FIAP

VINI CARIDÁ

Human-Centered Data & AI

Vinicius Caridá, Ph.D.

- Head of Digital Customer Service Platforms, PCP, WFM, Data and AI - Itaú Unibanco
- MBA Professor - FIAP

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Machine Learning

Data science and ML are **becoming core capabilities** for solving complex real-world problems, transforming industries, and delivering value in all domains. Therefore, many businesses are **investing in their data science teams and ML capabilities** to develop predictive models that can deliver business value to their users. While some companies have figured out how to succeed, **many companies still have difficulty to generate value with AI**.

“

As ML matures from research to applied business solutions, so do we need to improve the maturity of its operation processes

1 What is "ML Ops"?

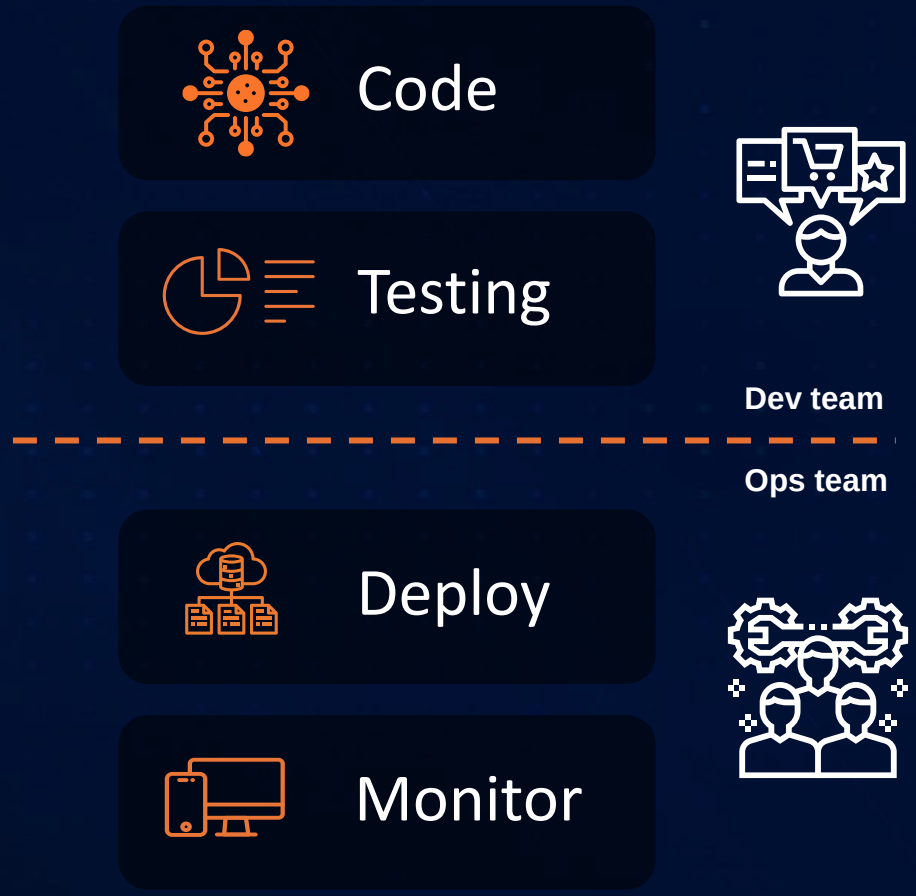
DevOps for ML

What is **DevOps**

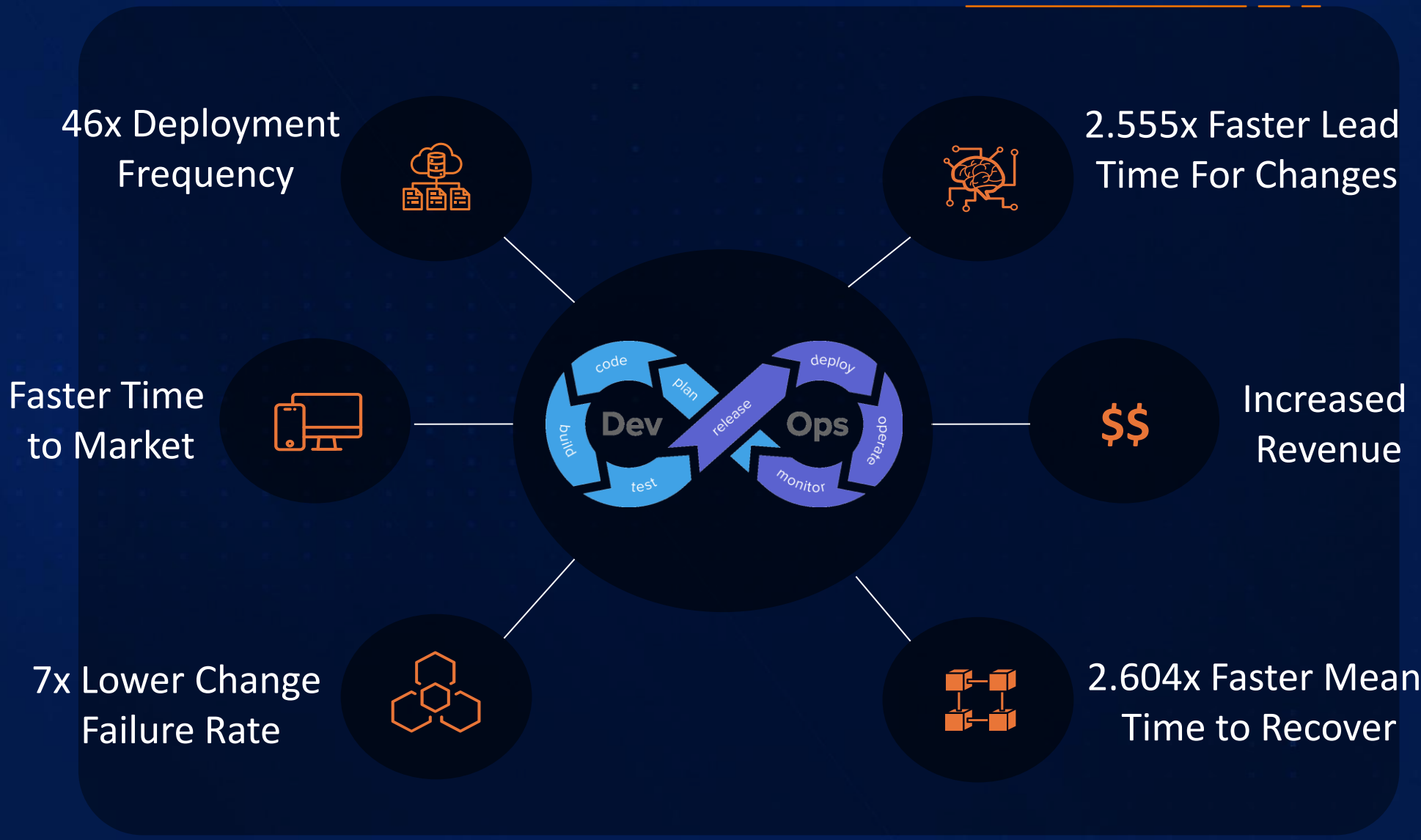
"DevOps is a software engineering culture and practice that aims at **unifying** software development (Dev) and software operation (Ops)."

"(DevOps is to) strongly advocate **automation and monitoring** at all steps of software construction, from integration, testing, releasing to deployment and infrastructure management."

- Wikipedia



People respond to incentives



Accelerate: State of DevOps 2018

Machine Learning

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Além de treinar um modelo incrível...

Código ML

Machine Learning

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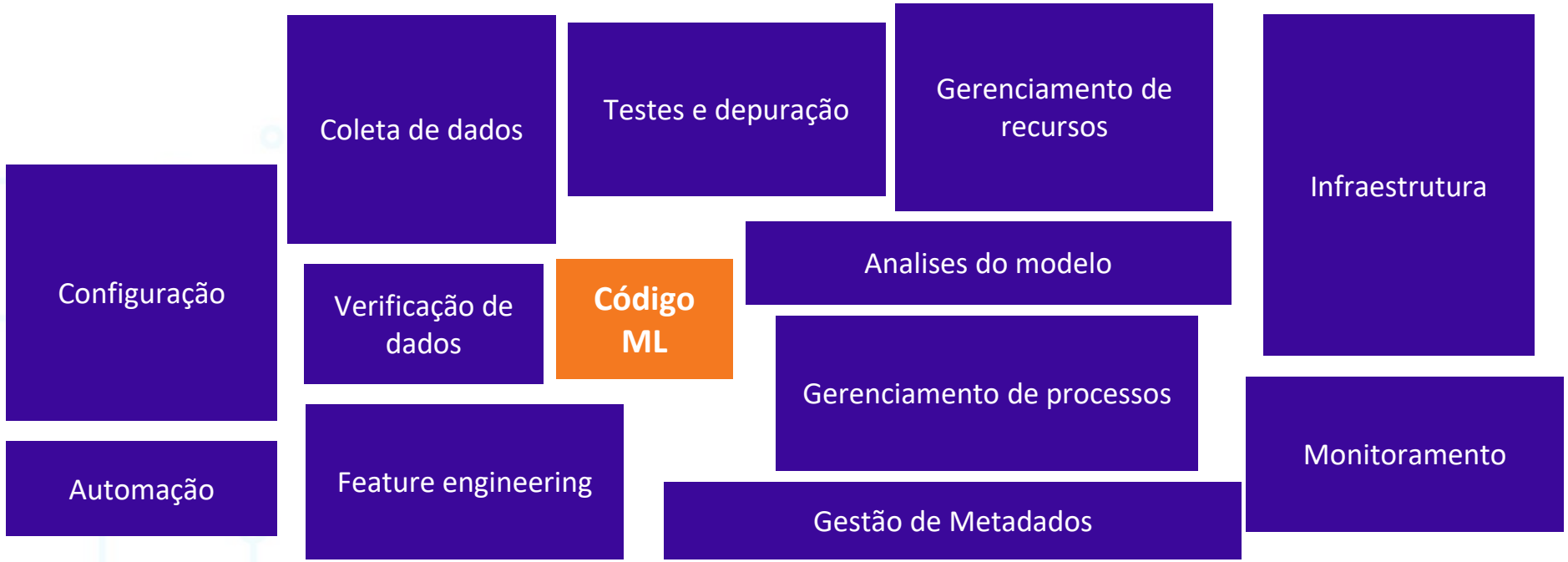
Realidade: ML requer DevOps



https://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf

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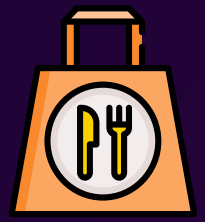
Dados

