Microsoft AI

Enabling Tech Intensity

State of Tech Intensity 2019 study

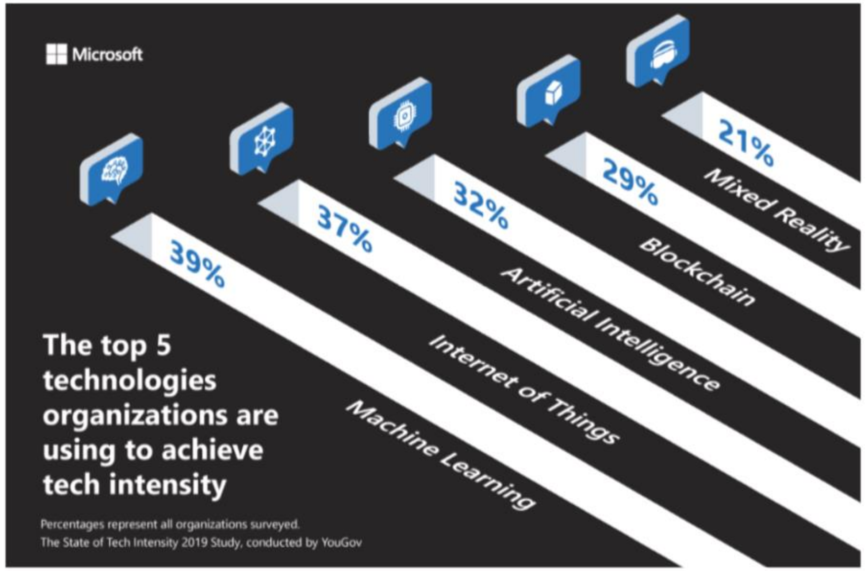
According to a study of 700 executives and decision-makers, organizations are betting on the power of advanced technologies and an entrepreneurial mindset to build their own unique digital capabilities

Every company is becoming a technology company

One of the key findings of the study was the extent to which companies have already embraced tech intensity. According to the study, tech intensity is already pervasive, with 73% of companies reporting they are currently creating their own first-party intellectual property using next-generation technologies such as machine learning (39%), IoT (37%), AI (32%), blockchain (29%) and mixed reality (21%).

The study also revealed broad agreement across industries that tech intensity is critical for current and future success. For example, 75% of respondents believe that harnessing tech intensity is the most effective way to build competitive advantage today, and 75% also believe it will be crucial to building competitive advantage in the future.

In addition to creating competitive advantage now and into the future, responses also revealed a strong belief that tech intensity will be a catalyst for ongoing disruption. Nearly half of those surveyed predict that existing companies will be forced to compete with new entrants in their industry that are building their own digital capabilities and intellectual property. Among the industries where that expectation is the highest are media and communications, financial services, retail, and automotive.



Global impact of tech intensity

Although much of the focus of tech intensity is on creating competitive business advantage, there was a strong consensus that tech intensity will have a positive impact on global communities. When asked about specific areas where tech intensity will serve as a driving force for societal improvement, 43% selected better public services at lower costs, 40% chose improved connectivity in rural areas, and 40% chose reduced corporate waste. Other key areas where respondents expect to see improvements include health care (36%), consumer safety (36%), worker safety (33%) and access to financial services (33%). Only 8% said they don't expect tech intensity to deliver any positive benefits for global communities.

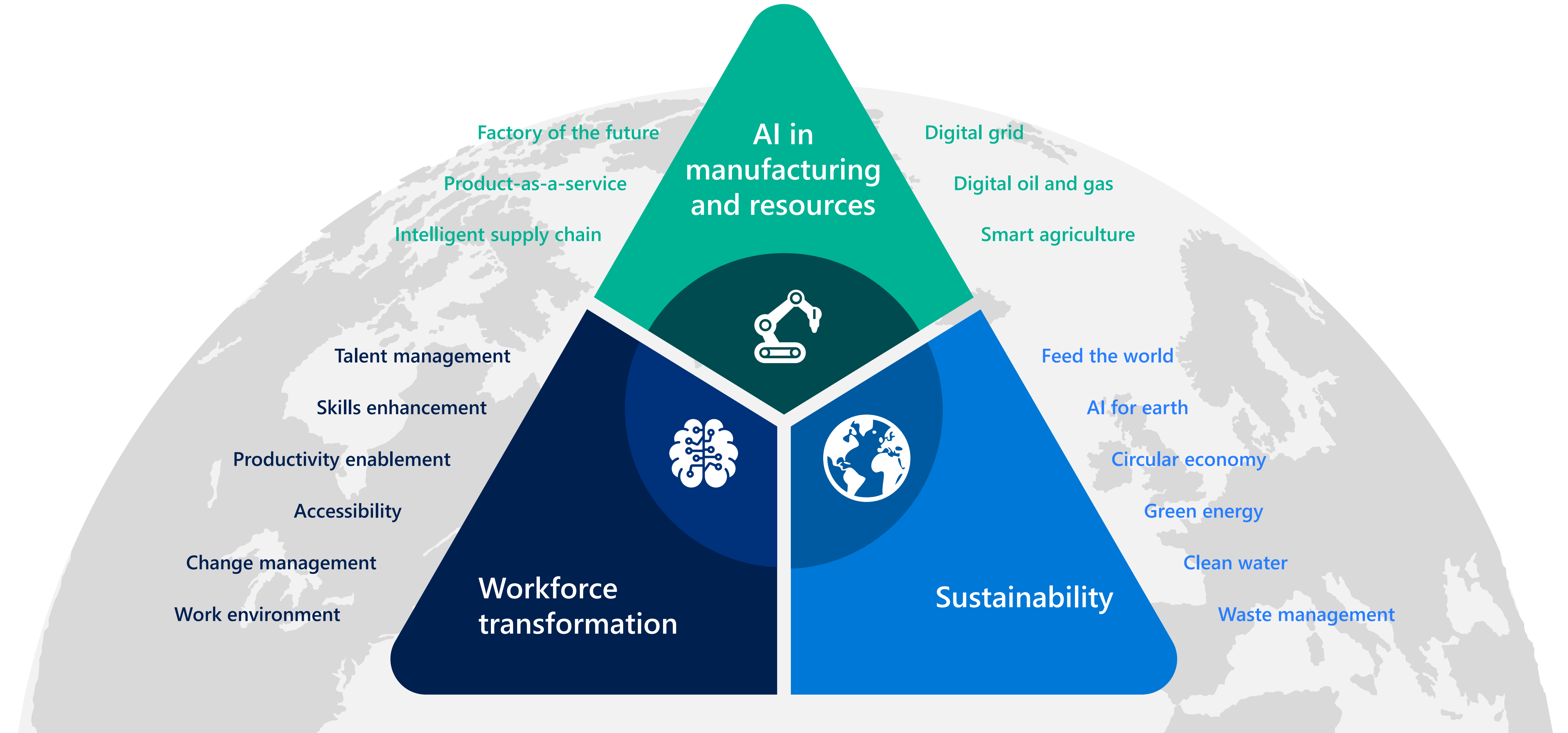
Tech intensity and corporate culture

Another key finding of the study was the effect of tech intensity on organizational culture. For example, there is a nearly unanimous belief that staying on the cutting edge of technologic progress is essential to retaining talent, with 92% of those surveyed agreeing it is important or very important to work for an organization that keeps up with software and application trends. That belief is particularly strong among millennials, only 2% of whom think that staying current with technology isn't important. In contrast, 9% of Gen Xers and 10% of baby boomers don't think that keeping up with technology is important.

