

HOW AI (AND DATA) HAVE BEEN CHANGING THE GAME IN THE AUTOMOTIVE INDUSTRY

NEW TRENDS, CHALLENGES
AND POTENTIAL SOLUTIONS

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AGENDA



1 ARTIFICIAL
INTELLIGENCE
vs SOFTWARE
KEY CONCEPTS

2 COMBINING VERY
DIFFERENT
ENGINEERING
LIFECYCLES

3 OVERVIEW OF
AI APPLICATIONS

4 EXAMPLE:
EMBEDDED SAFETY CRITICAL
SYSTEM RELYING ON
AI-POWERED CLOUD SERVICES

1

**ARTIFICIAL
INTELLIGENCE
vs SOFTWARE**

KEY CONCEPTS

AI & GENERATIVE AI – (TECHNICAL) DEFINITIONS



- > **ISO/IEC 22989** First edition (2022-07)
 - > **AI**: research and development of mechanisms and applications of AI systems
 - > **AI system**: engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives

**What it DOES
more than
what it really IS!**

- > **3 questions that are important to me**
 - > **How we (humans) create AI models.**
 - > **Why? What are the benefits?**
 - > **Are there any downsides?**

- > **AI Act (2024)**
 - > **AI system** means a machine-based system designed to operate with varying levels of autonomy and that may exhibit **adaptiveness after deployment** and that, for **explicit or implicit objectives**, infers, from the input it receives, how to **generate outputs** such as **predictions, content, recommendations, or decisions** that can influence physical or virtual environments
 - > **General Purpose AI model (GPAI)** means an AI model, including when trained with a large amount of data using self-supervision at scale, that **displays significant generality and is capable to competently perform a wide range of distinct tasks** regardless of the way the model is placed on the market and that can be integrated into a variety of downstream systems or applications.

DECODING AI: 2 FUNDAMENTAL CONCEPTS

HOW WE (HUMANS) CREATE AI MODELS | **LEARNING, TRAINING**



2016

W I R E D

BACKCHANNEL BUSINESS CULTURE GEAR IDEAS SCIENCE SECURITY

SIGN IN

SUBSCRIBE



JUNE 2016. SUBSCRIBE NOW.

JASON TANZ

IDEAS 05.17.2016 06:50 AM

Soon We Won't Program Computers. We'll Train Them Like Dogs

Welcome to the new world of artificial intelligence. Soon, we won't program computers. We'll train them. Like dolphins. Or dogs. Or humans.



DECODING AI: 2 FUNDAMENTAL CONCEPTS

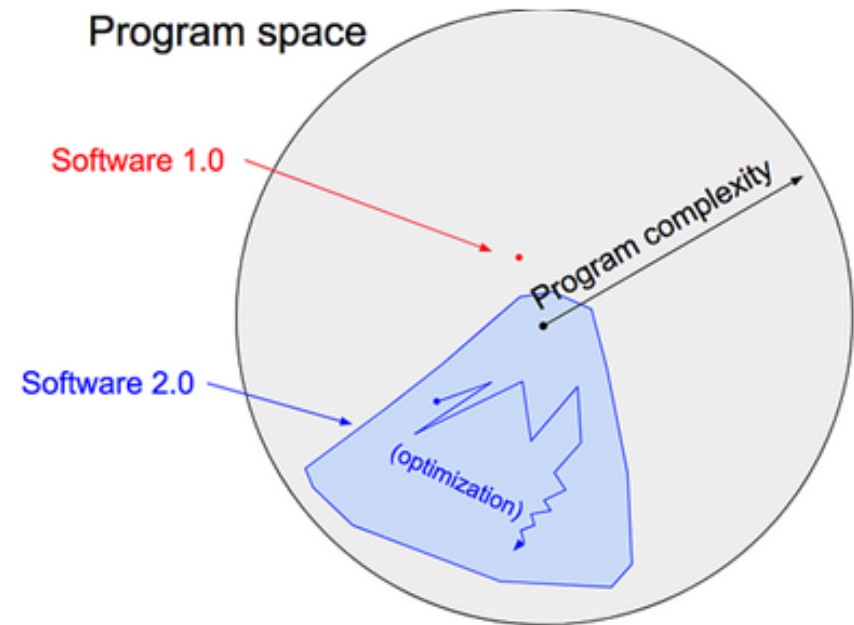
HOW WE (HUMANS) CREATE AI MODELS | **LEARNING, TRAINING**

- > Software 2.0: No need that we (humans) must describe step-by-step solutions in an algorithm
- > But still, humans organize and control the **data-driven training** of ML models
- > A **lot** of different approaches and techniques:
 - > **Complex** architectures (created by humans!)
 - > New concepts **every day/week**
 - > Most of them **open-source**
- > Machine Learning, Neural Networks, Deep Learning
- > Reinforcement Learning
- > Supervised Learning, Unsupervised Learning, **Self-supervised Learning**
- > Autoencoders
- > Generative Adversarial Networks
- > Diffusion Models
- > **Transformers (attention)**
- > Mamba (structured state space models)
- > **Generative AI**
- > Pretrained models, Foundation models
- > ...

2017

Software 2.0

 Andrej Karpathy Nov 11, 2017 · 9 min read



source: <https://karpathy.medium.com/software-2-0-a64152b37c35>

DECODING AI: 2 FUNDAMENTAL CONCEPTS

WHY USING AI? THE ABILITY TO **GENERALIZE**

- > ML model are capable of **generalization**
 - > Predictive AI: **Make (good) predictions from input data that have not been seen during training**
 - > Warning: out-of-distribution problem:
 - > unreliable predictions when encountering inputs significantly different from those seen during training

- > AI models are best suited for problems that can leverage generalization capabilities:
 - > eg: computer vision (cameras)
 - > High dimensionality, “Large” problems
 - > “Open” problems, possibly not completely defined, with many acceptable, “almost” optimal solutions
 - > Complex decisions at a constant computation cost



Semantic Segmentation
 Examples of DeepLabv3 Visualization results on Cityscapes dataset
<https://arxiv.org/pdf/1706.05587v3.pdf>

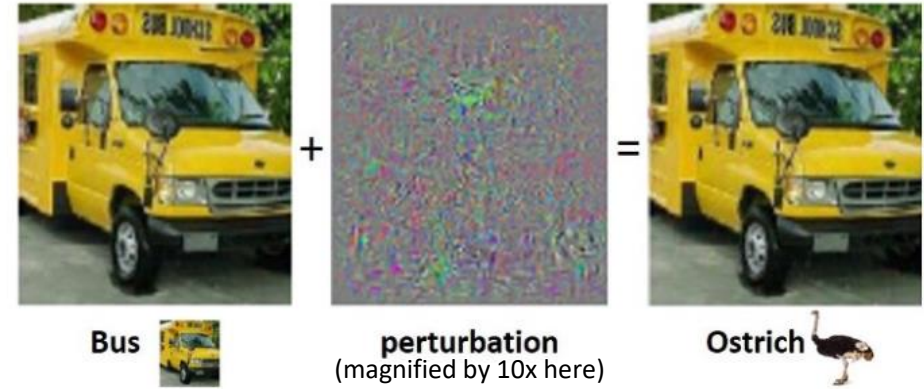
THE FLIP SIDE OF AI CAPABILITIES

LEARNING AND GENERALIZATION COME AT A PRICE...

