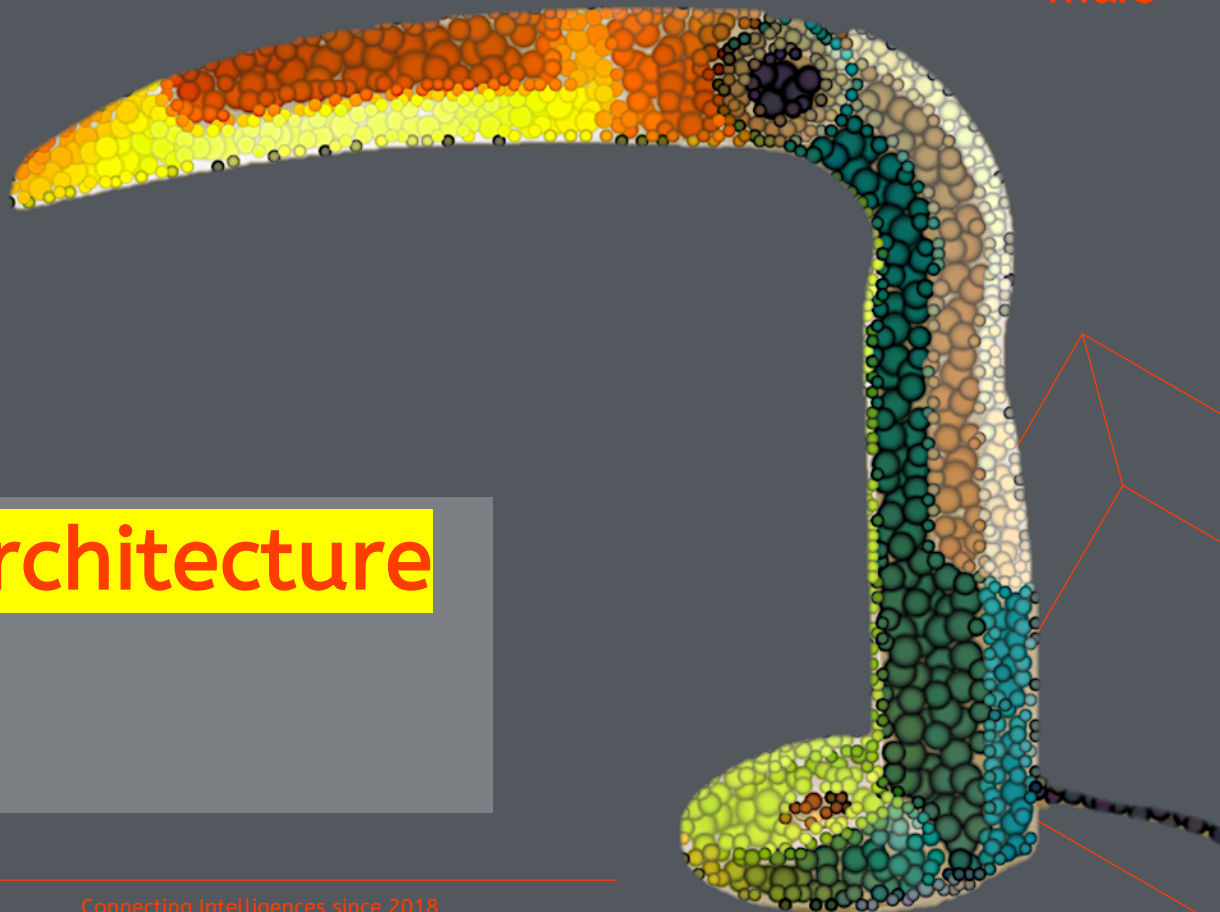


Intelligence Architecture

BERLIN. EARTH. AND BEYOND.

www.birdsonmars.com





[work](#) [birds](#) [clients](#) [aix](#) [sol](#) [merch](#) [take me to mars!](#)

