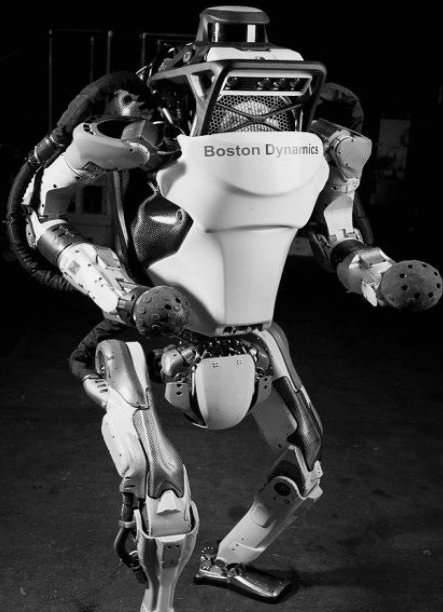
Meet Pepper

- Makes conversation, guides people
- Is seen as AI example, in- & output are present
- But is pre-programmed and not self learning



Meet Atlas

- Walks, runs, jumps, performs backward saltos
- Must be AI as well? In- & output are present
- But is highly pre-programmed too



SELF-LEARNING AI?

X Ray Readings

- Scans are screened for various diagnoses.
- Performed by a team of experienced doctors.
- Or performed by a self-learning algorithm.

Bank Loan Approvals

- Loan applications are screened for approval.
- Performed manually based on data.
- Or performed by a self-learned algorithm.



GAIN INTUITION IN HOW AI LEARNS

Iterative steps an AI system learns by

Step 0: *Initialization*

A random transformation from input to output gets initiated.

Step 3: *Tuning*

The transformation is slightly changed in each step, towards a slightly better performance.

Step 1: *Transformation*

The transformation is applied on the input, resulting in an output.

Step 2: *Evaluation*

The output is evaluated by how far off it is from performing the task well.



AI DECOMPOSED

Three buzzwords explained



ARTIFICIAL INTELLIGENCE

ANI performs tasks that seemingly require human intelligence.

MACHINE LEARNING

Performs tasks without being explicitly programmed

DEEP LEARNING

Performs tasks with neural networks, a self-learning algorithm.

TECHNICAL SUBCATEGORIES OF AI

SUPERVISED LEARNING

INPUT

OUTPUT

AI that tries to find relationships between a known input and output.

UNSUPERVISED LEARNING

INPUT

OUTPUT

AI that tries to find relationships within a known input only.

REINFORCEMENT LEARNING

INPUT

OUTPUT

AI that tries to generate an input to reach a known output.

TECHNICAL SUBCATEGORIES OF AI

SUPERVISED LEARNING

INPUT

OUTPUT

MACHINE TRANSLATION

"She rode her bicycle"

她騎著自行車

UNSUPERVISED LEARNING

INPUT

OUTPUT

CLUSTERING



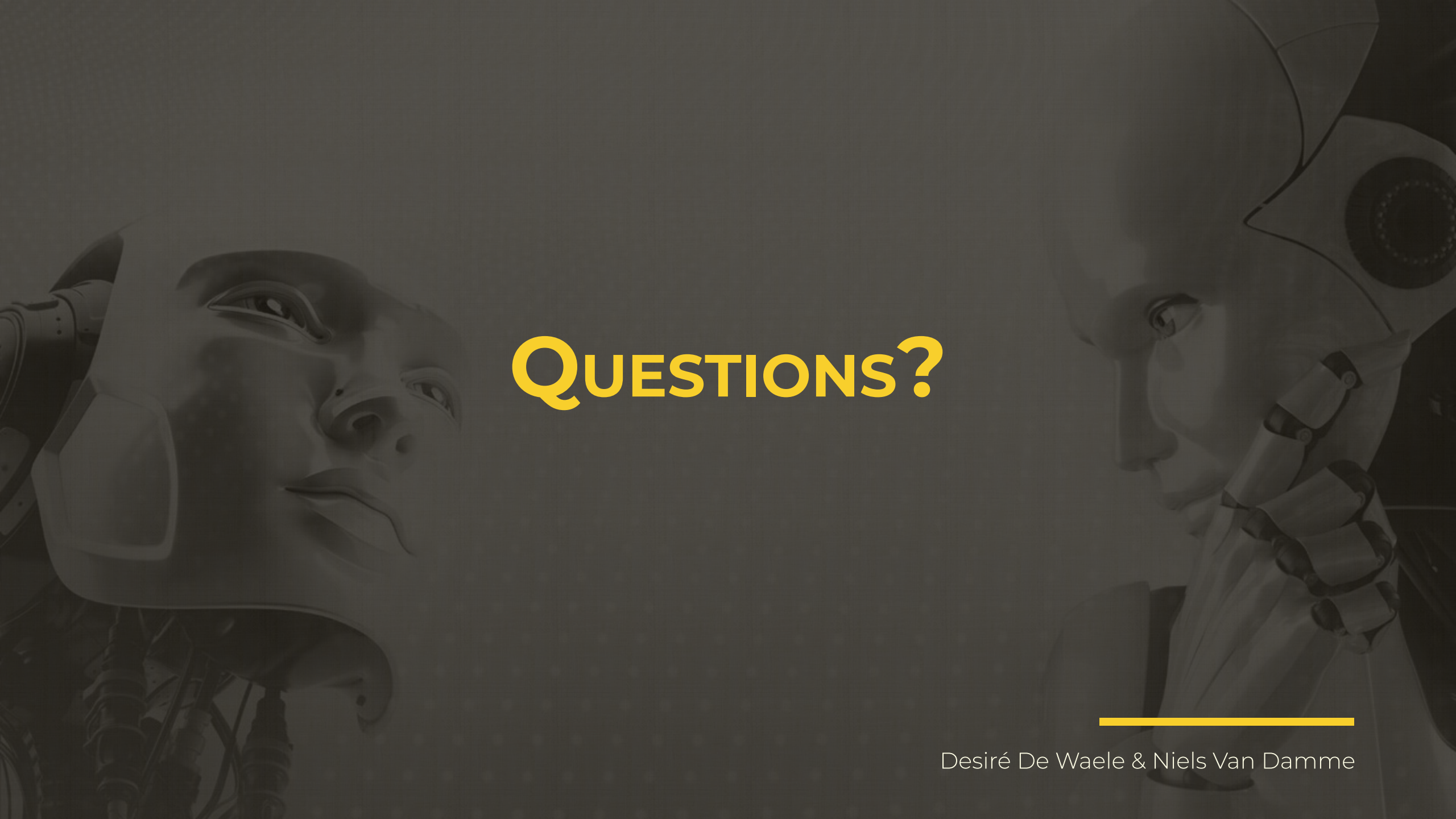
REINFORCEMENT LEARNING

INPUT

OUTPUT

SKILL LEARNING





QUESTIONS?

Desiré De Waele & Niels Van Damme

PART TWO. WHY INTRODUCE AI?

ADDED VALUE

VIRTUOUS CIRCLE OF AI

END-TO-END AUTOMATION

ACCESSIBILITY OF AI

ADDED VALUE

Reasons to prefer DL over other input transformations

SUPERIOR IN PERFORMANCE

DL generalizes other algorithms & tends to perform better

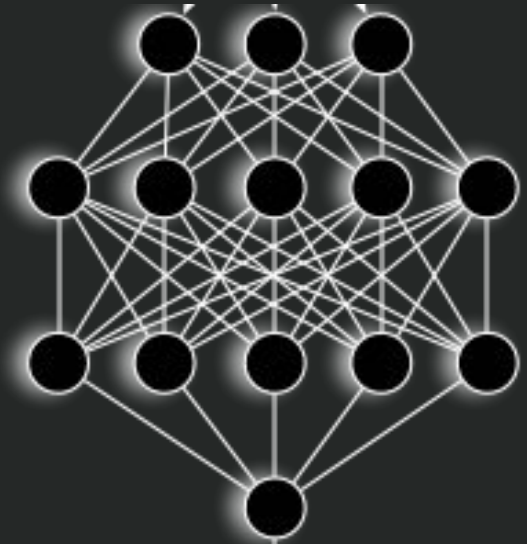
SCALES TO BIG DATA

DL algorithms can spot patterns in big data especially.

INPUT MELTING POT

Structured data, image data, sequential data... can be combined with less human intervention needed.