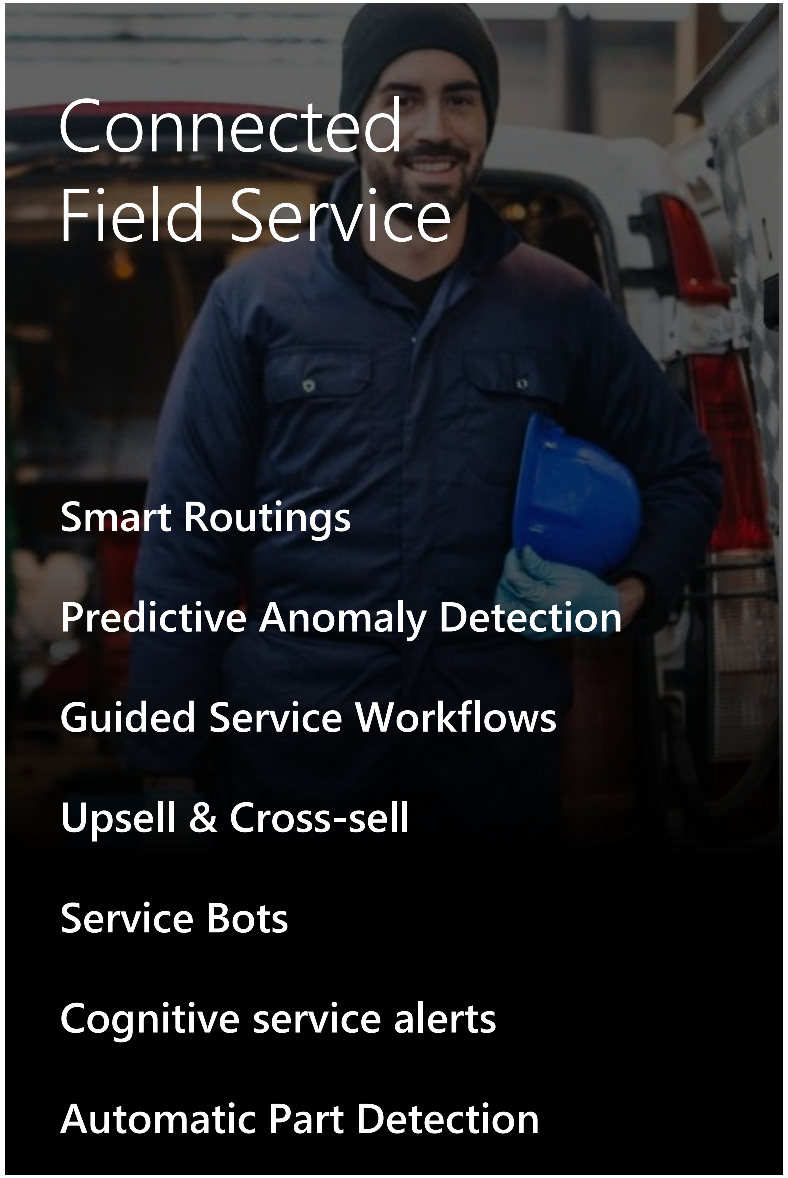
http://aka.ms/tech-intensity-study

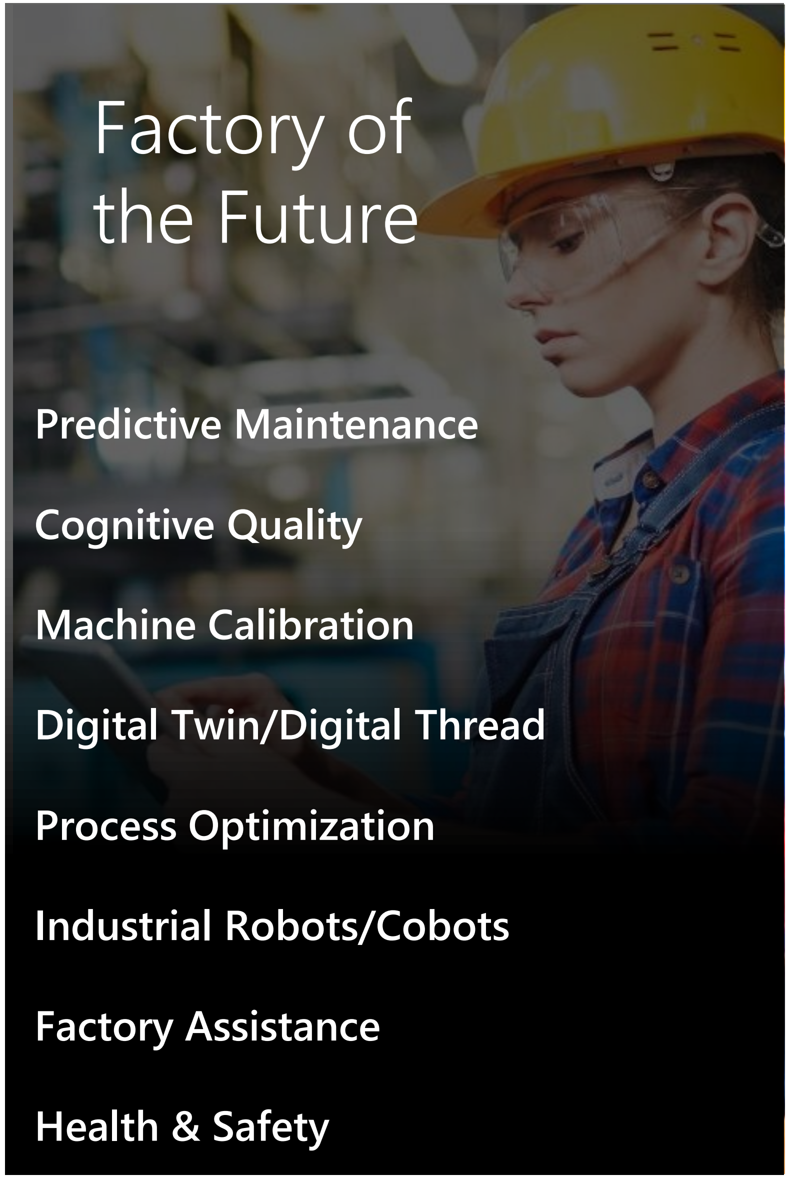
$$\text{Tech Intensity} = (\text{Tech adoption} \times \text{Tech capability})^{\text{Trust}}$$