Técnica de ML

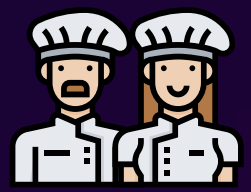
Técnica + Dados

Treinamento

Modelo



Modelo em produção



Cientista de Dados

Vinicius F. Caridá

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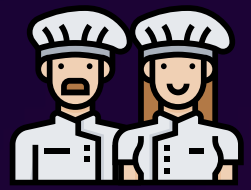
Dados

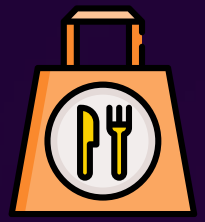
Técnica de ML

Técnica + Dados

Treinamento



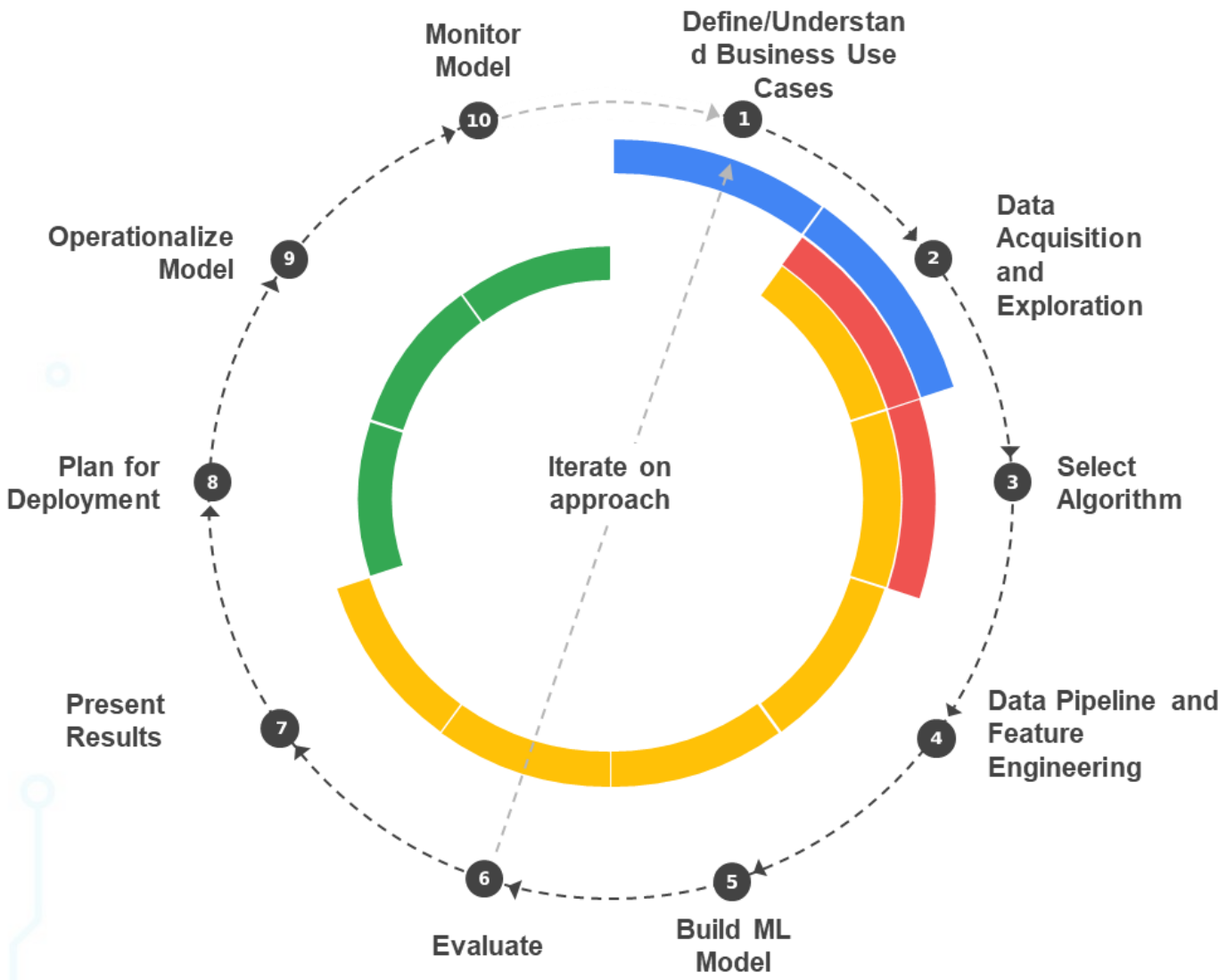
Cientista de Dados



Modelo em produção

Modelo

Vinicius F. Caridá


Monitor Model
Define/Understand Business Use Cases
Operationalize Model
Data Acquisition and Exploration
Plan for Deployment
Iterate on approach
Select Algorithm
Present Results
Data Pipeline and Feature Engineering
Evaluate
Build ML Model
1
2
3
4
5
6
7
8
9
10

If ML is a rocket engine,
data is the fuel

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Launching is easy, Operating is hard.

"The real problems with a ML system will be found while you are continuously operating it for the long term"

