







Building Scalable, Secure and Responsible AI Solutions in Azure

Caio Moreno
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**The DataHour**
Building Scalable, Secure and Responsible AI Solutions in Azure

**Caio Moreno**
Senior Cloud Solution Architect - AI/ML at Microsoft

 Tuesday, 21 June 2022

 8:30 PM - 9:30 PM IST



Agenda

- Introduction to Machine Learning
- How to become an Azure Data Scientist?
- Building a Data Science Team
- Data and AI Strategy & The AI/ML Journey
- Building Scalable, Secure and Responsible AI Solutions in Azure
 - ML Ops (Machine Learning Ops)
 - Responsible AI (Artificial Intelligence)

About me



Caio Moreno is a Senior Cloud Solution Architect at Microsoft, responsible for helping Microsoft empower every person and organization on the planet to achieve more using Data and AI. He has experience in artificial intelligence, machine learning, big data, IoT, distributed systems, analytics, streaming, business intelligence, data integration and visualization. He is also a PhD. Candidate at the Complutense University of Madrid. He enjoys travelling and all kinds of sports. He lives in London with his wife and 3 daughters.

<https://www.linkedin.com/in/caiomsouza/>

<https://linktr.ee/caiomoreno>



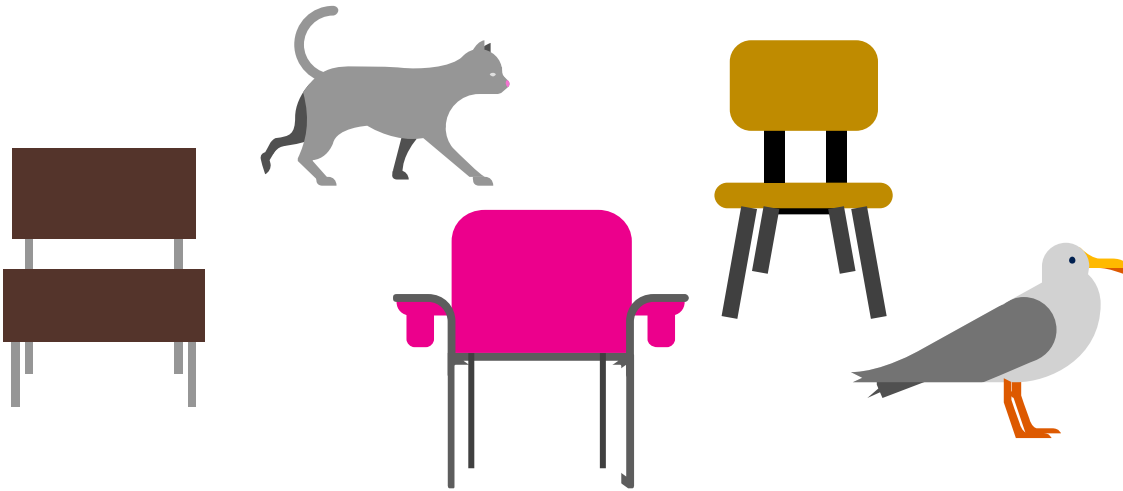
AI isn't just another piece of technology. It could be one of the **most fundamental pieces** of technology the human race has ever created.

Satya Nadella

Introduction to Machine Learning

Machine Learning

Grew out of artificial intelligence within computer science. Aims to learn from and make predictions on data.



Is this a chair?



Preliminary Concepts

Input vs output variables

- Input synonyms: feature, attribute, predictor variable
- Output synonyms: target, class, label

Type of variables

- Categorical / qualitative / nominal

Distinct category of values that is not meaningful to rank / measure difference, e.g. gender, color

- Numeric / quantitative

Values that can be ranked and compared in a meaningful way, e.g. weight, price

Supervised vs. Unsupervised

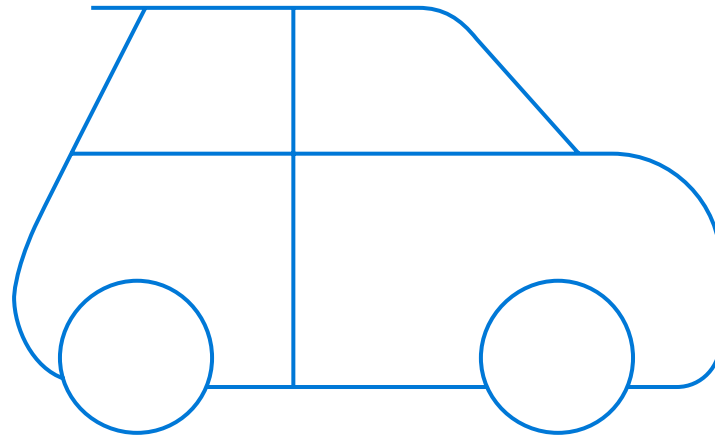
- Supervised: Learn from data with ground truth (the true answer, label)
 - Classification problems such as spam email detection
 - Regression problems such as income prediction
- Unsupervised: Learn without ground truth
 - Clustering problems such as user clustering
- Semi-supervised: Learn with some labelled and some unlabeled data

And More...

- Reinforcement Learning: Learn to take actions to achieve a goal and maximize (cumulative) reward
- Recommender Systems: A system that predicts how much a user will like an item
 - Simplified: Choose top n that user would like the most

Building your own AI models

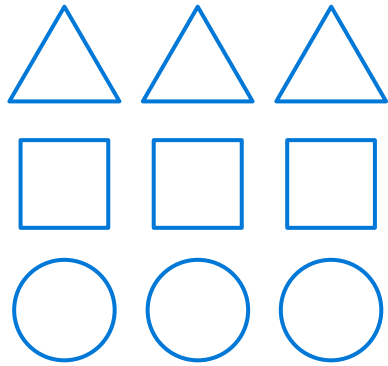
Transforming Data into Intelligence



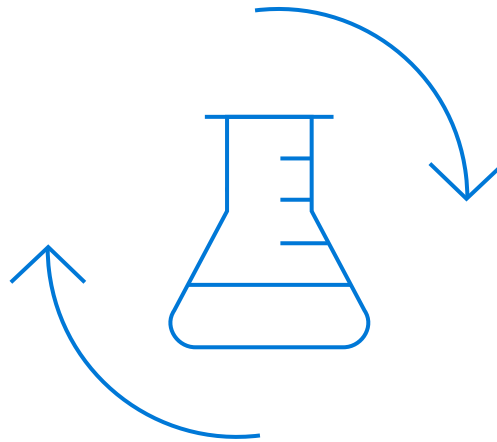
Q: How much is this car worth?

