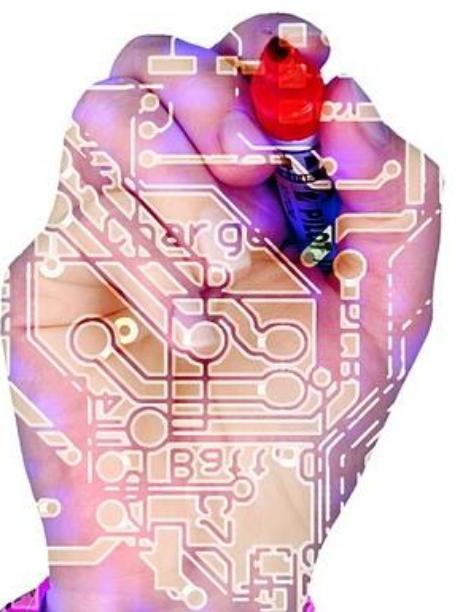


Challenges and opportunities in the integration of the Systems Engineering process and the AI/ML Lifecycle

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Let's *speak* some AI...



Digitalization

European companies

9/10

Digital technologies are
an “opportunity”.

Technology adoption

35%

Adopted 2 of 9 the key
digital technologies

Big Data Analytics & AI

46%

Increase in their annual turnover
being 24% BD and 5% AI

Context

Evolving and competitive market for Cyber-physical systems (CPS)

Legislation

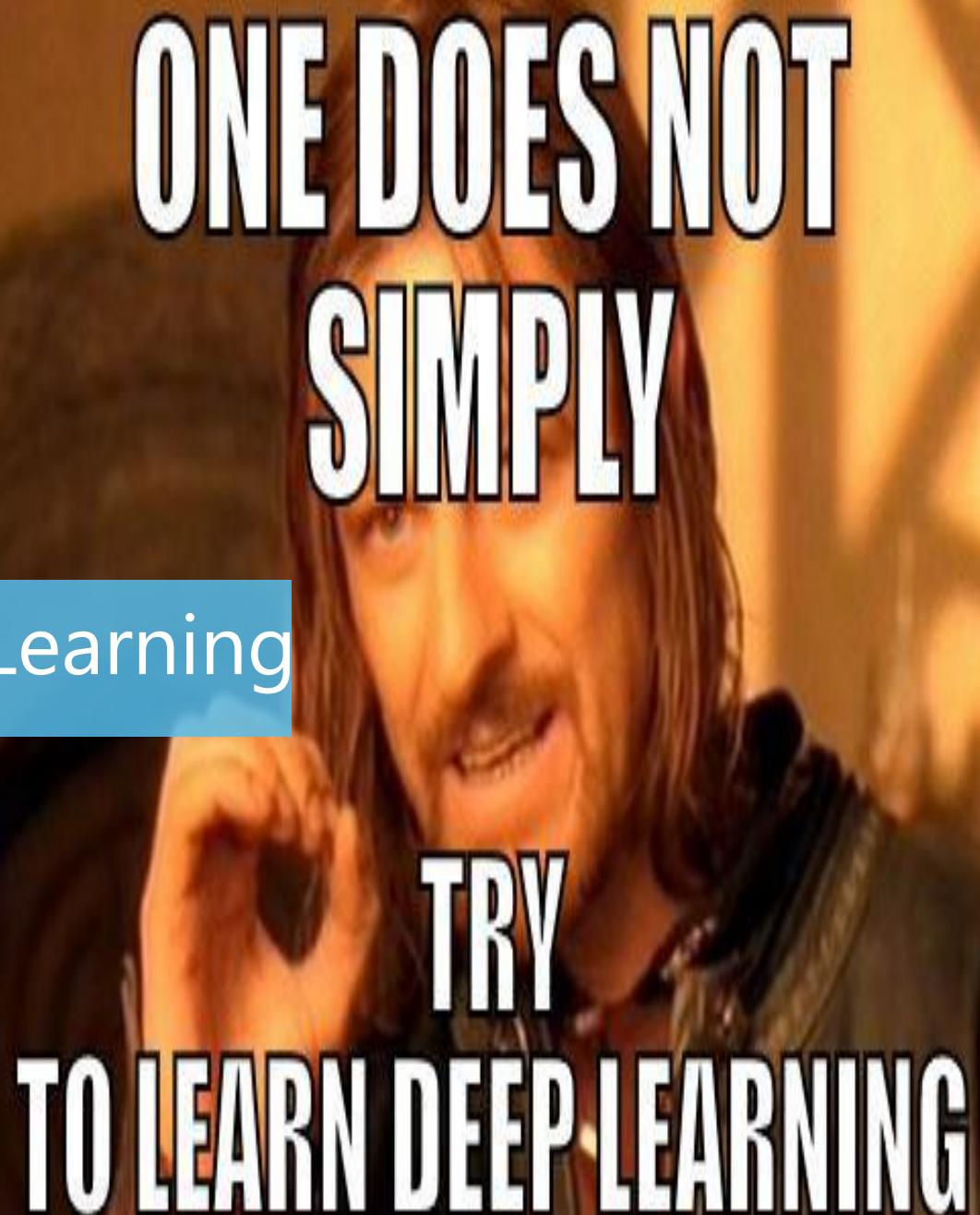
Business needs and models

Quality

- Safety
- Reliability
- Cyber-security
- Certification
- Environment
- Standardization
- Ethics
- ...

Engineering process , methods, technology & tooling

AI/ML & Deep Learning



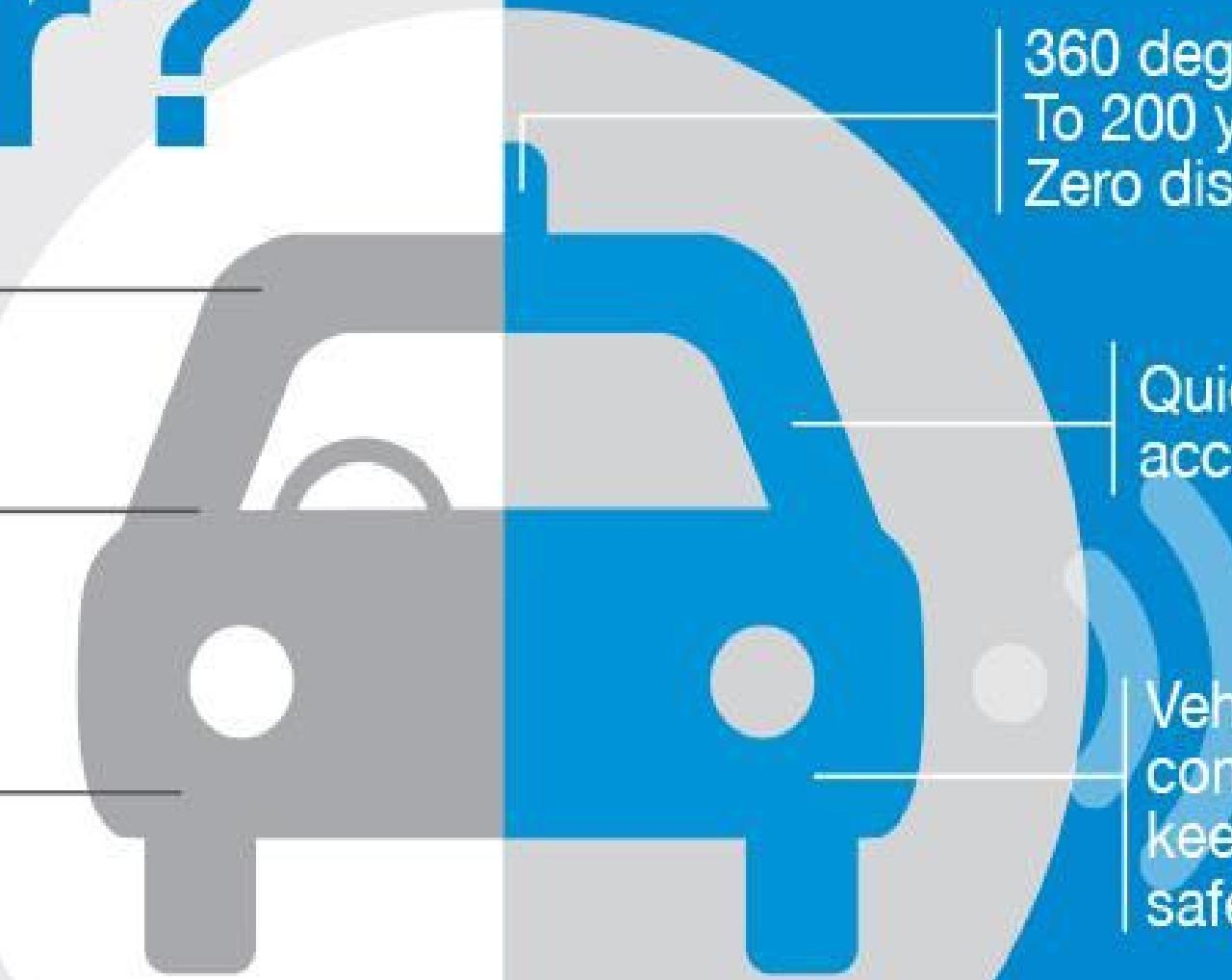
Are driverless cars Safer?

Source: <https://www.micron.com/insight/on-the-road-to-full-autonomy-self-driving-cars-will-rely-on-ai-and-innovative-memory>

Tired/distracted
driving

Slower
responses

Indecision
Poor judgement
Human error



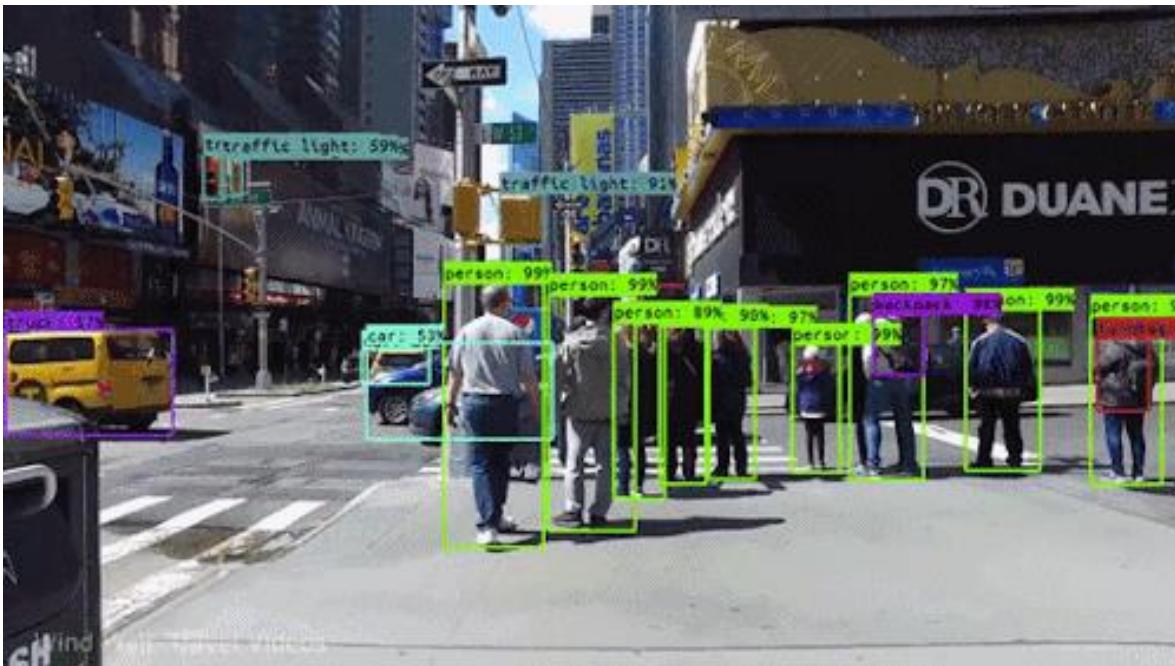
Standard Vehicle - Human Driver

Self Driving Vehicles



What can you see?

Self-Driving Cars (object recognition)



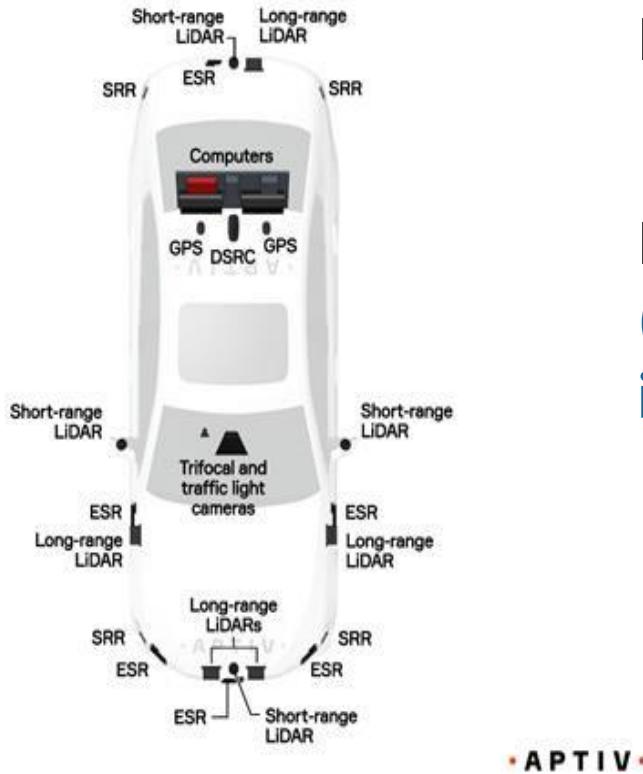
Source: <https://towardsdatascience.com/how-do-self-driving-cars-see-13054aee2503>

Source: <https://www.theverge.com/2015/7/17/8985699/stanford-neural-networks-image-recognition-google-study>

An example of architecture

Aptiv Autonomous Driving System

- 4 short-range LiDARs
- 5 long-range LiDARs
- 6 electronically scanning radars (ESR)
- 4 short-range radars (SRR)
- 1 trifocal camera
- 1 traffic light camera
- 2 GPS antennas
- 1 Dedicated Short Range Communications antenna (DSRC)
- 2 computer and software stacks for redundancy and safety, plus ControlTec CT-Edge data communications system.