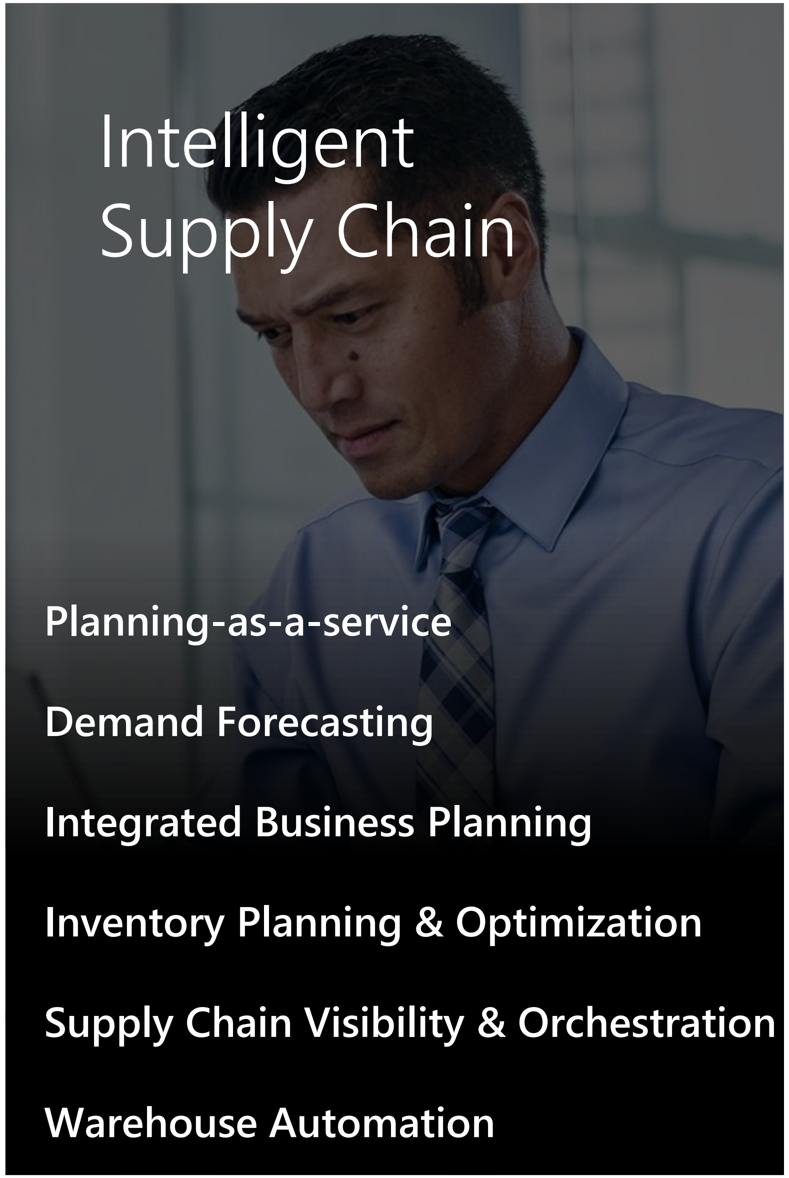
Business objectives with AI



Use cases in manufacturing

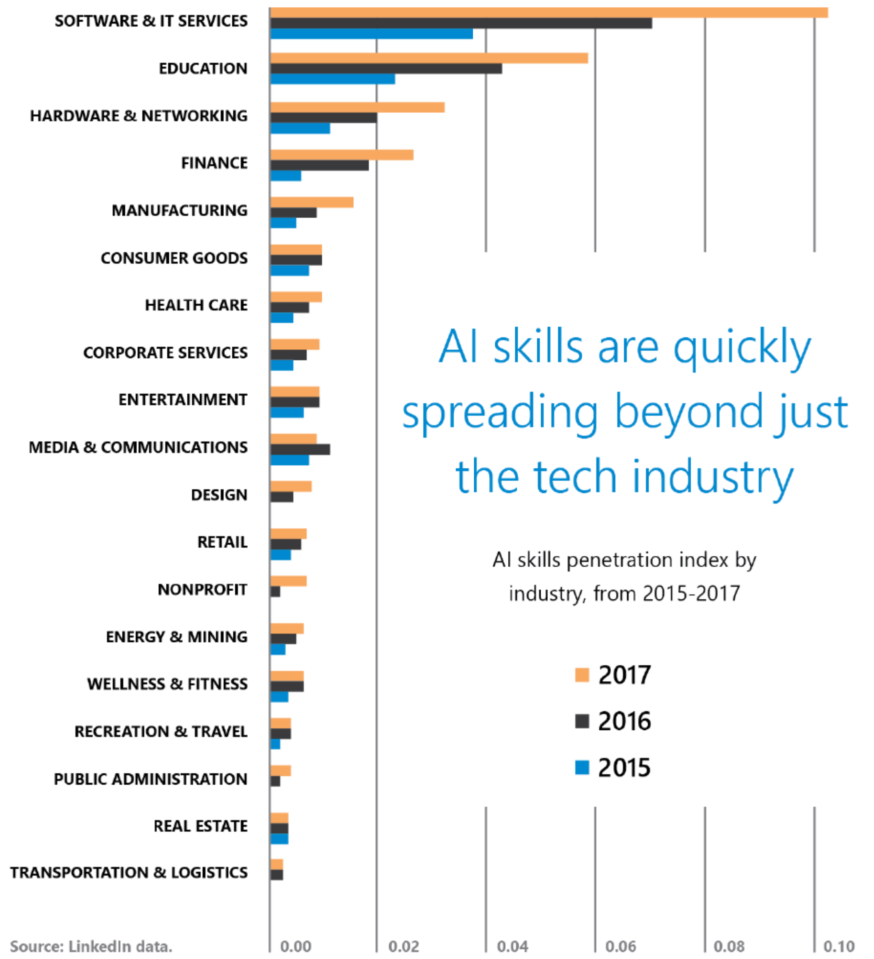






Tech Intensity Challenge #1

Skillset



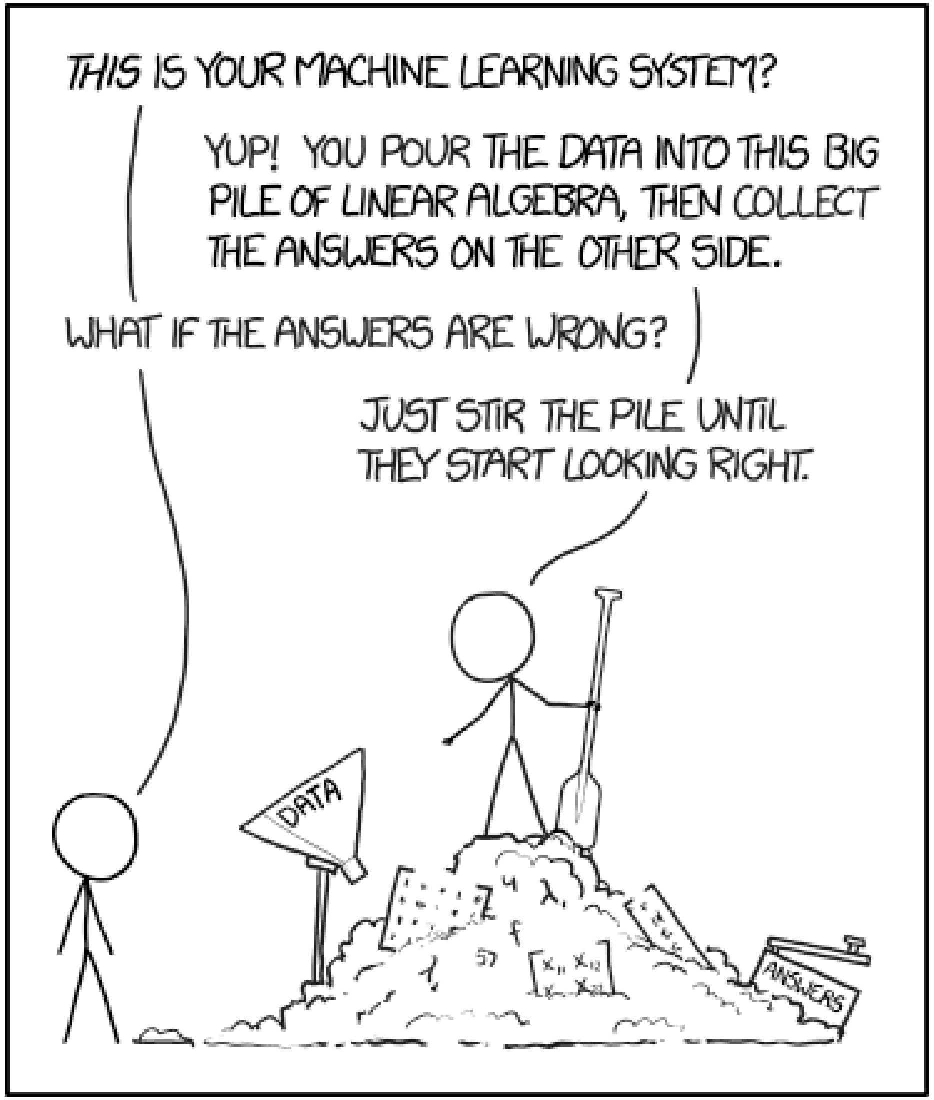
Note: The penetration index looks at how many of the AI skills appear among top 30 skills for each occupation in each industry. It computes the mean % of AI skills across occupations within each industry in year 2015, 2016 and 2017. By comparing the index across years, it gives us the time trend of industry-level AI skills penetration.