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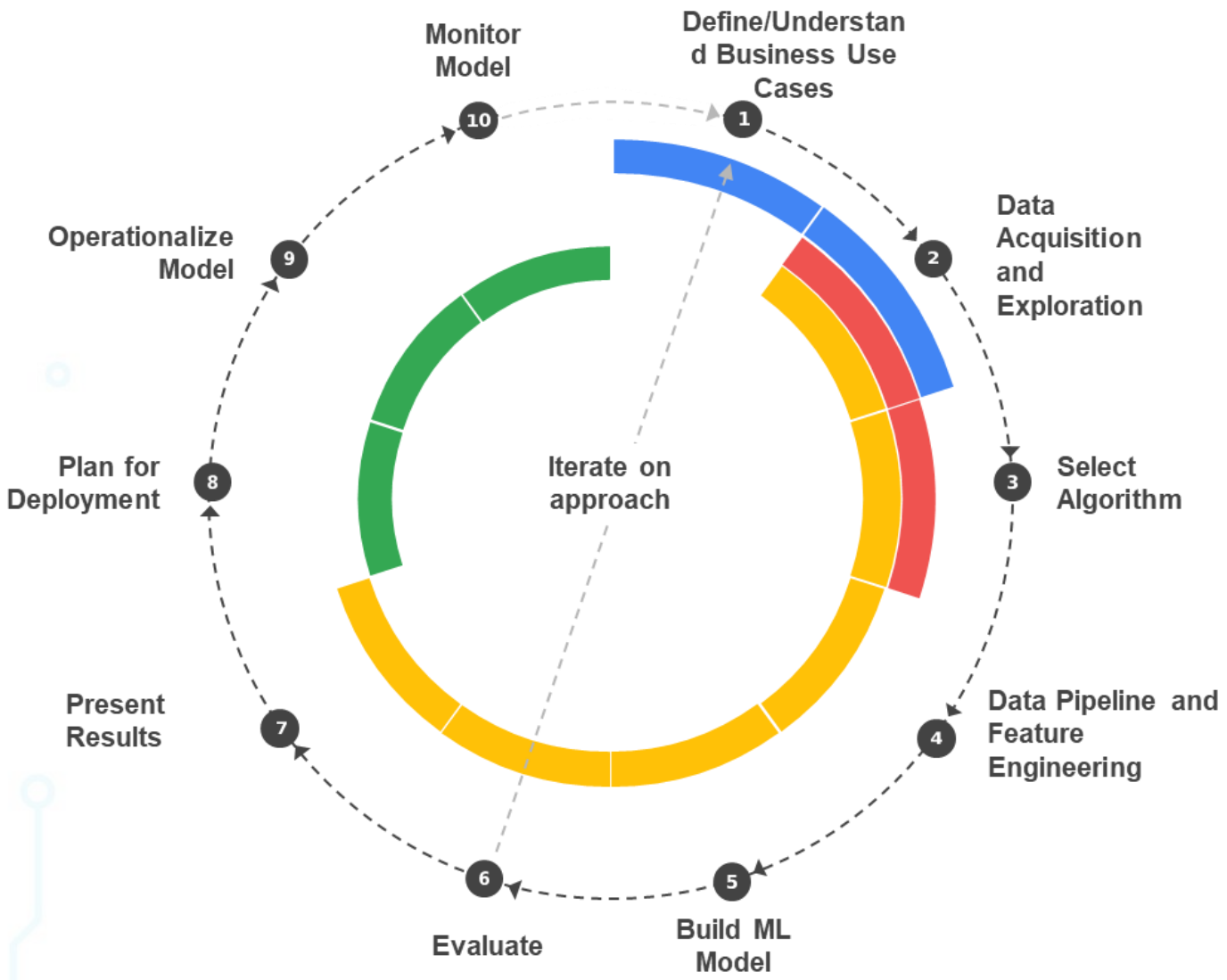
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7
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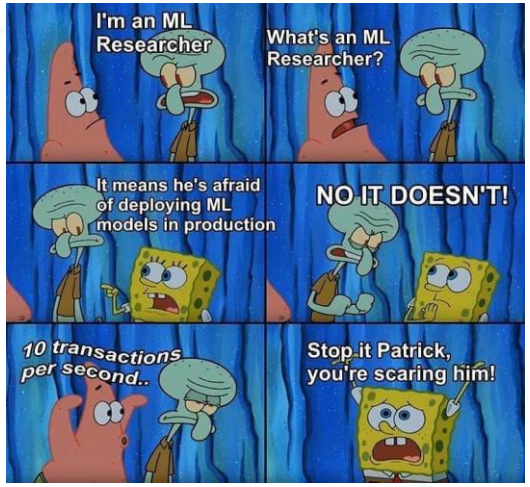
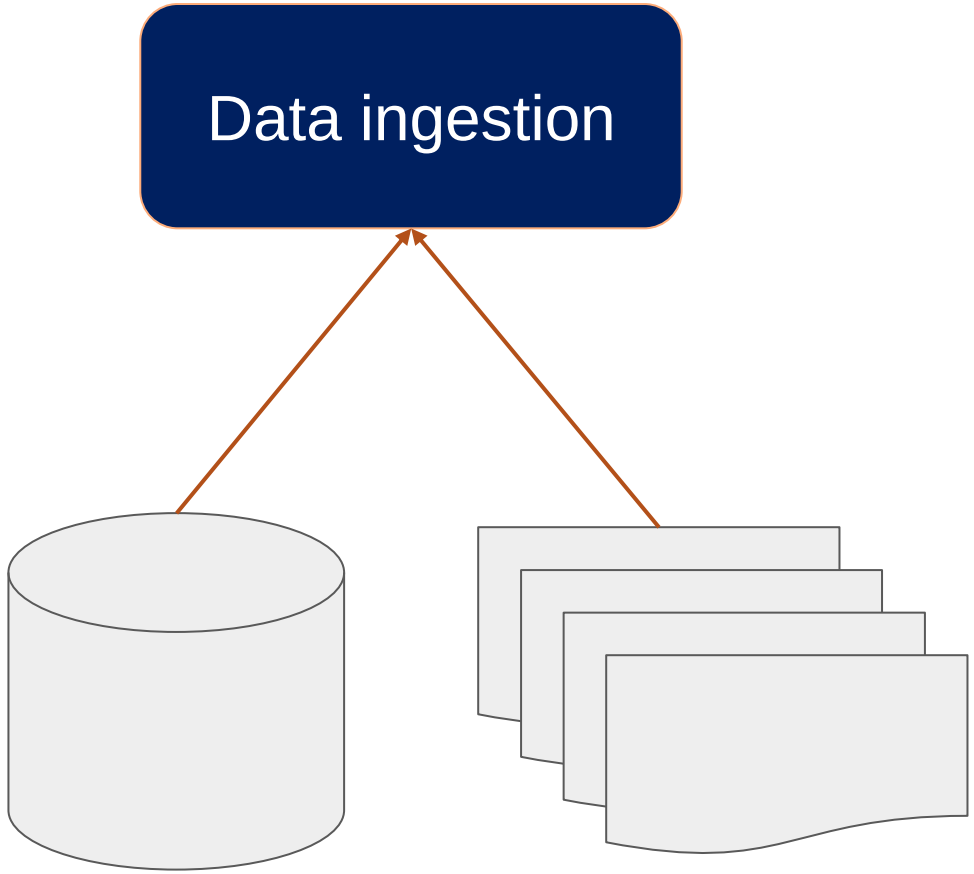
9
10

“More than 87% of data science projects never make it into production”

- Multiple studies and surveys -



Source: https://venturebeat.com/2019/07/19/why-do-87-of-data-science-projects-never-make-it-into-production/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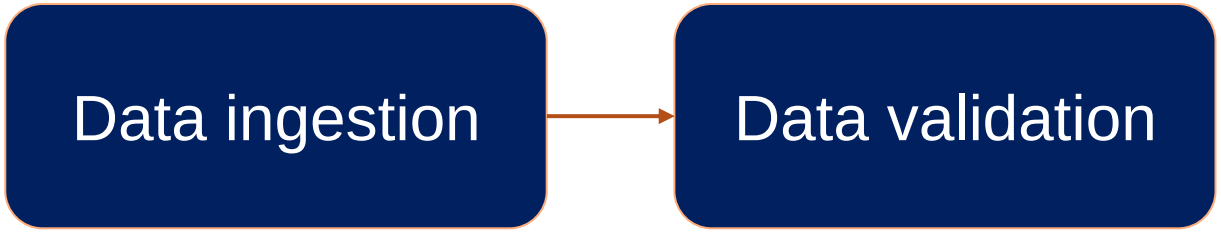
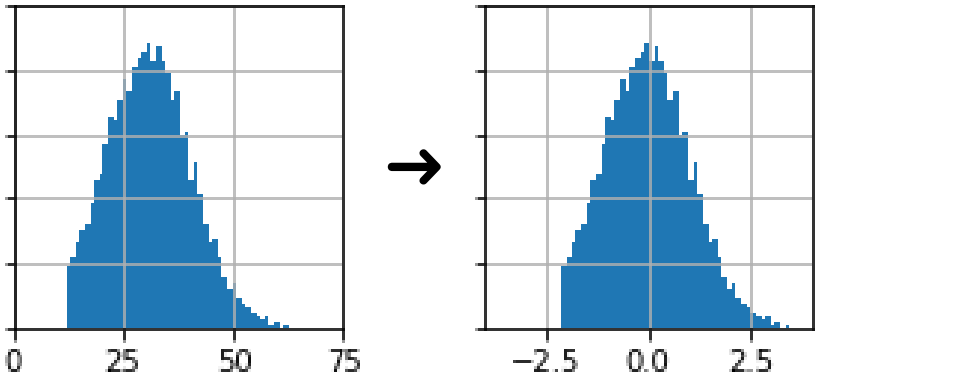


`age` is missing

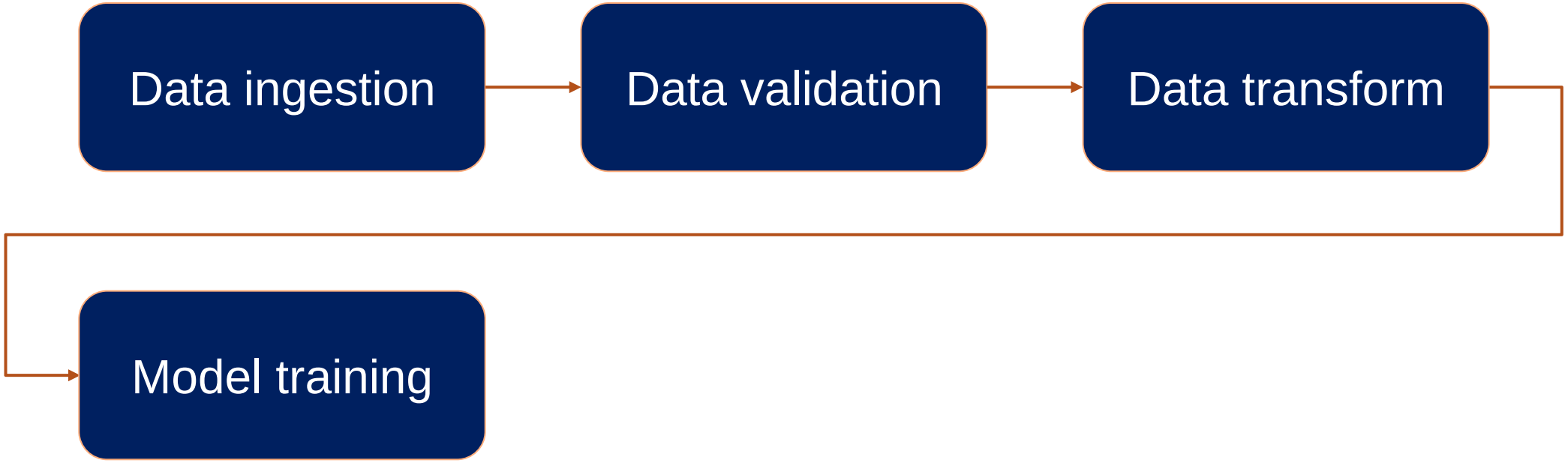
`country` not in:

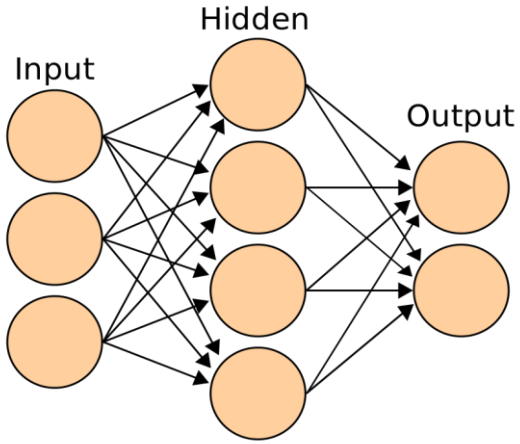
- China
- India
- USA

Data ingestion → Data validation → Data transform



China → [1, 0, 0]
India → [0, 1, 0]
USA → [0, 0, 1]


Data ingestion
Data validation
Data transform
Model training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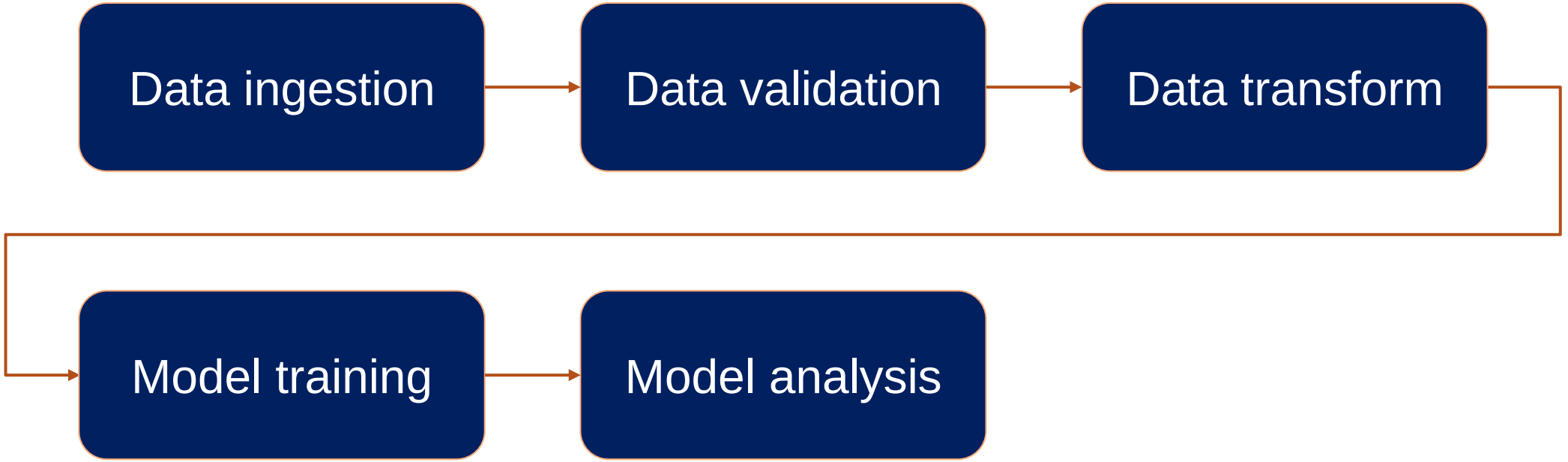
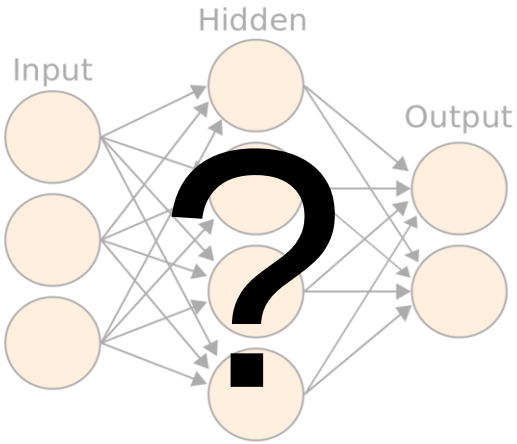
Input
Output


Data ingestion
Data validation
Data transform
Model training
Model analysis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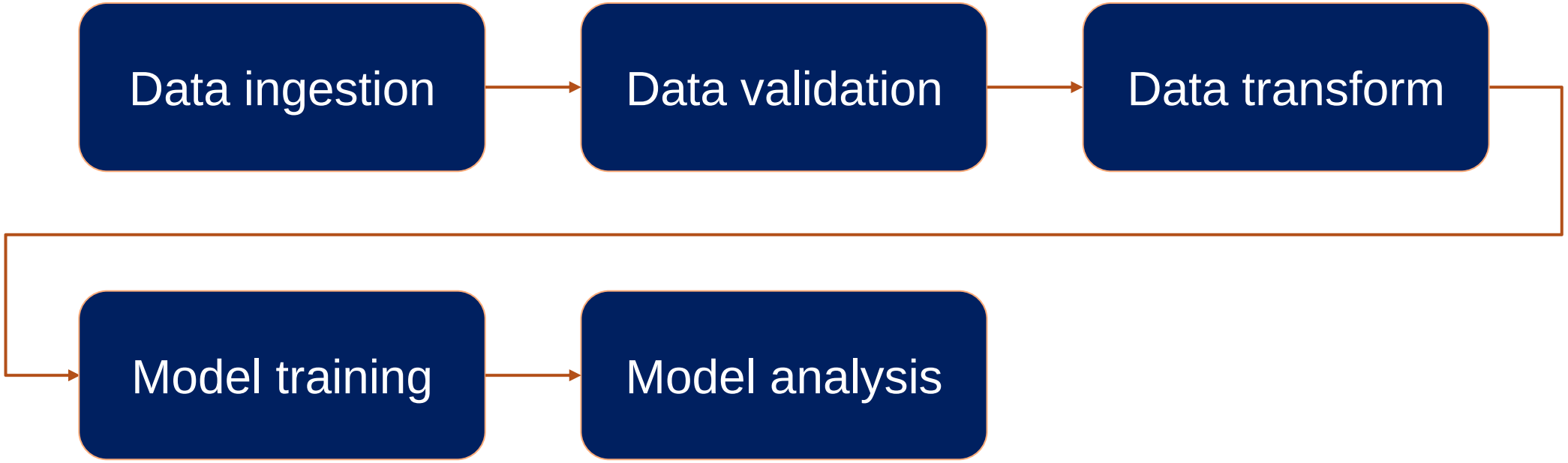
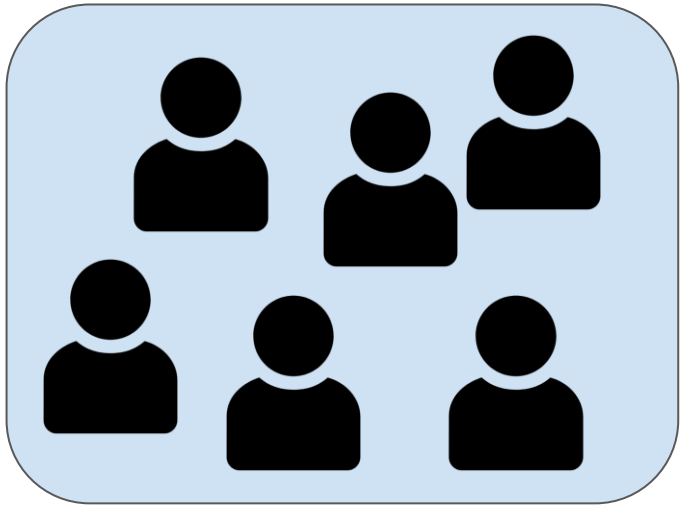
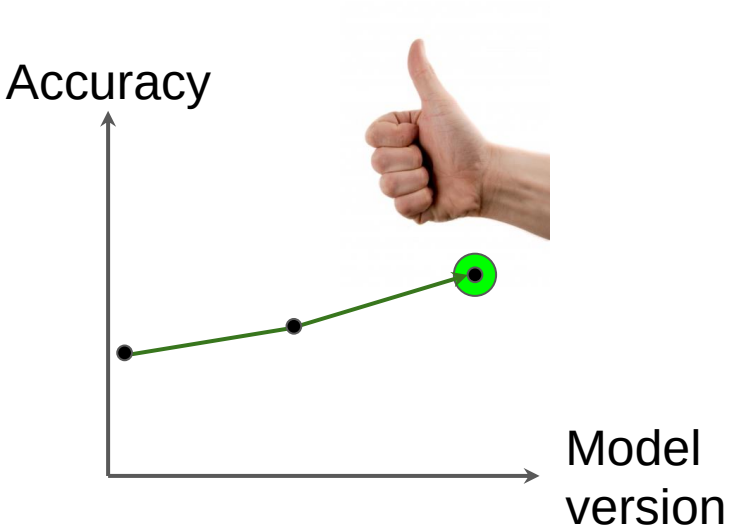
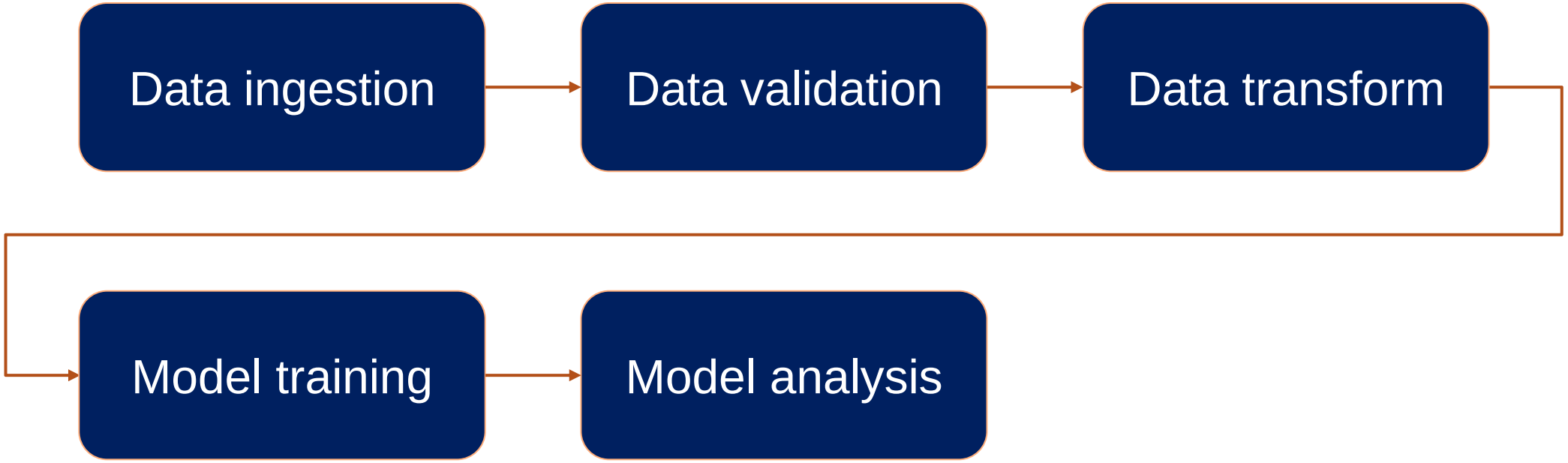
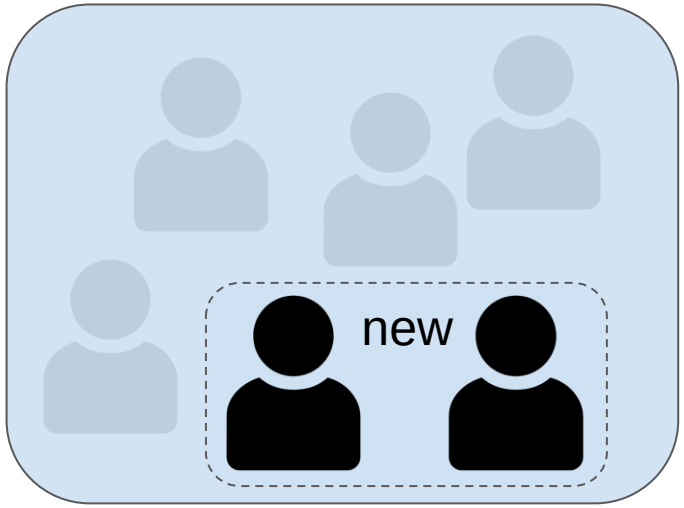
Input
Output
?