ADVANTAGES



ADDED VALUE

Pseudo reasons to prefer other input/output transformations over DL

EXPLAINABILITY

DL tends to be black box, but this area of DL is growing

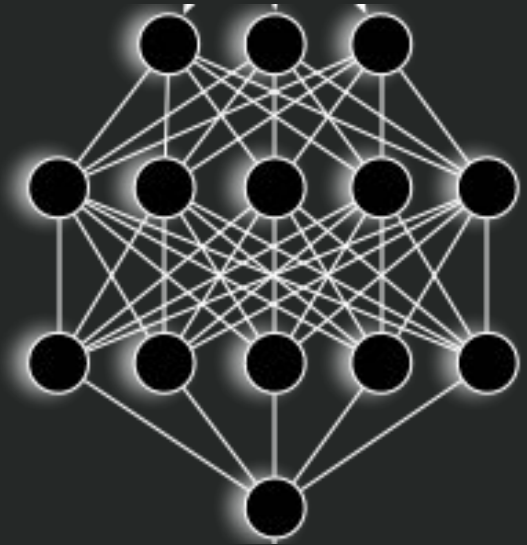
COMPUTATIONALLY INTENSIVE

DL requires computations which are heavy, but feasible

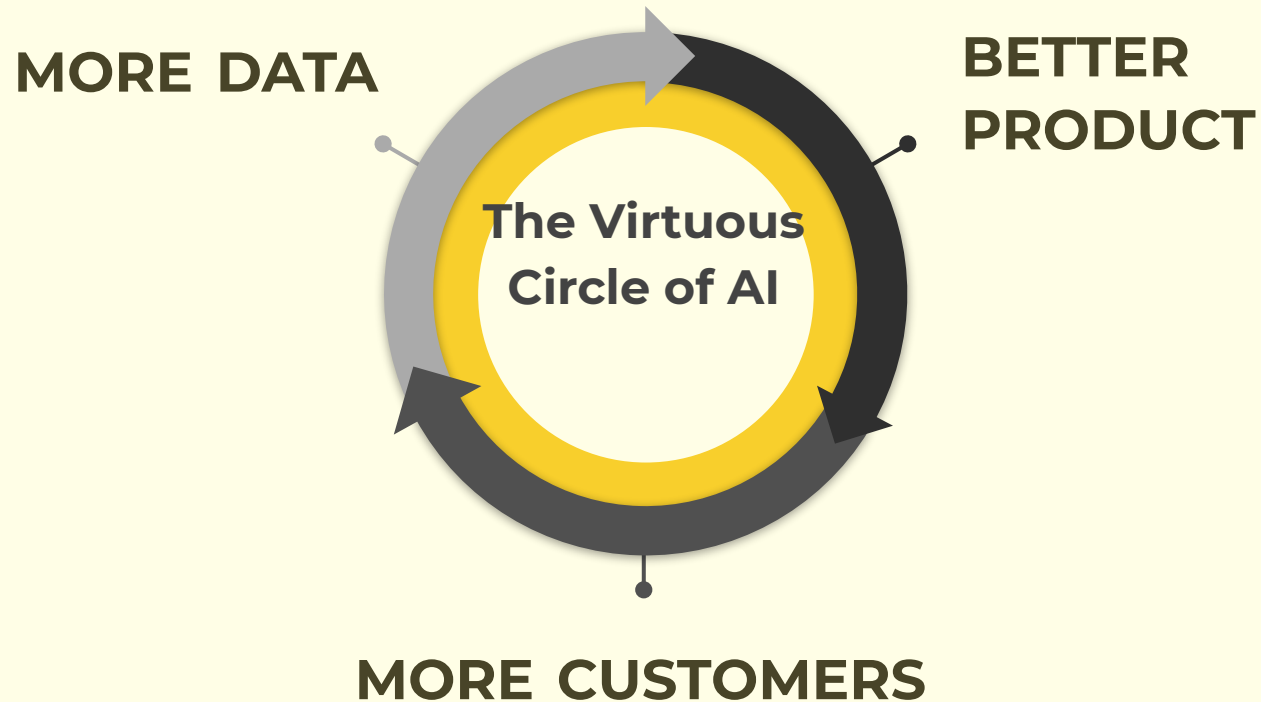
NOT YET WIDESPREAD

It takes effort to get your scientists up to speed

PSEUDO-DISADVANTAGES



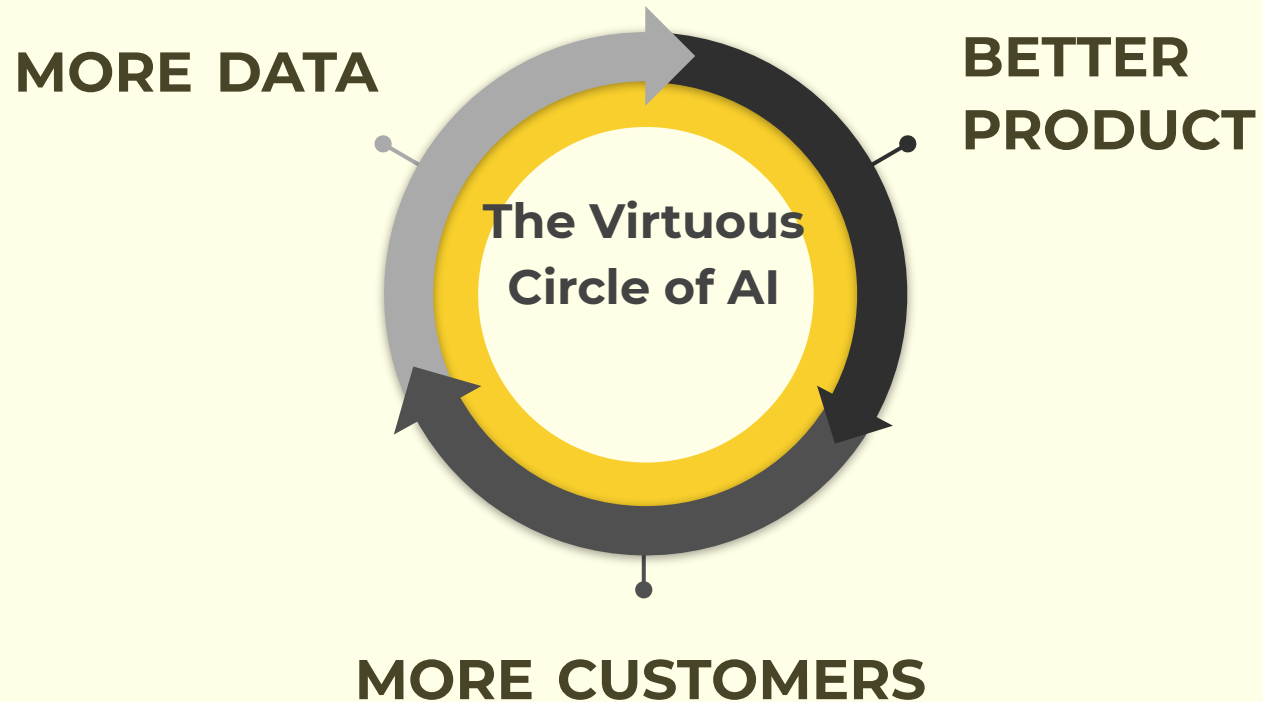
THE VIRTUOUS CIRCLE OF AI



*Get the wheel turning
as quickly as possible,
in your specialized,
vertical, domain.*

*Do NOT compare
yourself with Google,
Microsoft, Amazon, etc.*

THE VIRTUOUS CIRCLE OF AI



Companies that managed to get the wheel turning:

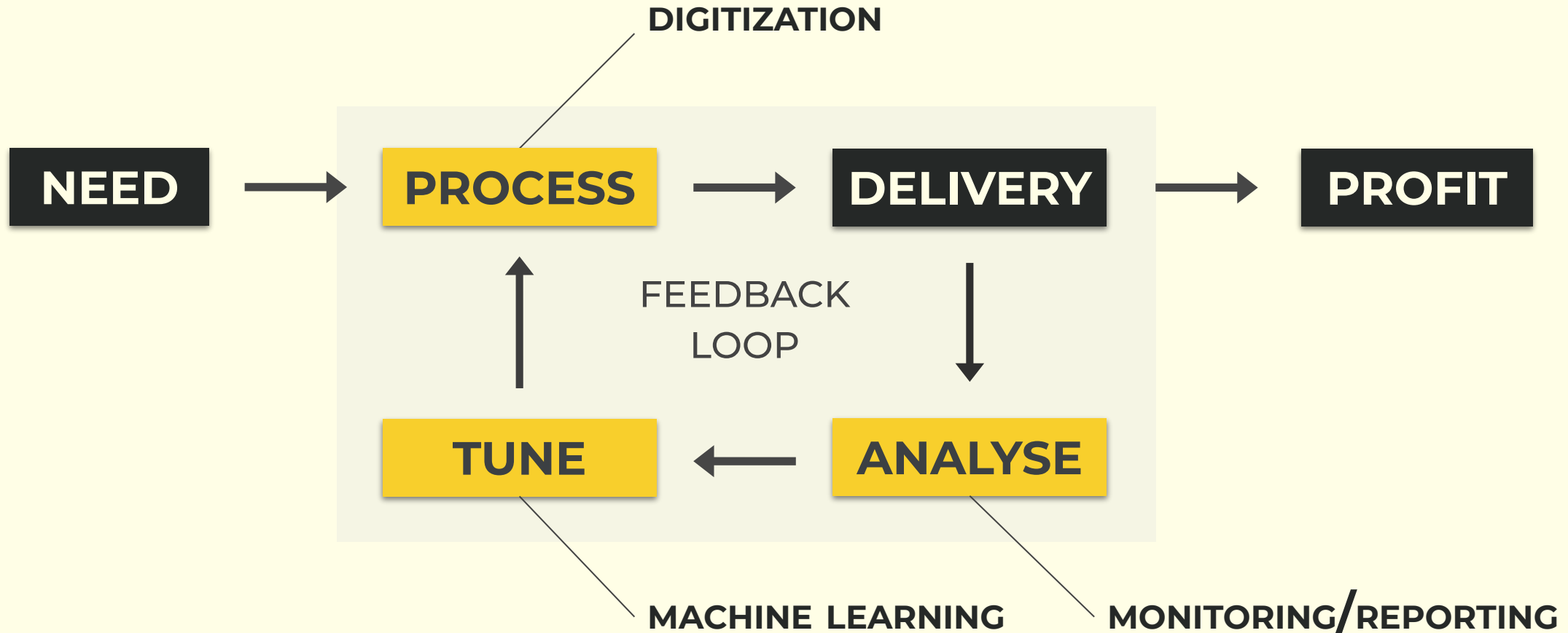
AB-InBev uses cash registration data to predict beer sales.