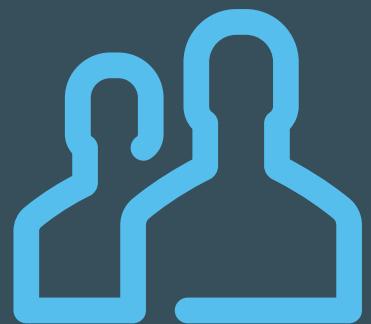
Is it a **Car**?

Is it a kind of a computer
(software and hardware intensive)?

Sensors/Actuators
GPUs
AI/ML models
5G
Edge Computing
...



Critical factors



Human factors

Adoption of intelligent evolving systems



Safety & Security

Ethics



Conceptual & technological

From business needs/value to system capabilities

Perspective



Software & Systems Engineering

AI/ML lifecycle

Software Engineering

11

Software production automation

Model-Driven Engineering/Architecture
Software Product Lines
etc.

Initial Focus

Methods and methodology to
tackle the problem of
software reliability



Agile methods & DevOps

Scrum, Kanban, BDD, TDD,
etc.

Standard notations

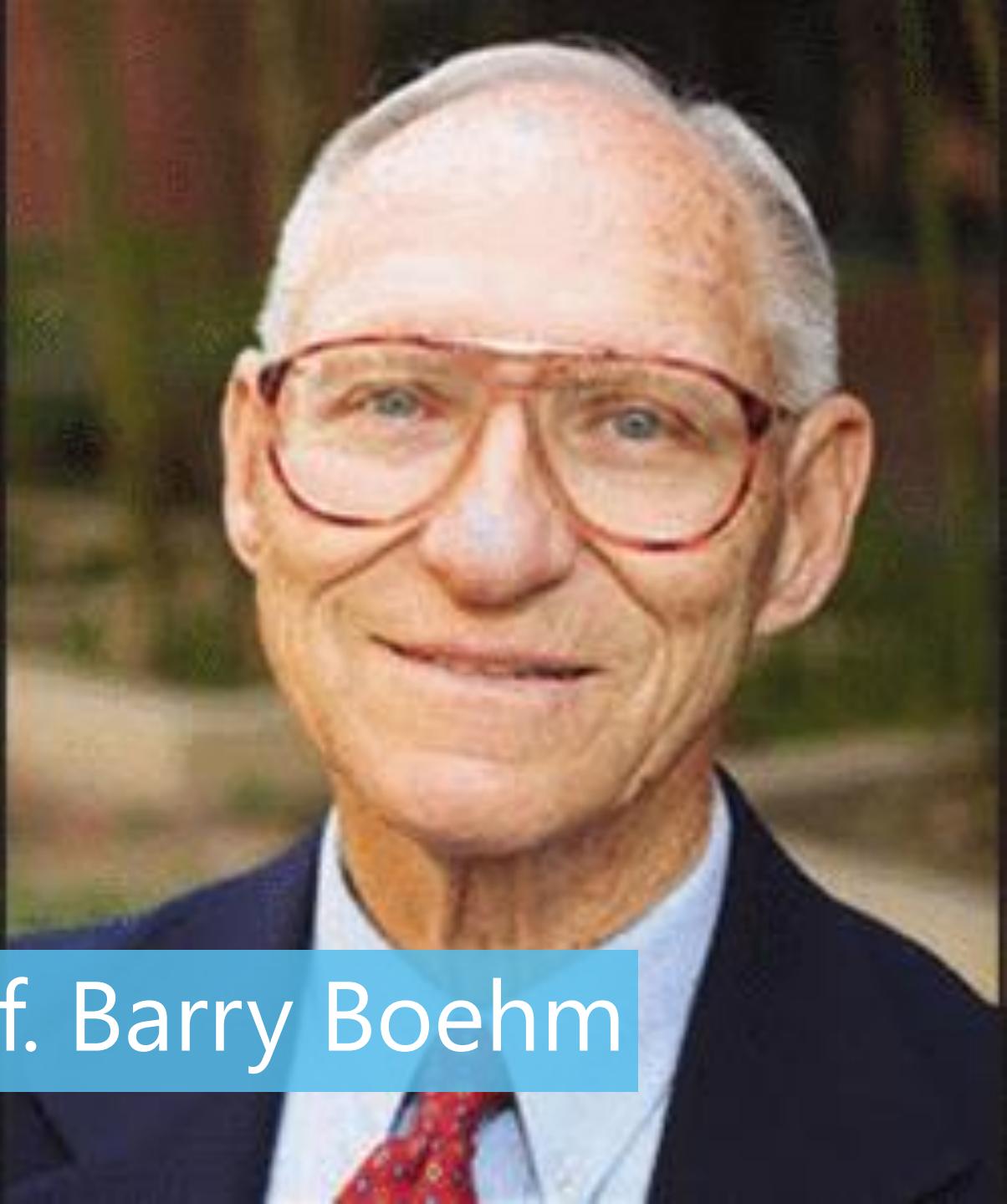
Languages, tools, quality
management, maturity
models, design patterns,
components, etc.



The way through

There is a huge body of **knowledge** and **practice** that allow us to **acknowledge which ARE, and which ARE NOT, the software engineering practices** that **really** represent **timeless scientific and technological foundations** for a proper software development process.

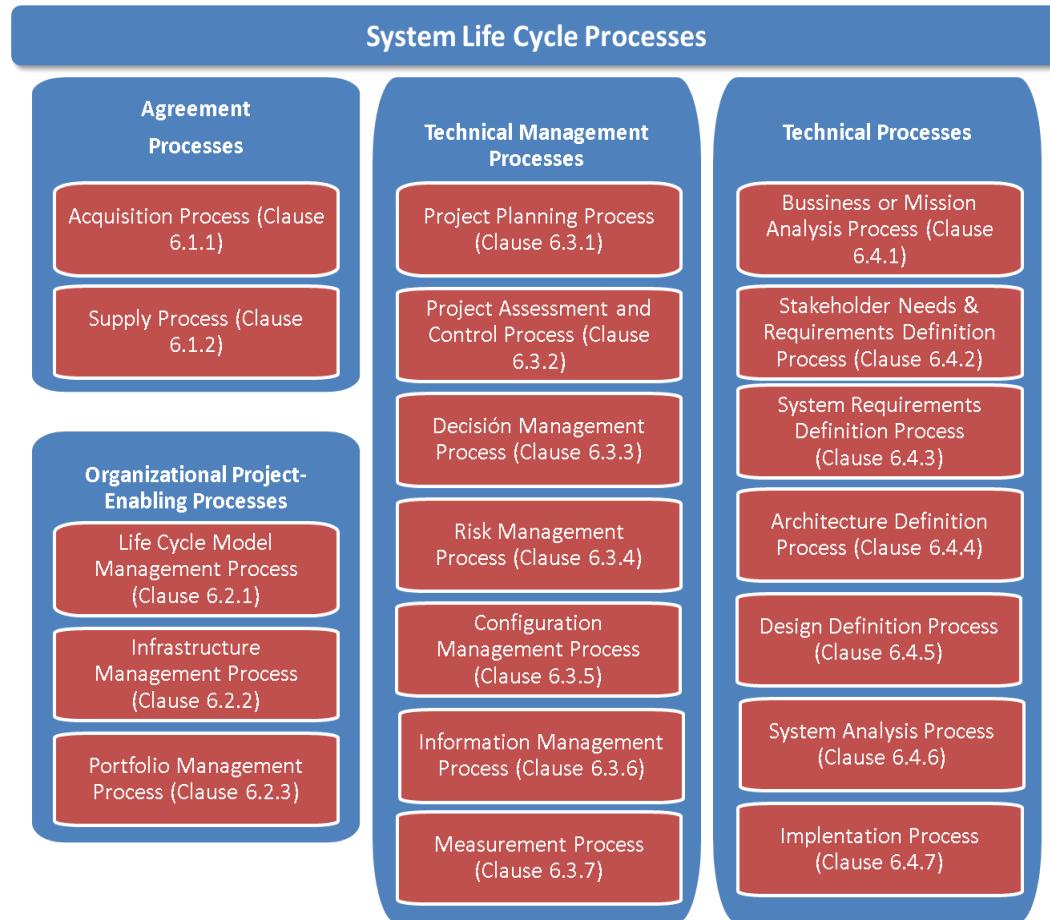
(My own summary based on [1])



Prof. Barry Boehm

- “A Conversation with Barry Boehm: Recollections from 50 Years of Software Engineering”. *IEEE Software*, vol. 35 (5). 2018
- “A View of 20th and 21st Century Software Engineering”

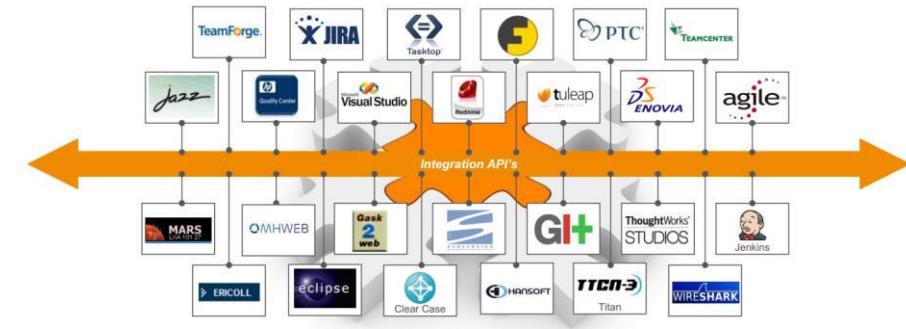
Software & Systems Engineering process



ISO 12207:2017

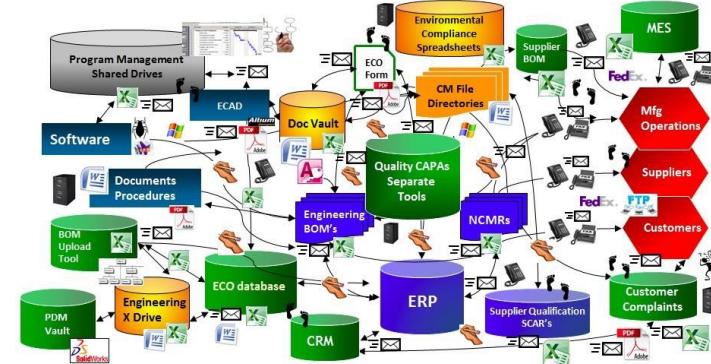
ISO 15288:2015

Engineering (and corporate) environment



Mats Berglund (Ericsson)
<http://www.ices.kth.se/upload/events/13/84404189f85d41a6a7d1caf0db4ee80.pdf>