Tech Intensity Challenge #1

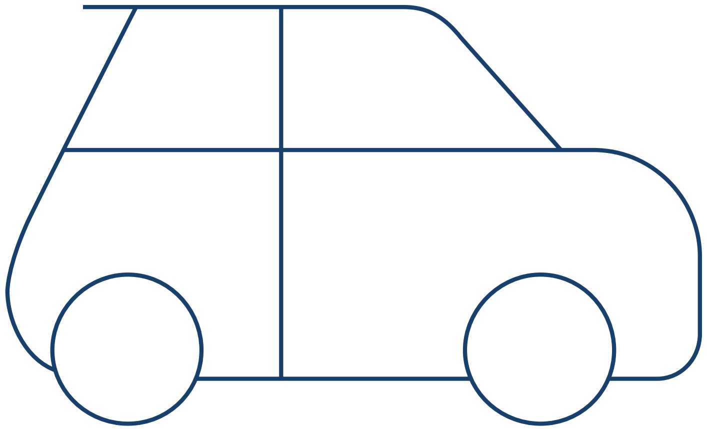
Skillset

- Machine Learning
- Domain expertise

Machine Learning



Machine Learning



How much is this car worth?

Machine Learning - Model creation

Which features? | **Which algorithm?** | **Which parameters?**

Which features?

- **Mileage**
- Condition
- **Car brand**
- **Year of make**
- Regulations
- …

Which algorithm?

- **Gradient Boosted**
- Nearest Neighbors
- SVM
- Bayesian Regression
- LGBM
- …

Which parameters?

- Parameter 1 / Criterion
- Parameter 2 / Loss
- Parameter 3 / Min Samples Split
- Parameter 4 / Min Samples Leaf
- Others

30%

Model

Machine Learning - Model creation

Which features?

- **Mileage**
- **Condition**
- **Car brand**
- **Year of make**
- Regulations
- …

Which algorithm?

- **Gradient Boosted**
- **Nearest Neighbors**
- SVM
- Bayesian Regression
- LGBM
- …

Which parameters?

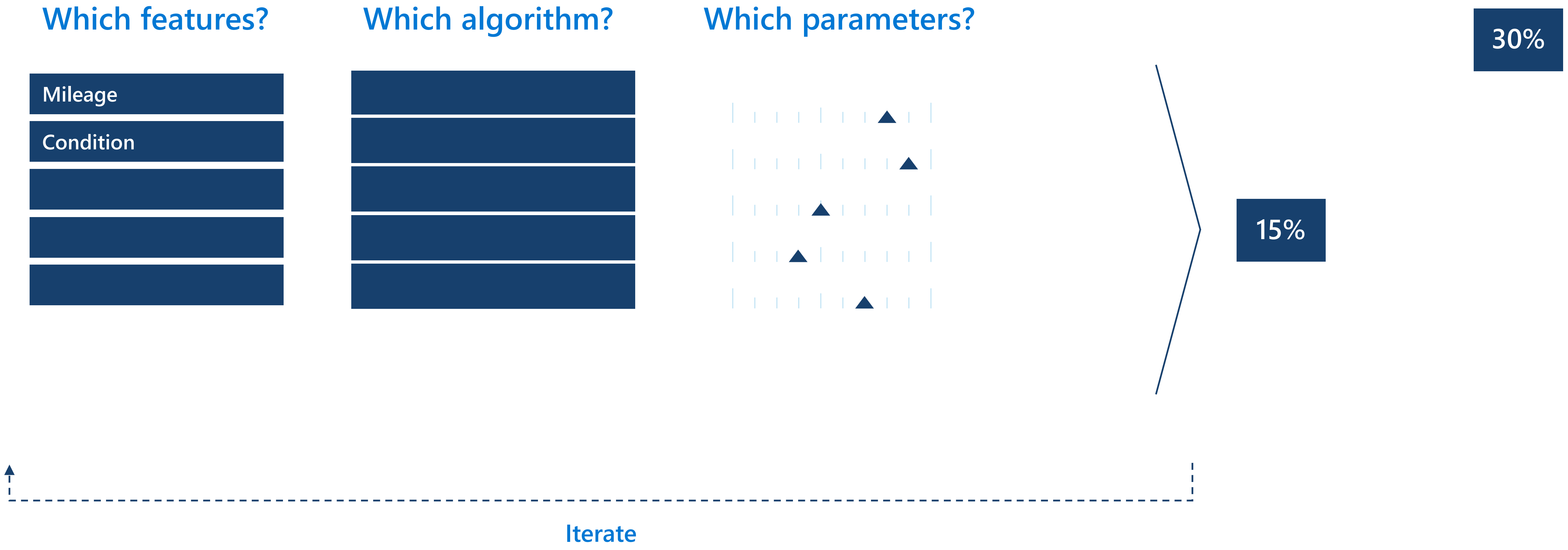
- N Neighbors
- Criterion
- Weights
- Loss
- Metric
- Min Samples Split
- P
- Min Samples Leaf
- Others

30%

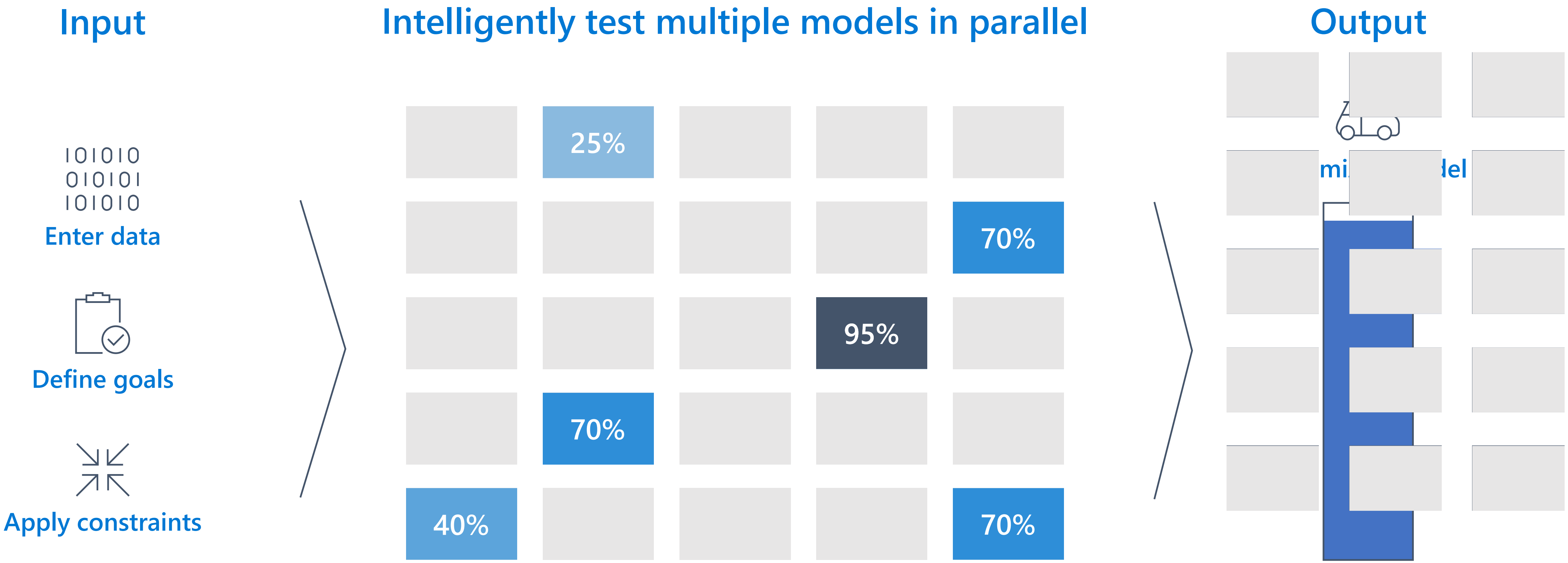
Model

Iterate

Machine Learning - Model creation



Automated ML Accelerates Model Development



Demo:

Enabling Citizen Developers and Data Scientists

Tech Intensity Challenge #2

Data! Data! Data!