Foodpairing matches ingredients to find new recipes for chefs.

Iceberg sport's analytics predicts performance based on athletes' data.

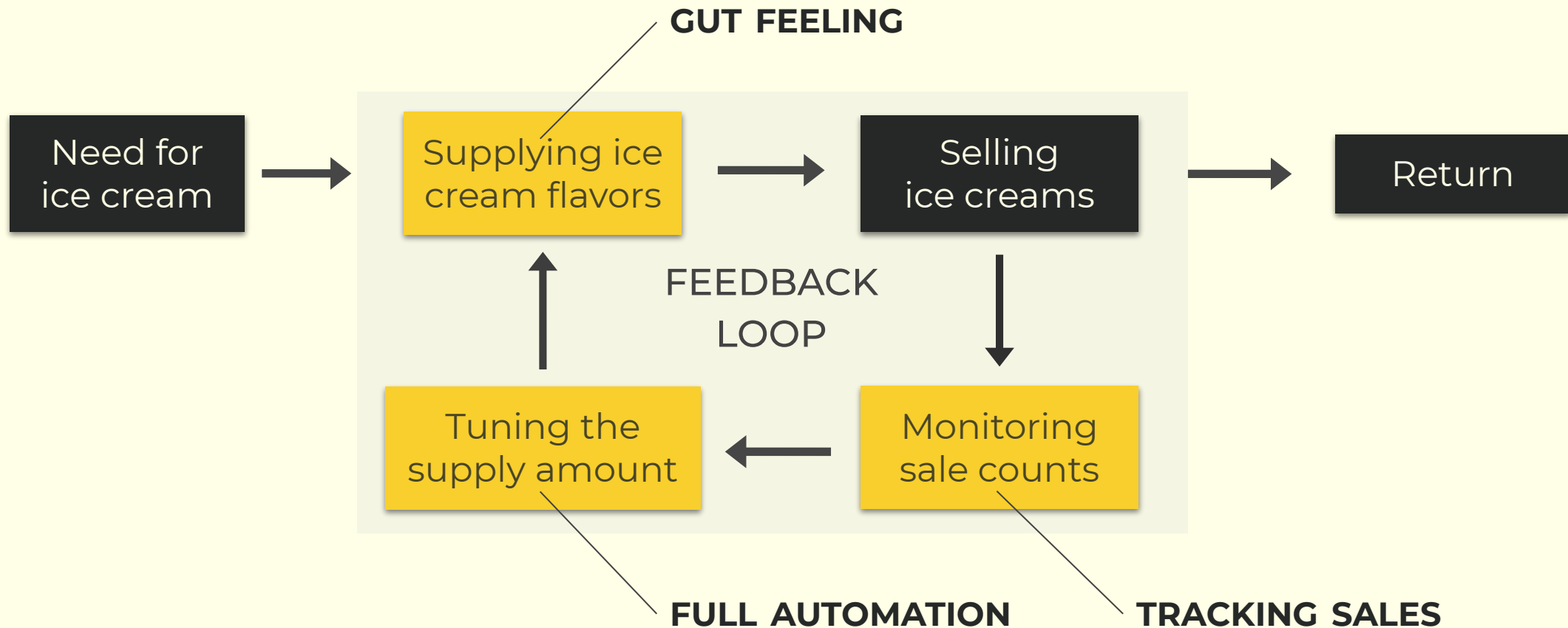
END-TO-END AUTOMATION

Automating the process, the analysis AND the tuning



END-TO-END AUTOMATION

Ice cream truck example



ACCESSIBILITY OF AI

BETTER HARDWARE

Hardware availability is a big factor in the scalability of ML applications.



MOORE'S LAW

Hardware doubles in capacity every 18 months



RISE OF GRAPHIC CARDS

GPU's allow for performant DL computing



CLOUD COMPUTING

High tech companies offer cheap hardware

ACCESSIBILITY OF AI

DATA GENERATION

We will be generating 163 ZB* data per year in 2025

INTERNET OF THINGS

True revolution is data generation, over remote control

DATA MONETIZING

Data is being traded as a product, or open-sourced

BIG DATA



Data is the fuel that drives deep learning applications.

*1 ZB or ZettaByte is a billion Terabytes

ACCESSIBILITY OF AI

BETTER ALGORITHMS

Although neural networks exist a long time, breakthroughs are emerging rapidly.

NEURAL NETWORKS EXIST SINCE THE 50's

Coined in 1958 by psychologist Frank Rosenblatt

BETTER ALGORITHMS EMERGED RECENTLY

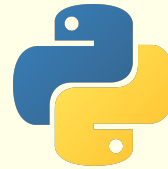
LSTM's, GRU's etc. are proposed by recent papers

CONTINUOUS BREAKTHROUGHS

Many things are yet to be discovered

ACCESSIBILITY OF AI

PYTHON



"Deep Learning has chosen Python"

TENSORFLOW



Developed and backed by Google for ML purposes

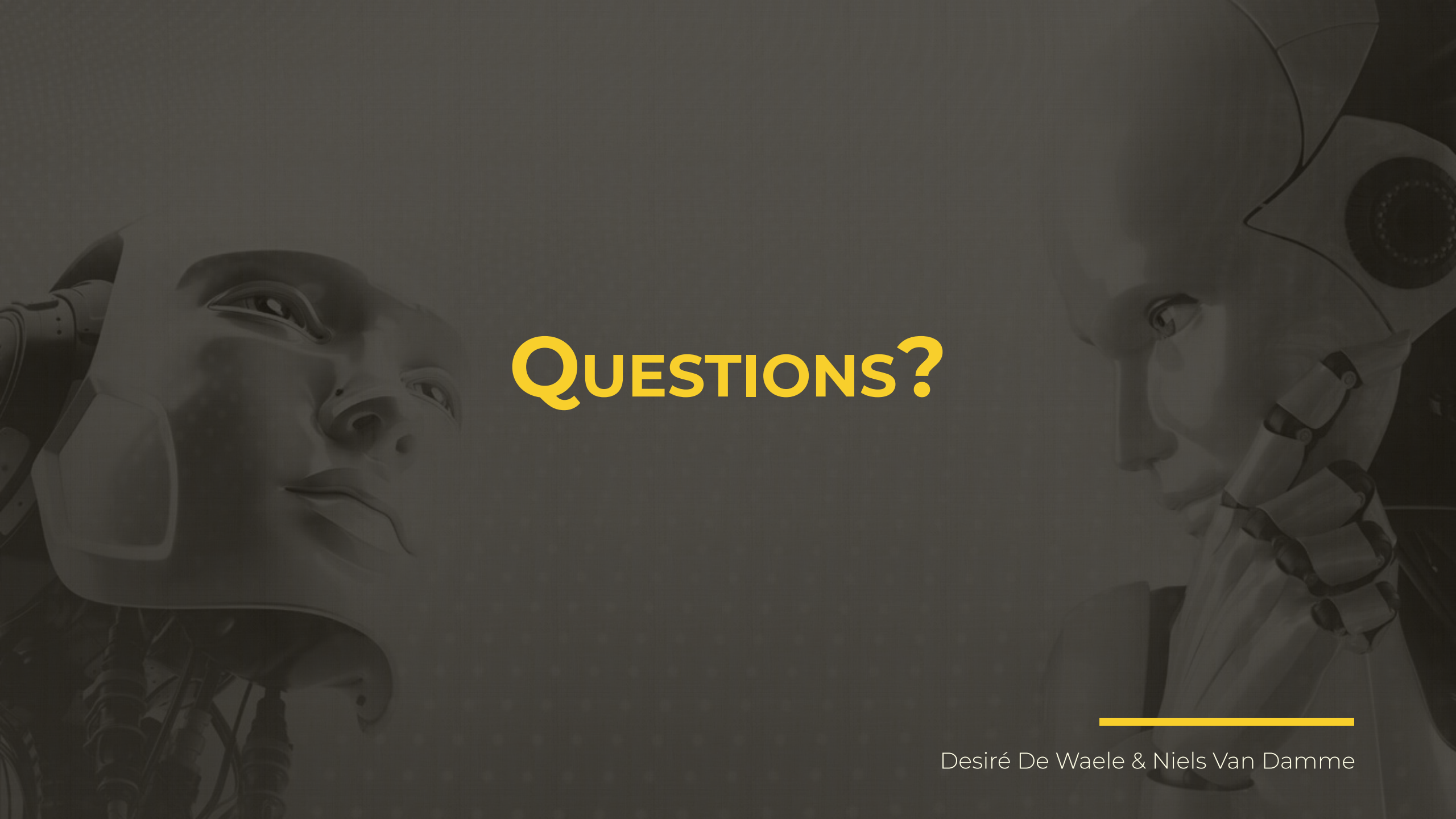
KERAS



High level software on top of tensorflow

BETTER TOOLING

Low level coding makes way for accessible, high level software and tools.