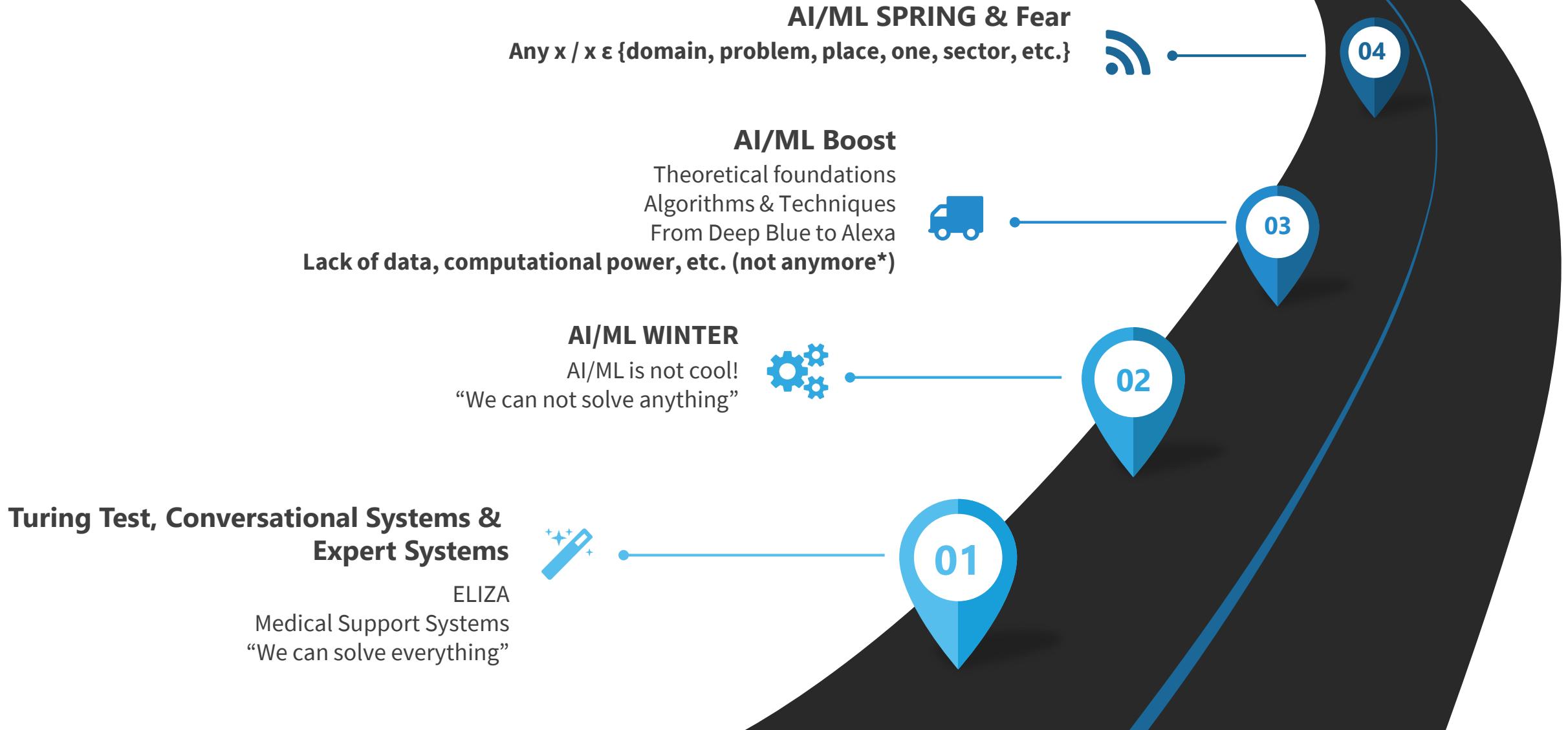
Disconnected Silos



Source: <http://beyondplm.com/2014/07/22/plm-implementations-nuts-and-bolts-of-data-silos/>

Artificial Intelligence

14

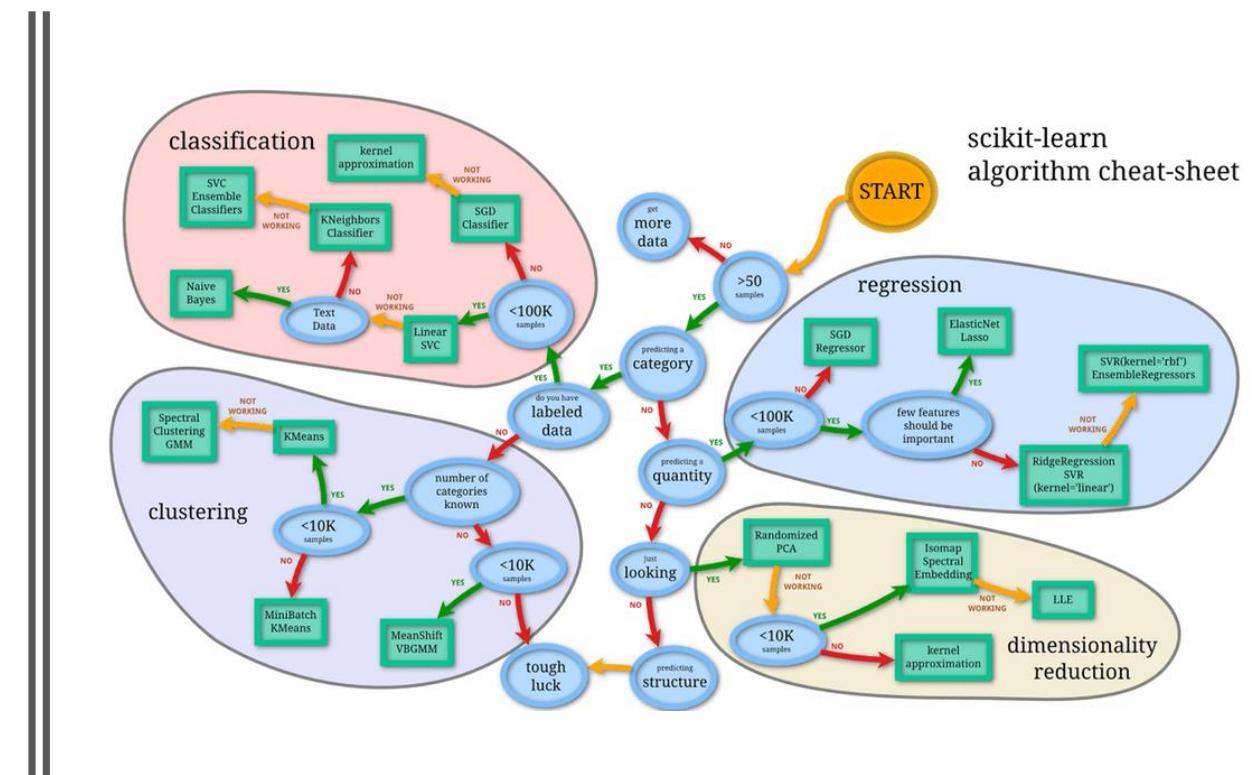
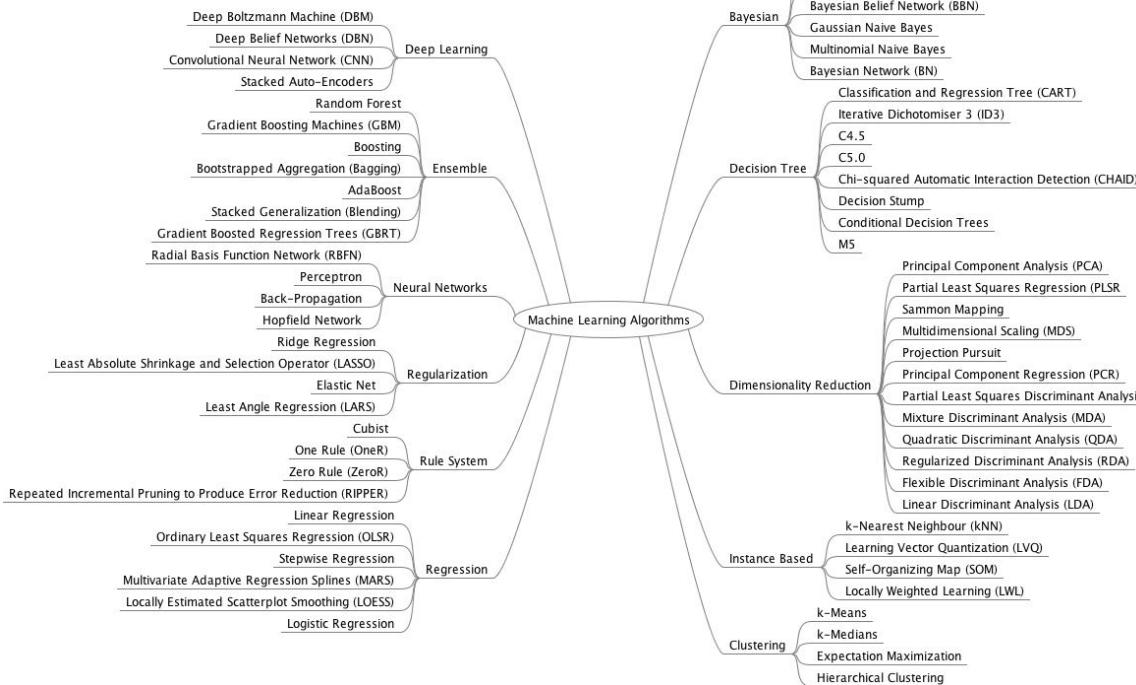


The way through

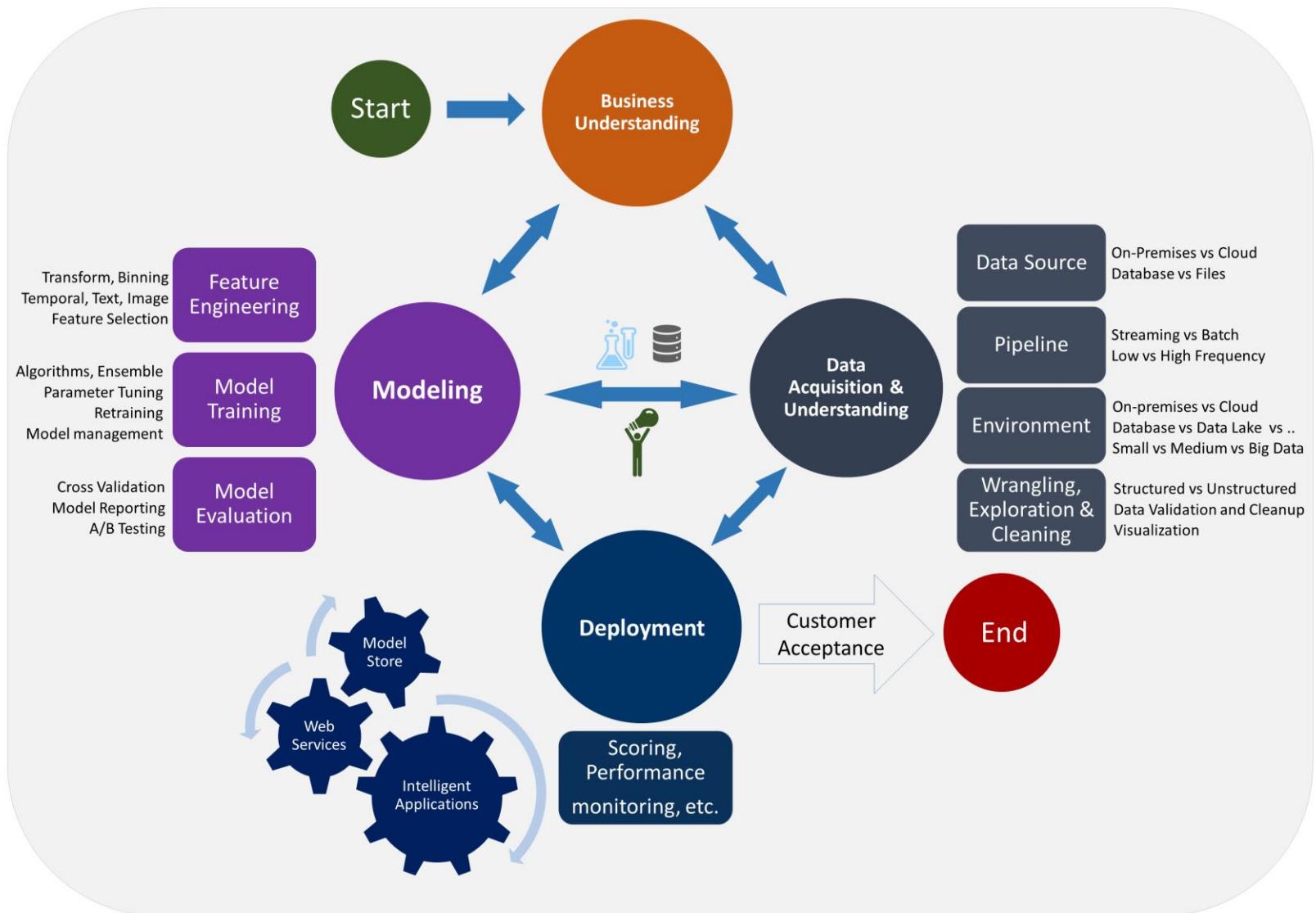
“The new spring in AI is the most significant development in computing in my lifetime. Every month, there are stunning new applications and transformative new techniques. But such powerful tools also bring with them new questions and responsibilities”