I can't make bricks without clay…

Source Systems

Supply Chain data
Factory data
Customer data
Connected Product data
External data
…

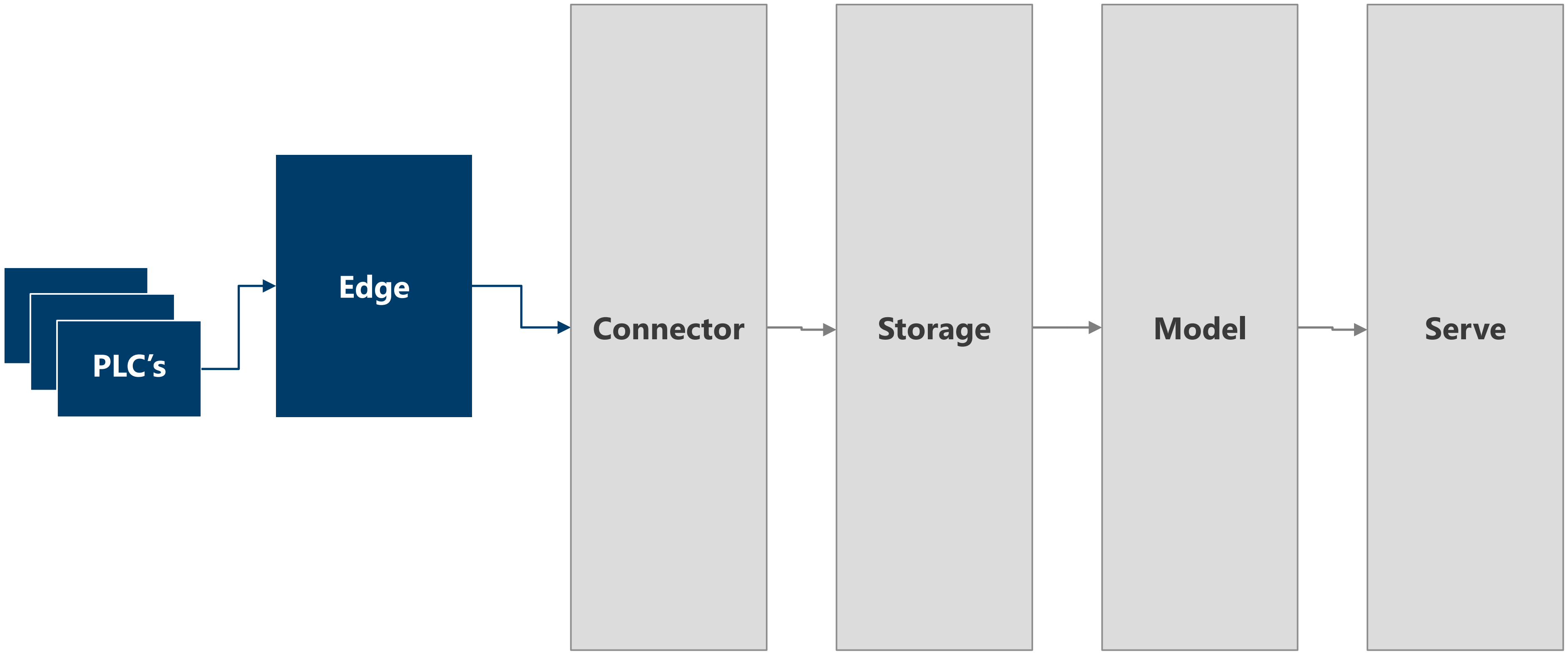
Enterprise Needs

Governance
Compliance
Security
Discovery
…

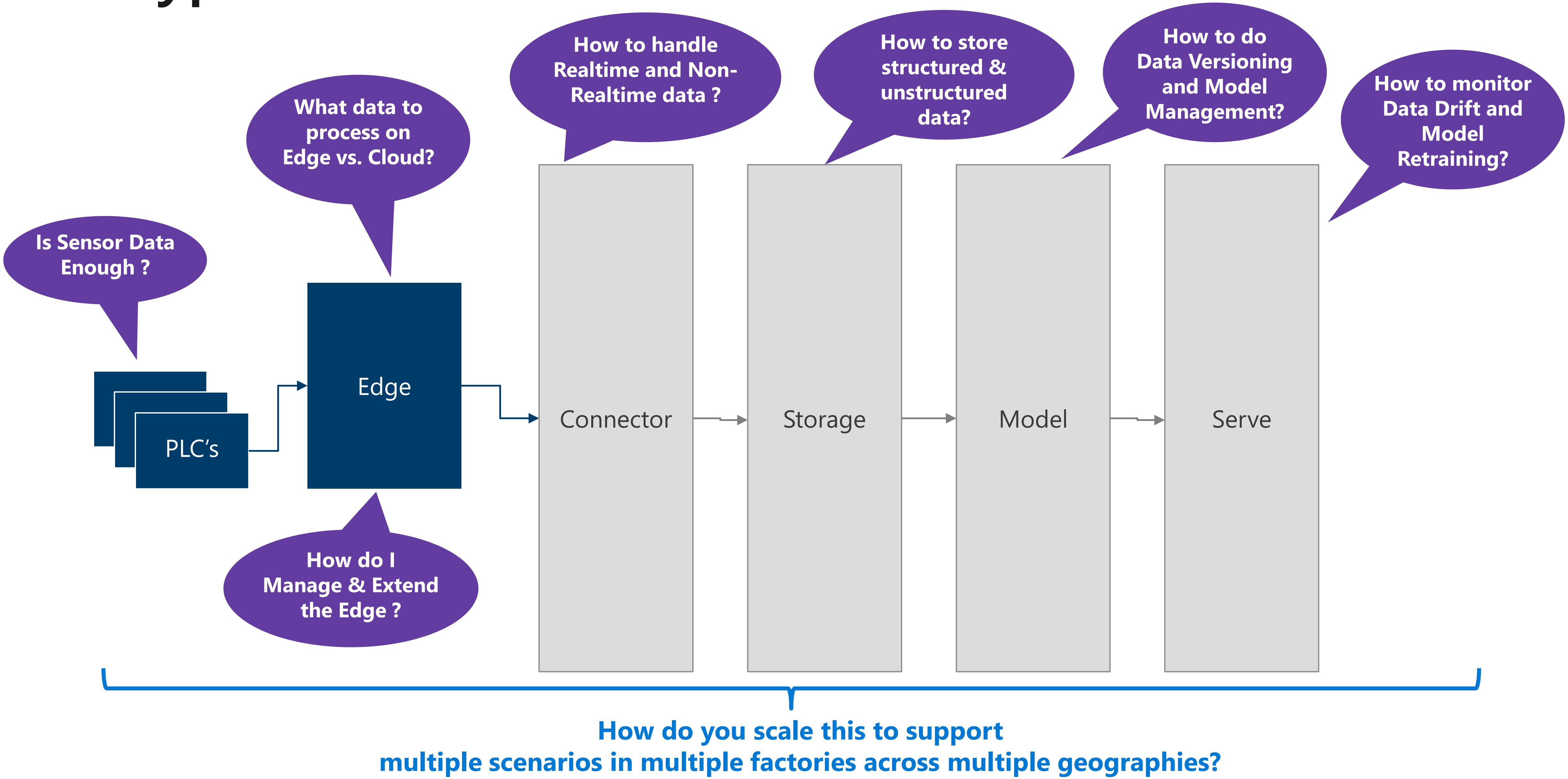
AI Needs

Relevant data
Enough data
Quality data
…

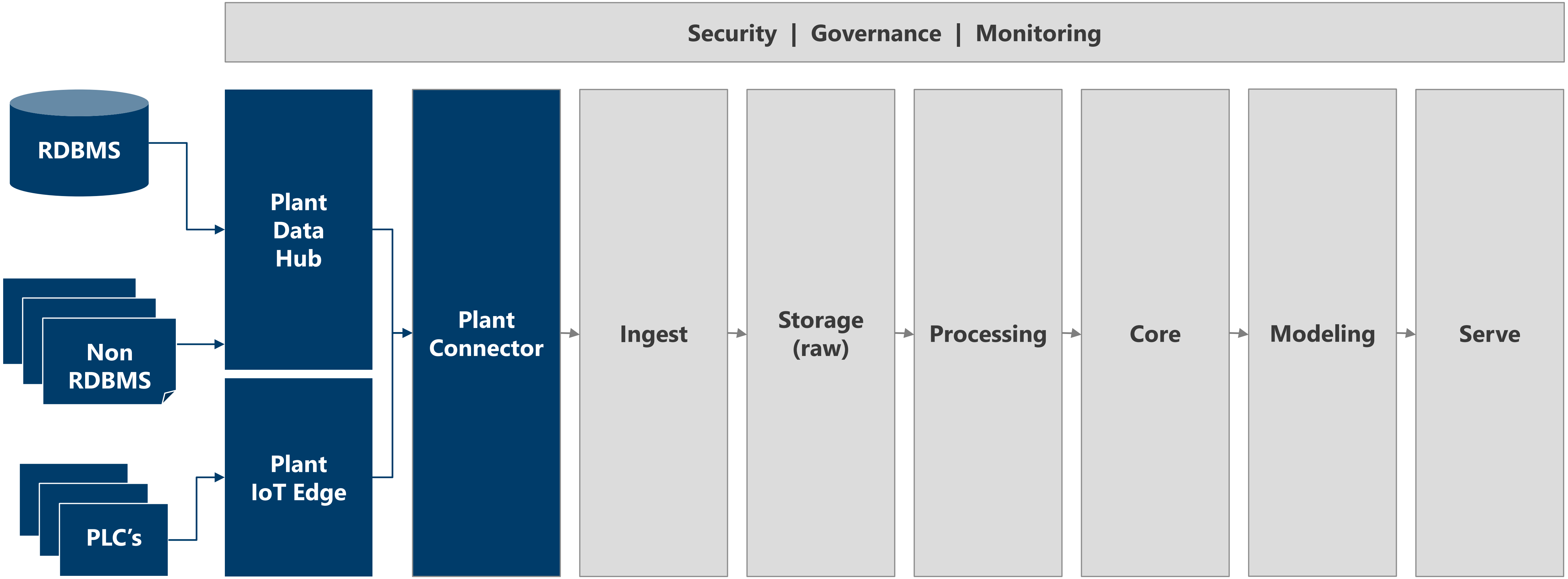
A typical use case solution



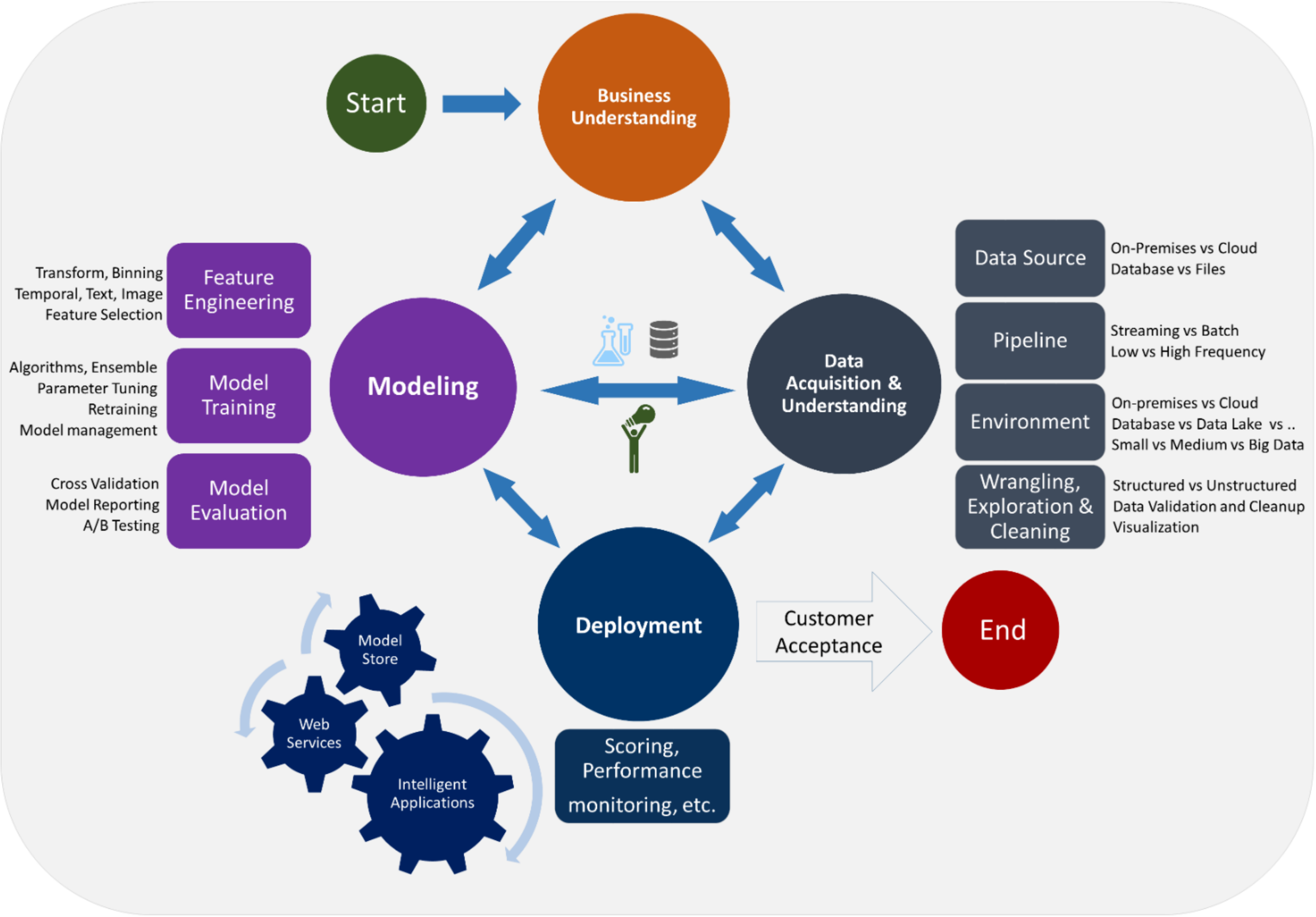
A typical use case solution



Platform Development



Data Science Lifecycle



Tech Intensity Challenge #3

Software Engineering for Machine Learning

To develop, operationalize and scale Data Science practices

Software Engineering for Machine Learning

Software Engineering for Machine Learning: A Case Study

Saleema Amershi
Microsoft Research
Redmond, WA USA
samershi@microsoft.com

Andrew Begel
Microsoft Research
Redmond, WA USA
andrew.begel@microsoft.com

Christian Bird
Microsoft Research
Redmond, WA USA
cbird@microsoft.com

Robert DeLine
Microsoft Research
Redmond, WA USA
rdeline@microsoft.com

Harald Gall
University of Zurich
Zurich, Switzerland
gall@ifi.uzh.ch

Ece Kamar
Microsoft Research
Redmond, WA USA
eckamar@microsoft.com

Nachiappan Nagappan
Microsoft Research
Redmond, WA USA
nachin@microsoft.com

Besmira Nushi
Microsoft Research
Redmond, WA USA
besmira.nushi@microsoft.com

Thomas Zimmermann
Microsoft Research
Redmond, WA USA
tzimmer@microsoft.com

***Abstract*—Recent advances in machine learning have stimulated widespread interest within the Information Technology sector on integrating AI capabilities into software and services. This goal has forced organizations to evolve their development processes. We report on a study that we conducted on observing software teams at Microsoft as they develop AI-based applications. We consider a nine-stage workflow process informed by prior experiences developing AI applications (e.g., search and NLP) and data science tools (e.g. application diagnostics and bug reporting). We found that various Microsoft teams have united this workflow into preexisting, well-evolved, Agile-like software engineering processes, providing insights about several essential engineering challenges that organizations may face in creating large-scale AI solutions for the marketplace. We