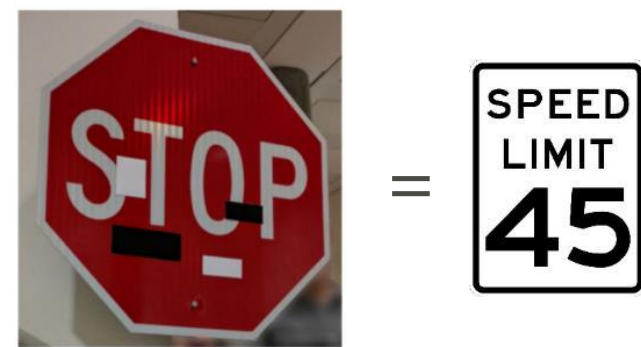
- > What does “good predictions” mean?
 - > We cannot list all possible cases (and requirements)!
 - > We cannot just look at the neural network weights!
 - > Chaos theory, strong dependence on initial conditions
 - > Sparsity, only a small portion of the input space contains significant data points or information

Always a confidence level < 100%

- > Consequence: many **transformation** stakes!
 - > Engineering processes for data and AI systems are **radically different** than software development
 - > Need for **new trustworthiness concepts** and indicators (never 100%)



Source “Intriguing properties of neural networks”
<https://arxiv.org/abs/1312.6199>



Source “Robust Physical-World Attacks on Deep Learning Models”
<https://arxiv.org/abs/1707.08945>



GENERATIVE AI – A STEP BEYOND

GENERATING DATA THAT ARE SIMILAR TO TRAINING DATA

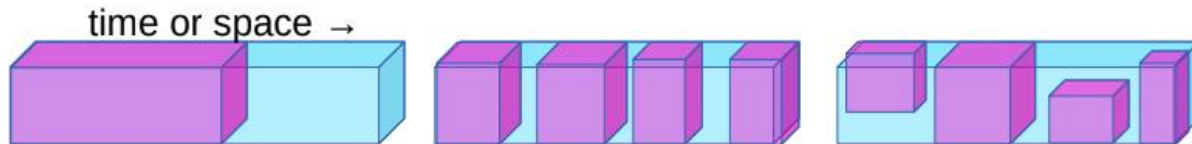
- > Learning **scaled to the limits** with Self-Supervised Learning
 - > The “guess the next word” game is quite easy to setup
 - > Same for “guess the noise I’ve added” for images
- > Very large scale
 - > Models with billions of parameters (1B to 500B)
 - > Training data: 1 to 2 trillion tokens
- > After such massive training, surprising capabilities are emerging
- > “Confidence level” has no sense anymore!

No more confidence level!

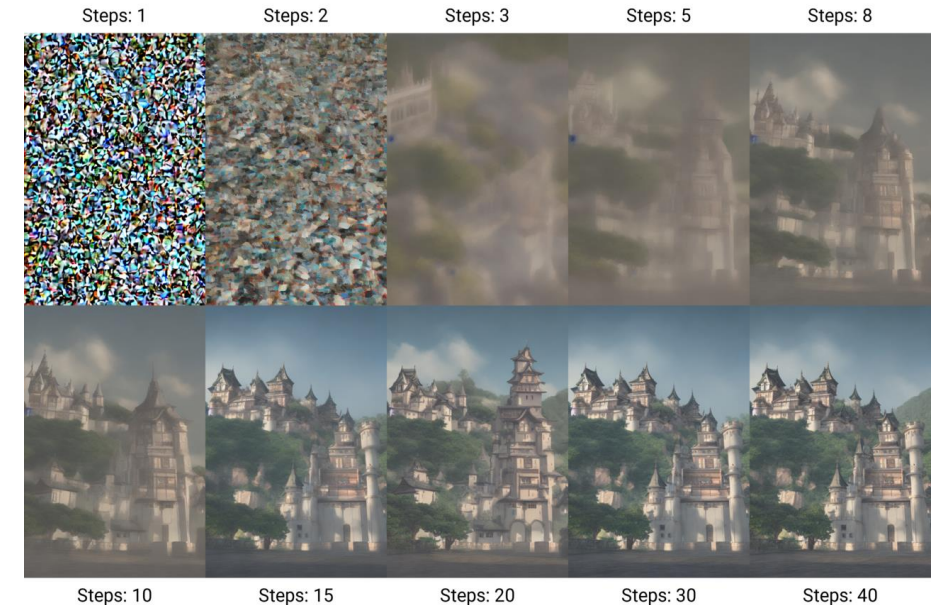
Self-Supervised Learning = Learning to Fill in the Blanks

Y. LeCun

► Reconstruct the input or Predict missing parts of the input.

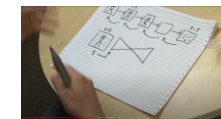


source: Yann LeCun



The denoising process used by Stable Diffusion

https://en.wikipedia.org/wiki/Diffusion_model#/media/File:X-Y_plot_of_algorithmically-generated_AI_art_of_European-style_castle_in_Japan_demonstrating_DDIM_diffusion_steps.png



How AI Image Generators Work – Computerphile (short video <20 min)
<https://www.youtube.com/watch?v=1ClpzeNxlhU>

2

**COMBINING VERY
DIFFERENT
ENGINEERING
LIFECYCLES**

ONCE UPON A TIME IN THE AUTOMOTIVE INDUSTRY

(WITH THE PERSPECTIVE OF A SOFTWARE ENGINEER)



Automotive Products Lifecycle



2- 5 YEARS
(new product)

*millions of
vehicles*





A REVOLUTION IN PROGRESS

ELECTRIFICATION, NEW ELECTRIC/ELECTRONIC ARCHITECTURES, SOFTWARE-DEFINED VEHICLE

Automotive Products Lifecycle



FROM AUTOMOTIVE PRODUCTS TO MOBILITY SERVICES



Mobility Services & Ecosystem



Automotive Products Lifecycle



CARMAKERS BECOMING TECH COMPANIES

RENAULTION (2021)



> “We’ll move from a car company working with tech to a tech company working with cars.”

> <https://group.renault.com/en/our-company/strategic-plan/>



CARMAKERS BECOMING TECH COMPANIES

STELLANTIS SOFTWARE DAY (2021)

> “This transformation will move Stellantis’ vehicles from today’s dedicated electronic architectures to an open software-defined platform that seamlessly integrates with customers’ digital lives.”