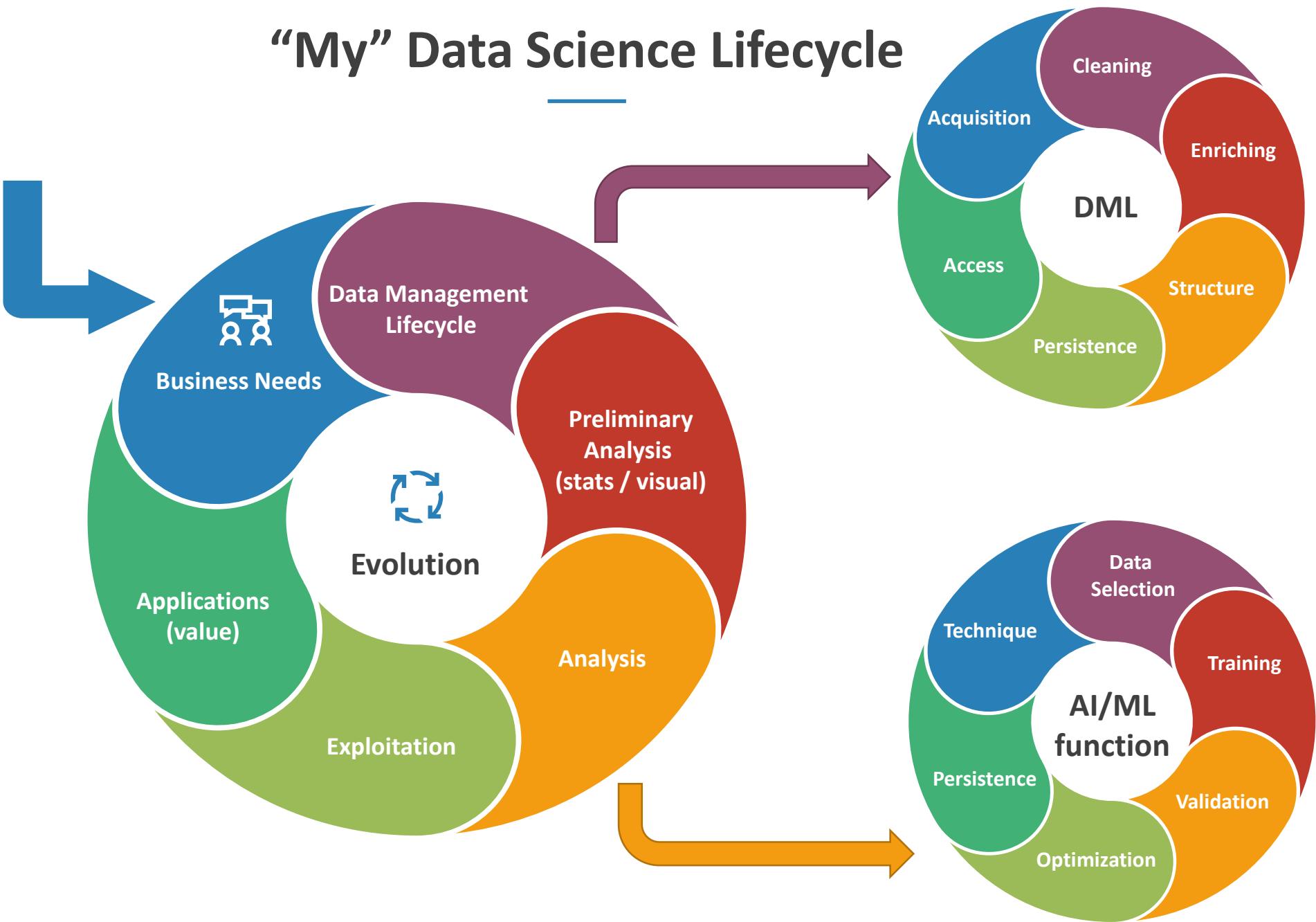
Sergey Brin



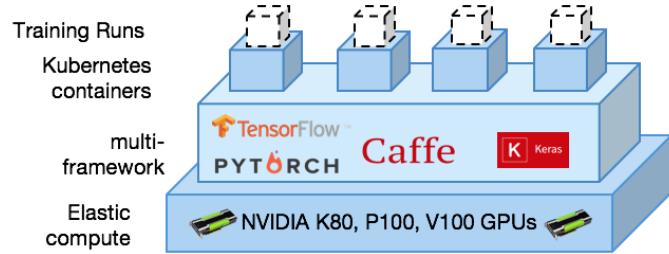
Data Science Lifecycle



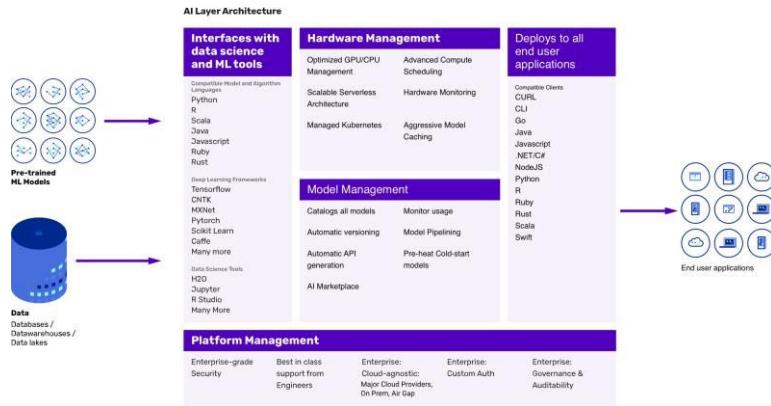
“My” Data Science Lifecycle



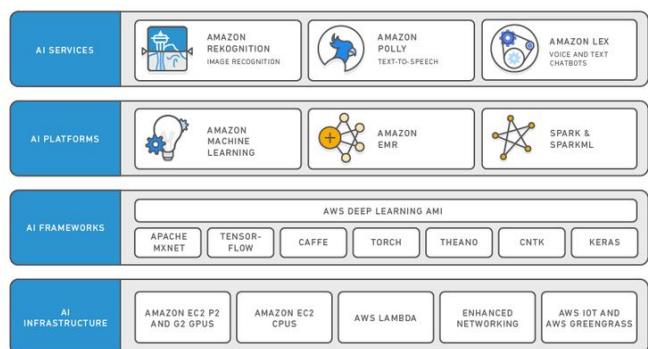
Frameworks/Platforms/... → AI/ML as a Service



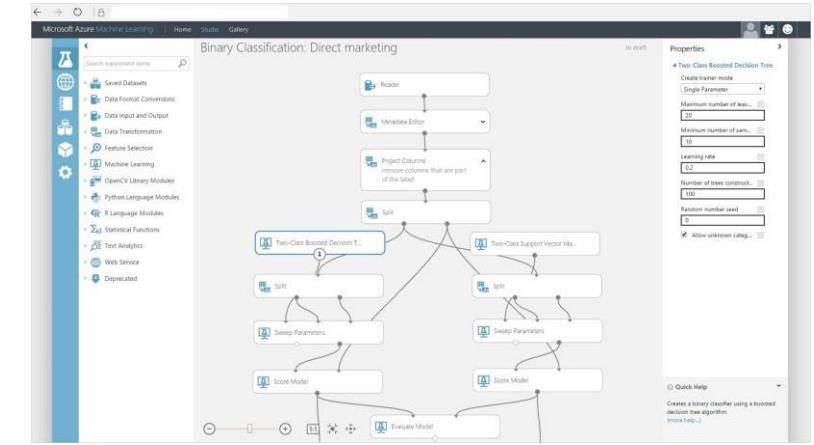
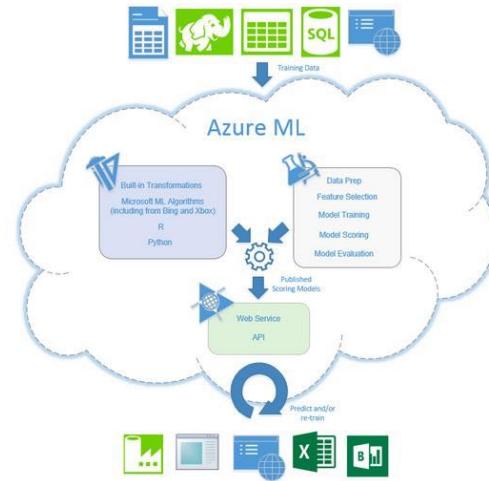
Source: <https://www.ibm.com/blogs/research/2018/03/deep-learning-advances/>



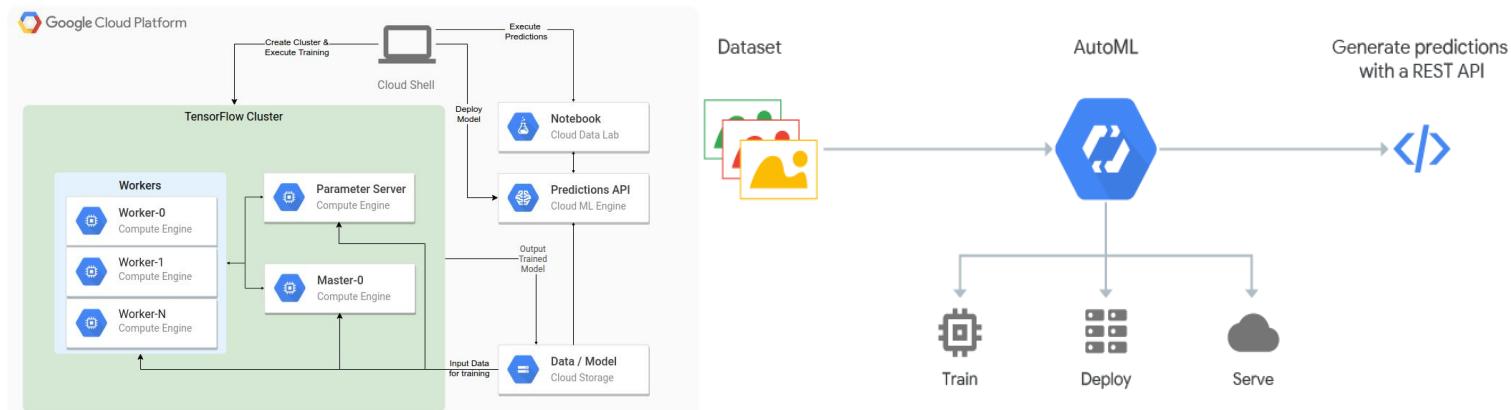
Source: <https://algorithmia.com/>



Source: <https://www.morpheusdata.com/blog/2017-09-14-cloud-and-ai-a-work-in-progress-with-unlimited-upside>



Source: <https://azure.microsoft.com/es-es/services/machine-learning-studio>

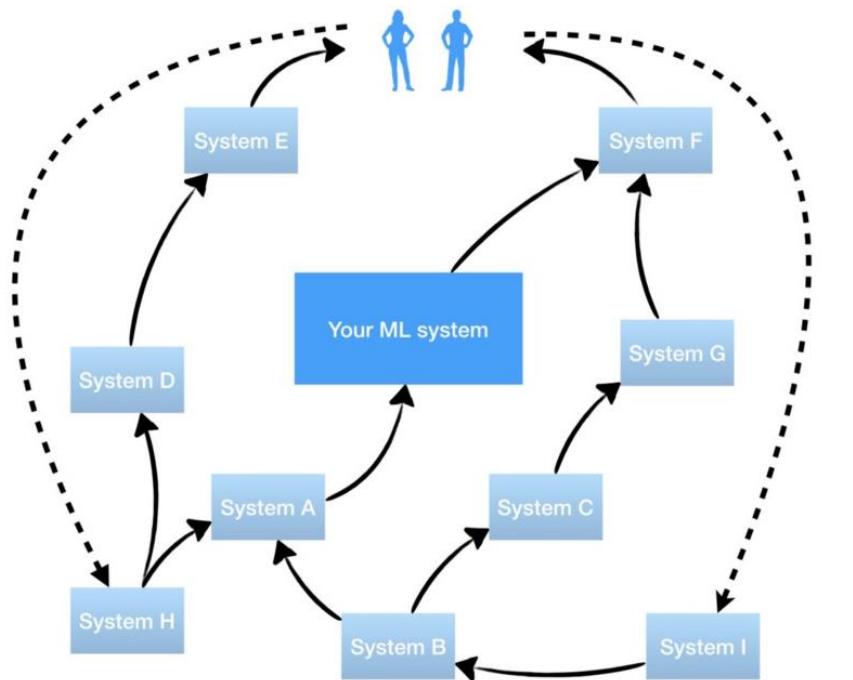


Source: <https://cloud.google.com/automl/?hl=es-419>

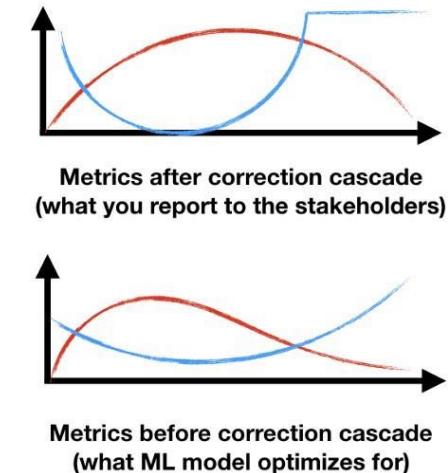
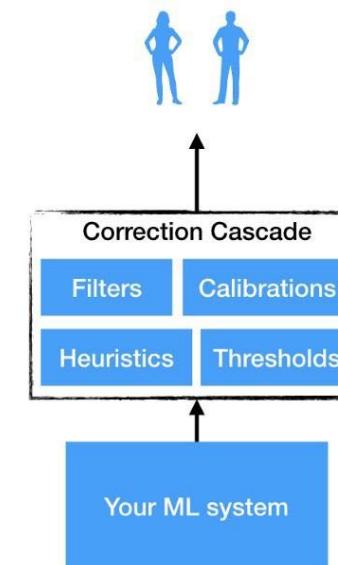
Technical debt in AI/ML functions [2, 4]