QUESTIONS?

Desiré De Waele & Niels Van Damme

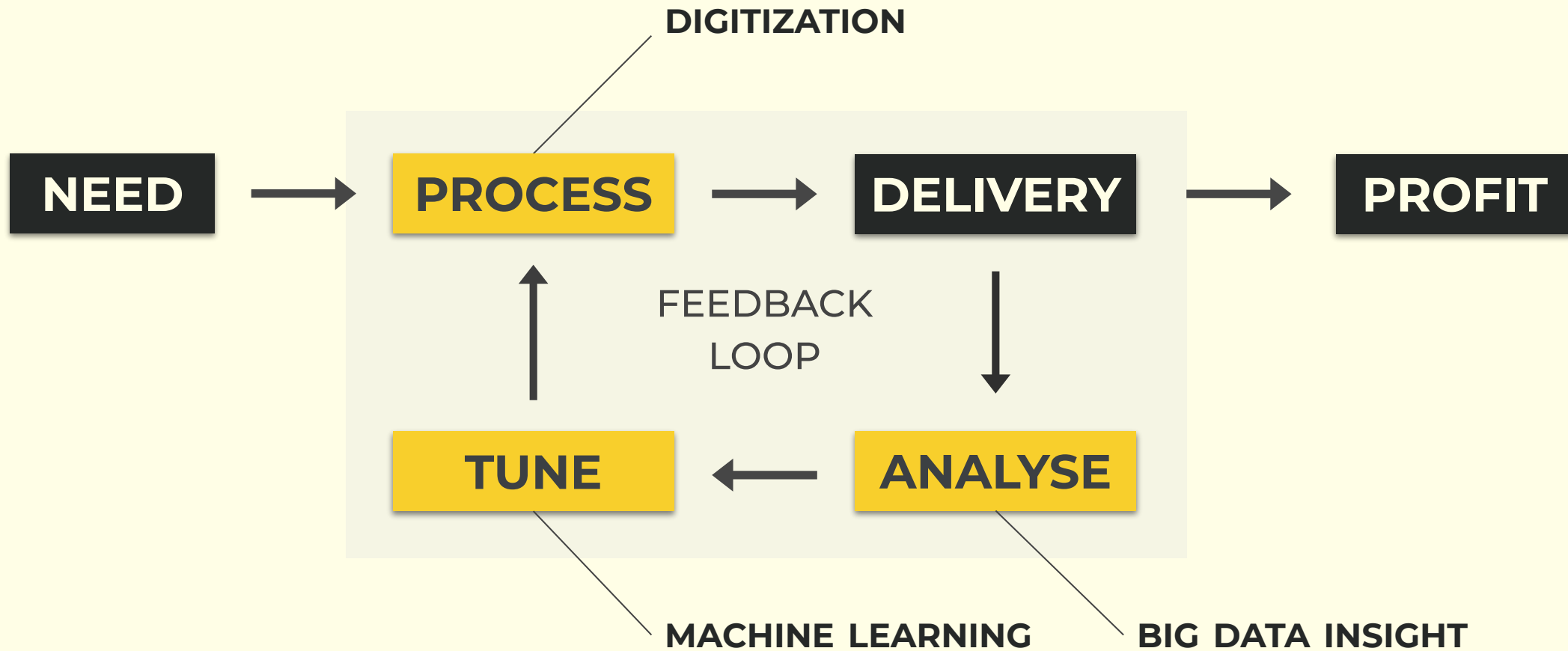
PART THREE. HOW TO INTRODUCE AI?