collected some best practices from Microsoft teams to address these challenges. In addition, we have identified three aspects of the AI domain that make it fundamentally different from prior software application domains: 1) discovering, managing, and versioning the data needed for machine learning applications is much more complex and difficult than other types of software engineering, 2) model customization and model reuse require very different skills than are typically found in software teams, and 3) AI components are more difficult to handle as distinct modules than traditional software components — models may be "entangled" in complex ways and experience non-monotonic error behavior. We believe that the lessons learned by Microsoft teams will be valuable to other organizations.**

***Index Terms*—AI, Software engineering, process, data**

techniques that have powered recent excitement in the software and services marketplace. Microsoft product teams have used machine learning to create application suites such as Bing Search or the Cortana virtual assistant, as well as platforms such as Microsoft Translator for real-time translation of text, voice, and video, Cognitive Services for vision, speech, and language understanding for building interactive, conversational agents, and the Azure AI platform to enable customers to build their own machine learning applications [1]. To create these software products, Microsoft has leveraged its preexisting capabilities in AI and developed new areas of expertise across the company.

In this paper, we describe a study in which we learned how various Microsoft software teams build software applications with customer-focused AI features. For that, Microsoft has integrated existing Agile software engineering processes with AI-specific workflows informed by prior experiences in developing early AI and data science applications. In our study, we asked Microsoft employees about how they worked through the growing challenges of daily software development specific to AI, as well as the larger, more essential issues inherent in the development of large-scale AI infrastructure and applications. With teams across the company having differing amounts of work experience in AI, we observed that many issues reported