Building your own AI models

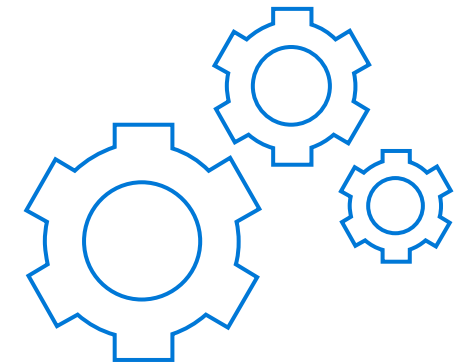
Transforming data into intelligence



Prepare data



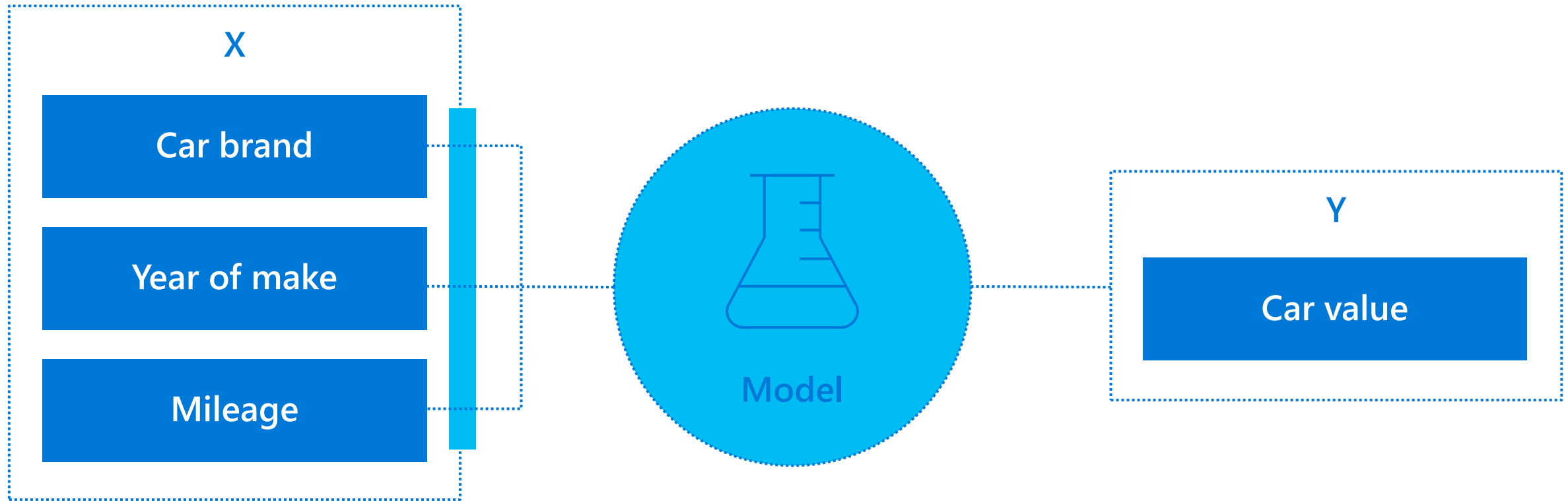
Build and train



Deploy

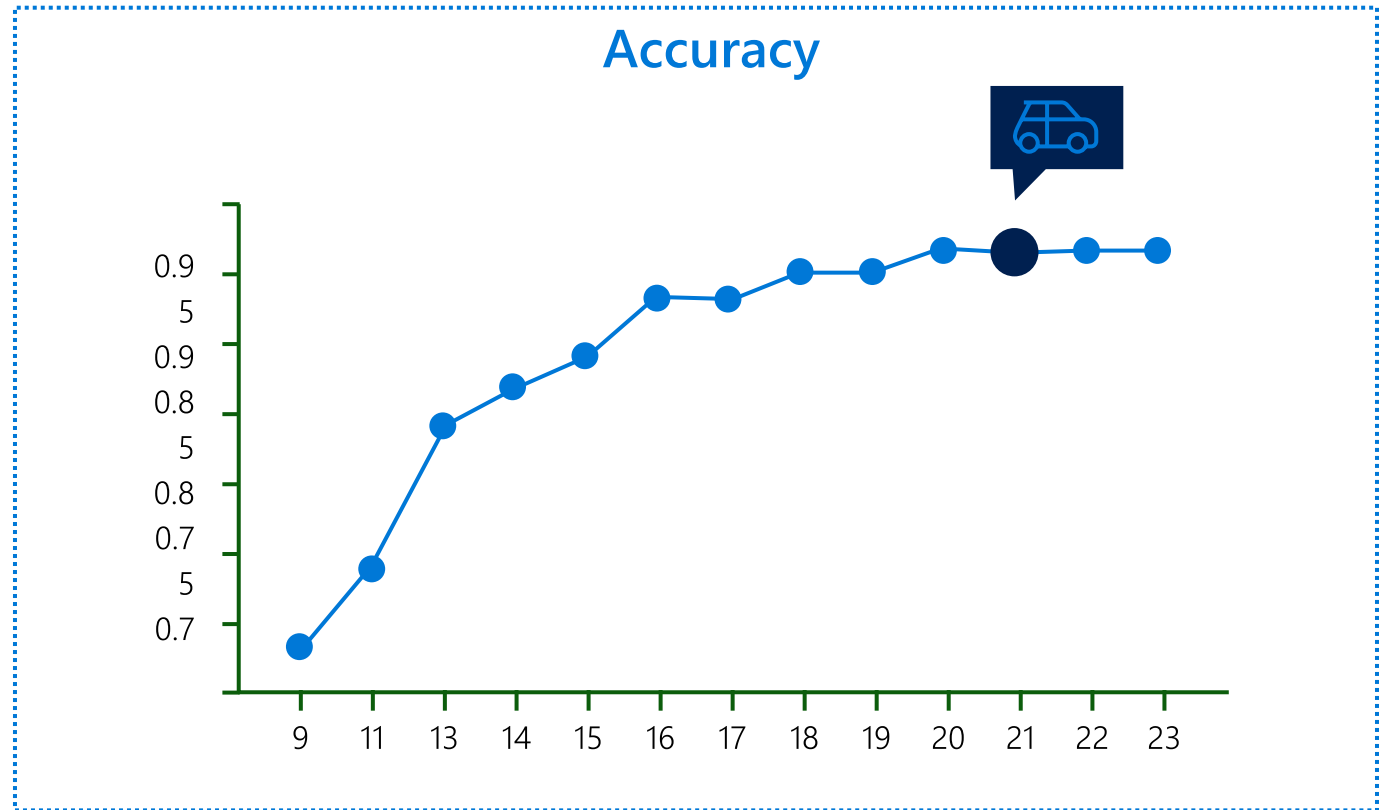
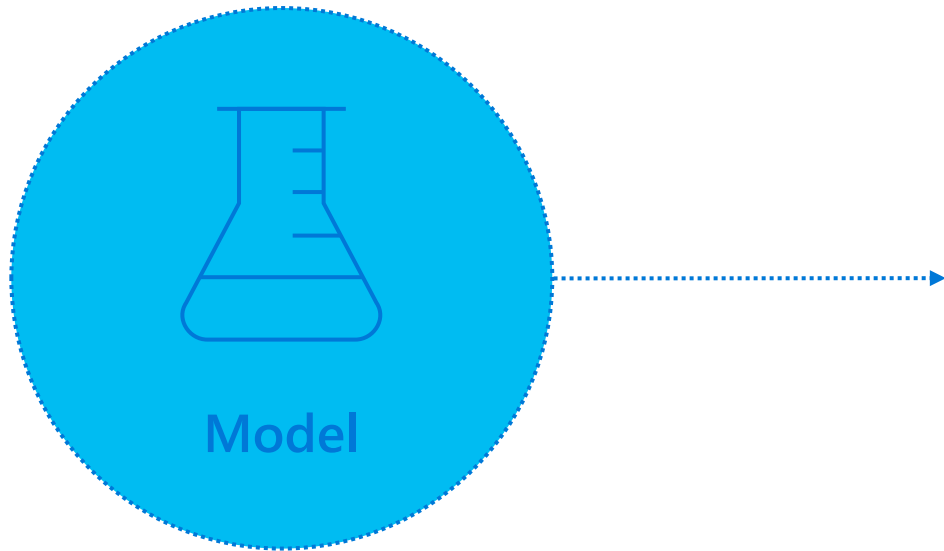
Building your own AI models

Step: Build and Train



Building your own AI models

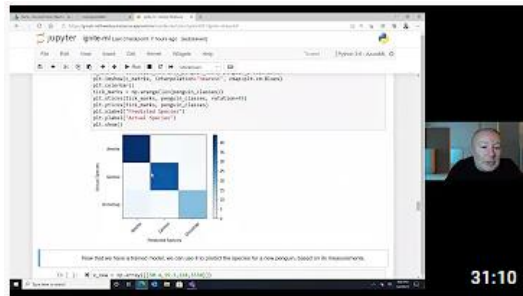
Step: Build and train



How to become an Azure Data Scientist?

How to become an Azure Data Scientist?

How do I start?



How to be a Data Scientist on Azure | LRN236

<https://www.youtube.com/watch?v=n6OOowy7wAc>



How to become an Azure Data Scientist

<https://www.youtube.com/watch?v=iYBKTkDBB8g>

Building a Data Science team

Data Science Team



Isabel
Team Lead

Own the AI Data Product(s). Manage the team.



Caio
AI Solution Architect

Design the AI technical solution that meets business requirements, and operations architecture for those solutions.



Chen
Data Scientist

Frame business problem, exploratory data analysis, develop machine learning models, communicate outcomes.



Roger
Data Engineer

Operate and maintain the data stack, pull data from different sources, data integration and prep, set up data pipelines.



Ana
Data Visualization Expert

Create data visualizations to help leaders make business decisions.



Helena
Data Architect

Design databases for mission-critical line-of-business apps. Designing and implementing data security.



Matt
ML Ops Engineer

Design and build end to end ML Ops pipelines to deploy AI Solutions to production.