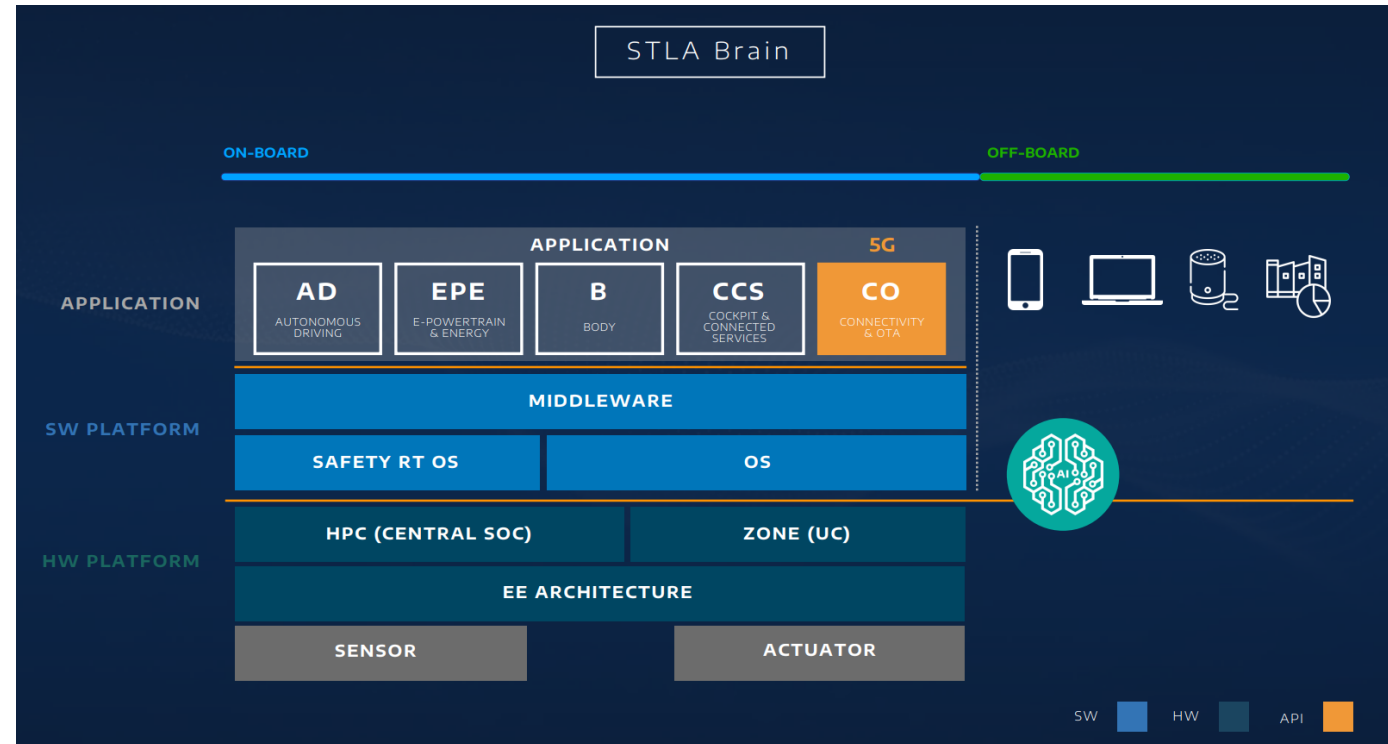
> “Our electrification and software strategies will support the shift to become a sustainable mobility tech company to lead the pack [...]

With the three all-new **AI-powered technology platforms** to arrive in 2024, [...] we will leverage the **speed and agility associated with the decoupling of hardware and software cycle.**” - *Carlos Tavares, Group CEO*

> <https://www.stellantis.com/en/investors/events/sw-day-2021>



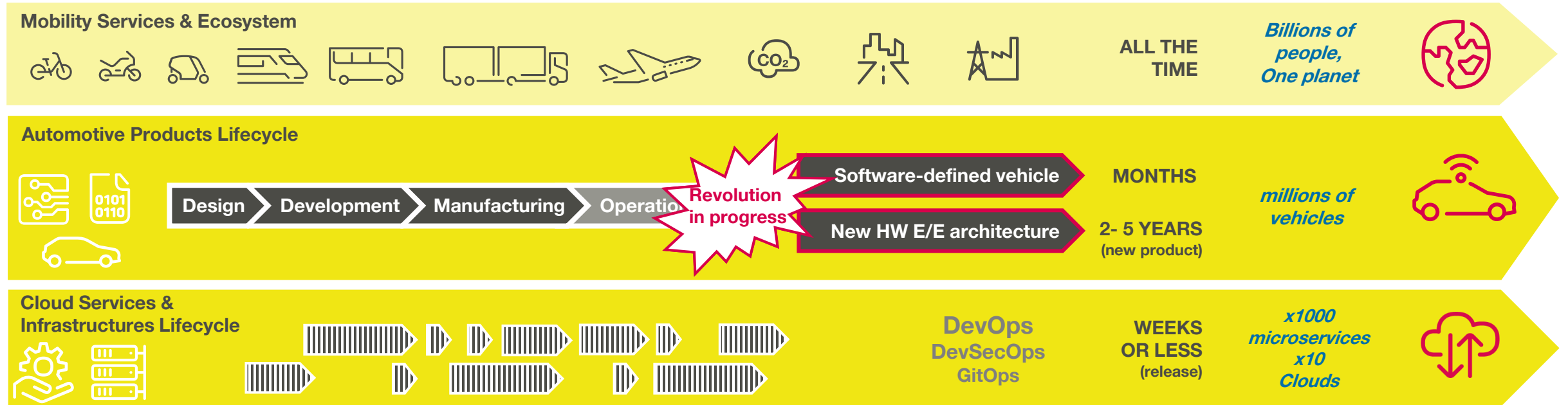
December 7, 2021 - Stellantis Software Day 2021



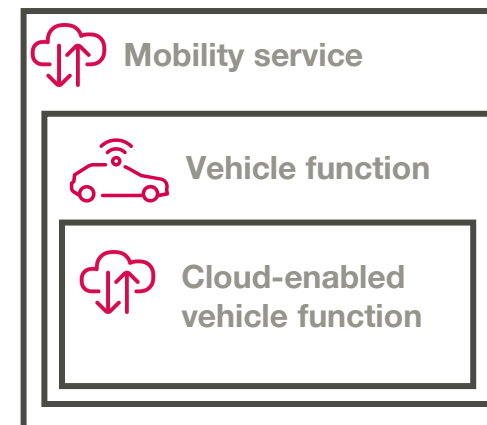
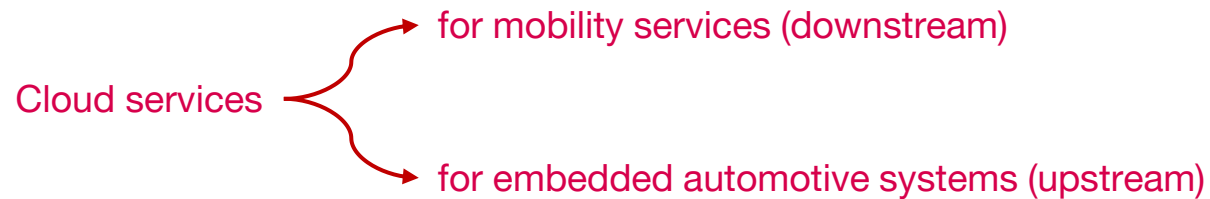