IDENTIFY USE CASES

TALENT RESOURCES

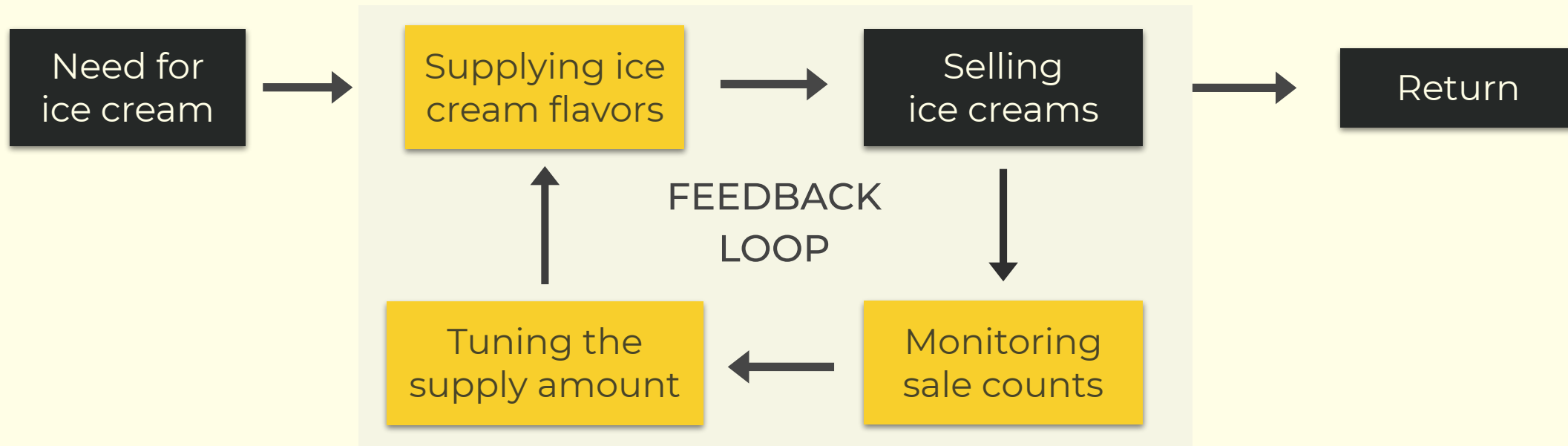
PROJECT ROADMAP

IDENTIFY POTENTIAL Use CASES



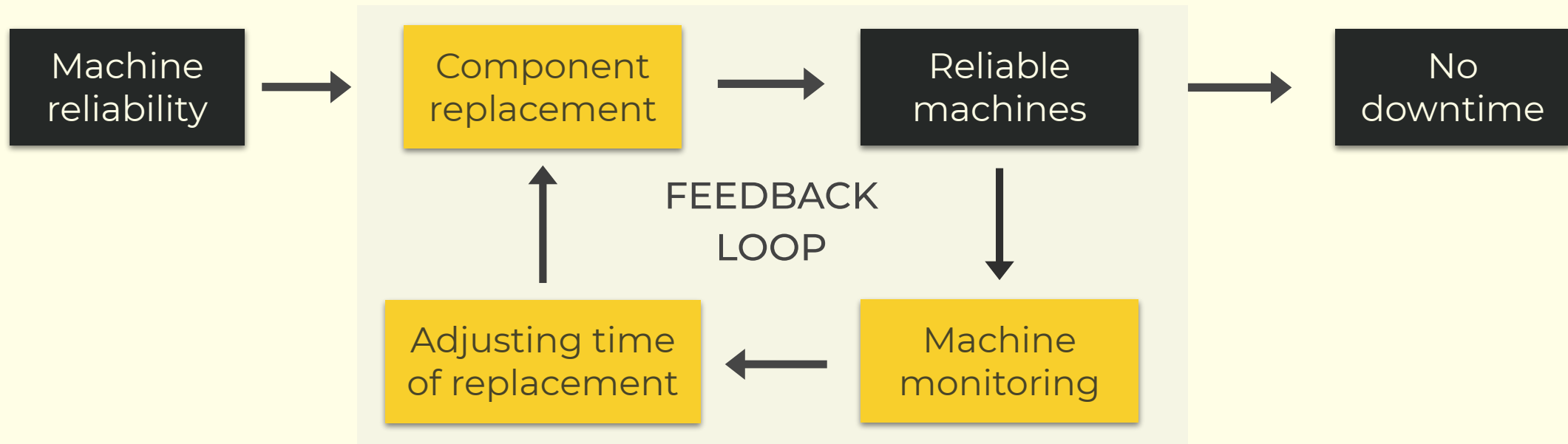
IDENTIFY POTENTIAL USE CASES

ICE CREAM TRUCK EXAMPLE



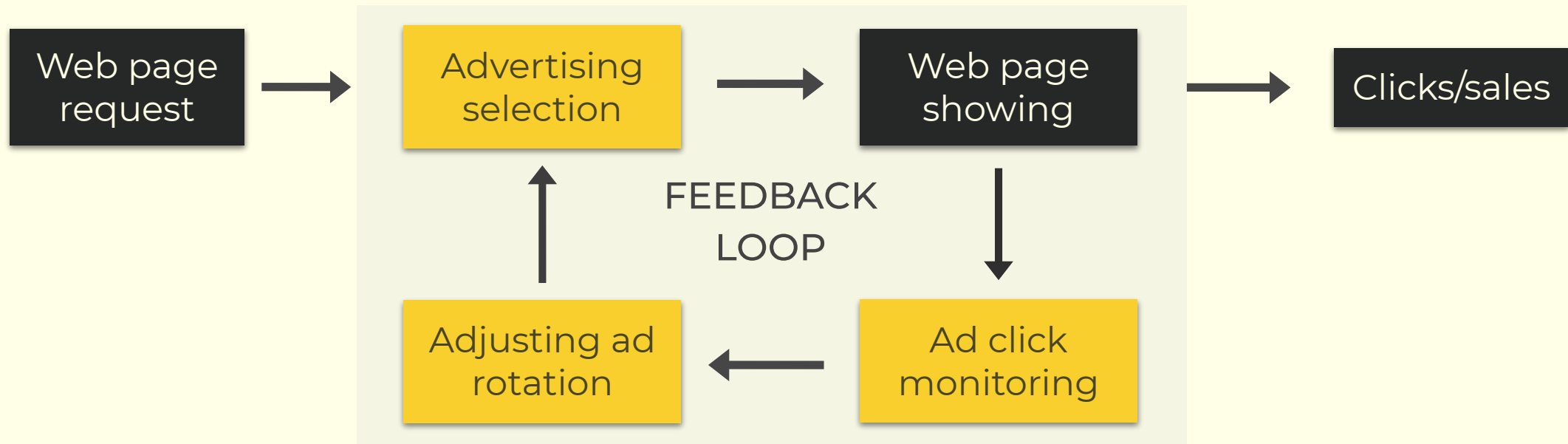
IDENTIFY POTENTIAL USE CASES

MACHINE MAINTENANCE EXAMPLE



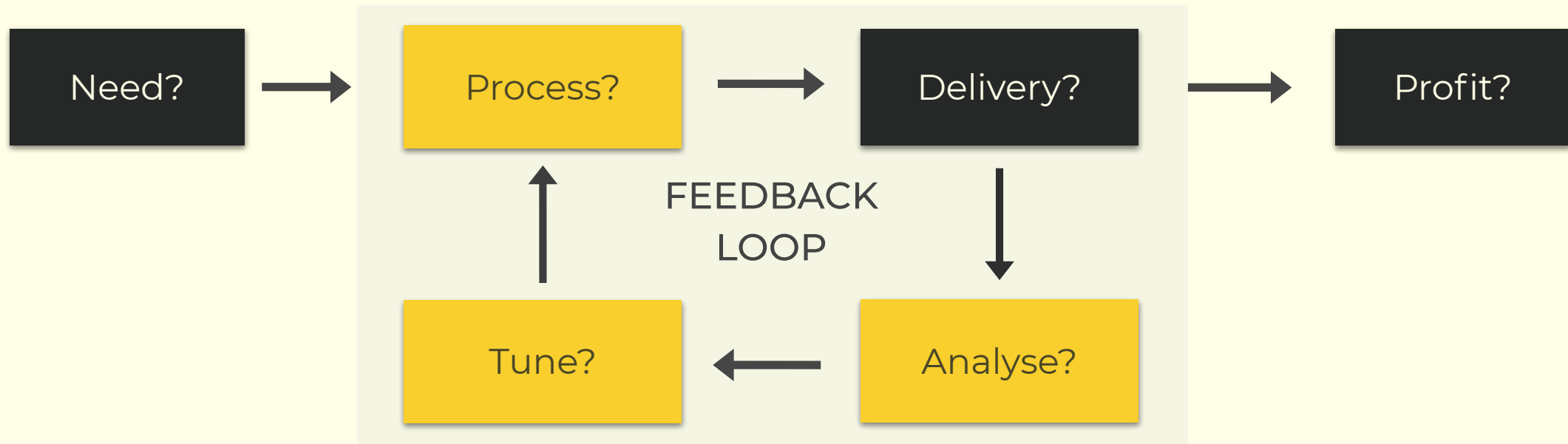
IDENTIFY POTENTIAL USE CASES

ONLINE ADVERTISING EXAMPLE

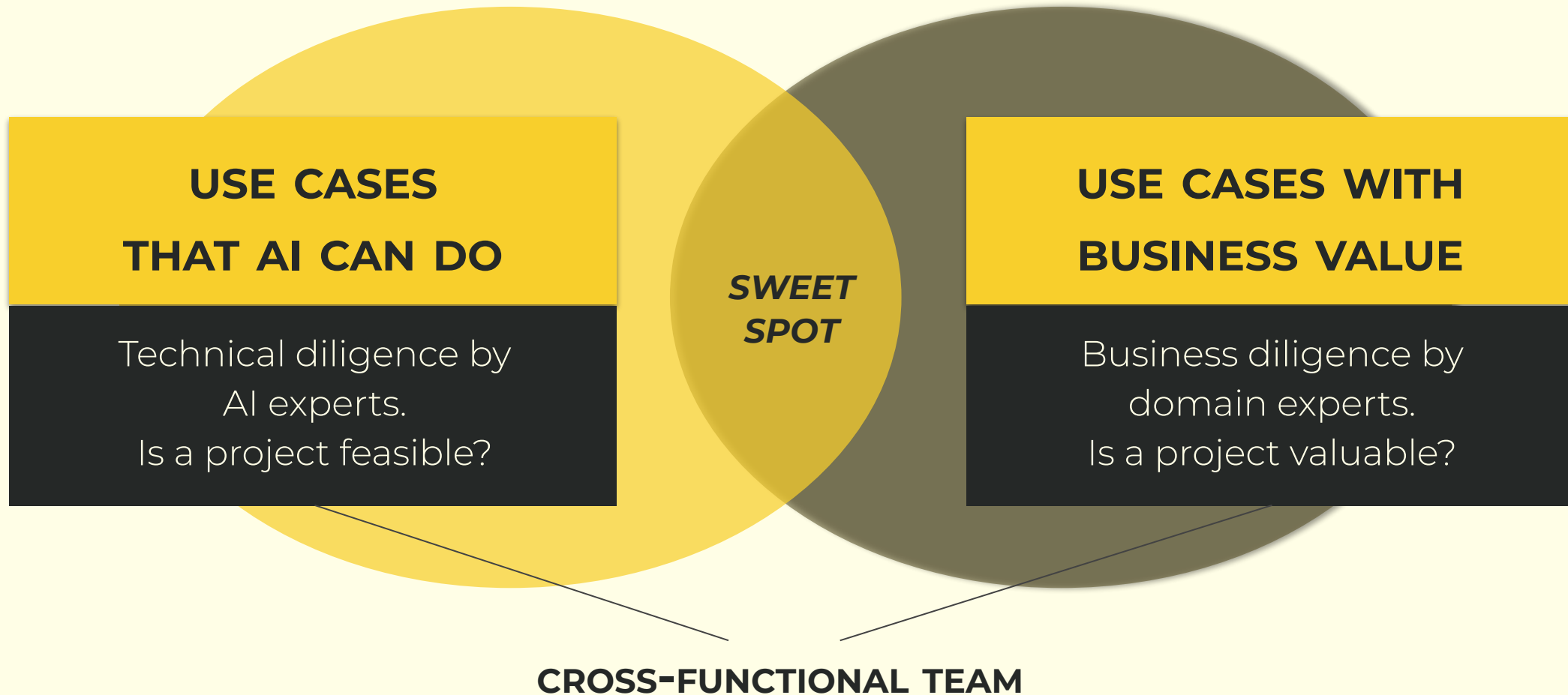


IDENTIFY POTENTIAL USE CASES

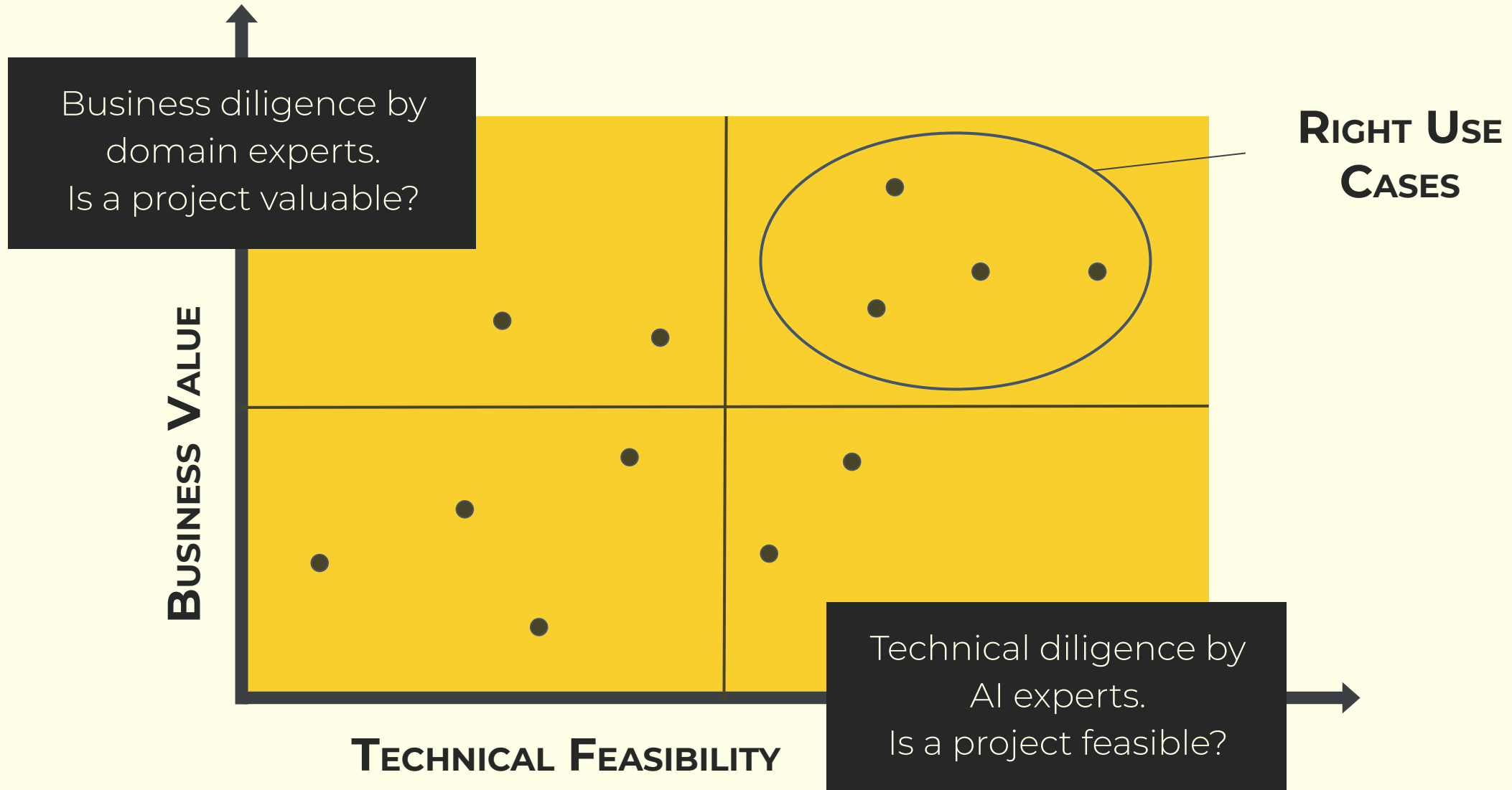
YOUR TURN!