David
App Developer

Build apps that use data and analytic models.

General Roles in a Data Science Project



3. Data Engineer

Acquire, transform and stage/store data sources

Orchestrate data acquisition and flow through to organizational data stores

Create, schedule and provision foundational orchestration services



1. Data Architect

Architect the whole data platform

Design the data governance strategy

Ensure data security and privacy

2. Data Scientist

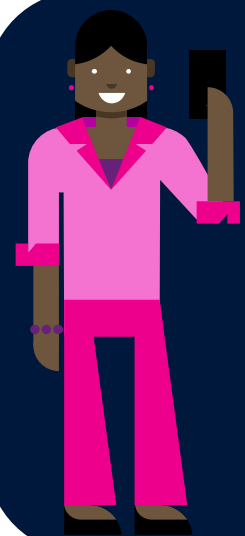


Understand and help refine/shape the analytical question to answer

Craft approaches for new analytic technical foundations (i.e., Statistical Testing, Machine Learning, Data Lakes, etc.)

Conduct analytical modeling, testing, evaluation and interpretation

Assist in monitoring and adjusting for model performance over time



4. Machine Learning Engineer

Implement the MLOps pipeline

Deploy machine learning solution into production

Optimize solutions for performance and scalability

Data & AI Strategy

It is proposed a new formal framework for companies that want to adapt to a Big Data MO strategy.



Data and Artificial Intelligence Strategy: A Conceptual Enterprise Big Data Cloud Architecture to Enable Market-Oriented Organisations

unir
LA UNIVERSIDAD
EN INTERNET

<https://doi.org/10.9781/ijimai.2019.06.003>

Moreno, C., González, R. A. C., & Viedma, E. H. (2019). Data and artificial intelligence strategy: A conceptual enterprise big data cloud architecture to enable market-oriented organisations. *IJIMAI*, 5(6), 7-14.