https://aka.ms/mlstudy

Differences in engineering AI applications and platforms

A. Data discovery and management

B. Customization and Reuse

C. ML Modularity

Best practices with Machine Learning in Software Engineering

A. End-to-end pipeline support

B. Data Availability, collection, cleaning and management

C. Education and Training

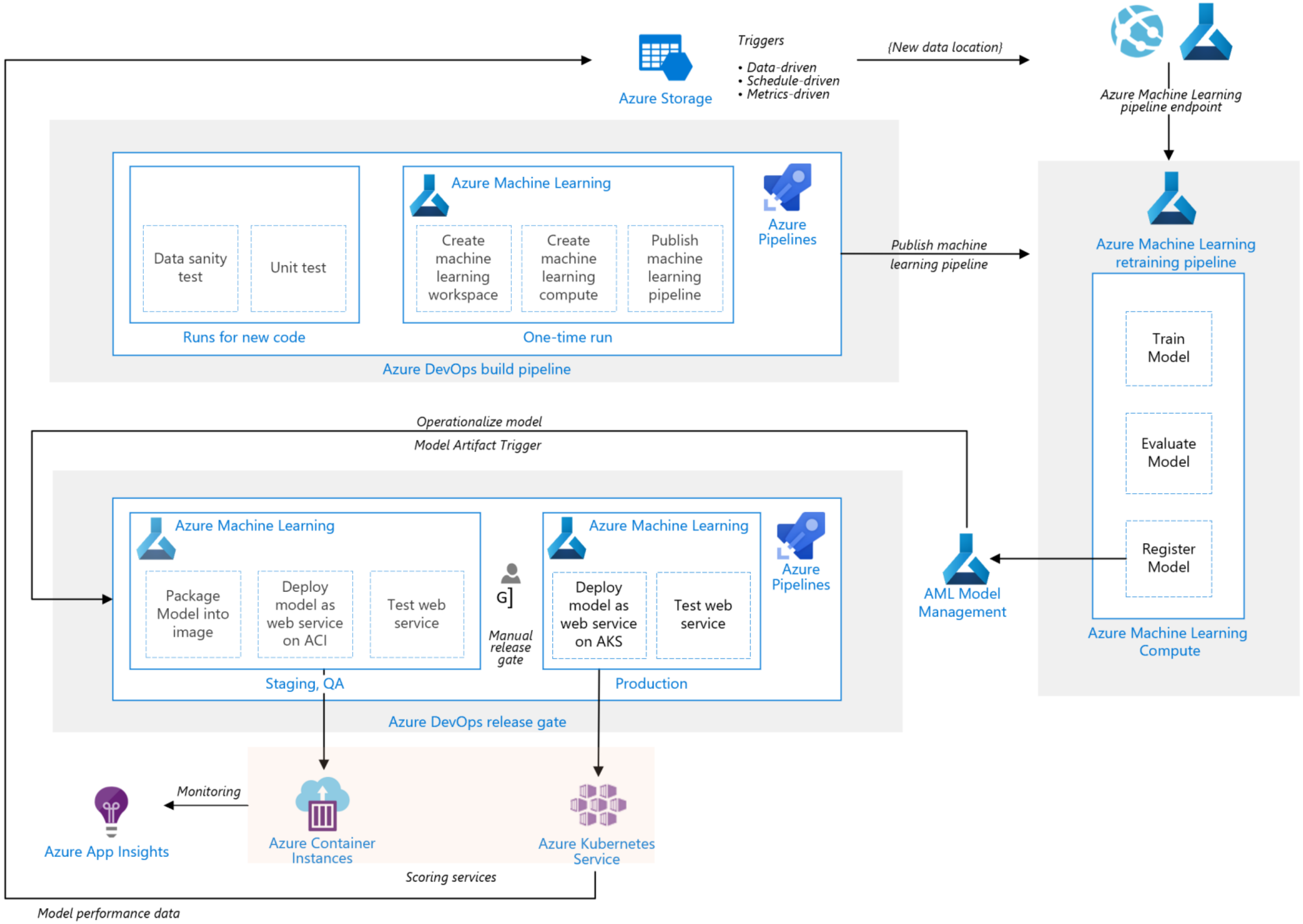
D. Model Debugging and Interpretability

E. Model Evolution, Evaluation, and Deployment

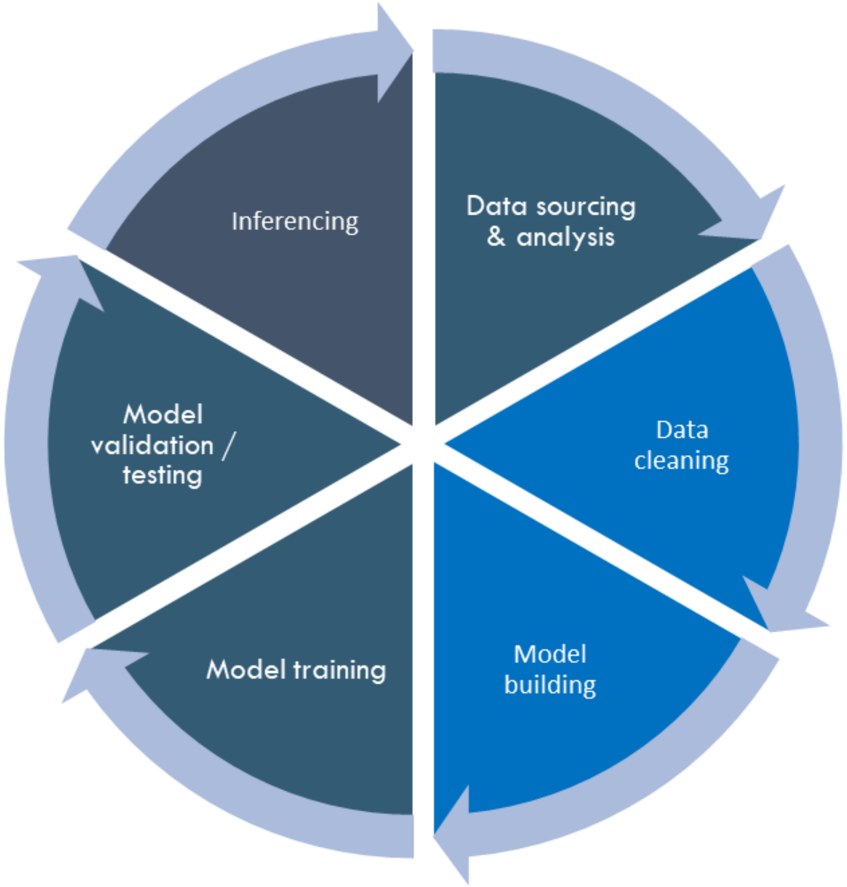
F. Compliance

G. Varied Perception

Example: Machine Learning Operationalization (MLOps)

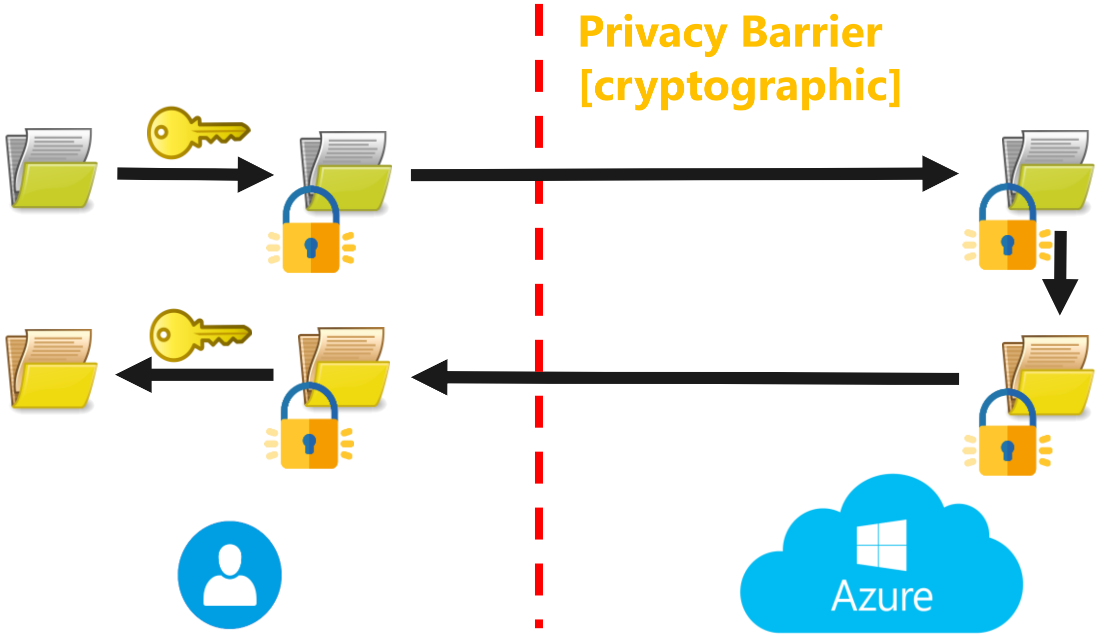


Privacy Problem in ML



- Training data is exposed to the model builder
- During inferencing, prediction data is exposed to the model owner
- ML model can leak sensitive data

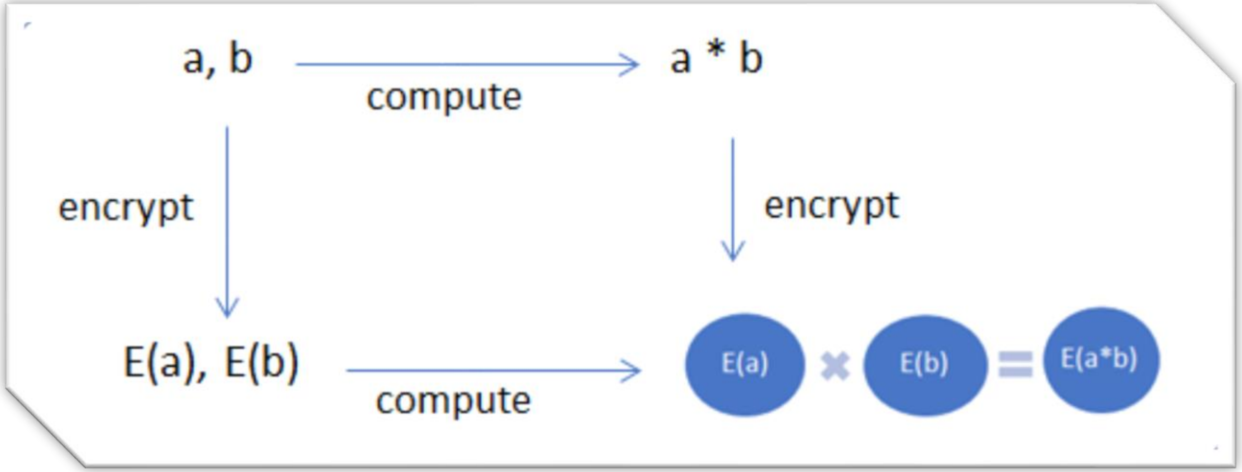
Private AI Framework



- Use Homomorphic Encryption to perform computations on encrypted data
- Customer always holds the keys
- Customer is in charge of all data release

Private AI Framework

- **Homomorphic Encryption (HE)**
  - Computation on encrypted data without decrypting it!
  - 2009: Considered impractical
  - 2011: Surprise breakthrough at Microsoft Research
  - Orders of magnitude speed-up
  - Widespread enthusiasm about results



Private AI Framework

- **Simple Encrypted Arithmetic Library (SEAL)**
  - Public release by Microsoft Research in 2015
  - Mathematical operations performed in milliseconds
  - Microsoft SEAL (v.3.2) widely adopted by teams worldwide
- **CryptoNets** performance break-through 2016
  - Evaluates neural net predictions on encrypted data
- **Standardization of HE: November 2018**

http://sealcrypto.org

Key Takeaways

^ TRUST

Build vs. Buy → **Create your IP vs. Use someone else's IP**

PoC vs. Pilot → **Build a use case solution vs. Build an AI Platform**

Questions?