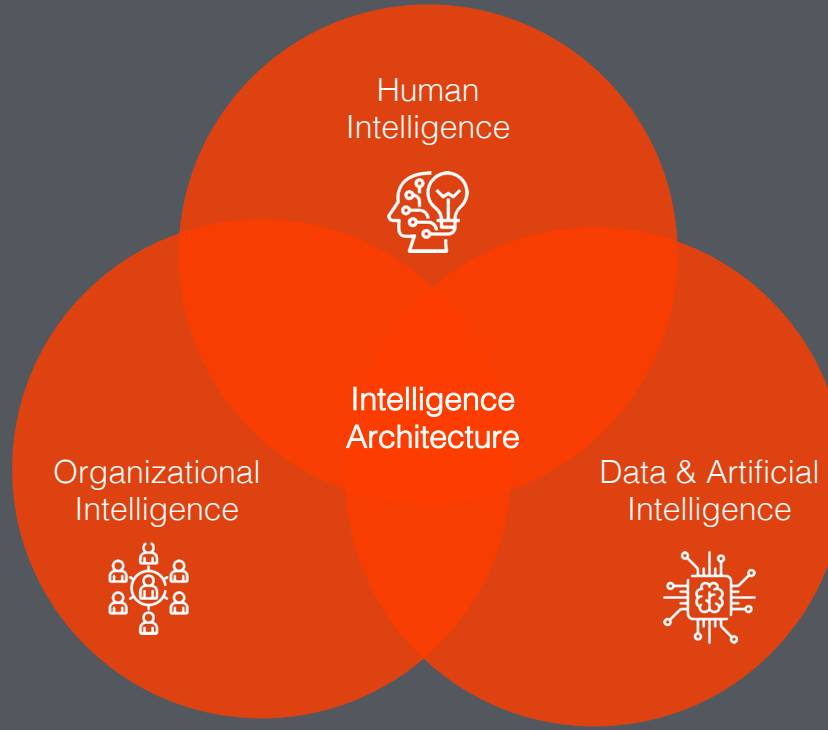
CONNECTING INTELLIGENCES

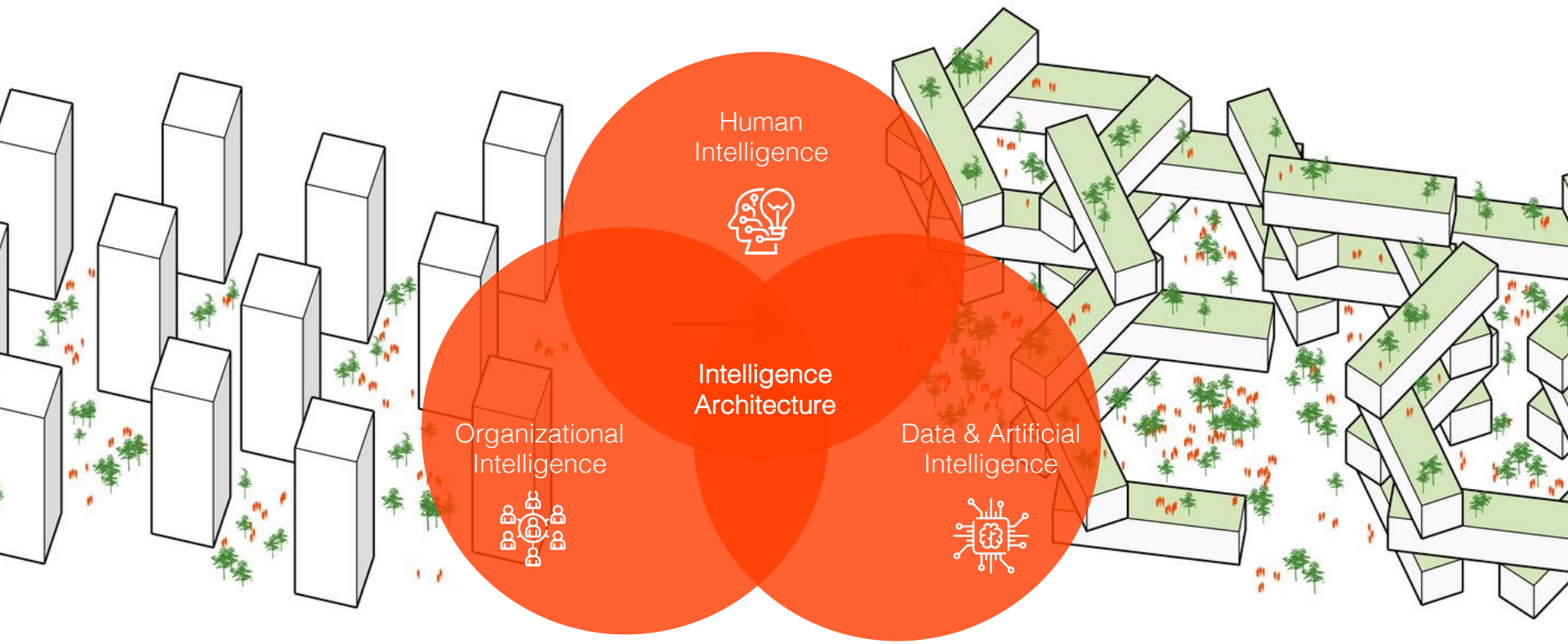
human + artificial + organizational

We are a new generation consulting company and AI
agency highly specialized in data and artificial
intelligence.

Every day, we build innovative enterprise solutions that
combine human creativity, machine intelligence and
organizational identity.

Everything we do happens somewhere here





Of course we need to talk IT!
And new paradigms.