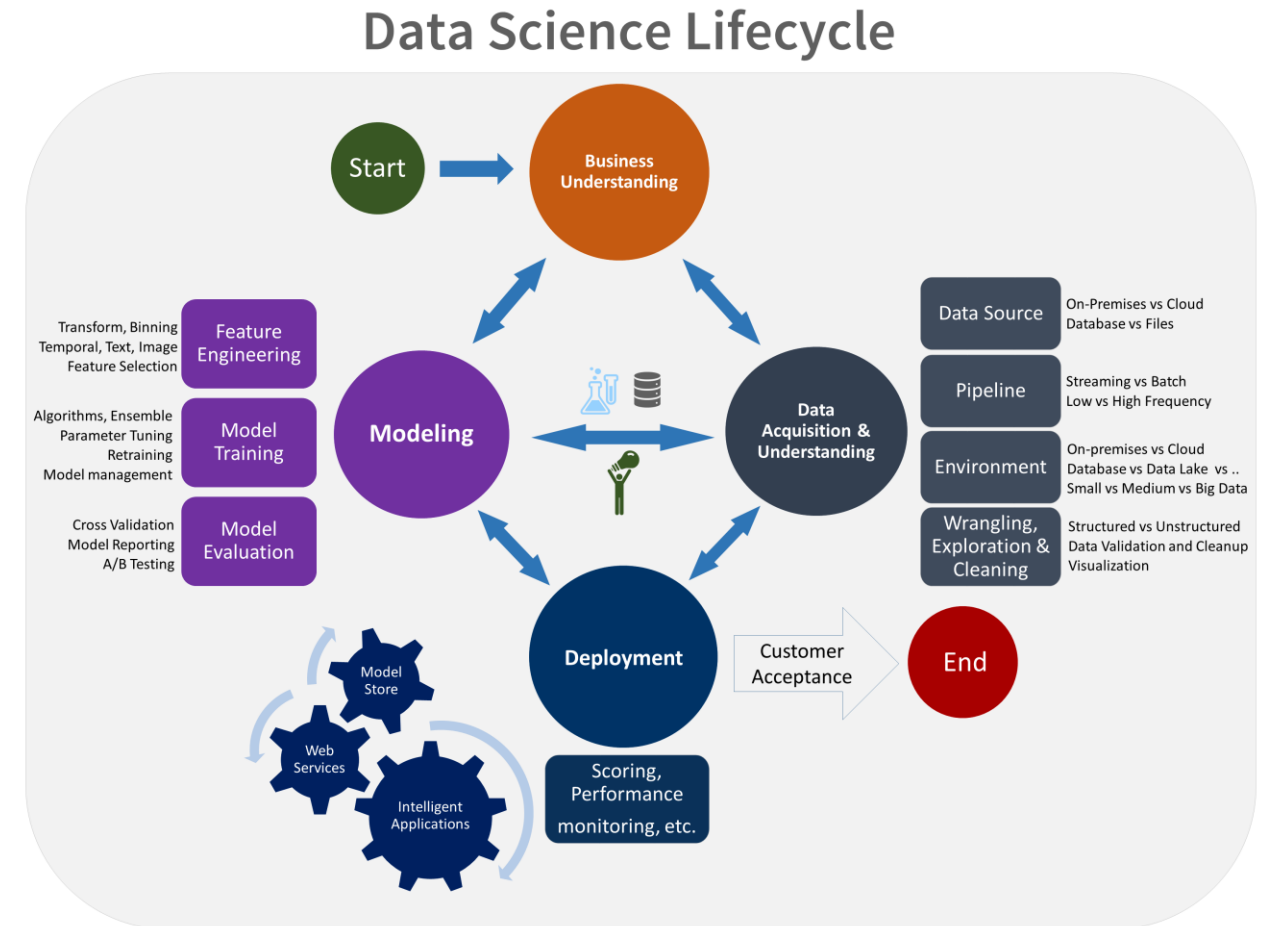
The AI/ML Journey

Data Science Lifecycle

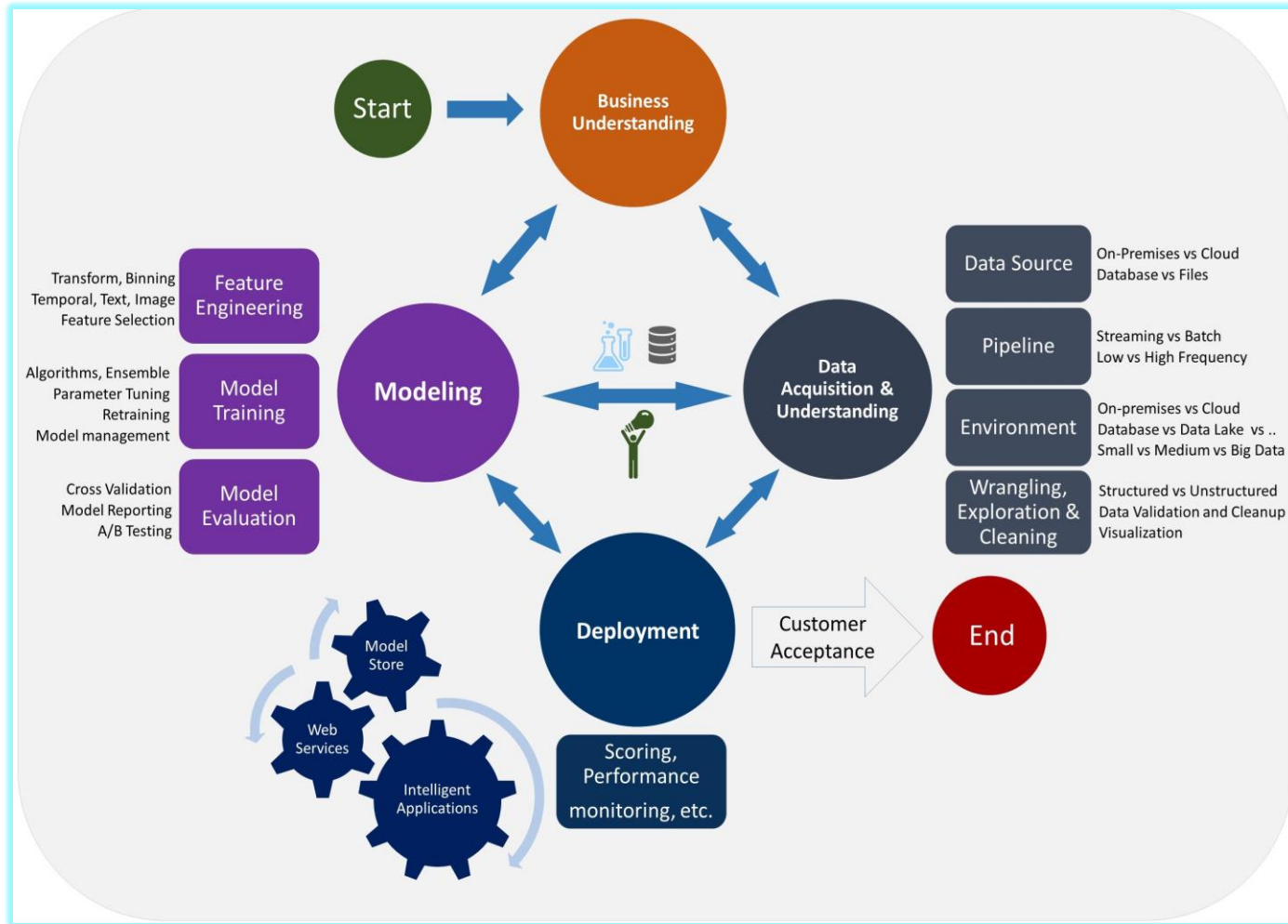
The lifecycle outlines the major stages that projects typically execute, often iteratively:

- **Business Understanding**
- **Data Acquisition and Understanding**
- **Modeling**
- **Deployment**

Here is a visual representation of the **Team Data Science Process lifecycle**.

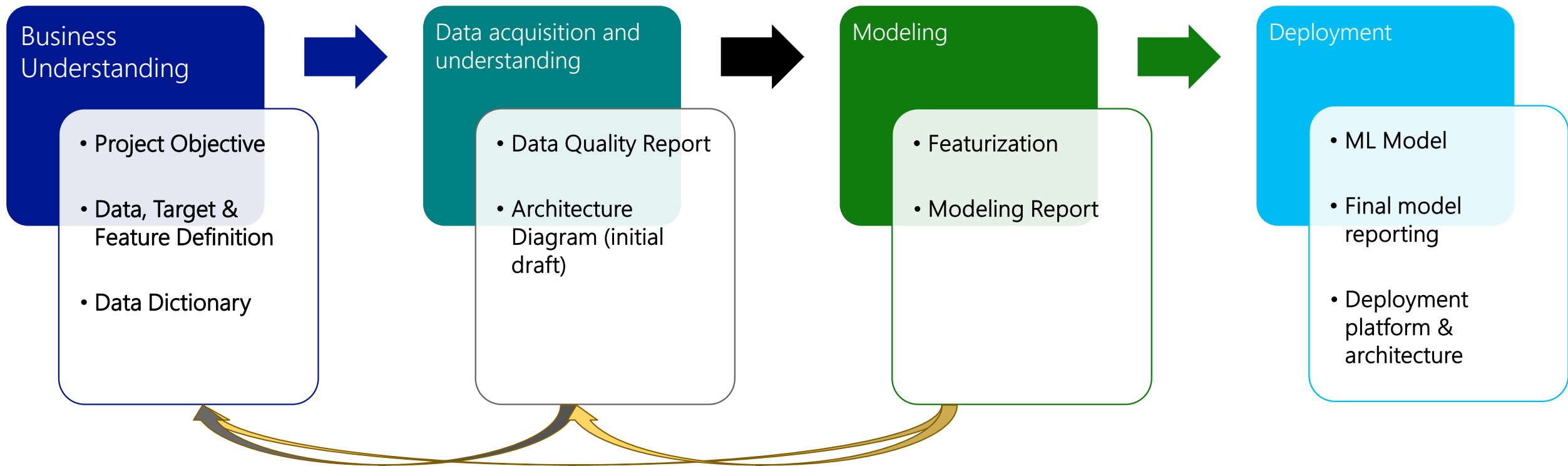


Data Science Lifecycle



- **Business Understanding**
 - Identify business problem
 - Find relevant data sources
 - Establish a business strategy
- **Data Acquisition and Understanding**
 - Data discovery
 - Data cleansing and prep
 - Data pipeline
- **Modeling**
 - Optimal data features
 - Determine ML model
 - Implement data pipeline
- **Deployment**
 - Deploy
 - Monitor
 - Retrain
 - Visualize

Lifecycle stages can be integrated with specific deliverables & checkpoints



Build Business Understanding



Begin with the exploration of a problem

"We spend a lot of money to acquire and retain customers. Turning over a customer, or reacquiring them is also expensive."



Arrive at an analytical question that addresses the problem

"It would be great if we could predict whether a customer is likely to leave us next month and target them for retention."

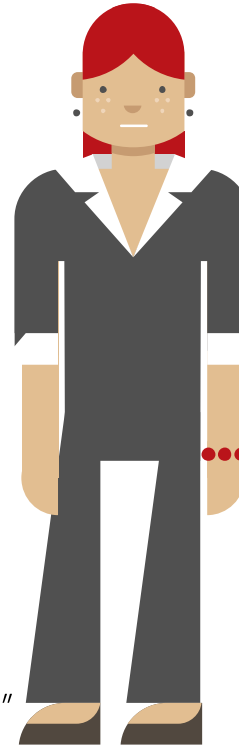


1011

101

Understand the data required to address the problem

"We have historical data representing customer acquisition and turnover for the past n years, including all customer interactions."



Define business goals with "sharp" questions that can be answered by Data Science:

- How much or how many? (regression)
- Which category? (classification)
- Which group? (clustering)
- Is this weird? (anomaly detection)
- Which option should be taken? (recommendation)



Define the consumption experience

How will people or systems use these conclusions, on which devices. How will they want to consume the analytic output and what will they do with it?