IDENTIFY THE RIGHT USE CASES



IDENTIFY THE RIGHT USE CASES



TALENT RESOURCES



HOW TO BUILD RESOURCES

From an AI perspective

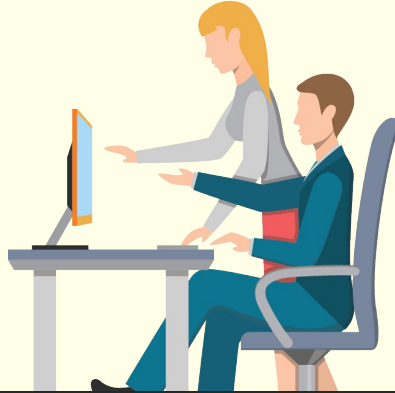
TECHNICAL CURRICULUM

Develop your own, or use the one we propose

Desiré De Waele & Niels Van Damme

HIRING OR TEACHING - AI CONSIDERATIONS

TEACH AI TALENT



Digital AI education

- ❖ Highly available for AI
- ❖ Changes dynamically
- ❖ Centered skill set in AI
- ❖ Pragmatically oriented

HIRE AI TALENT



Academic AI education

- ❖ Slowly emerging for AI
- ❖ Changes statically
- ❖ Broad skill set around AI
- ❖ Theoretically oriented

DEVELOP A DIGITAL CURRICULUM

“DON’T CREATE, BUT CURATE”

Everything is out there, don’t reinvent the wheel.

AIM FOR A UNIFORM SKILL SET

Resources acquire the same proficiencies.

CURRENT INDUSTRY STANDARDS

Digital content is up to date and made by industry experts.

 coursera

 edX

 Udemy

 DataCamp

 UDACITY

 Khan Academy

 Linked in

 YouTube

OR USE OUR CURRICULUM

FROM SCRATCH TO PROFESSIONAL IN UNDER **500** HOURS

Starting from zero skills, to applying AI professionally.

PEOPLE GET IN AT THEIR LEVEL

Often, people have a skill set and don't start from scratch.

CAN BE AN ACCEPTANCE REQUIREMENT

MOOCS* offer certificates upon completion.

*Massive Open Online Course

 coursera

 edX

 Udemy

 DataCamp

 UDACITY

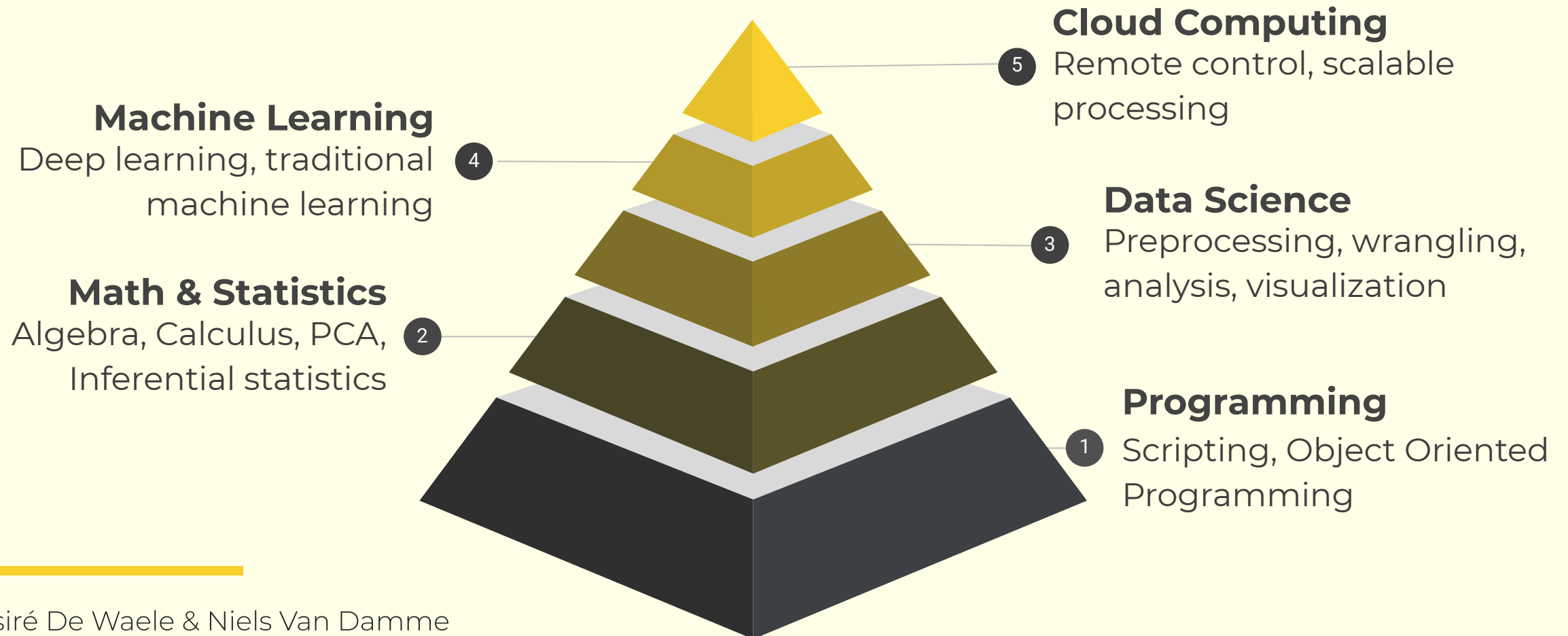
 Khan Academy

 Linked in

 YouTube

DIGITAL CURRICULUM

Five components for end-to-end machine learning



DIGITAL CURRICULUM

Five components for end-to-end machine learning

		Skills	Tooling
01	Programming	Scripting, Object Oriented Programming	Python, SQL, Bash, Git
02	Math & Statistics	Algebra, Calculus, PCA, Inferential statistics	-
03	Data Science	Preprocessing, wrangling, analysis, visualization	Jupyter, Numpy, Pandas, Plotly
04	Machine Learning	Deep learning, traditional machine learning	Sklearn, Tensorflow, Keras, Pytorch
05	Cloud Computing	Collaboration, remote control, scalable processing	GCP, AWS, Linux

DIGITAL CURRICULUM

01

Programming

Scripting, Object
Oriented Programming

Python, SQL, Bash,
Git

01

Python 3 Specialization

Coursera

[Link](#)

60 hours

43€

Five courses on Python fundamentals, data processing, scripting and classes/inheritance.

02

The Unix Workbench

Coursera

[Link](#)

15 hours

Free

Course on the command line interface. Independent IT language lying at the base.

03

SQL Beginner's Course

FreeCodeCamp

[Link](#)

4 hours

Free

Course on SQL, number one language for data retrieval.

04

Git Essential Training

LinkedIn

[Link](#)

6 hours

Free

Training on version control. Optimize workflow and collaboration.

DIGITAL CURRICULUM

02

Math & Statistics

Algebra, Calculus, PCA,
Inferential Statistics

-

01

Statistics Specialization

Coursera

[Link](#)

50 hours

43€

Three courses on data fundamentals, inferential statistics, and model fitting.

02

Math for ML Specialization

Coursera

[Link](#)

60 hours

43€

Three courses on linear algebra, multivariate calculus and principal component analysis.

DIGITAL CURRICULUM

03

Data Science

Data Preprocessing,
wrangling, visualization

Jupyter, Numpy,
Pandas, Plotly

01

Data Science Specialization

Coursera

[Link](#)

90 hours

43€

Five courses on data processing, visualization, text mining and machine learning.