„One of the biggest mistakes leaders make is to view AI as a plug-and-play technology with immediate returns.“

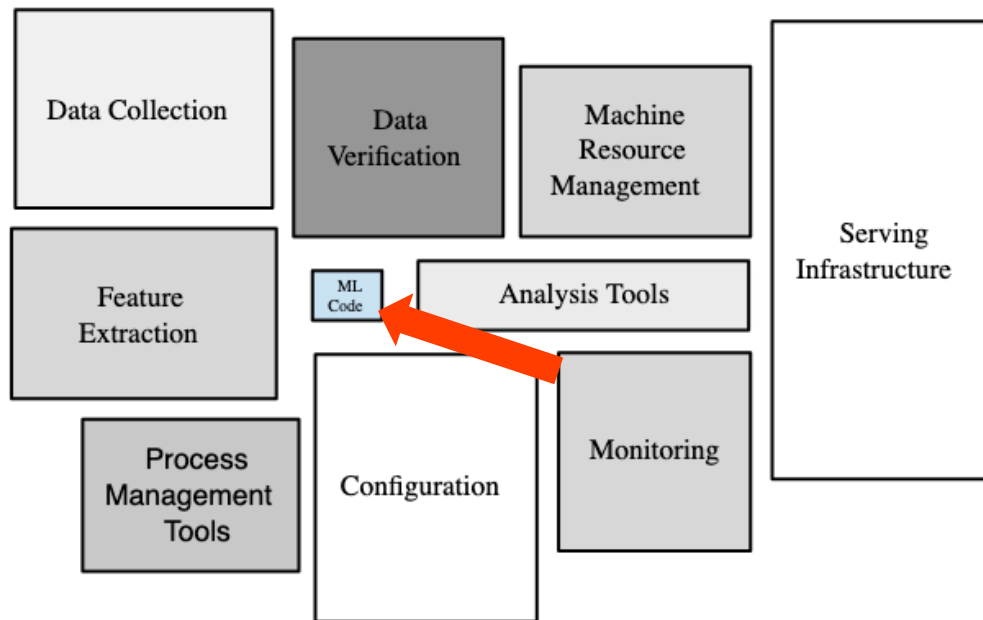
<https://hbr.org/2019/07/building-the-ai-powered-organization>

Microsoft's CEO, Satya Nadella, refers to *AI*
as the new "runtime" of the firm.

...a kind of **Operating System!**

Most quoted paper!

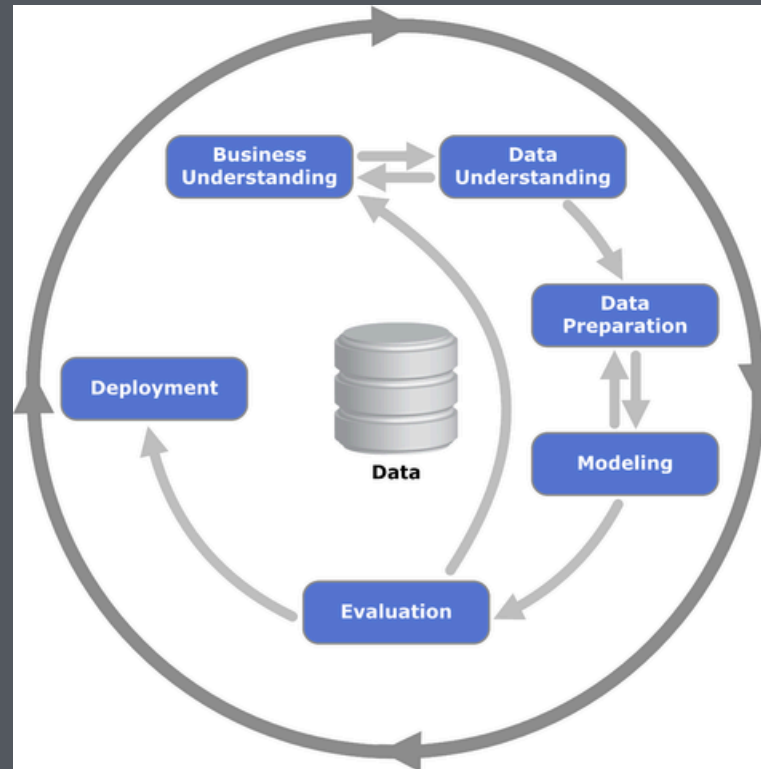
„Real-world production ML systems are large ecosystems of which the model is just a single part.“