Data Prep and Modelling

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Acquire data sets

Plan and locate potential sets of data. Gather data from internal and external sources

```
R Interactive
+ data2$x <- 20:1
+ data2$y <- 1
+ data1 <- data.frame(
+   x = 1:20,
+   y = 0,
+   colour = 'forestgreen',
+   stringsAsFactors = FALSE)
+ data2 <- data1
+ data2$x <- 20:1
+ data2$y <- 1
```

Explore and transform the data

Using data transformation tools and engineering techniques, mine, extract, clean, mark up, label, transform, enrich and stage data



Experimentation may cause re-visitation of data understanding or even the business problem

Data prep tasks can be repeated multiple times

Rigorous model evaluation

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Begin the modelling experimentation

Feature engineering, model fitting, model evaluation on "unseen" data



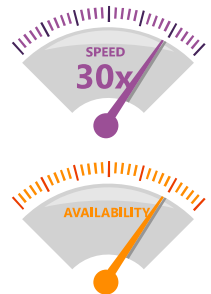
Deploy and Monitor Performance



Model deployment/ operationalization

Systematic integration into dashboards, systems, applications including continued data ingestion and training

Move beyond “experimentation” into production



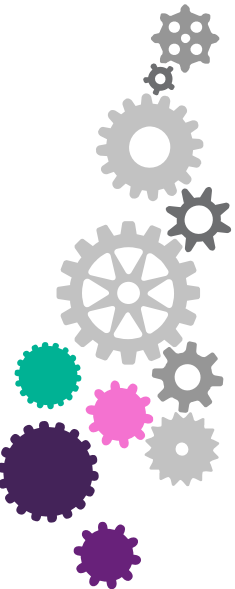
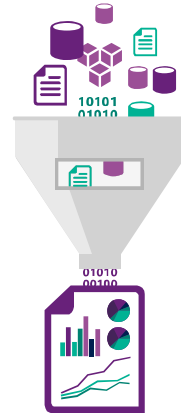
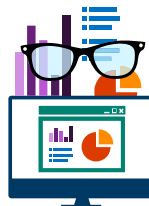
Monitor performance

Continuous monitoring of model performance, refine model based on field feedback, retrain model on new data

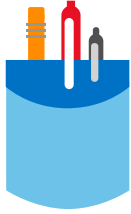
Integrate into dashboards, apps and acquire new data sets

Monitor performance accuracy

Revisit the modelling stage to refine the model as needed



Success Ingredients for a Data Science Project



Know your problem

Is there a clear business need?
Is the outcome measurable?



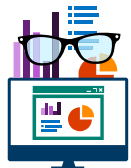
Know your data

Is there data to support the business scenario? What are the caveats? Data exploration and validation are essential.



Build relevant models

Which types of models can answer the business question? Is it a regression, classification, anomaly detection, clustering, recommendation, or other problem?



Integrate with business

Trust building through testing and validation, then deploy

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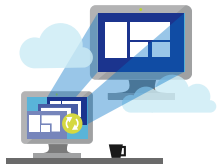


Azure Machine Learning service

Bring AI to everyone with an end-to-end, scalable, trusted platform



Boost your data science productivity



Increase your rate of experimentation



Deploy and manage your models everywhere



Built with your needs in mind

- Automated machine learning
- Managed compute
- Simple deployment
- DevOps for machine learning
- Support for open source frameworks
- Tool agnostic Python SDK