CONNECTED CARS

COMPLEX DEPENDENCIES BETWEEN EMBEDDED AND CLOUD SOFTWARE



Note: actually, this is NOT a stack 😊





ADDING DATA & AI IN THE PICTURE

COMBINING VERY DIFFERENT ENGINEERING LIFECYCLES

Mobility Services & Ecosystem

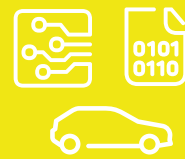


ALL THE TIME

Billions of people, One planet



Automotive Products Lifecycle



Software-defined vehicle

New HW E/E architecture

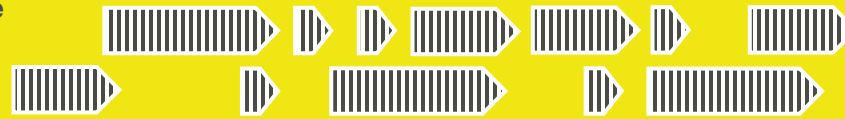
MONTHS

2- 5 YEARS (new product)

millions of vehicles



Cloud Services & Infrastructures Lifecycle



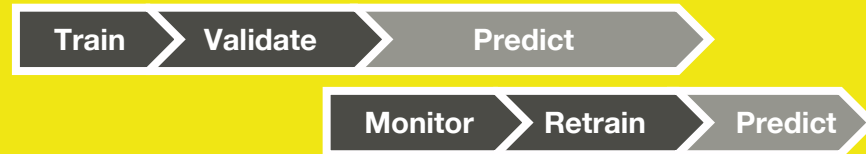
DevOps
DevSecOps
GitOps

WEEKS OR LESS (release)

x1000 microservices
x10 Clouds



AI/ML Models Lifecycle



MLOps
ModelOps

MONTHS OR LESS

x100 models



Data Lifecycle



DataOps

FROM SECONDS TO 10+ YEARS

x10 data lakes



Typical lifecycle
Cognitive load for engineering teams

Onboard / Offboard



GENERATIVE AI IS CHANGING THE AI GAME

WITH PRETRAINED FOUNDATION MODELS, FINE-TUNING...

Mobility Services & Ecosystem



ALL THE TIME

Billions of people, One planet



Automotive Products Lifecycle



Software-defined vehicle

MONTHS

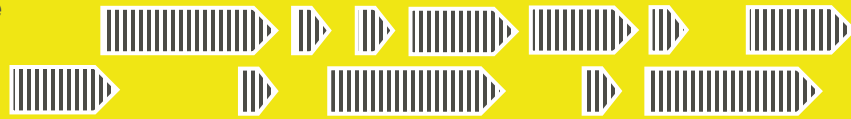
millions of vehicles



New HW E/E architecture

2- 5 YEARS (new product)

Cloud Services & Infrastructures Lifecycle



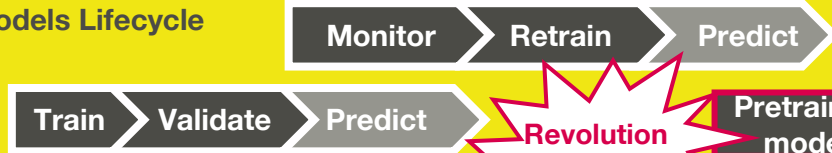
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AI/ML Models Lifecycle



MLOps
ModelOps

MONTHS OR LESS

x100 models



Data Lifecycle



DataOps

FROM SECONDS TO 10+ YEARS

x10 data lakes



Typical lifecycle
Cognitive load for engineering teams

Typical scale

Onboard / Offboard

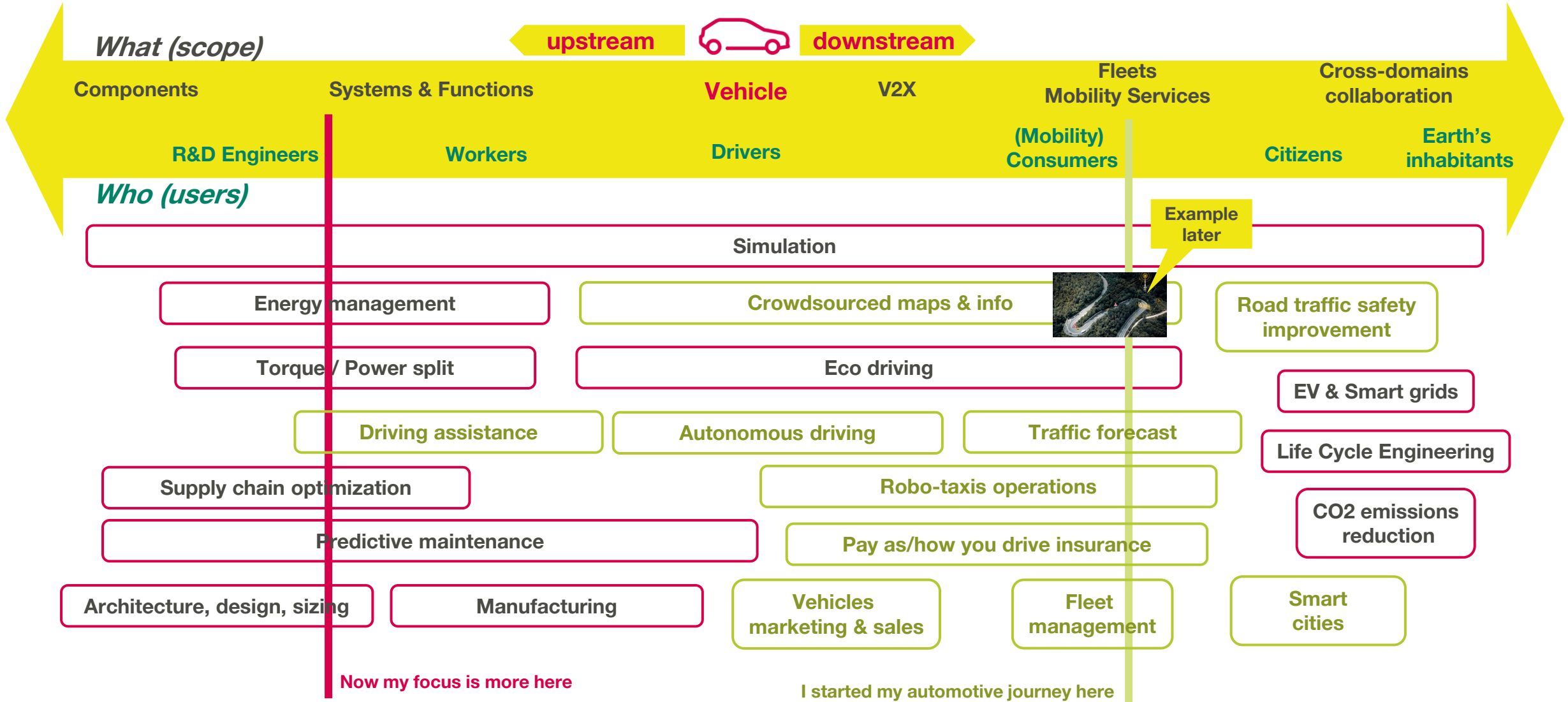
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OVERVIEW OF AI APPLICATIONS