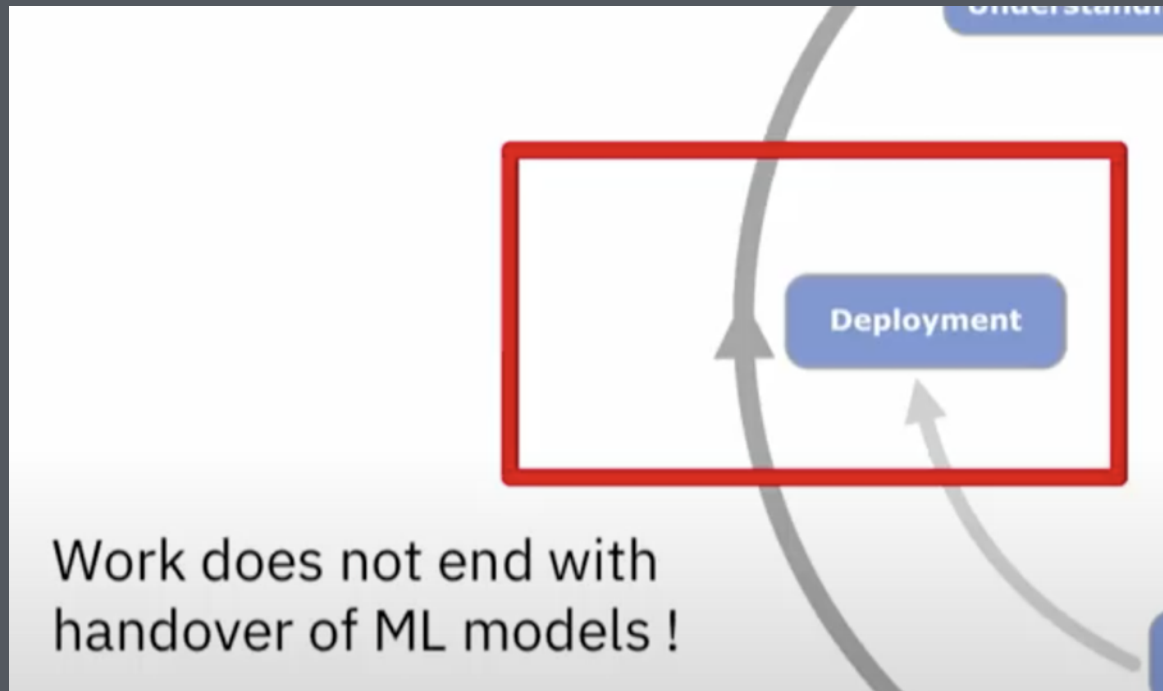
AI = the software of our generation!

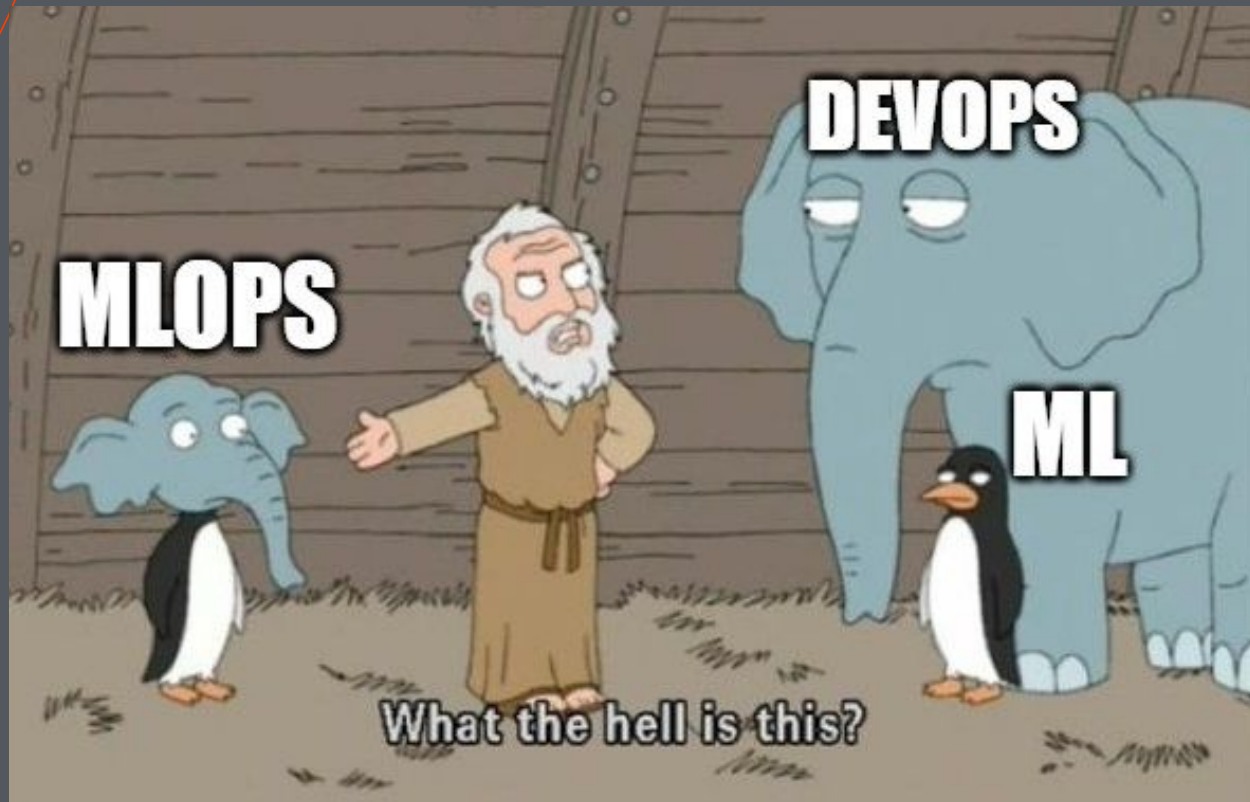
<https://developers.google.com/machine-learning/crash-course/production-ml-systems?hl=de>

Our Data Science approaches today...