Seamlessly integrated with the Azure Portfolio

Machine Learning on Azure

Domain specific pretrained models

To reduce time to market



Vision



Speech



Language



Search

Familiar Data Science tools

To simplify model development



PyCharm



Jupyter



Visual Studio Code



Command line

Popular frameworks

To build advanced deep learning solutions



Pytorch



TensorFlow



Scikit-Learn



Onnx

Productive services

To empower data science and development teams



Azure
Databricks



Azure Machine
Learning



Machine
Learning VMs

Powerful infrastructure

To accelerate deep learning



CPU



GPU



FPGA

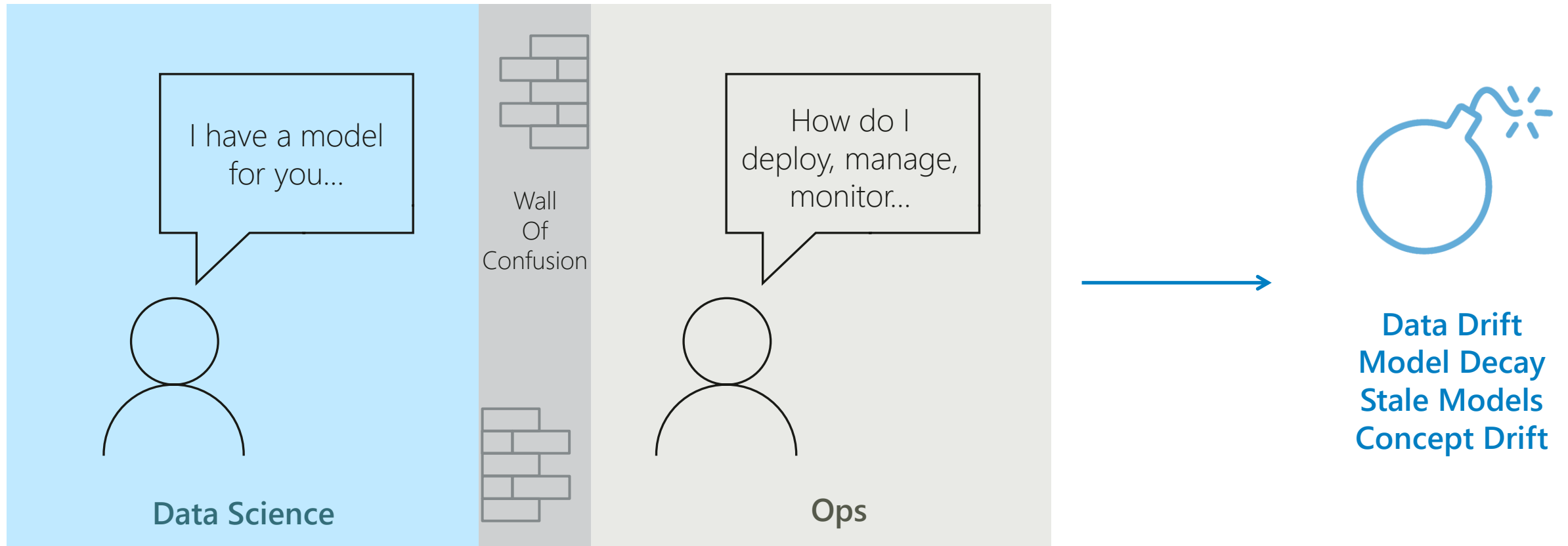


From the Intelligent Cloud to the Intelligent Edge



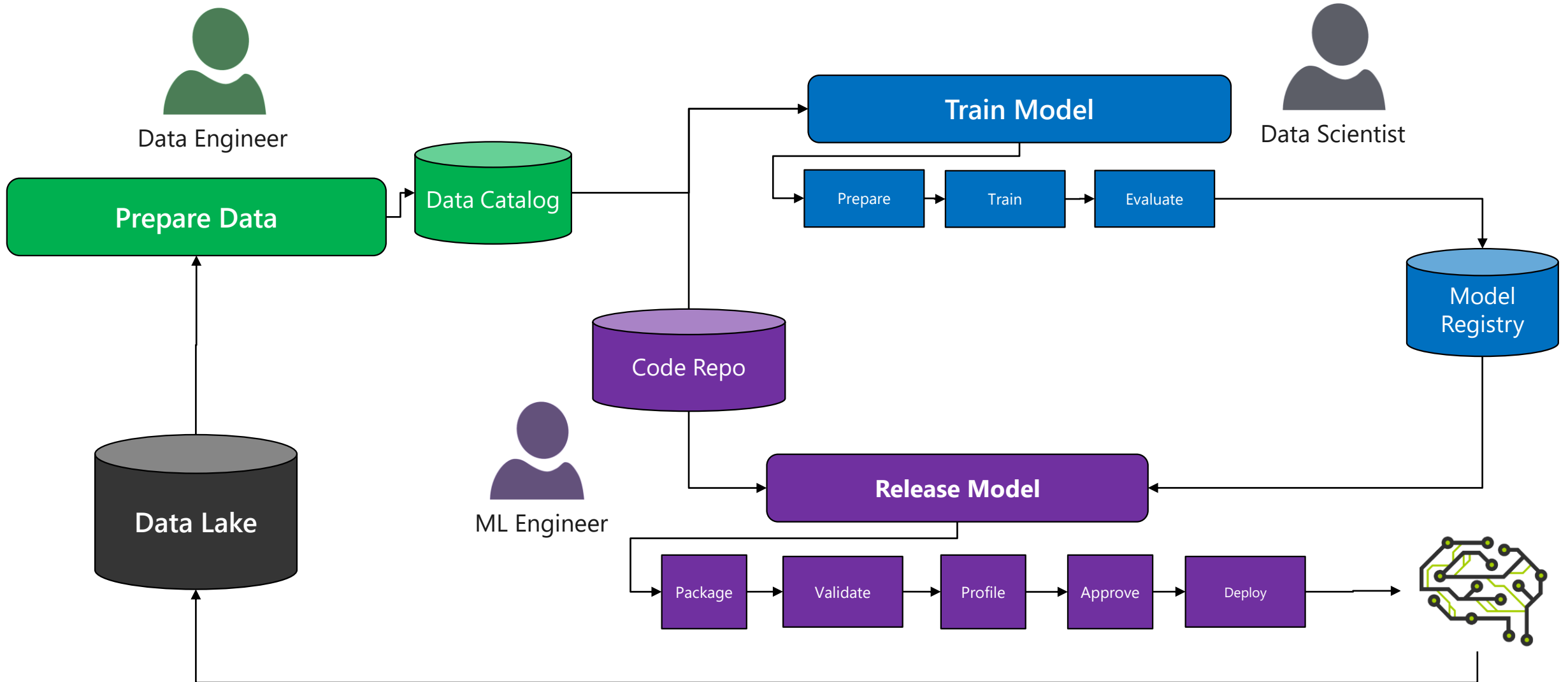
ML Ops (Machine Learning Ops)

Traditional DS Delivery

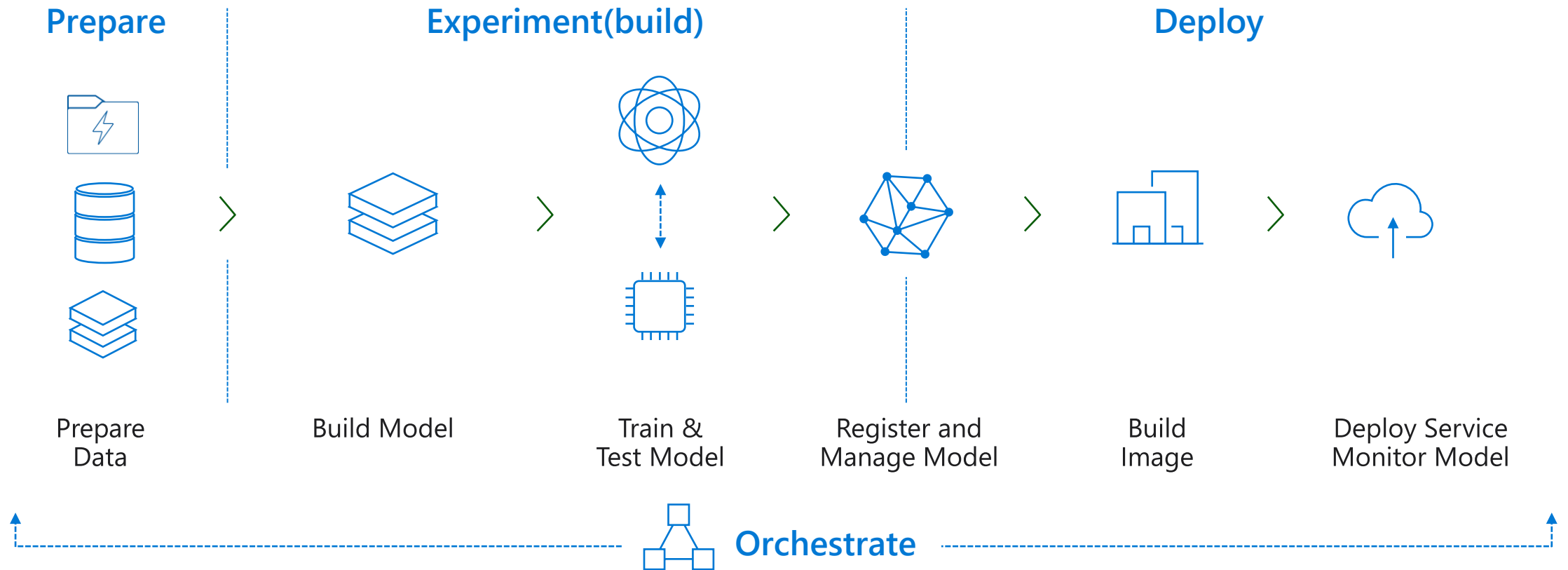



MLOps Process


Enterprise ready machine learning development




MLOps Workflow





Boards
(Azure DevOps)