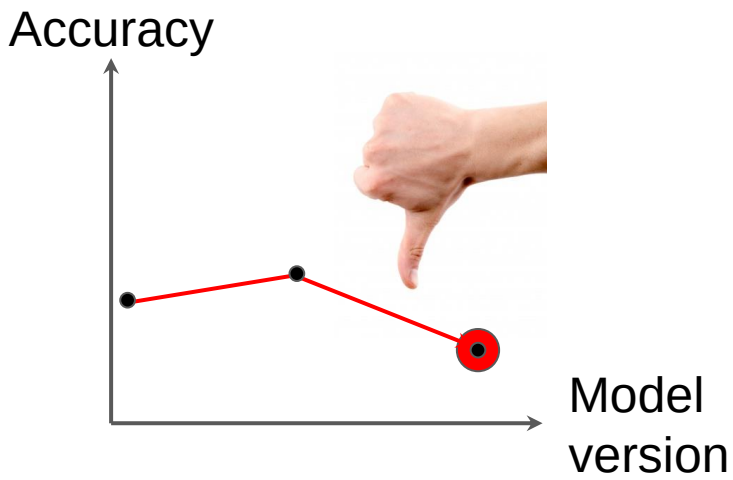

Data ingestion
Data validation
Data transform
Model training
Model analysis

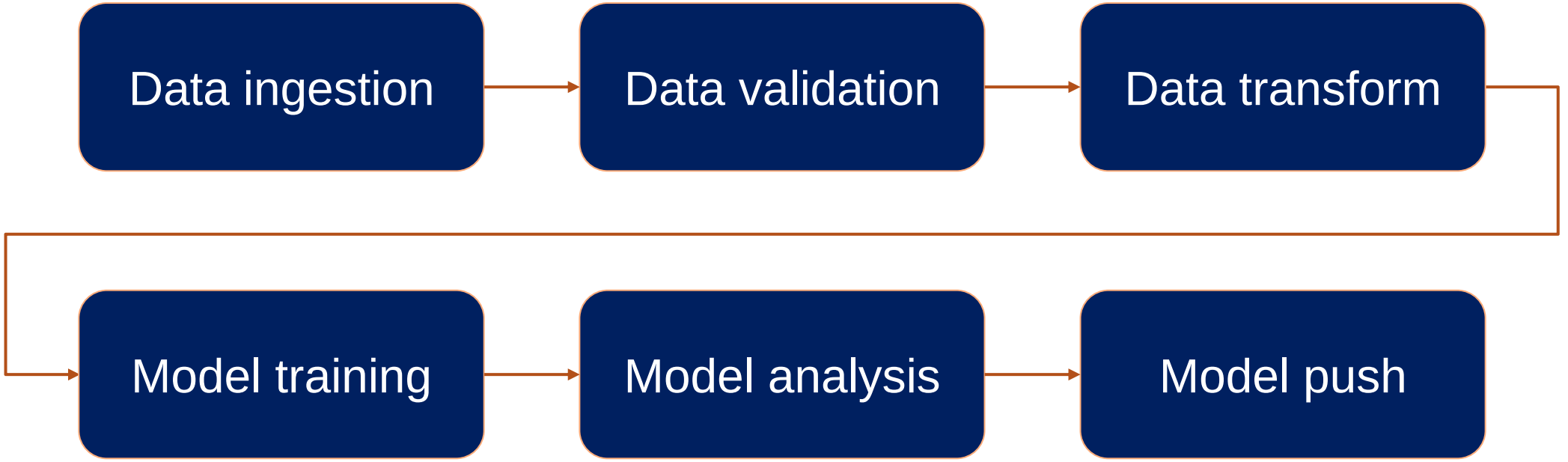


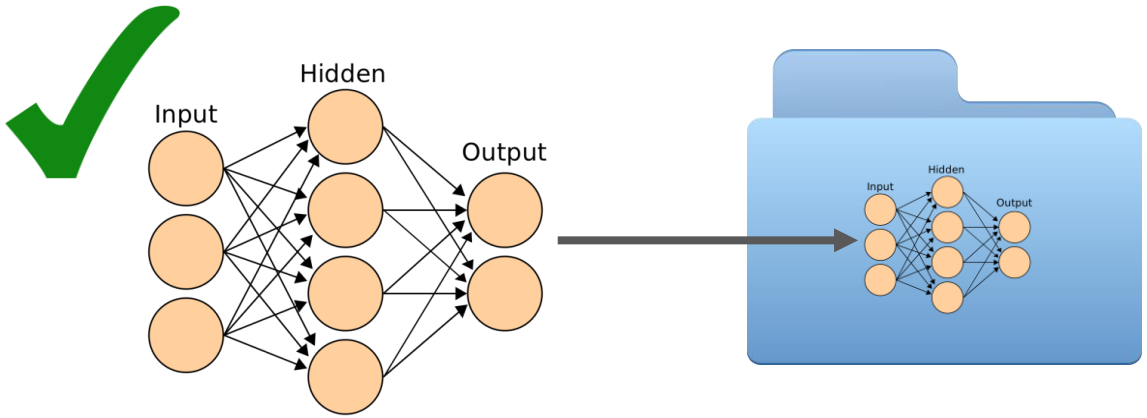

Accuracy
Model
version

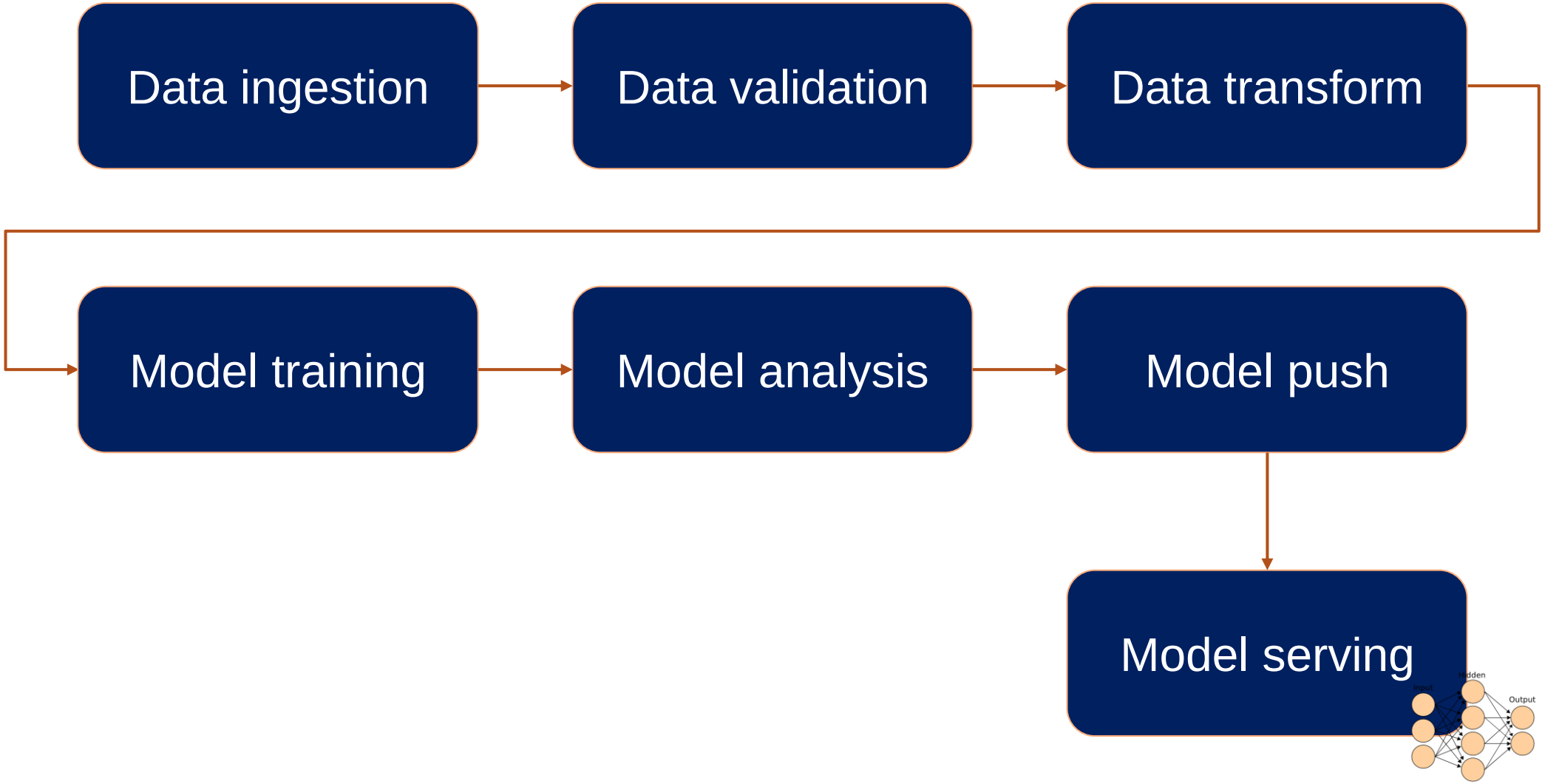

Data ingestion
Data validation
Data transform
Model training
Model analysis

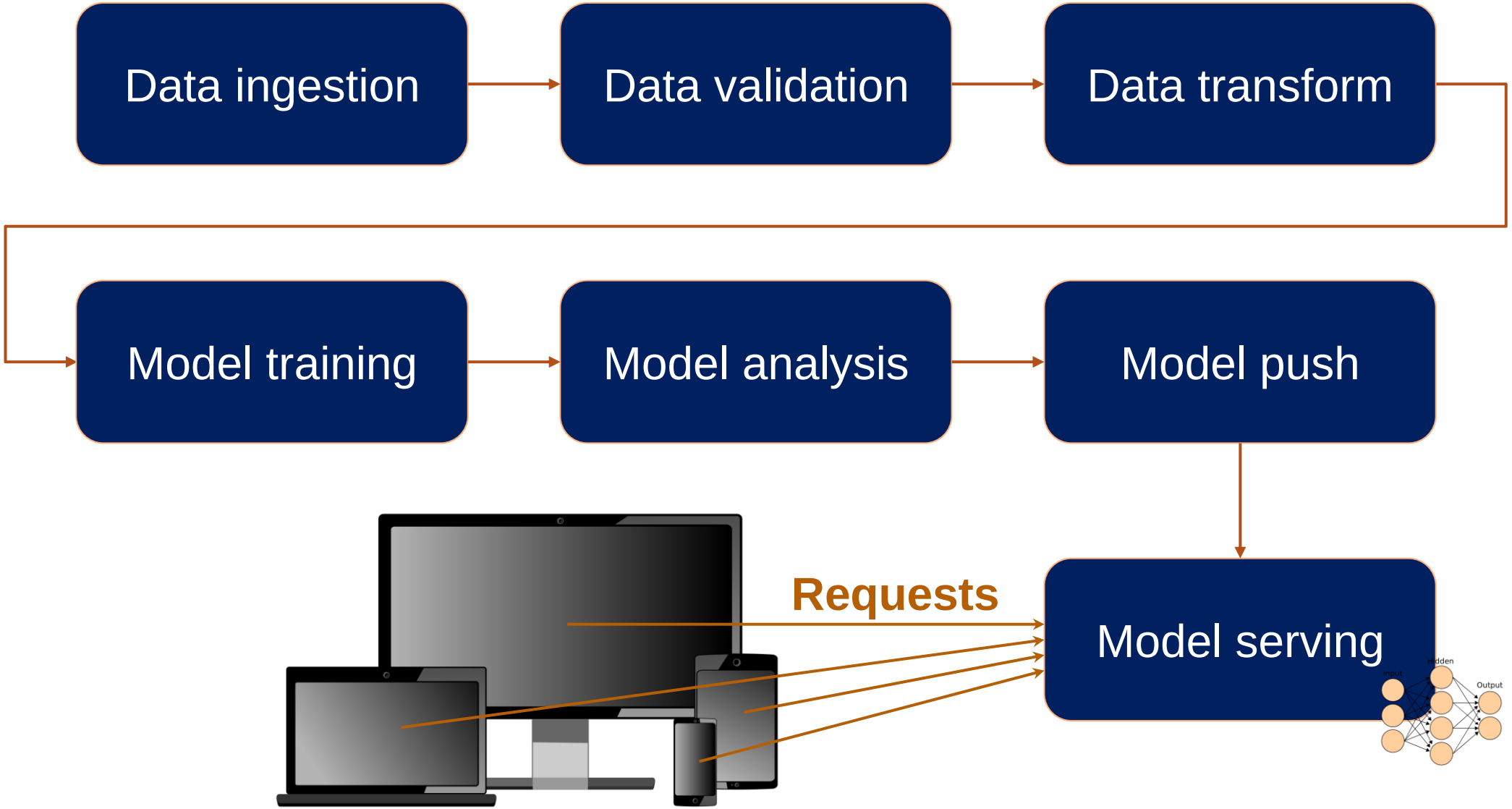

new

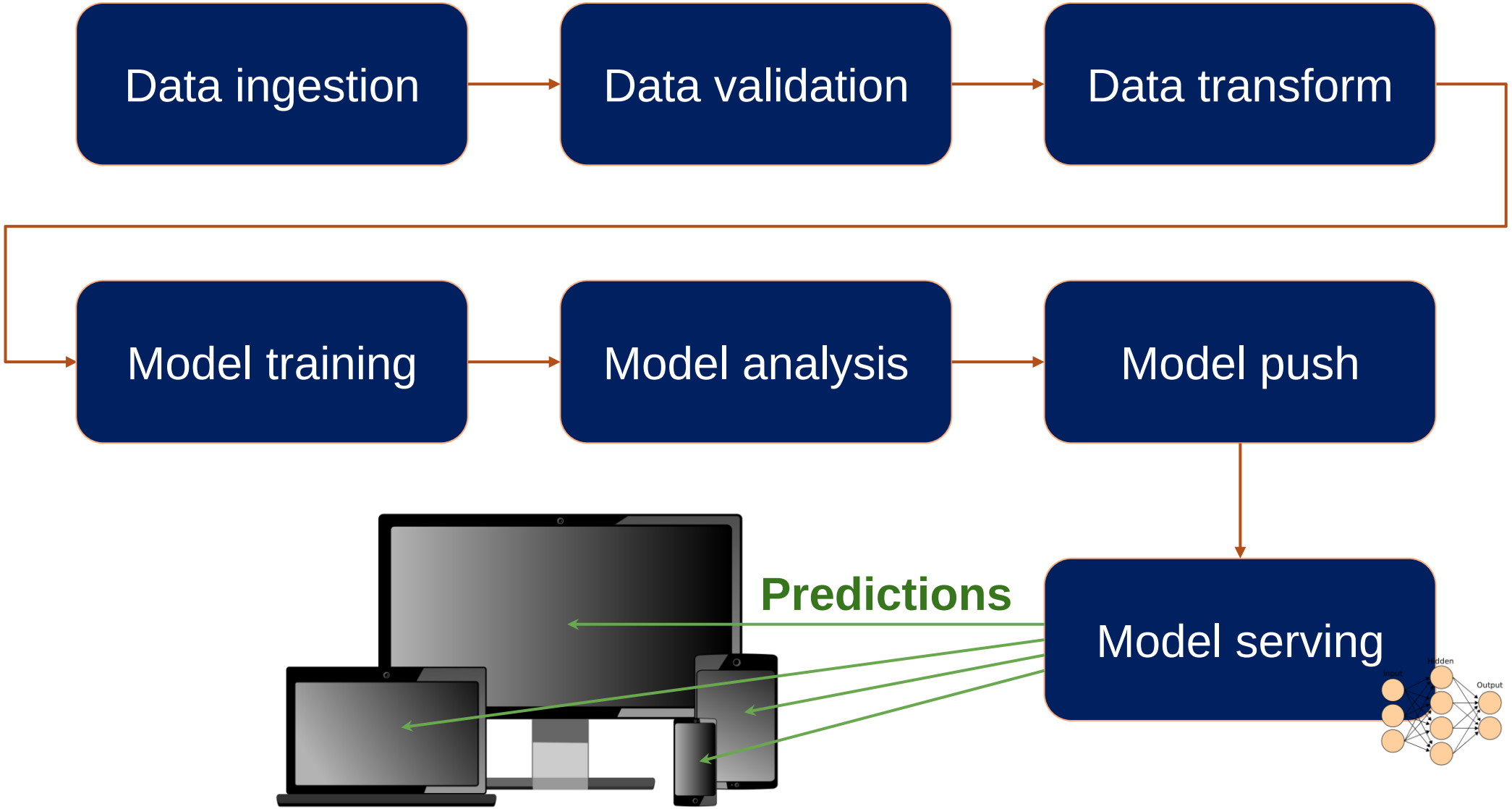

Accuracy
Model
version

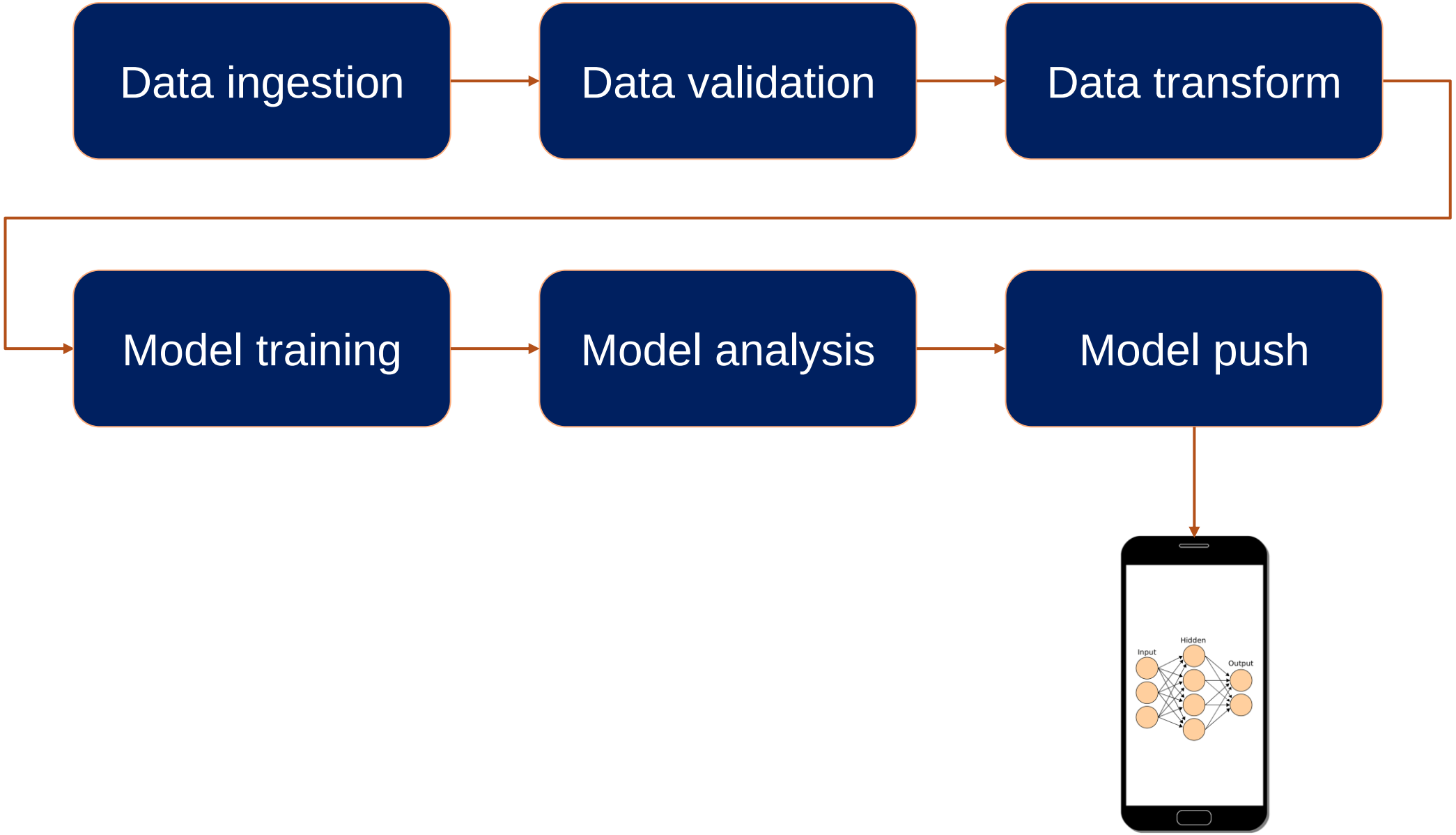

Data ingestion
Data validation
Data transform
Model training
Model analysis
Model push


Input
Hidden
Output
Input
Hidden
Output


Data ingestion
Data validation
Data transform
Model training
Model analysis
Model push
Model serving
Hidden
Output


Data ingestion
Data validation
Data transform
Model training
Model analysis
Model push