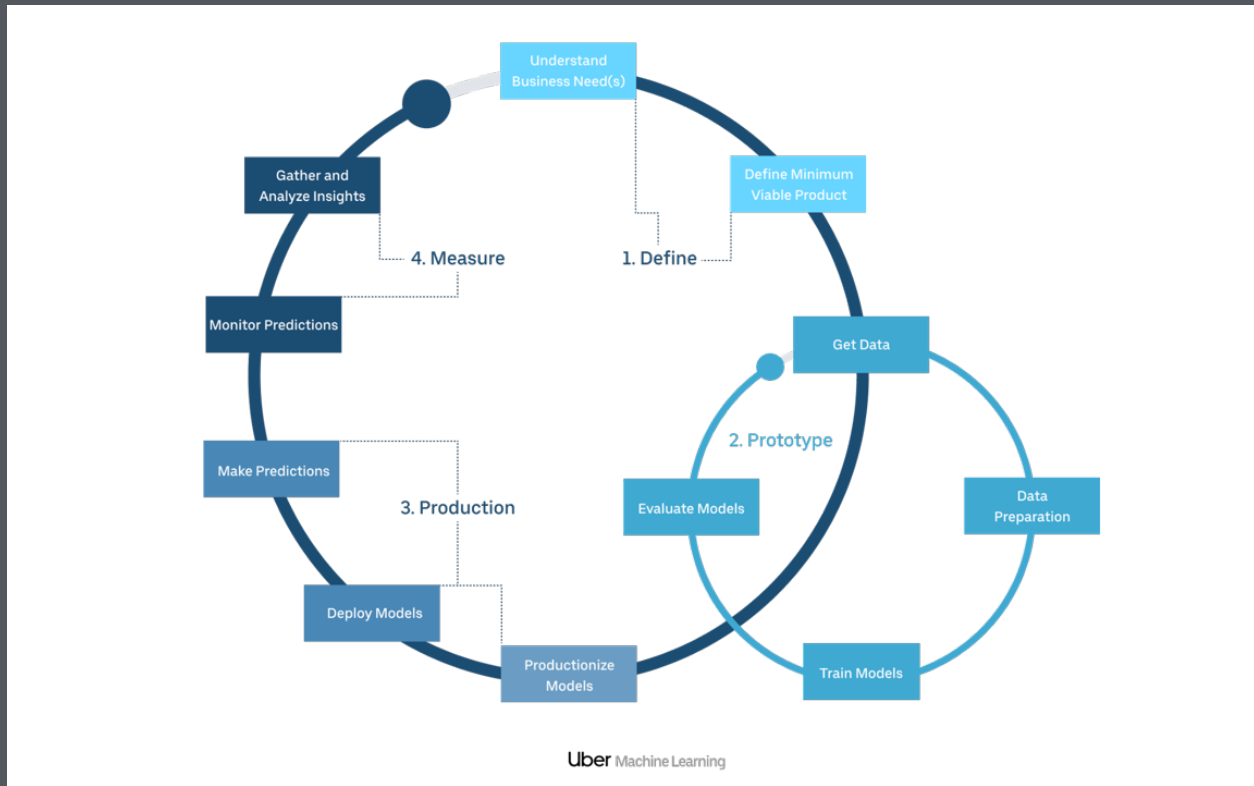


...fall short when it comes to ML/AI!