20

Garbage features



Feedback loops



Correction cascades

Harmonization



**Software & Systems
Engineering**

AI/ML lifecycle

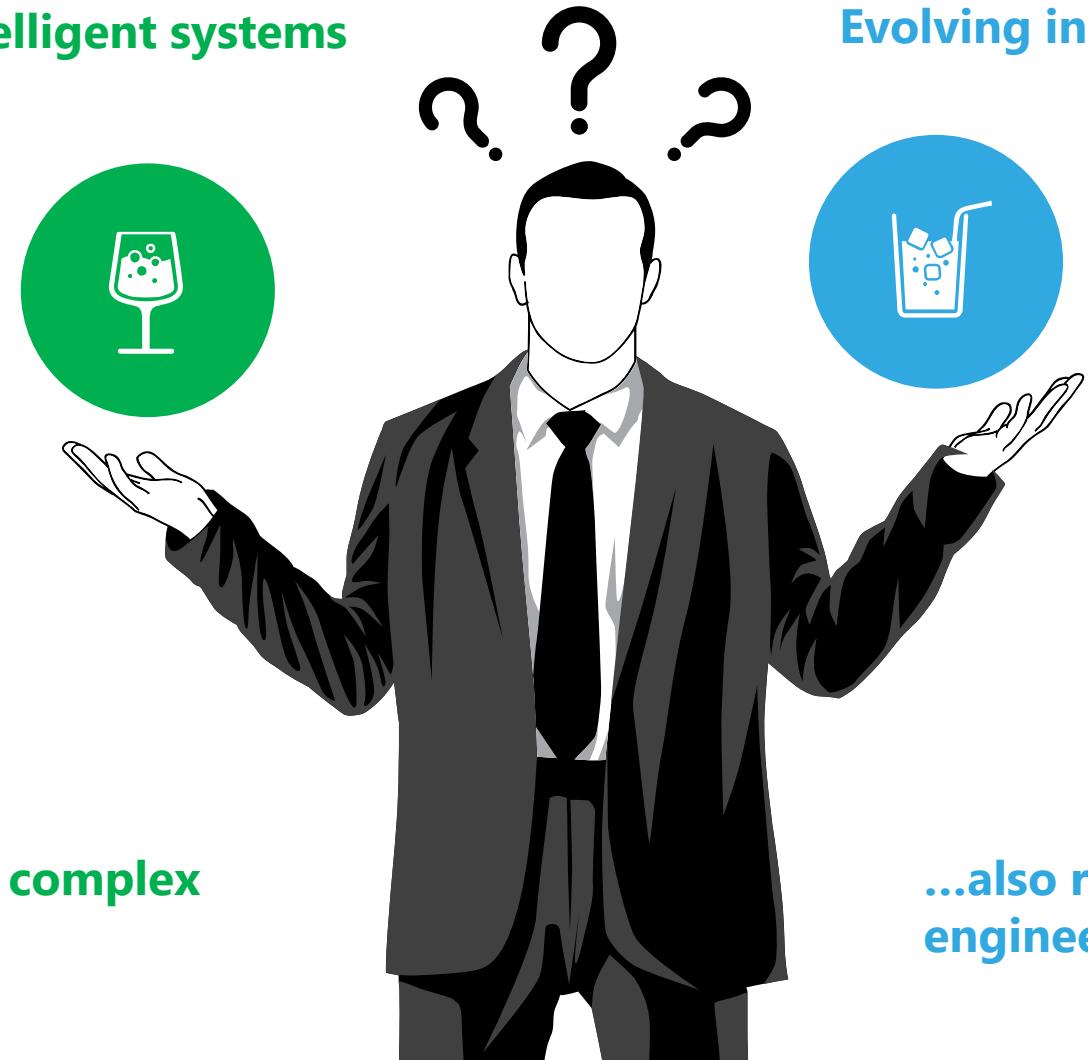
Engineering (of→←for) AI/ML

22

Engineering of evolving intelligent systems

How to integrate the engineering process with the AI/ML lifecycle?

- + Current trend
- + Challenges ahead
- + Opportunities ahead
- No clear view
- Lack of expertise: from deterministic to evolving systems



Evolving intelligent systems for engineering

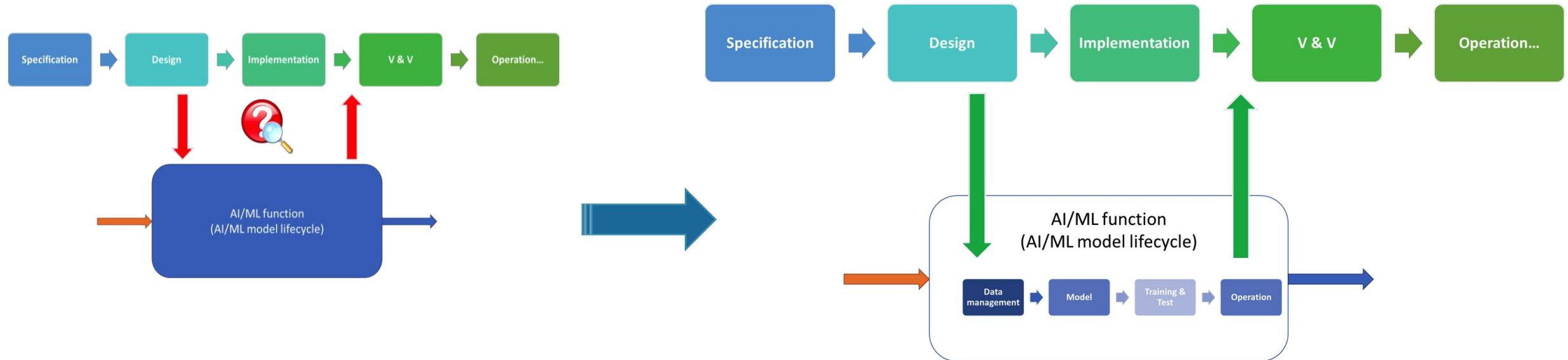
How to use intelligence to help engineering processes?

- + Technology available
- Methods not ready
- Change resistance
- + Room for improvement
- + Cultural change and new mindset

Engineering more intelligent complex products/services...

...also requires more intelligent engineering methods and tools.

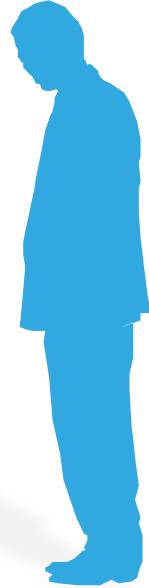
Harmonization of the SE process and the AI/ML function



Paying the “hidden” technical debt

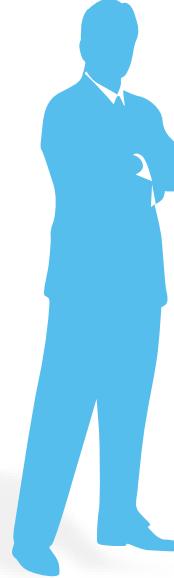
10 major challenges & coffee evaluation

24



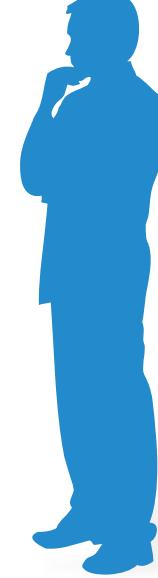
Status

How we do things now?



Concept

Can we define a challenge?



Opportunity

What to do to tackle the challenge?



Debate

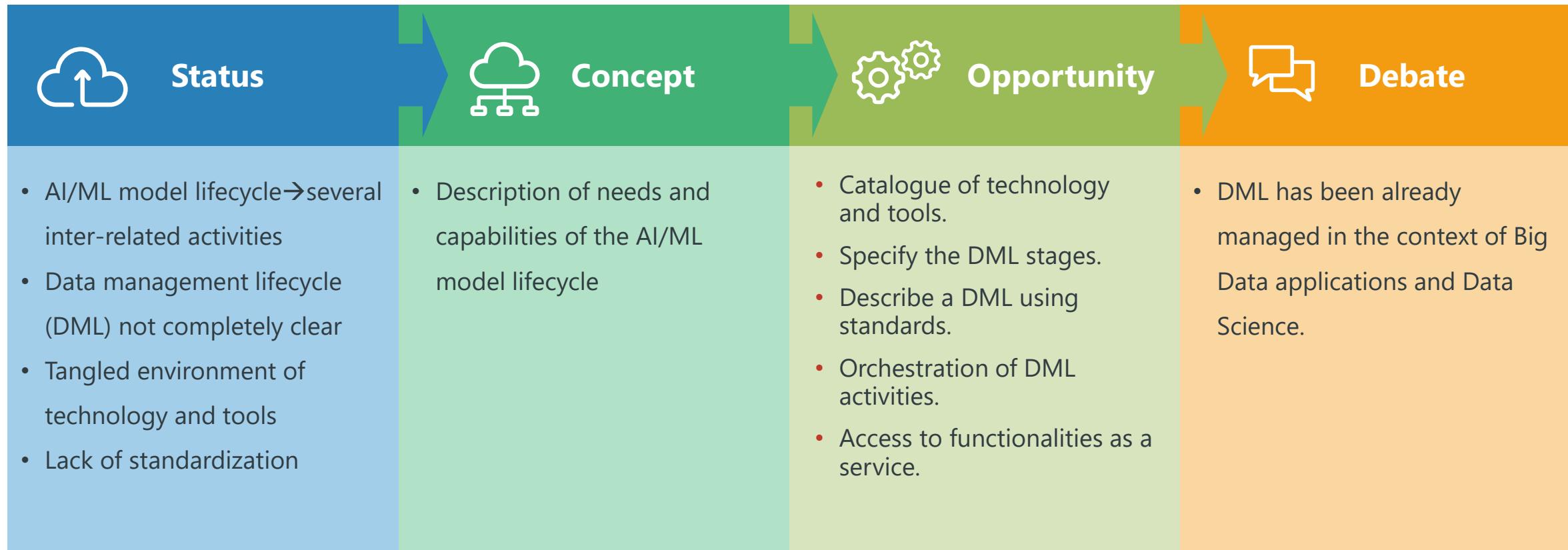
Is it really a challenge?

Is there an opportunity?

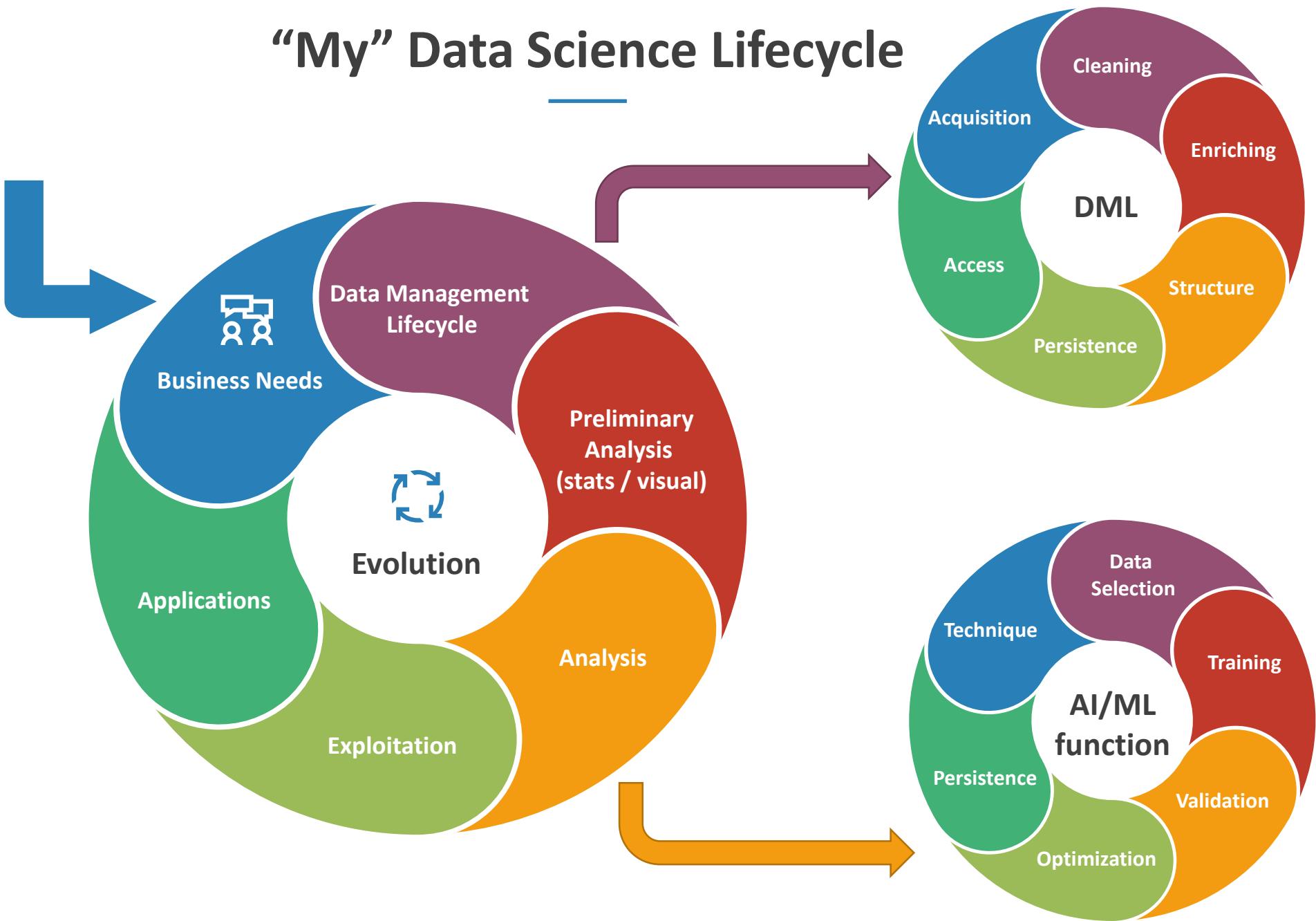
...and the necessary tea/coffee cups per hour