02

Visualization with Plotly & Dash

Udemy

[Link](#)

20 hours

10€

Course on the number one open source visualization tool.

03

End-to-end Analysis Pipeline

Kaggle

[Link](#)

40 hours

Free

Pick three Kaggle datasets to perform analysis and report insight.

DIGITAL CURRICULUM

04

Machine Learning

Deep learning, traditional machine learning

Sklearn, Tensorflow, Keras, Pythorch

01

Deep Learning Specialization

deeplearning.ai

[Link](#)

80 hours

43€

Five courses on data processing, visualization, text mining and machine learning.

02

Machine Learning Yearning

deeplearning.ai

[Link](#)

20 hours

Free

Book with over 50 machine learning best practices that are short, practical and valuable.

03

End-to-end Modelling Pipeline

Kaggle

[Link](#)

40 hours

Free

Pick three Kaggle datasets (structured, visual, sequential) to build a model for prediction.

DIGITAL CURRICULUM

05

Cloud Computing

Collaboration, remote control, scalable processing

GCP, AWS, Linux

01

ML on Google Cloud Platform

Coursera

[Link](#)

80 hours

43€

Ten courses on data processing, visualization, text mining and machine learning.

02

ML on Amazon Web Services

Amazon

[Link](#)

20 hours

Free



PROJECT ROADMAP

*A PROJECT MANAGER'S
PERSPECTIVE*

FIVE STAGES

From defining metrics to model deployment.

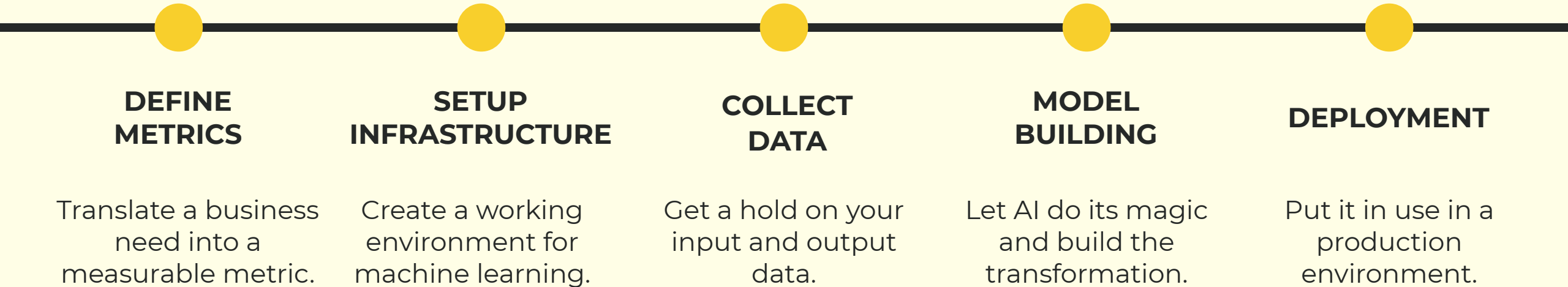
ROADMAP TIMELINE

Set the right expectations for your project.

Desiré De Waele & Niels Van Damme

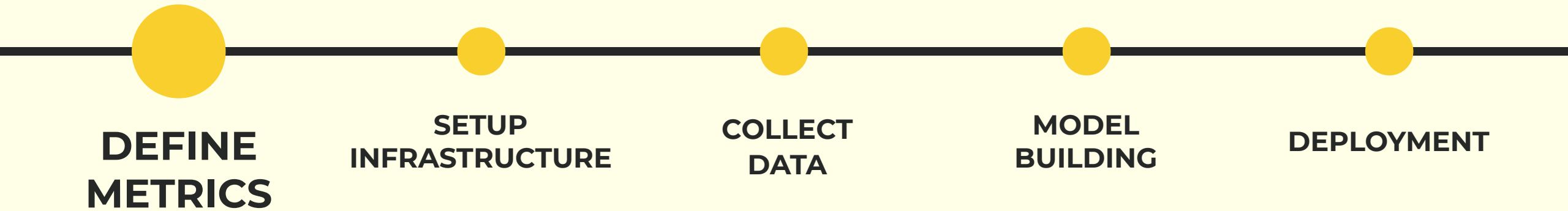
PROJECT ROADMAP

Best practices from an AI perspective



PROJECT ROADMAP

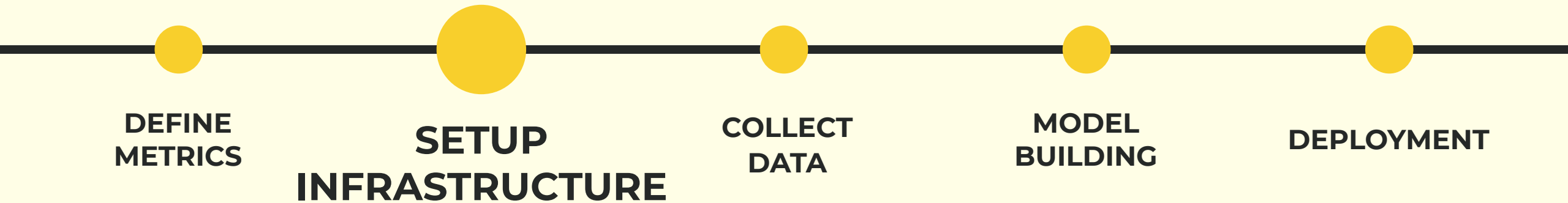
Best practices from an AI perspective



- *Define a measurable metric*
- *Split a metrics in various sub-metrics*

PROJECT ROADMAP

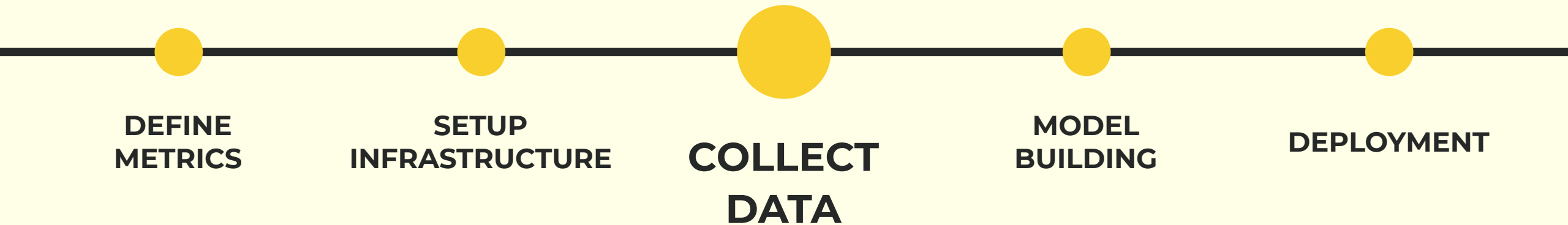
Best practices from an AI perspective



- *Have a cloud or local environment*
- *Develop with reproducibility in mind*

PROJECT ROADMAP

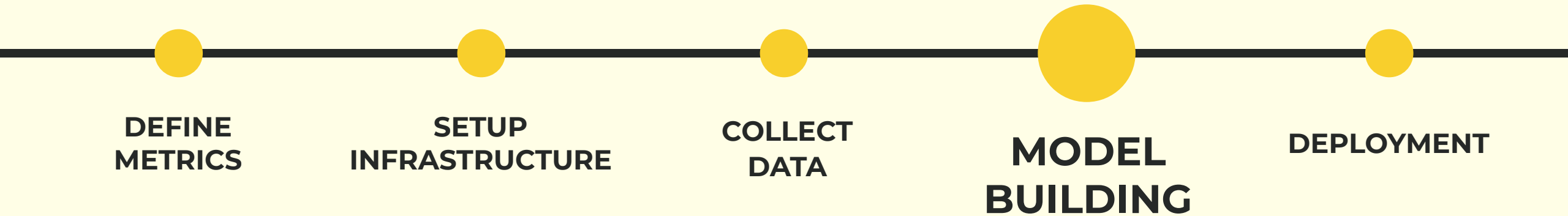
Best practices from an AI perspective



- *Iterate quickly with subsamples*
- *Consider present before absent data*

PROJECT ROADMAP

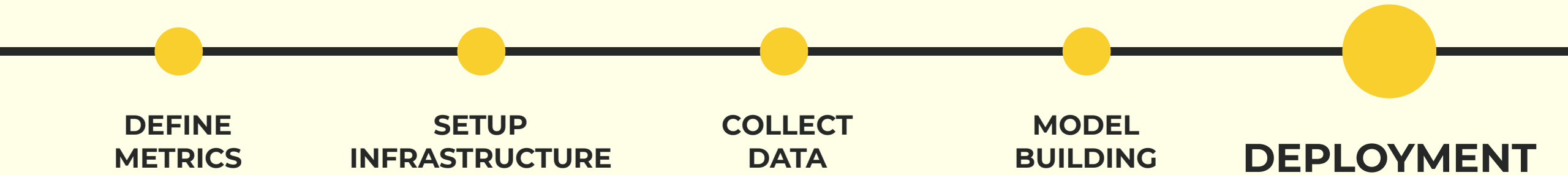
Best practices from an AI perspective



- *Evaluate models asap, only then scale up*
- *Don't keep fine tuning, do deliver with timeboxing*

PROJECT ROADMAP

Best practices from an AI perspective



- *Benefit from reproducibility*
- *Evaluate models before and after deployment*

ROADMAP TIMELINE



EXPECTATION



REALITY



BEST PRACTICES

GAIN MOMENTUM

Get the ball rolling with a medium sized project, having a high success probability

START WITH A SMALL TO MIDDLE SIZED PROJECT

Big enough to be noticed, without taking high risks.