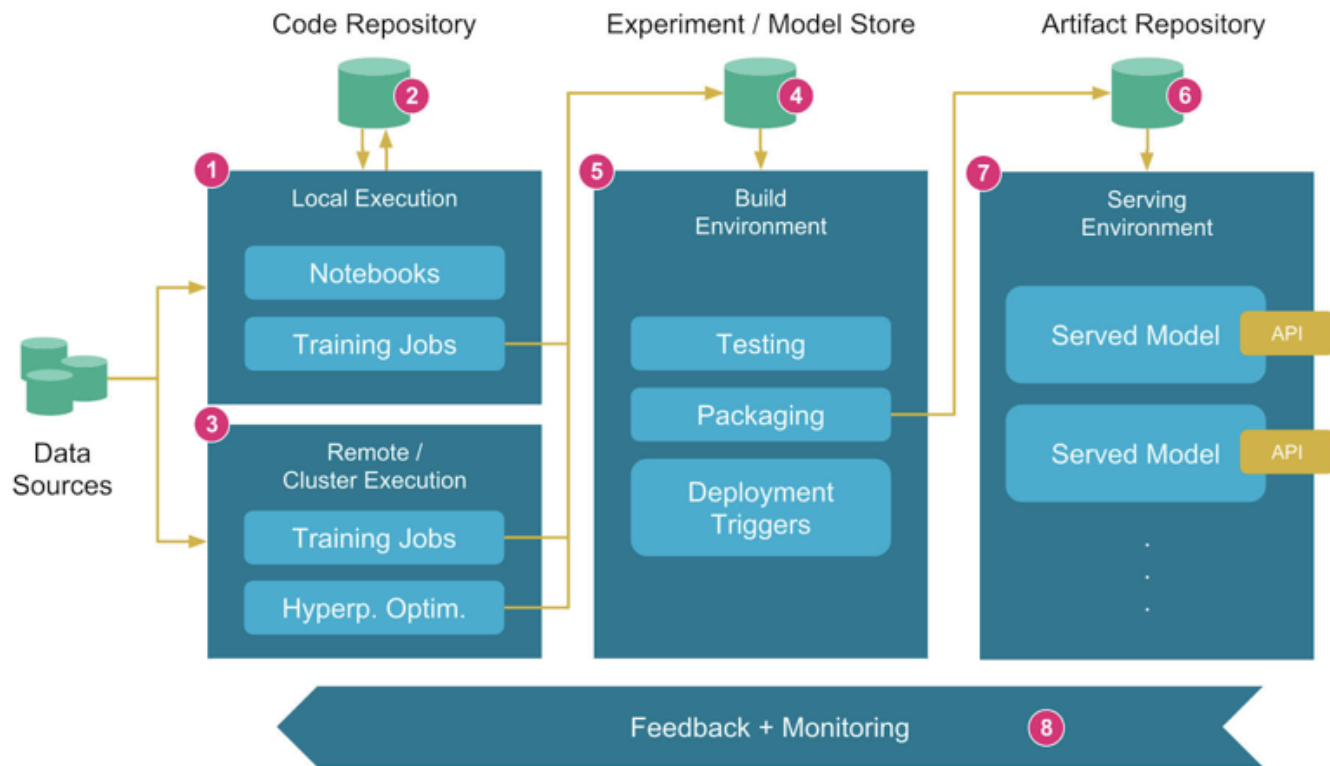


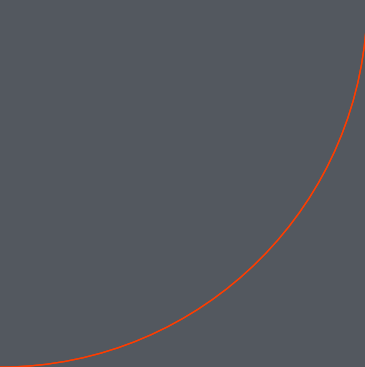
„Continuous Intelligence“



We must continuously
orchestrate **data, models
and code!**

„New Architectures“



A decorative orange arc is located in the top-left corner of the slide.

Problem Space = **ML is not ML!**

Example: Booking.com

“People building Machine Learning models do it in many very different ways. Some use a small data set and R, others a huge data set and a command line tool like Vowpal Wabbit. Some like to write their own optimization algorithm in Java, others use sklearn or H2O. Some build Deep Learning models in Pytorch, others in Tensorflow, and so on. **We believe in such diversity and therefore encourage it and support it with tools, courses, infrastructure and more...**”

<https://booking.ai/https-booking-ai-machine-learning-production-3ee8fe943c70>

Model Serving (selected)

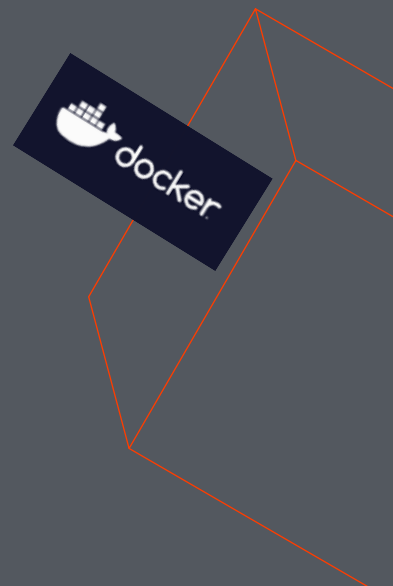
Once a suitable model is found, we need to decide how it will be served and used in production. We have seen a few patterns to achieve that:

Embedded model: this is the simpler approach, where you treat the model artifact as a dependency that is built and packaged within the consuming application. From this point forward, you can treat the application artifact and version as being **a combination of the application code and the chosen model**.

Model deployed as a separate service: in this approach, **the model is wrapped in a service** that can be deployed independently of the consuming applications. This allows updates to the model to be released independently, but it can also introduce latency at inference time, as there will be some sort of remote invocation required for each prediction.

Model published as data: in this approach, the model is also treated and published independently, but the consuming **application will ingest it as data at runtime**. We have seen this used in streaming/real-time scenarios where the application can subscribe to events that are published whenever a new model version is released, and ingest them into memory while continuing to predict using the previous version.