Challenge #1: to describe the needs and capabilities of the resources which are part of the AI/ML model lifecycle

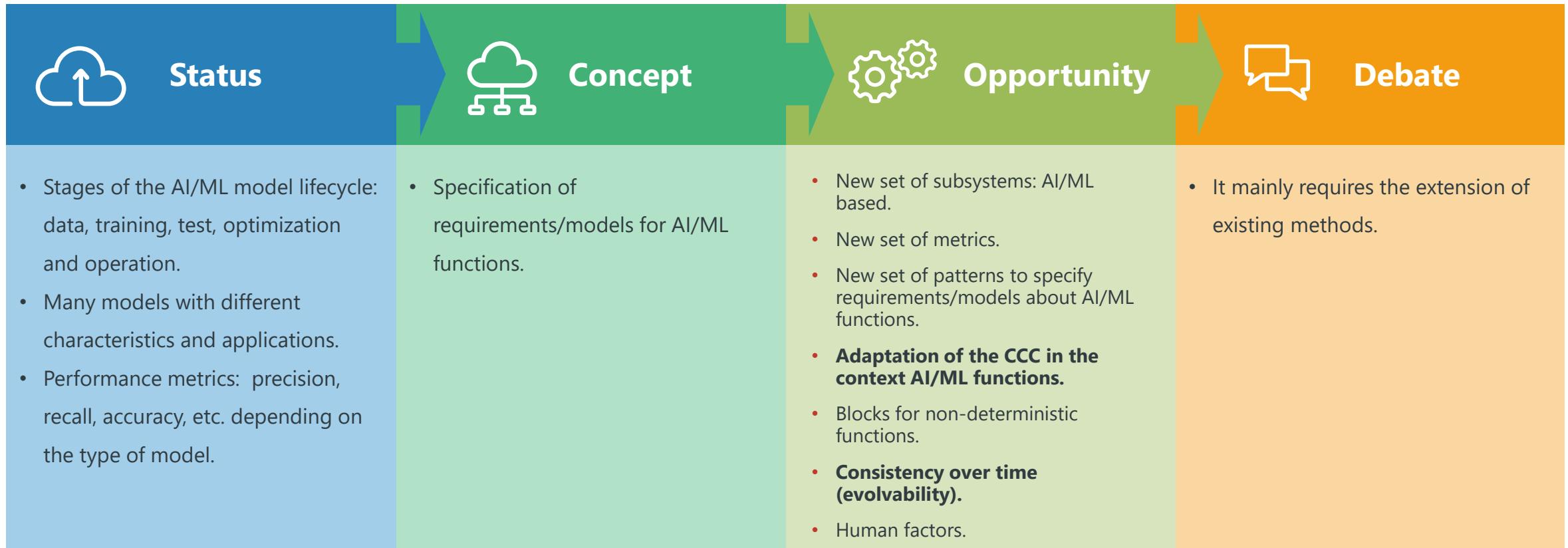


“My” Data Science Lifecycle



Challenge #2: to integrate the AI/ML model lifecycle within the specification process of a system

27



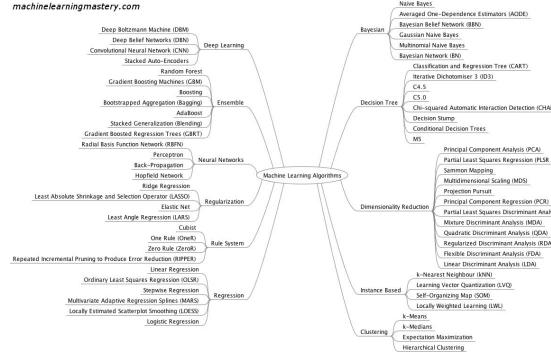
DSL for requirements (patterns, metrics, etc.)

28



Vocabulary

Techniques, metrics, types of problems to solve, etc.



Quality metrics

Consistency over time

Consistency between techniques and metrics.

Consistency between requirements and techniques.

Patterns

P1: The <AI_system> shall <action> <entity> with a <metric> of <value> <unit> under <weather_condition_type>.

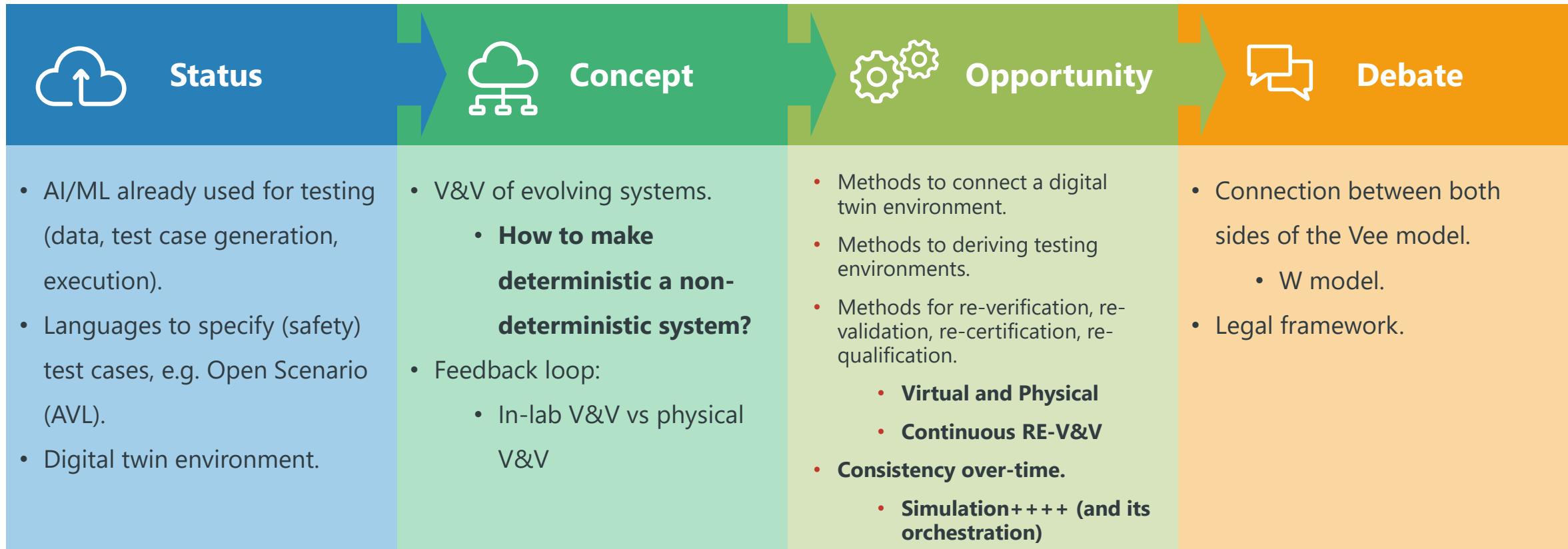
Requirements

R1: *"The entity recognition subsystem shall provide an explanation of at least 10 words about the recognized objects.*

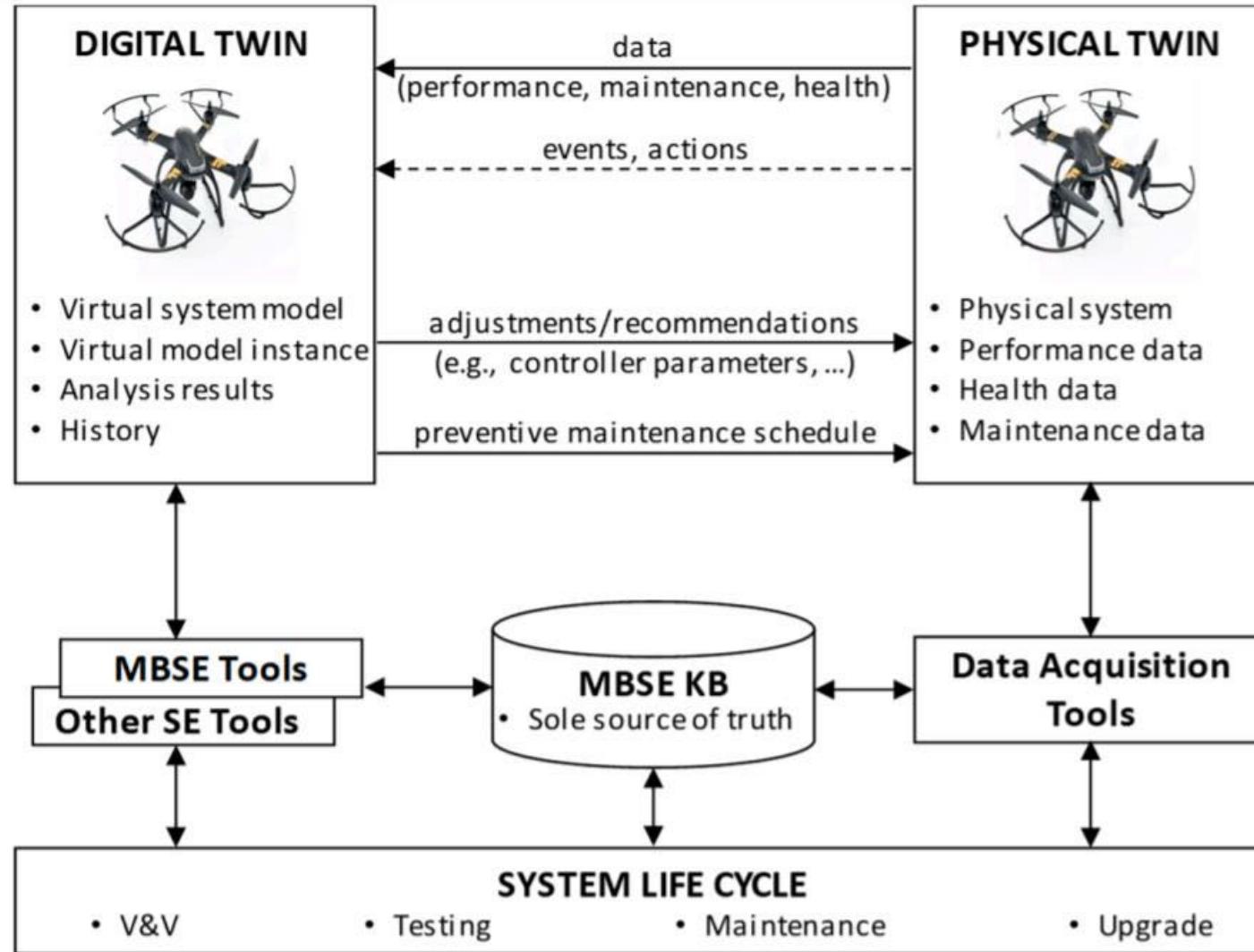
R2: *"The entity recognition subsystem shall recognize a person with an accuracy of 90% under light snow."*

Challenge #3: to integrate the AI/ML model lifecycle within the verification and validation (V&V) process of a system.