AI APPLICATIONS LANDSCAPE IN AUTOMOTIVE & MOBILITY



A WIDE RANGE OF PRODUCTS AND SERVICES – A WIDE RANGE OF USERS

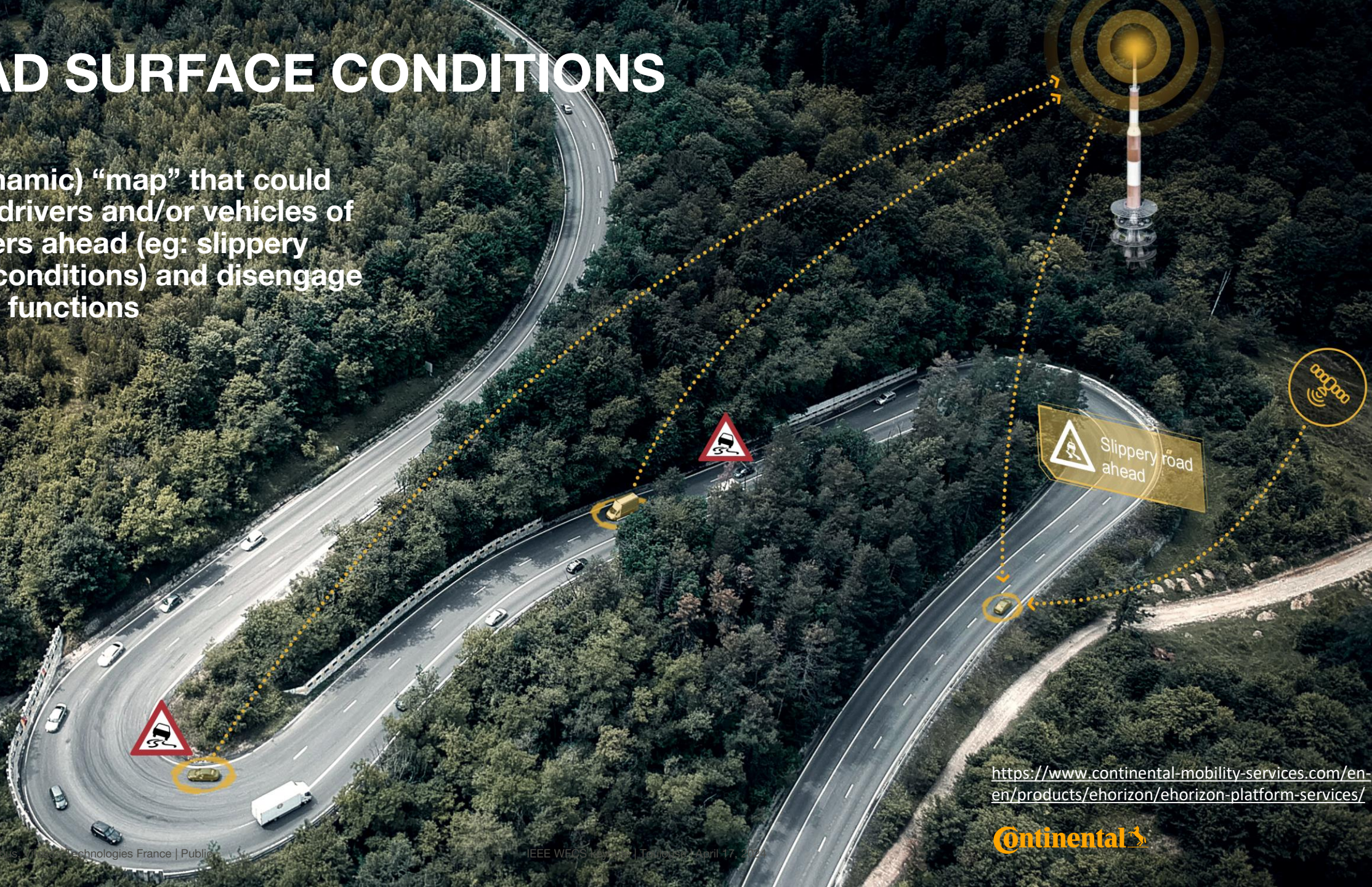


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EXAMPLE: EMBEDDED SAFETY CRITICAL SYSTEM RELYING ON AI-POWERED CLOUD SERVICES