<https://martinfowler.com/articles/cd4ml.html>




Elements of a solution space...



GO WITH THE FLOW - QUEENS OF THE STONE AGE



Free, Easy, Accurate & Printable
Beginner Guitar Chords & Strumming




What are the „typical“ AI use-uses?
What do they require along the full lifecycle?
Where and how do they differ?
...


„Fingerprinting“ + „Thinking backwards from production“



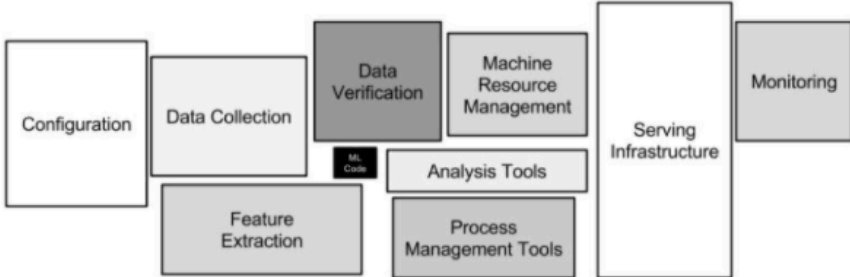
What is our status quo in tech, tools, processes?
Where are the gaps?
How can we start thinking in pipelines and flows?
...




If you're a data science leader, think about how to make deployment and industrialization as easy as possible for your data scientists, so the way from a beautiful algorithm to an analytical product is as fast as it can be.

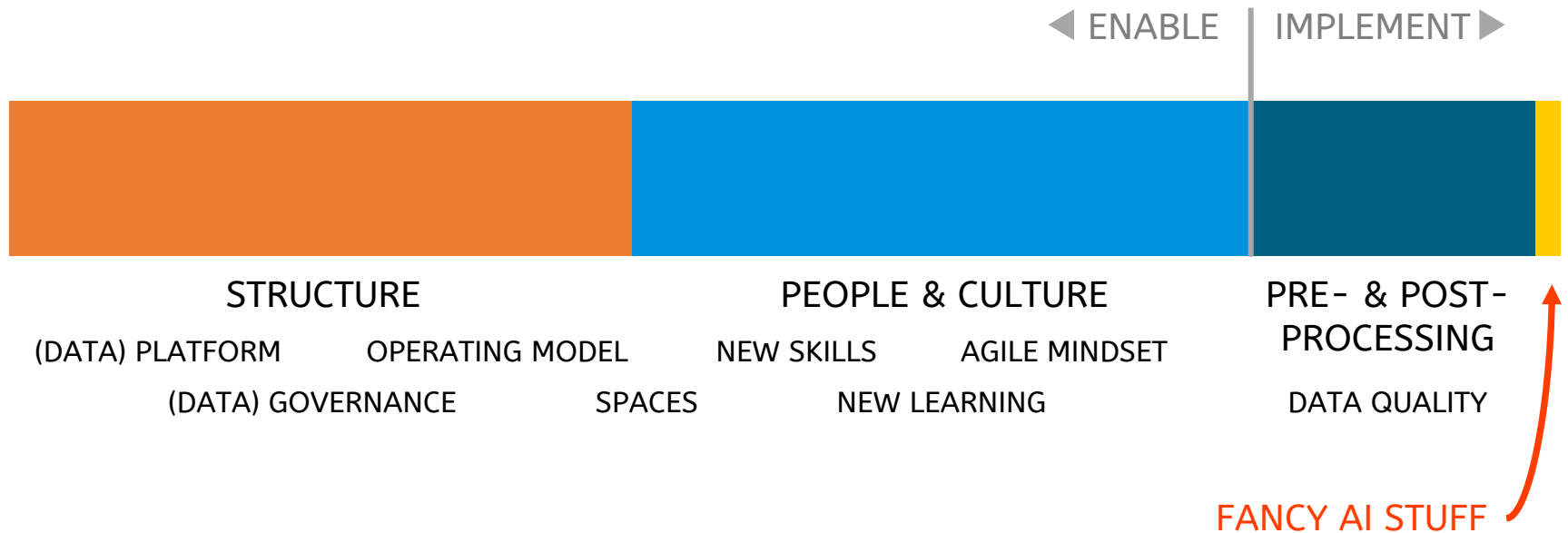


Dr. Michael Kachala • 2nd
 Global Head of Data Science at Bayer Consumer Health
 1d • 

Machine learning is just a tiny fraction of overall data science work. The image that you can see below (source: <https://lnkd.in/d/fBnnJ9>) is the best illustration showing how many things should be in place for the successful machine learning (or AI) project. What conclusions we can make from it? If you're a data scientist it make sense not only to go deeper in the ML part by learning new sexy algorithms, but also expand your knowledge on data and infrastructure topics. In the next years, added value will come from how your algorithms are integrated in the business processes, rather than from the stand-alone solutions. And if you're a data science leader, think about how to make deployment and industrialization as easy as possible for your data scientists, so the way from a beautiful algorithm to an analytical product is as fast as it can be. [#datascience](#) [#machinelearning](#) [#ai](#) [#deeplearning](#) [#data](#) [#infrastructure](#)