Repos
(Azure DevOps)


Pipelines & Test Plans
(Azure DevOps)


Artifacts & Pipelines
(Azure DevOps)


Model monitoring
(Azure Machine Learning Service)

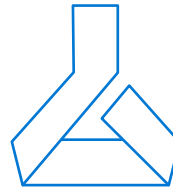

Application Insights

Model management in detail



Create/Retrain Model

Enable DevOps with full CI/CD integration with VSTS



Register Model

Track model versions with a central model registry



Monitor

Oversea deployments through Azure AppInsights

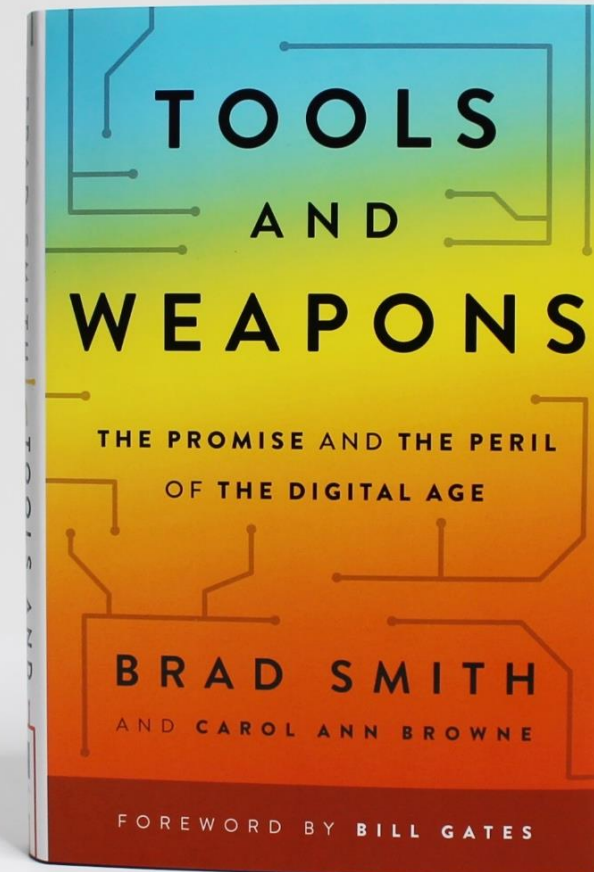
Responsible AI (Artificial Intelligence)

Why responsible AI?

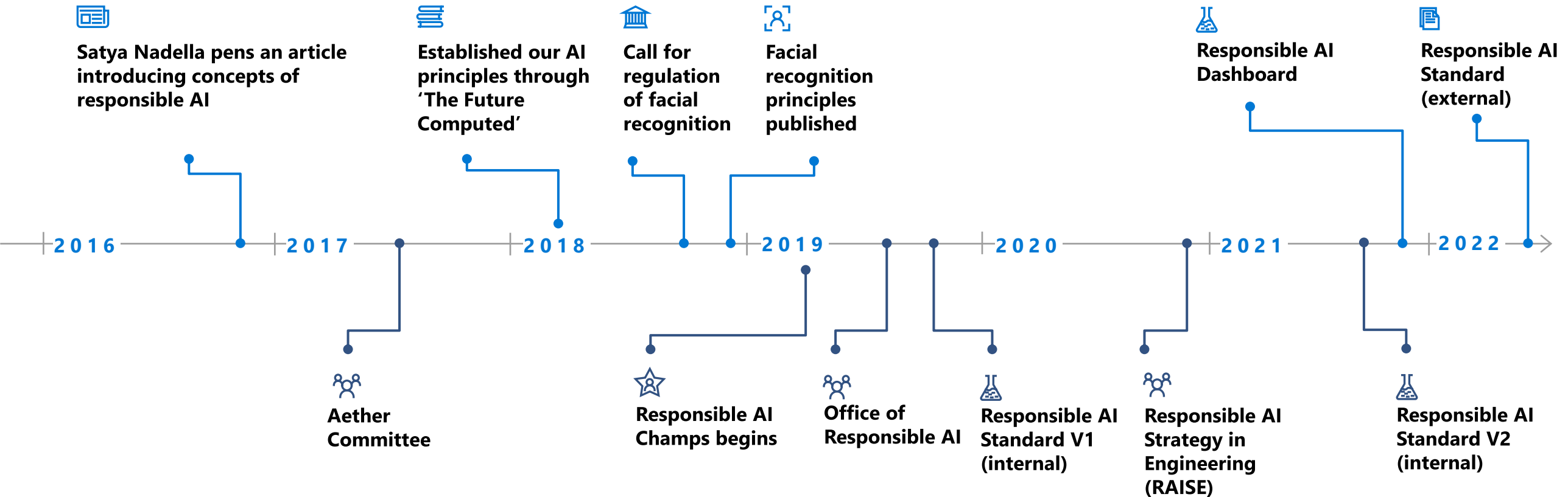
"When you create technology that changes the world, you have to assume a responsibility for the world that you've helped to create."

Brad Smith

President and Chief Legal Officer, Microsoft



Our Responsible AI journey



Learn Microsoft's AI principles



Fairness



Reliability
& Safety



Privacy &
Safety



Inclusiveness



Transparency



Accountability

Customer Story: NHS



Northumbria Healthcare NHS Foundation adopts Responsible AI philosophy with Azure Machine Learning: <https://www.youtube.com/watch?v=LRZHcipcweY>

Thank you
Gracias
Obrigado