29



Digital twin environment



Challenge #4: to integrate the technology stack of the AI/ML model lifecycle within the system execution environment

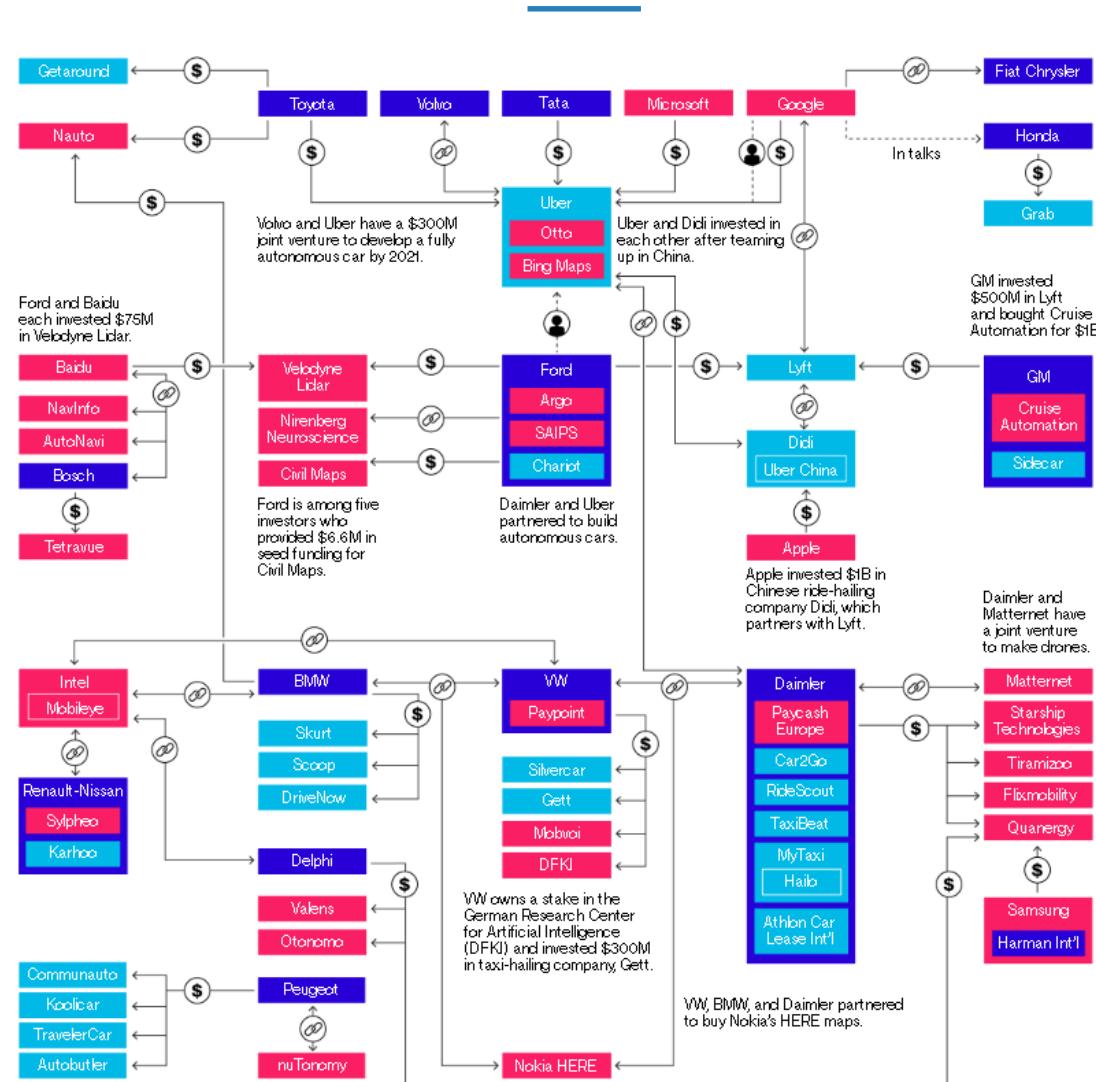
31

 Status	 Concept	 Opportunity	 Debate
<ul style="list-style-type: none">Many technology providers	<ul style="list-style-type: none">Include a new technology stack:<ul style="list-style-type: none">HardwareSoftwareCommunication systemComputation system	<ul style="list-style-type: none">Automatic generation of execution environments (DevOps approach).Artificial “Intelligence as a Service” (AlaaS)“Machine Learning as a Service” (MLaaS) [5]Share models? (competitive advantage)	<ul style="list-style-type: none">In the car industry, there are already strategic alliances between:<ul style="list-style-type: none">Car manufacturers (OEM)Hardware providersAI/ML providers(Software) infrastructure providersResearch centers



Technology and Car Companies

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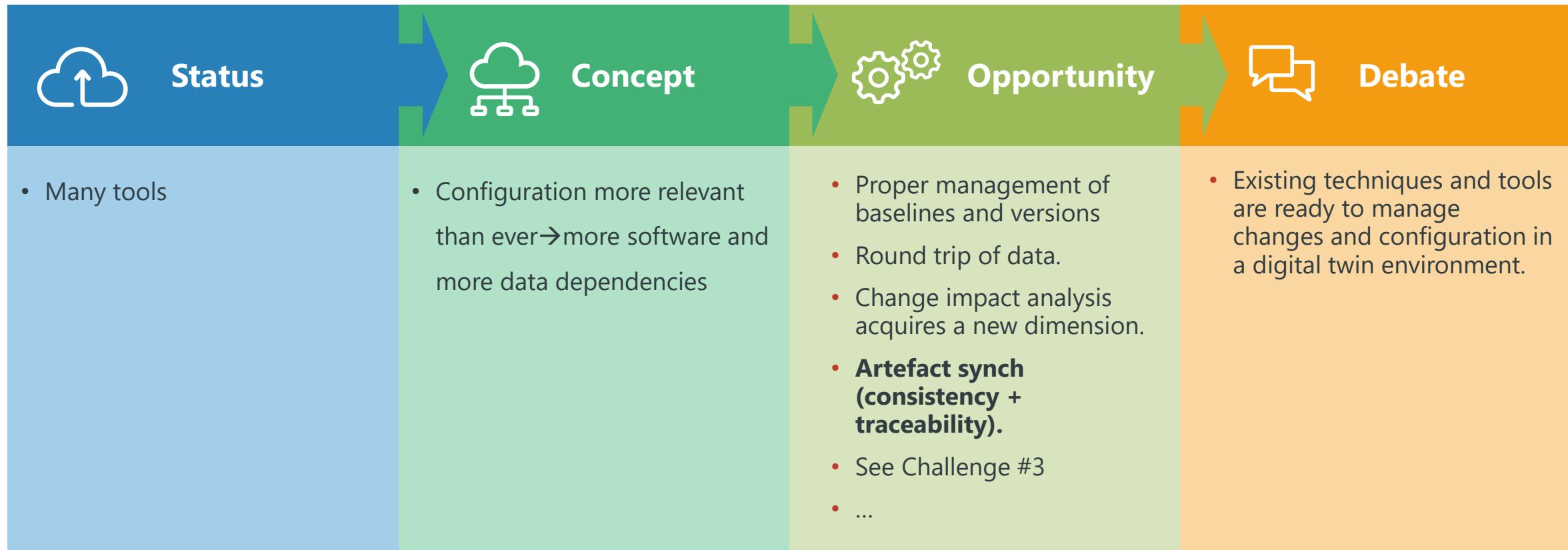


Source: Data compiled by Bloomberg
Additional work: John Lippert, Keith Naughton, Cedric Sam and Kevin Tynan

Source: <https://www.bloomberg.com/graphics/2016-merging-tech-and-cars/>

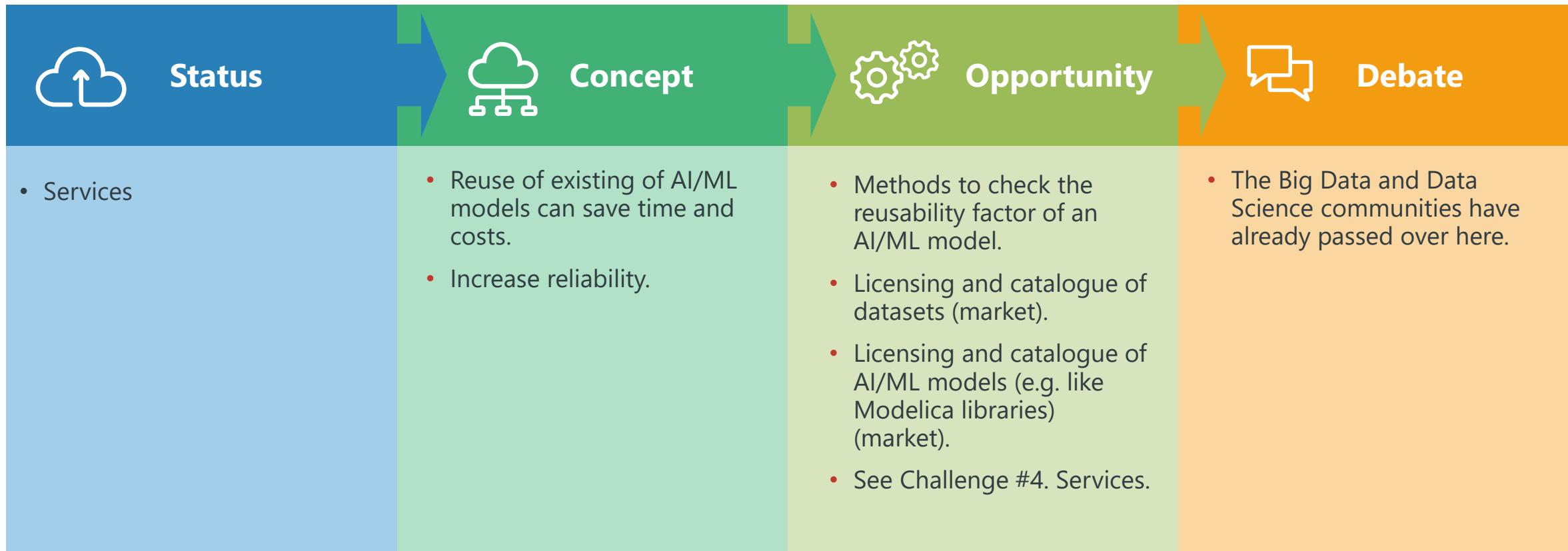
Challenge #5: to integrate the AI/ML model lifecycle within the configuration and change management processes

33



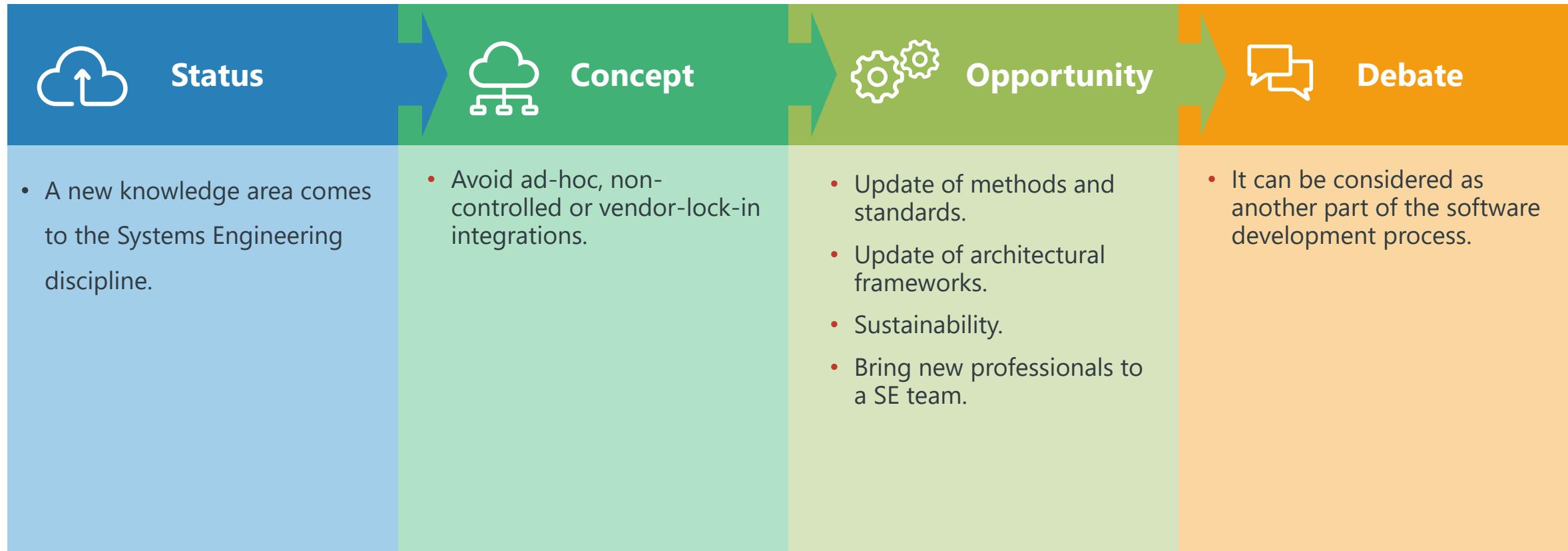
Challenge #6: to ease the reuse of existing AI/ML models

34



Challenge #7: to standardize the integration of AI/ML model lifecycle within the engineering process

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Framework for Highly Automated Vehicle Safety Validation