Requests
Model serving
Hidden
Output


Data ingestion
Data validation
Data transform
Model training
Model analysis
Model push
Predictions
Model serving
Hidden
Output


Data ingestion
Data validation
Data transform
Model training
Model analysis
Model push
Input
Hidden
Output

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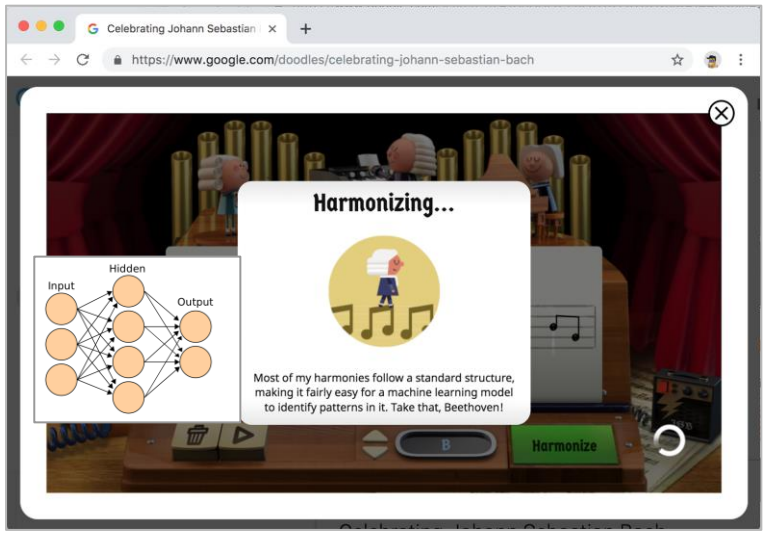
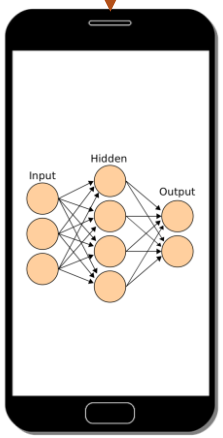
Data ingestion → Data validation → Data transform

Model training → Model analysis → Model push





Production Machine Learning

Machine Learning Development

- Labeled data
- Feature space coverage
- Minimal dimensionality
- Maximum predictive data
- Fairness
- Rare conditions
- Data lifecycle management

Production Machine Learning

Machine Learning Development

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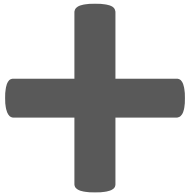

Modern Software Development

- Scalability
- Extensibility
- Configuration
- Consistency & Reproducibility
- Modularity
- Best Practices
- Testability
- Monitoring
- Safety & Security

Writing Software (Programming)

Programming **in the small** (Coding)	Programming **in the large** (Engineering)
Monolithic code	Modular design and implementation
Non-reusable code	Libraries for reuse (ideally across languages)
Undocumented code	Well documented contracts and abstractions
Untested code	Well tested code (exhaustively and at scale)
Unbenchmarked or hack-optimized once code	Continuously benchmarked and optimized code
Unverified code	Reviewed and peer verified code
Undebuggable code or adhoc tooling	Debuggable code and debug tooling
Uninstrumented code	Instrumentable and instrumented code
...	...