ROAD SURFACE CONDITIONS

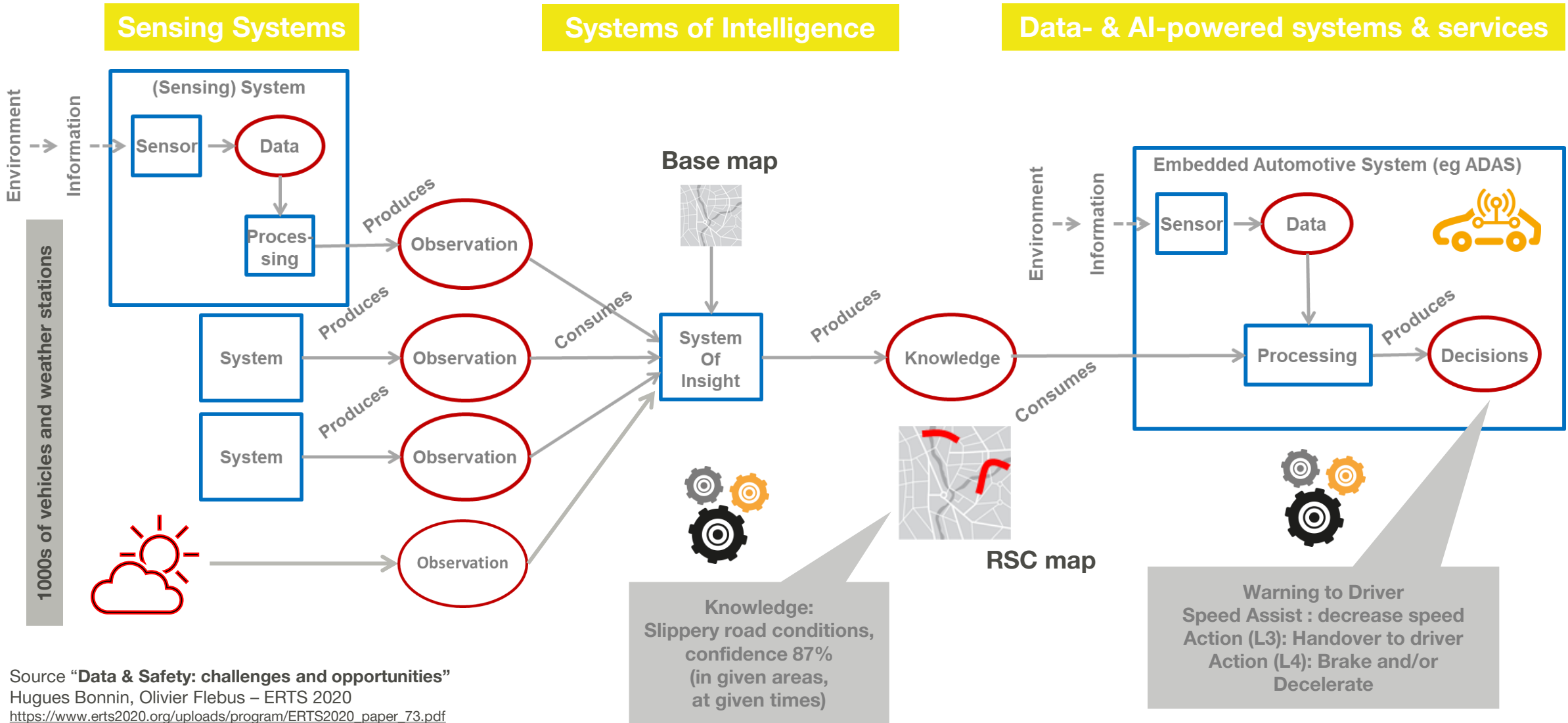
A (dynamic) “map” that could warn drivers and/or vehicles of dangers ahead (eg: slippery road conditions) and disengage ADAS functions



<https://www.continental-mobility-services.com/en-en/products/ehorizon/ehorizon-platform-services/>



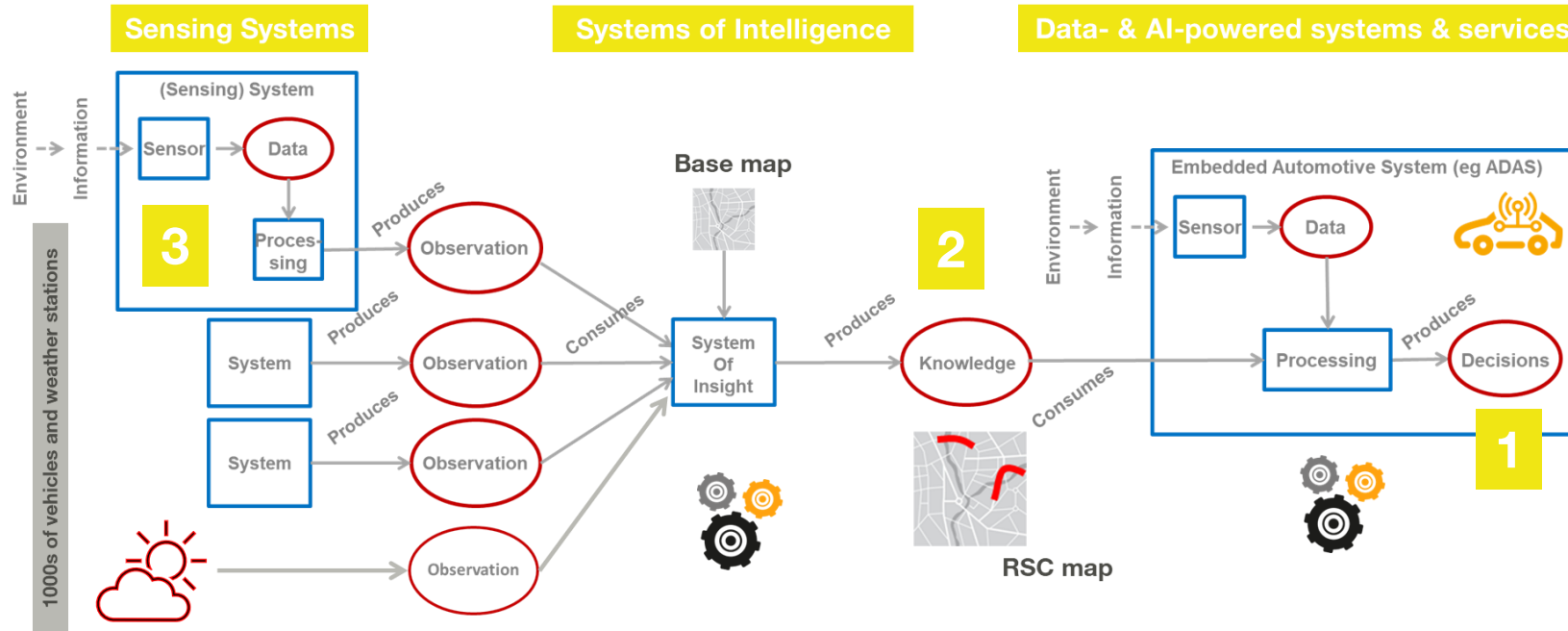
A (SIMPLIFIED) SOLUTION FOR ROAD SURFACE CONDITIONS



Source "Data & Safety: challenges and opportunities"
 Hugues Bonnin, Olivier Flebus – ERTS 2020
https://www.erts2020.org/uploads/program/ERTS2020_paper_73.pdf

A FEW CHALLENGES

AND MAIN QUESTION: CAN WE CONSIDER ALL OF THEM AT THE SAME TIME?