 36 · 3 Comments



◀ ENABLE | IMPLEMENT ▶



STRUCTURE

(DATA) PLATFORM

OPERATING MODEL

(DATA) GOVERNANCE

SPACES

PEOPLE & CULTURE

NEW SKILLS

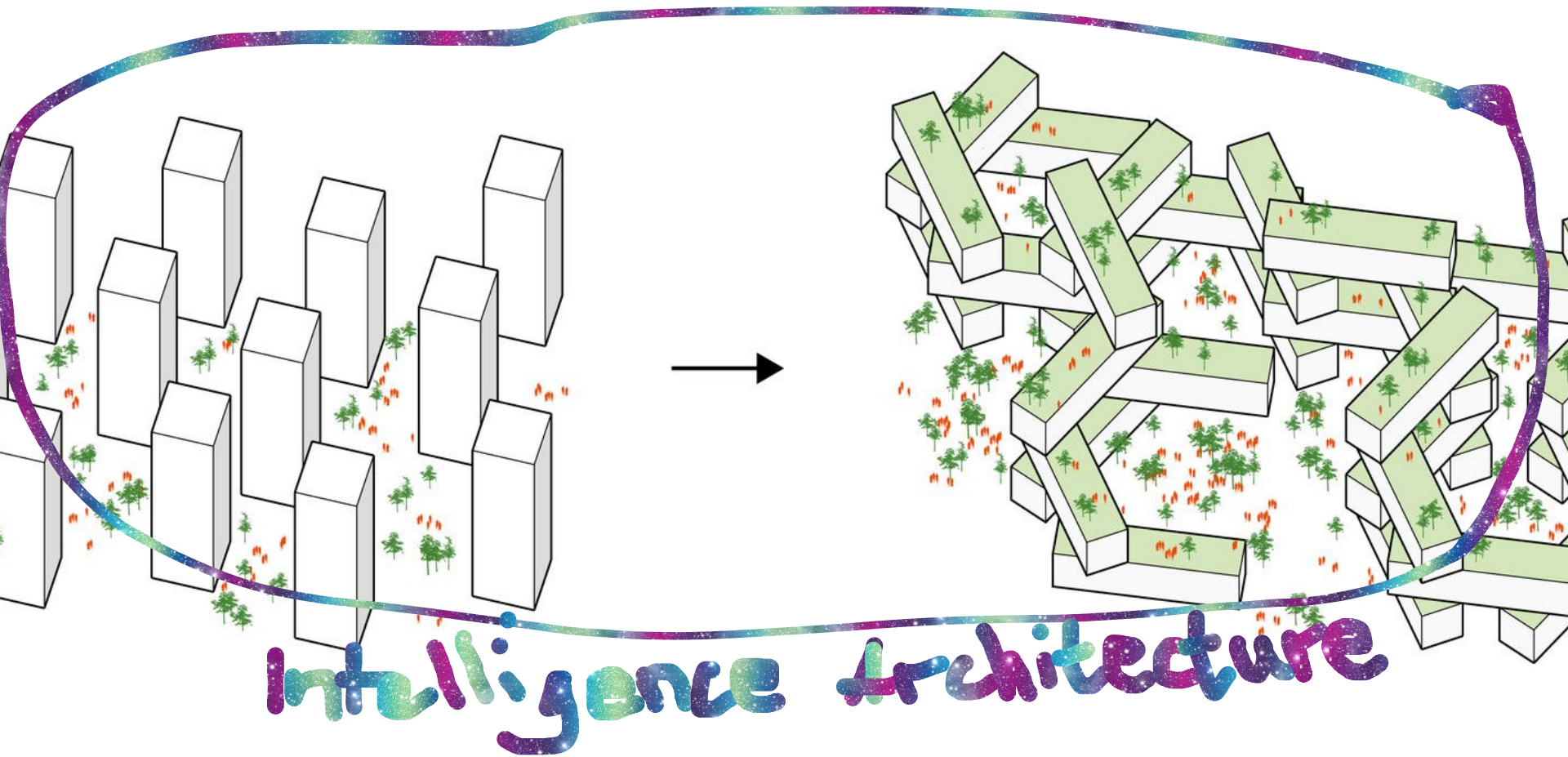
AGILE MINDSET

NEW LEARNING

PRE- & POST- PROCESSING

DATA QUALITY

Intelligence Architecture



"The paradox is that
the new is new.
In this sense, one
cannot buy or sell
something new.
You can only develop
it..."



Prof. Dr. Sabine Fischer
Professor of Idea Economics in Digital Transformation and member of the
Sounding Board of Birds on Mars

A large, thin orange arc is positioned in the top-left corner of the slide.

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