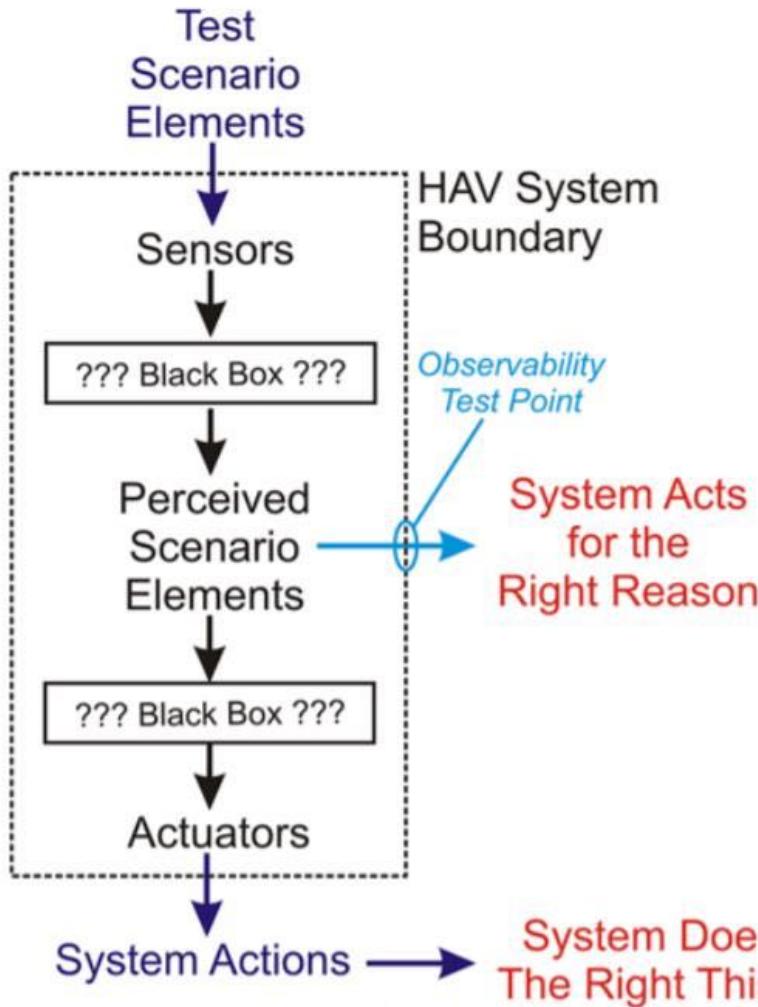
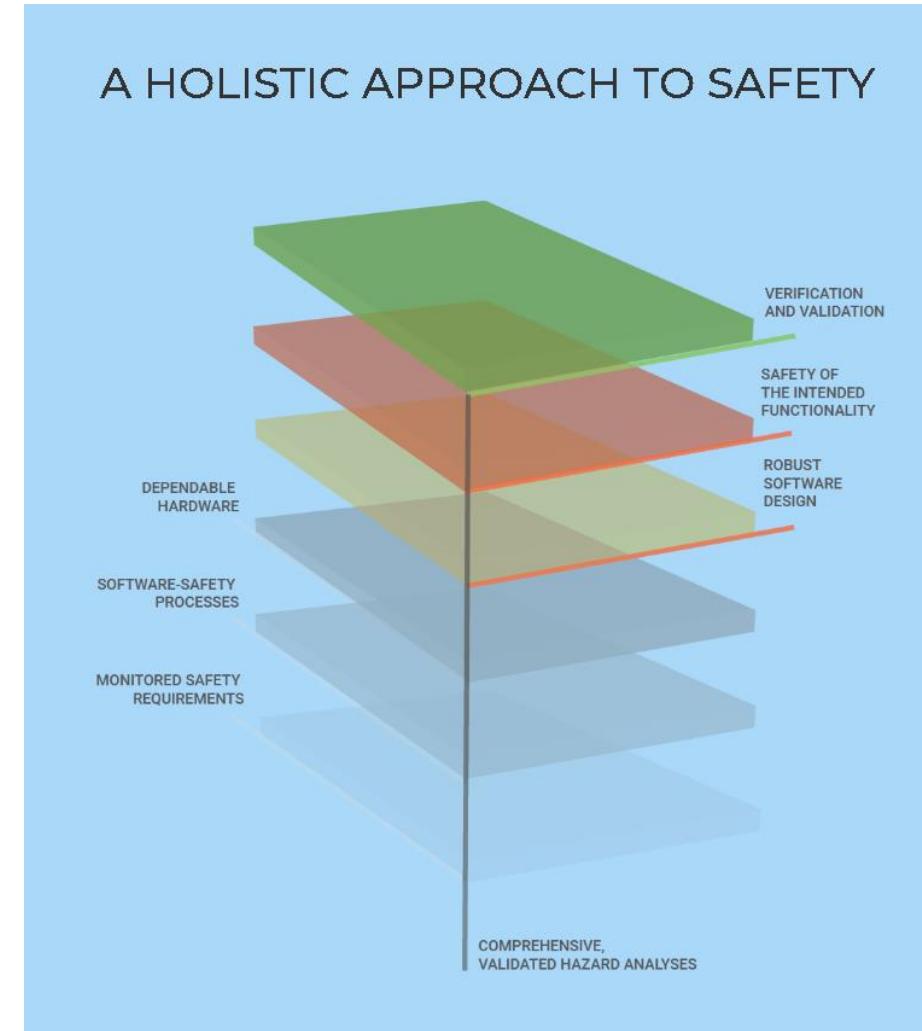


Figure 1. System validation should determine that the system does the right thing for the right reason.

Source: https://users.ece.cmu.edu/~koopman/pubs/koopman18_av_safety_validation.pdf



"First Comprehensive Autonomous Product Safety Standard (UL 4600)"
 Source: <https://edge-case-research.com/>

Challenge #8: to educate a new wave of professionals to deal with AI/ML applying engineering methods

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New roles and positions in AI

The Jobs That Artificial Intelligence Will Create (Continued from page 15)

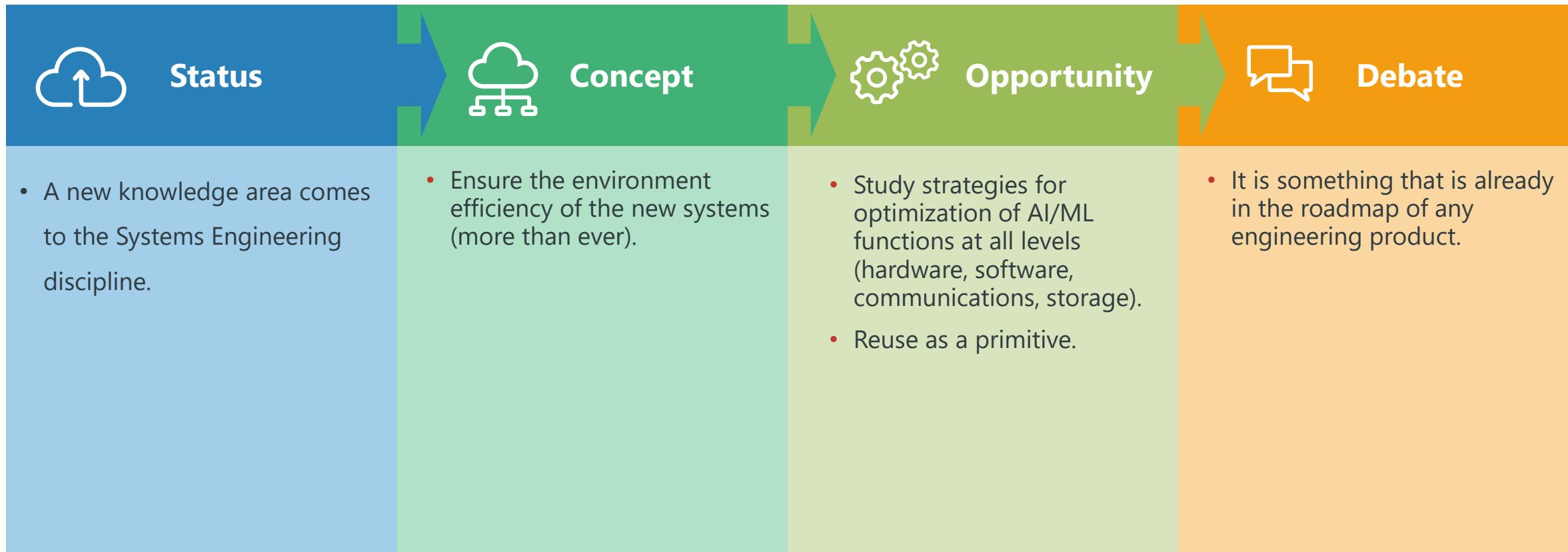
REPRESENTATIVE ROLES CREATED BY AI

Accenture's global study of more than 1,000 large companies identified the emergence of three new categories of uniquely human jobs.

TRAINERS	Customer-language tone and meaning trainer	Teaches AI systems to look beyond the literal meaning of a communication by, for example, detecting sarcasm.
	Smart-machine interaction modeler	Models machine behavior after employee behavior so that, for example, an AI system can learn from an accountant's actions how to automatically match payments to invoices.
	Worldview trainer	Trains AI systems to develop a global perspective so that various cultural perspectives are considered when determining, for example, whether an algorithm is "fair."
EXPLAINERS	Context designer	Designs smart decisions based on business context, process task, and individual, professional, and cultural factors.
	Transparency analyst	Classifies the different types of opacity (and corresponding effects on the business) of the AI algorithms used and maintains an inventory of that information.
	AI usefulness strategist	Determines whether to deploy AI (versus traditional rules engines and scripts) for specific applications.
SUSTAINERS	Automation ethicist	Evaluates the noneconomic impact of smart machines, both the upside and downside.
	Automation economist	Evaluates the cost of poor machine performance.
	Machine relations manager	"Promotes" algorithms that perform well to greater scale in the business and "demotes" algorithms with poor performance.

Challenge #9: to fulfill environmental requirements

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Challenge #10: to ensure the construction of ethical machines

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Summary



Conclusions



Keypoints

Key points and next steps



- 1 Research on AI/ML and Systems Engineering is a key/active area.
- 2 Cyber-physical systems must be safer, cost-effective and environmentally friendly and...deliver on time (reacting to market needs).
- 3 Engineering processes must integrate a new discipline and adapt engineering methods to support the new technical capabilities.
- 4 Engineering of intelligent and evolving systems also requires “intelligent” tools.
- 5 Ethics is IMPORTANT, Safety a MUST.

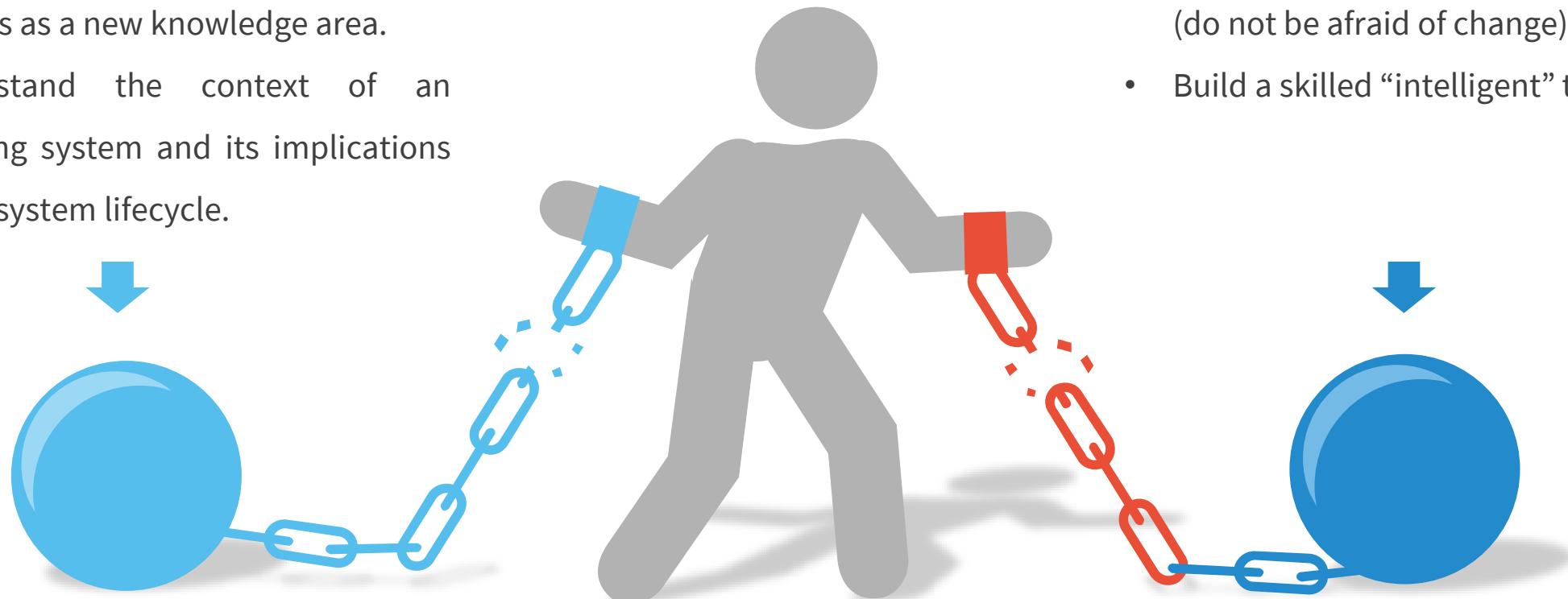
Do NOT be a “*technological*” slave

Build intelligent systems...

- Integrate the background of AI/ML experts as a new knowledge area.
- Understand the context of an evolving system and its implications in the system lifecycle.

...with intelligence

- Make use of existing and new tools (do not be afraid of change).
- Build a skilled “intelligent” team.



Take a seat and comment with us!

Thank you
for your
attention!



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Josemaria.alvarez@uc3m.es

@chema_ar

References

1. C. Ebert, “50 Years of Software Engineering: Progress and Perils,” *IEEE Softw.*, vol. 35, no. 5, pp. 94–101, Sep. 2018.
2. F. Khomh, B. Adams, J. Cheng, M. Fokaefs, and G. Antoniol, “Software Engineering for Machine-Learning Applications: The Road Ahead,” *IEEE Softw.*, vol. 35, no. 5, pp. 81–84, Sep. 2018.
3. D. Sculley et al., “Hidden Technical Debt in Machine Learning Systems,” in *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 2*, Cambridge, MA, USA, 2015, pp. 2503–2511.
4. D. Sculley et al., “Machine Learning: The High Interest Credit Card of Technical Debt”. Google Research, 2014.
5. M. Ribeiro, K. Grolinger, and M. A. M. Capretz, “MLaaS: Machine Learning as a Service,” in *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*, Miami, FL, USA, 2015, pp. 896–902.