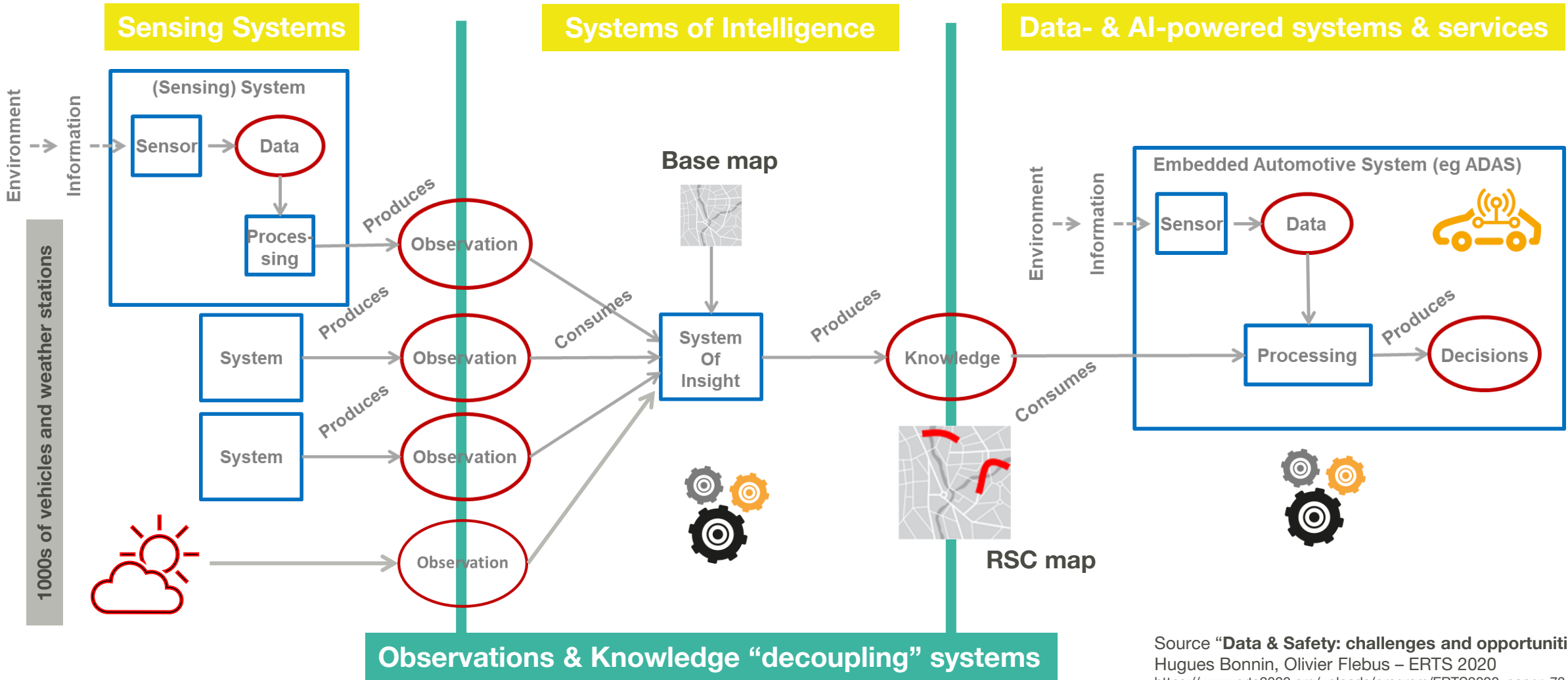


- 1 Safety of Decisions?
 - > Trust in Knowledge from the cloud
 - > New interface?
- 2 Trust in Knowledge?
 - > Safety of IA/ML
 - > Data redundancy
- 3 Trust in Observation?
 - > Data Quality
 - > Sensor Quality
 - > Processing Quality

Source "Data & Safety: challenges and opportunities"
 Hugues Bonnin, Olivier Flebus – ERTS 2020
https://www.erts2020.org/uploads/program/ERTS2020_paper_73.pdf

PROPOSED APPROACH

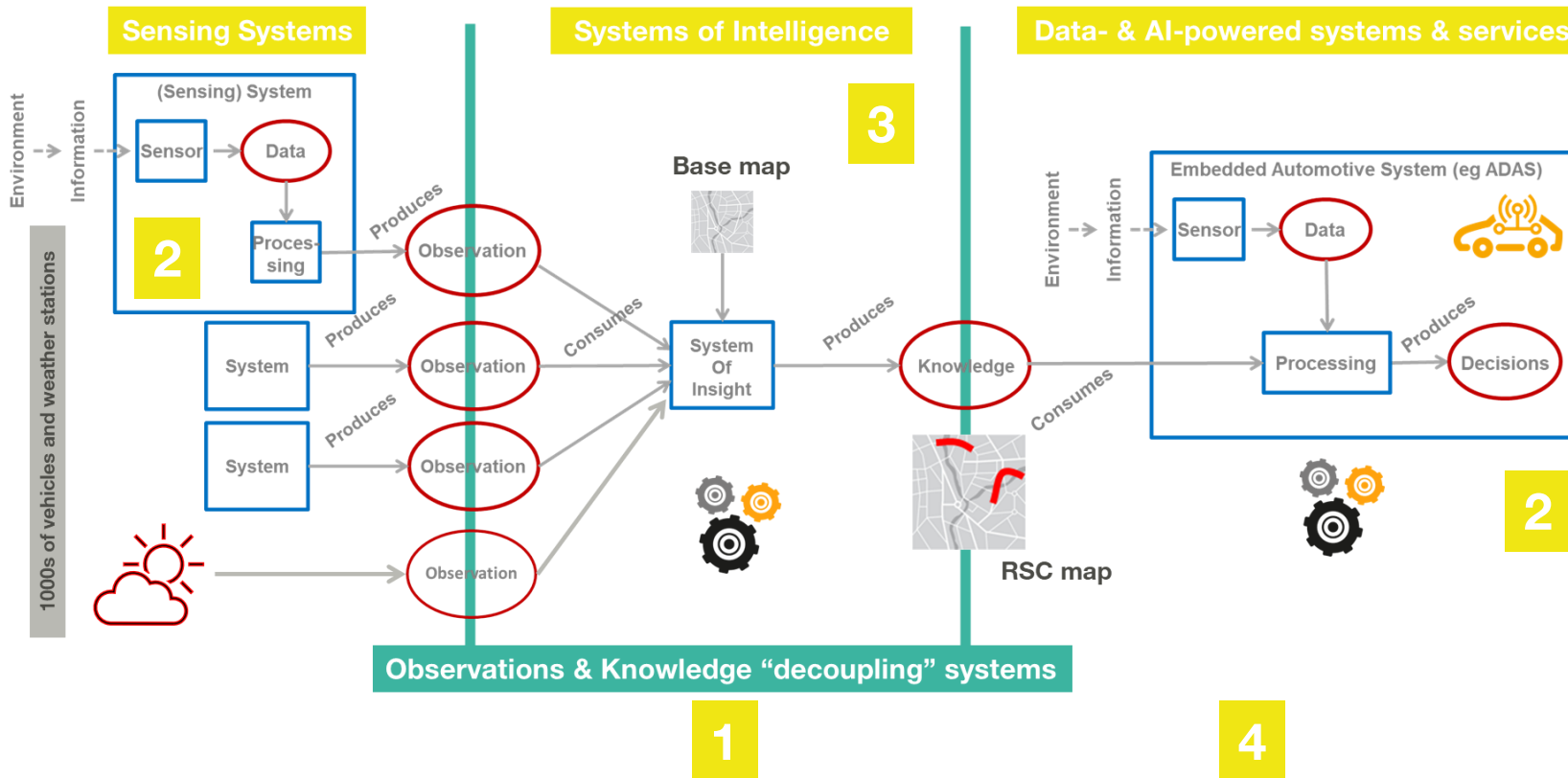
(EXTERNAL) DATA TO DECOUPLE SYSTEMS



Source "Data & Safety: challenges and opportunities"
 Hugues Bonnin, Olivier Flebus – ERTS 2020
https://www.erts2020.org/uploads/program/ERTS2020_paper_73.pdf

CHAINS OF TRUST COMBINING DATA & SYSTEMS

WHAT ARE THE NEXT STEPS?