ENSURE A HIGH SUCCESS PROBABILITY

It will act as a reference for future projects.

CAN BE IN- OR OUTSOURCED

Only goal is to get the ball rolling, remove AI scepticism.

THREE TAKEAWAYS

I. IDENTIFY USE CASES

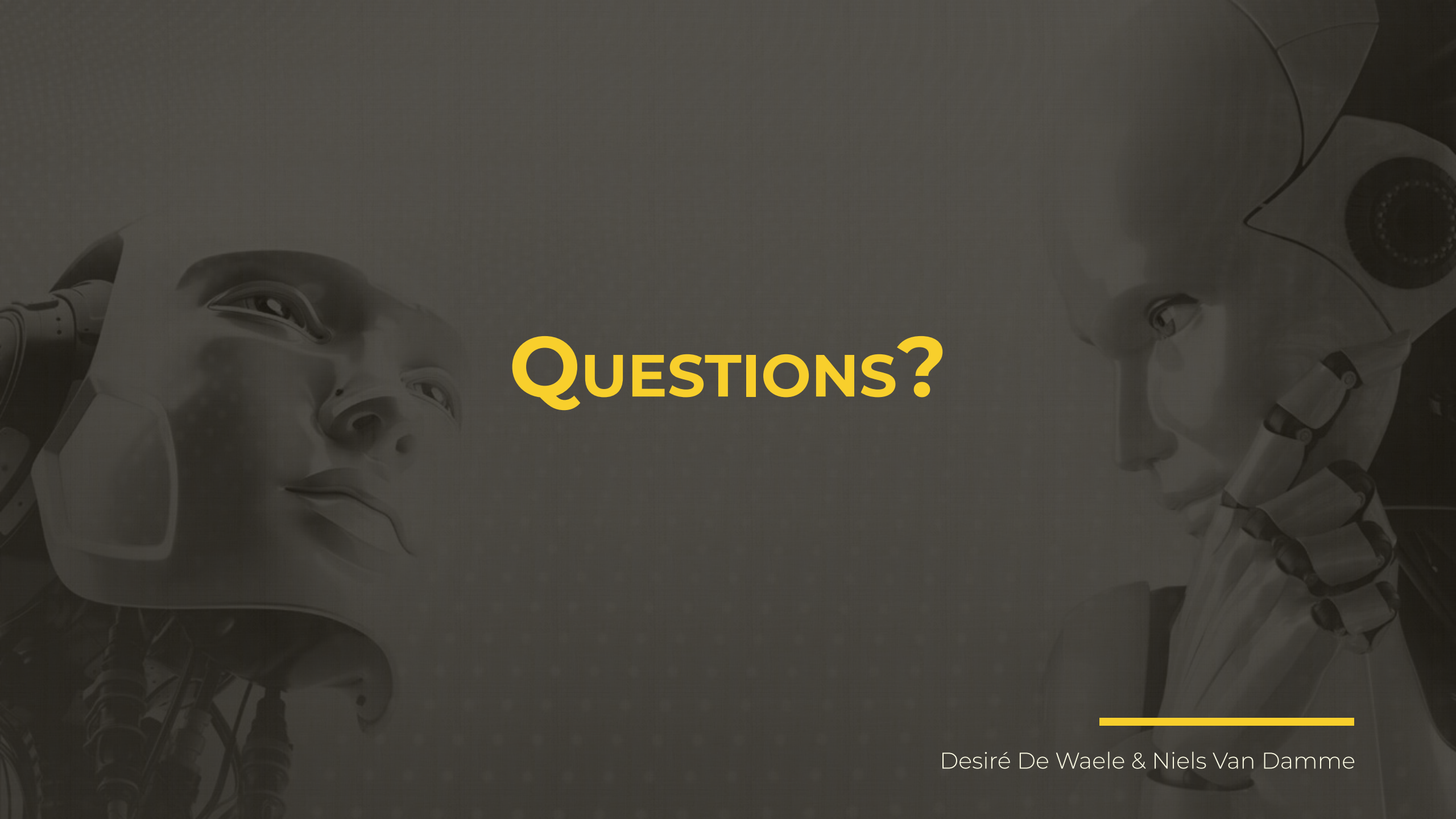
By systematically listing potential feedback loops

II. CURATE A CURRICULUM

Look for digital content that teaches required skills

III. PLAN A ROADMAP

With attention for potential pitfalls per step



QUESTIONS?

Desiré De Waele & Niels Van Damme

PARTIAL SOURCE

Desiré De Waele & Niels Van Damme

AI FOR EVERYONE

Course taught by AI's leading man Andrew Ng,
offered on Coursera.org



Deeplearning.ai



Google Brain Team



LET'S TALK

Reach out to us

MAIL

dewaele.desire@gmail.com
ndc.van.damme@gmail.com

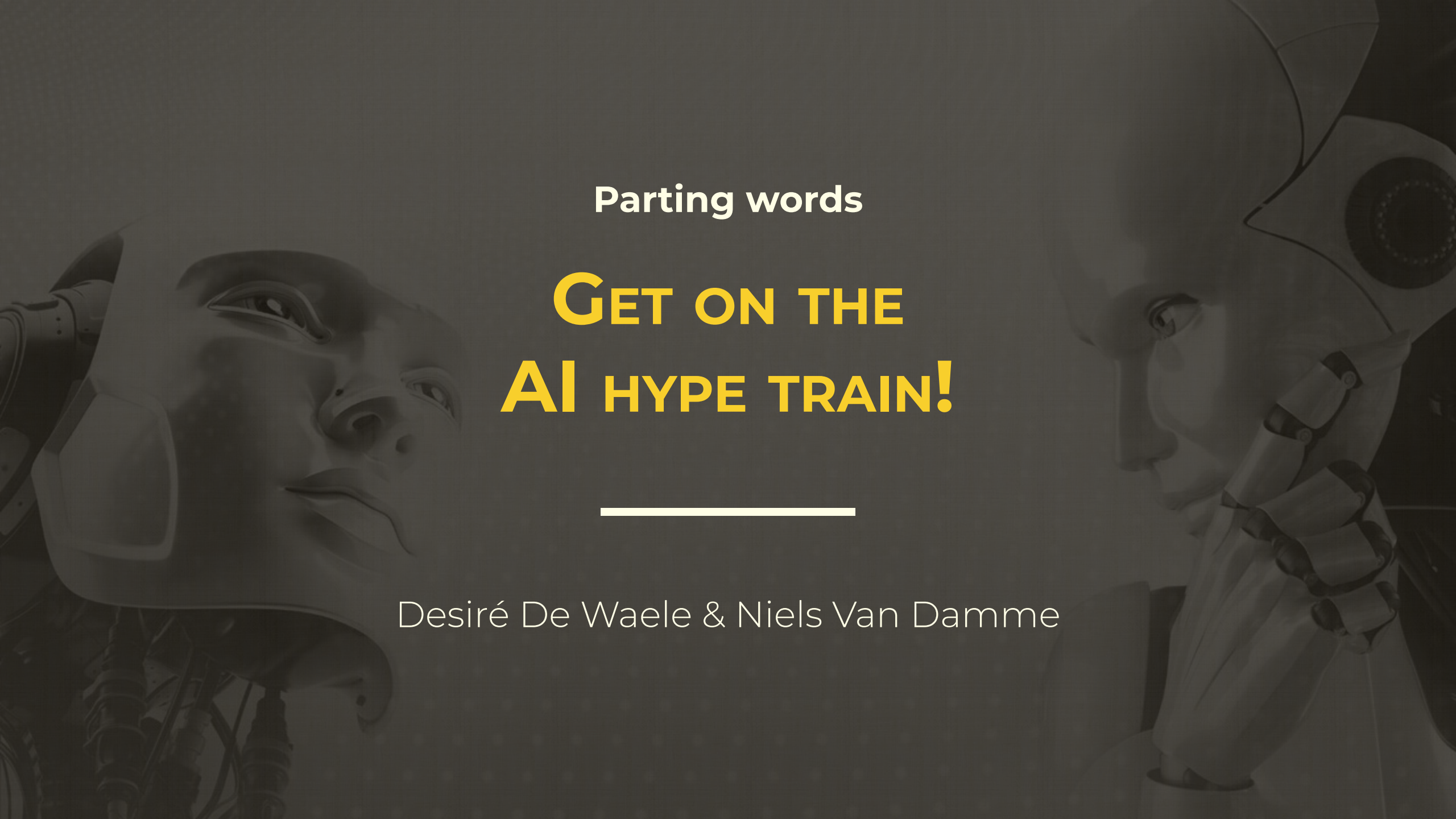
LINKEDIN

Desiré De Waele
Niels Van Damme

WEBSITE

learnfromdata.ai/workshop

Desiré De Waele & Niels Van Damme



Parting words

GET ON THE AI HYPE TRAIN!

Desiré De Waele & Niels Van Damme