- 1 Build the confidence in data (means, level, methods)
- 2 Adjust (or not) the existing standards to integrate the "Safe Data" ones
- 3 Define Safety for systems of intelligence
- 4 Don't forget the transfer integrity! (everywhere)

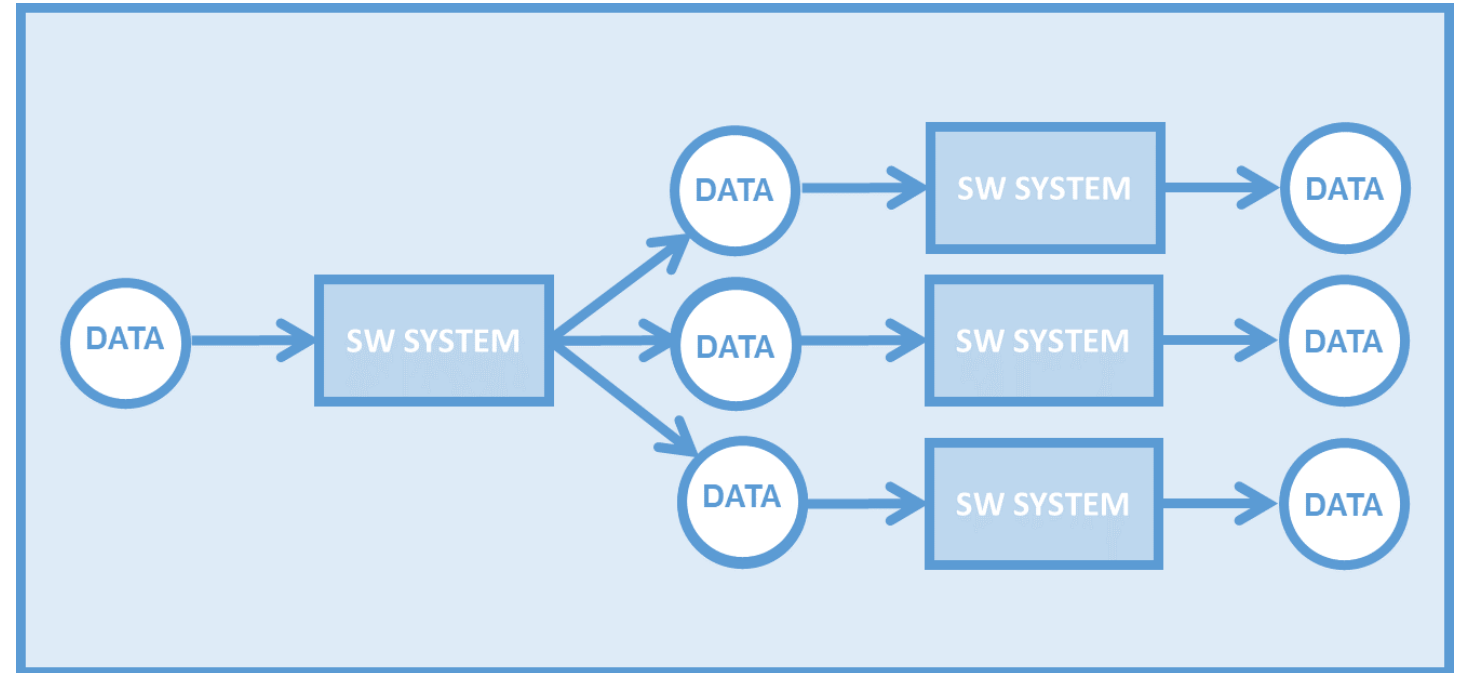
Source "Data & Safety: challenges and opportunities"
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DATA INSIDE SYSTEMS

THE TRADITIONAL APPROACH...

- > Data as a way to exchange/distribute information to “processors”
 - > “Real-Time”

- > Data as a way to connect Systems (into “bigger Systems”)
 - > Limits?

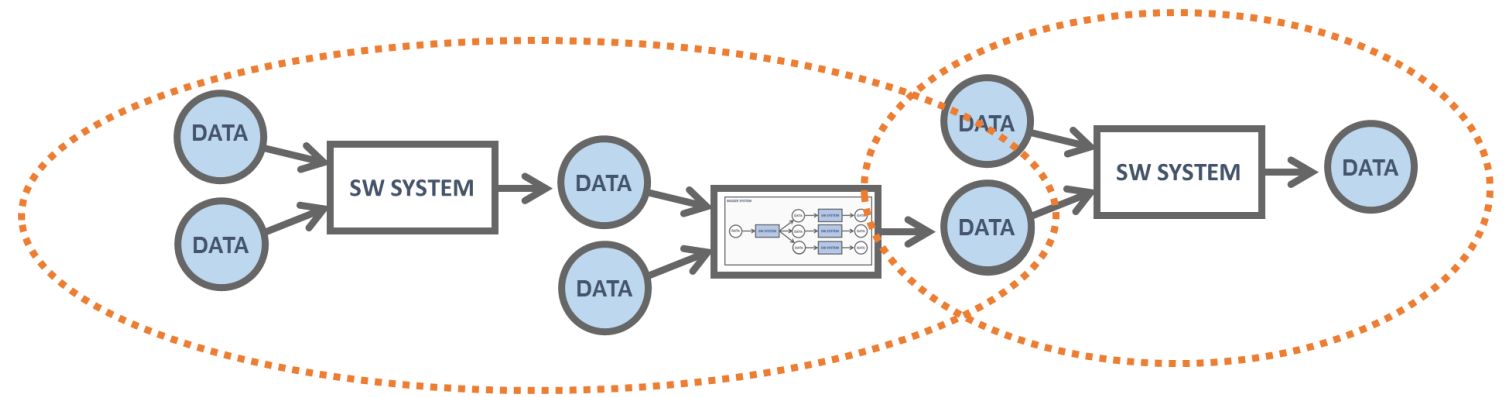


In that case Data MAY be governed by the System it belongs to

DATA OUTSIDE SYSTEMS ≈ DATA AS A PRODUCT

THE DATA-DRIVEN APPROACH...

- > Data as a way to **decouple systems**
- > Data that **outlive** the systems that have created/processed them!
- > **Data as a product**, data as an asset
- > Data to build “**Chains of trust**” that cover extended lifecycles across multiple organizations



traditional system engineering does not work for this (complex adaptive digital ecosystems)

In that case Data is likely to be governed on its own

CONCLUSION

AND A QUESTION

- > Knowing that data outlive the systems that created them...
- > ...What should we most care about?
 - > The pipes?
 - > The water?
- > BTW the lake is another system like the pipe...
 - > Its governance a more complex though



ARE YOU INSPIRED?