Writing ML Software (The “Code” view)

ML Programming **in the small** (Coding)	**ML** Programming **in the large** (Engineering)
Monolithic code	Modular design and implementation
Non-reusable code	Libraries for reuse (ideally across languages)
Undocumented code	Well documented contracts and abstractions
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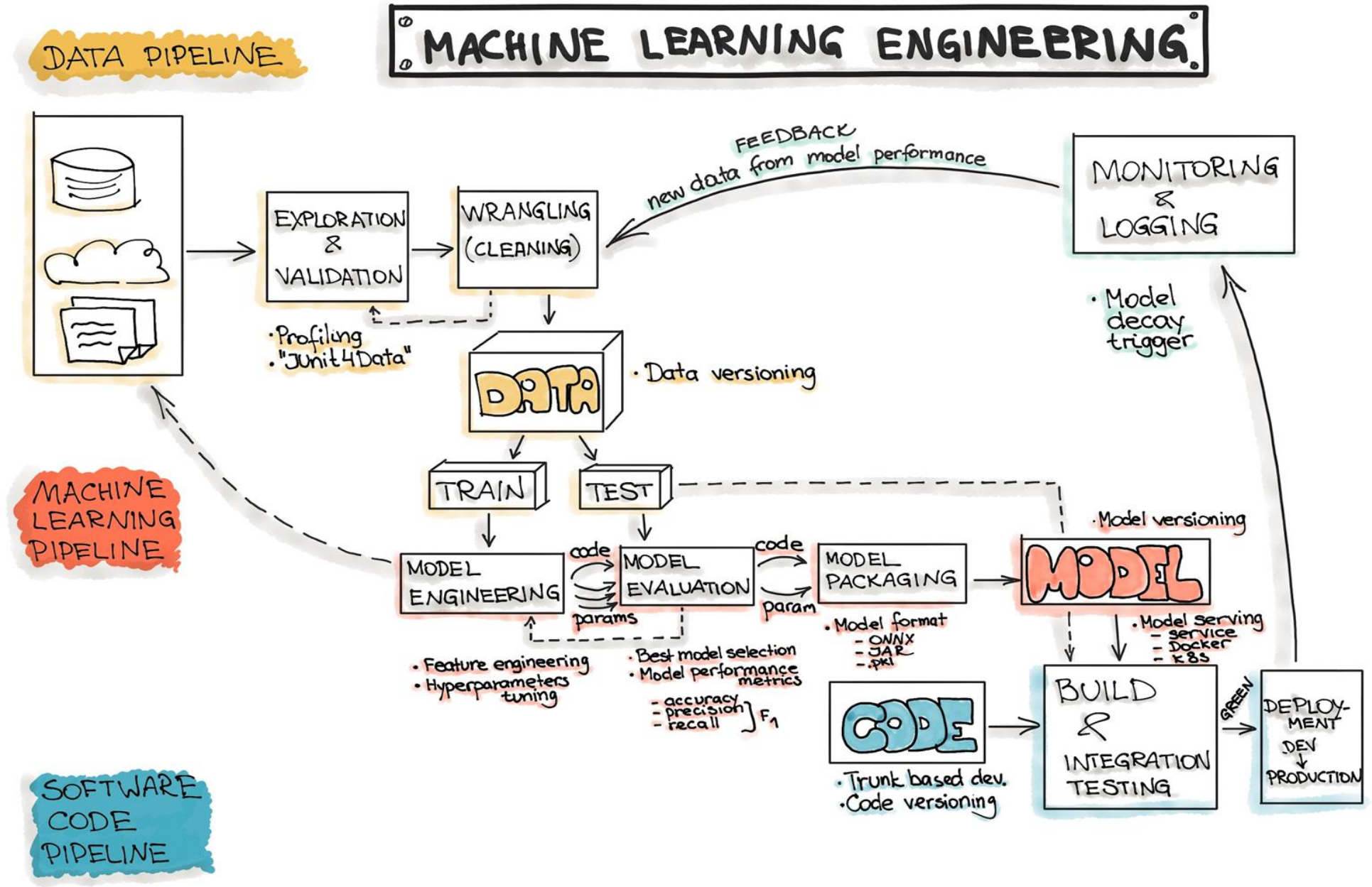
Undebuggable code or adhoc tooling	Debuggable code and debug tooling
Uninstrumented code	Instrumentable and instrumented code

This slide is, not surprisingly, the same as the previous one however it is **only half** the story :)

Writing ML Software (The “Data and other Artifacts” view)

ML Programming **in the small** (Coding)	ML Programming **in the large** (Engineering)
~~Monolithic code~~ Fixed Datasets	Evolving Datasets (Data, Features, ...) and Objectives
~~Non-reusable code~~ Unmergeable Artifacts	Reusable Models aka Modules, Mergeable Statistics ...
~~Undocumented code~~ No Problem Statements	Problem Statements, Discoverable Artifacts
~~Untested code~~ Non-validated Datasets, Models	Expectations, Data Validation, Model Validation ...
Unbenchmarked or hack-optimized once ~~code~~ Models	Quality and Performance Benchmarked Models ...
~~Unverified code~~ Biased Datasets / Artifacts	{Data, Model} x {Understanding, Fairness}
~~Undebuggable code or adhoc tooling~~	Visualizations, Summarizations, Understanding ...
~~Uninstrumented code~~	Full Artifact Lineage

This is the **remaining half!**


MACHINE LEARNING ENGINEERING
DATA PIPELINE
EXPLORATION & VALIDATION
WRANGLING (CLEANING)
FEEDBACK
new data from model performance
MONITORING & LOGGING
· Profiling
· "Junit4Data"
DATA
· Data versioning
· Model decay trigger
MACHINE LEARNING PIPELINE
TRAIN
TEST
· Model versioning
MODEL ENGINEERING
code
params
MODEL EVALUATION
code
param
MODEL PACKAGING
MODEL
· Model format
- ONNX
- JAR
- pkl
· Model serving
- service
- Docker
- K8S
· Feature engineering
· Hyperparameters tuning
· Best model selection
· Model performance metrics
- accuracy
- precision
- recall
F1
CODE
BUILD & INTEGRATION TESTING
GREEN
DEPLOY-MENT
DEV
PRODUCTION
· Trunk based dev.
· Code versioning
SOFTWARE CODE PIPELINE

Intrinsic Complexities with Machine Learning

- Understanding the business domain
- Selecting the appropriate Model
- Selecting the appropriate Features
- Fine tuning

Incidental Complexities with Machine Learning

- Integrating with Data Warehouse
- Scaling model training & serving
- Keeping consistency between: Prototyping vs Production, Training vs Inference
- Keeping track of multiple models, versions, experiments
- Supporting iteration on ML models

→ ML models take on average 8 to 12 weeks to build
→ ML workflows tended to be slow, fragmented, and brittle

Bighead Airbnb's | Andrew Hoh

ML Deploy Platforms

- Uber - Michelangelo
- AirBnB - Bighead
- Facebook - FB Learner
- Lyft - Lyft Learn
- Data Robot - ParallelM

Bighead Airbnb's | Andrew Hoh

Deploying big-data analytics, data science, and machine learning (ML) applications in real-world

Google

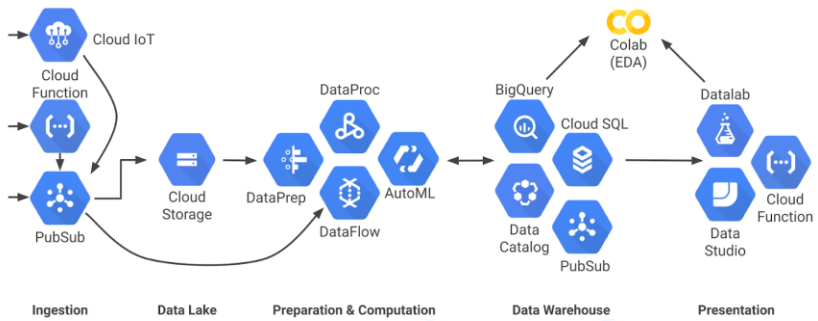
aws

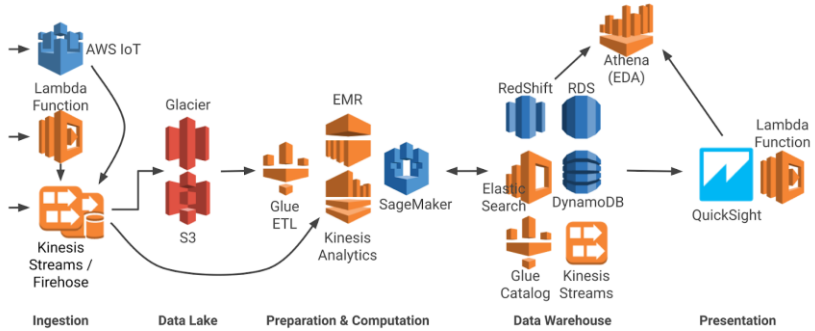
Microsoft Azure

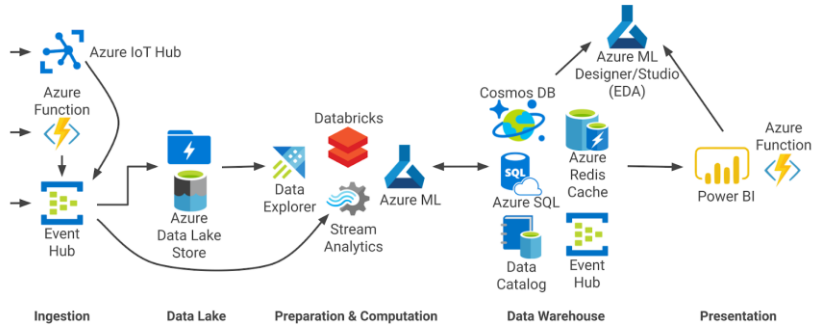
AI Platform

Amazon SageMaker

Azure Machine Learning







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https://www.satishchandragupta.com/tech/scalable-efficient-big-data-analytics-machine-learning-pipeline-architecture-on-cloud.html

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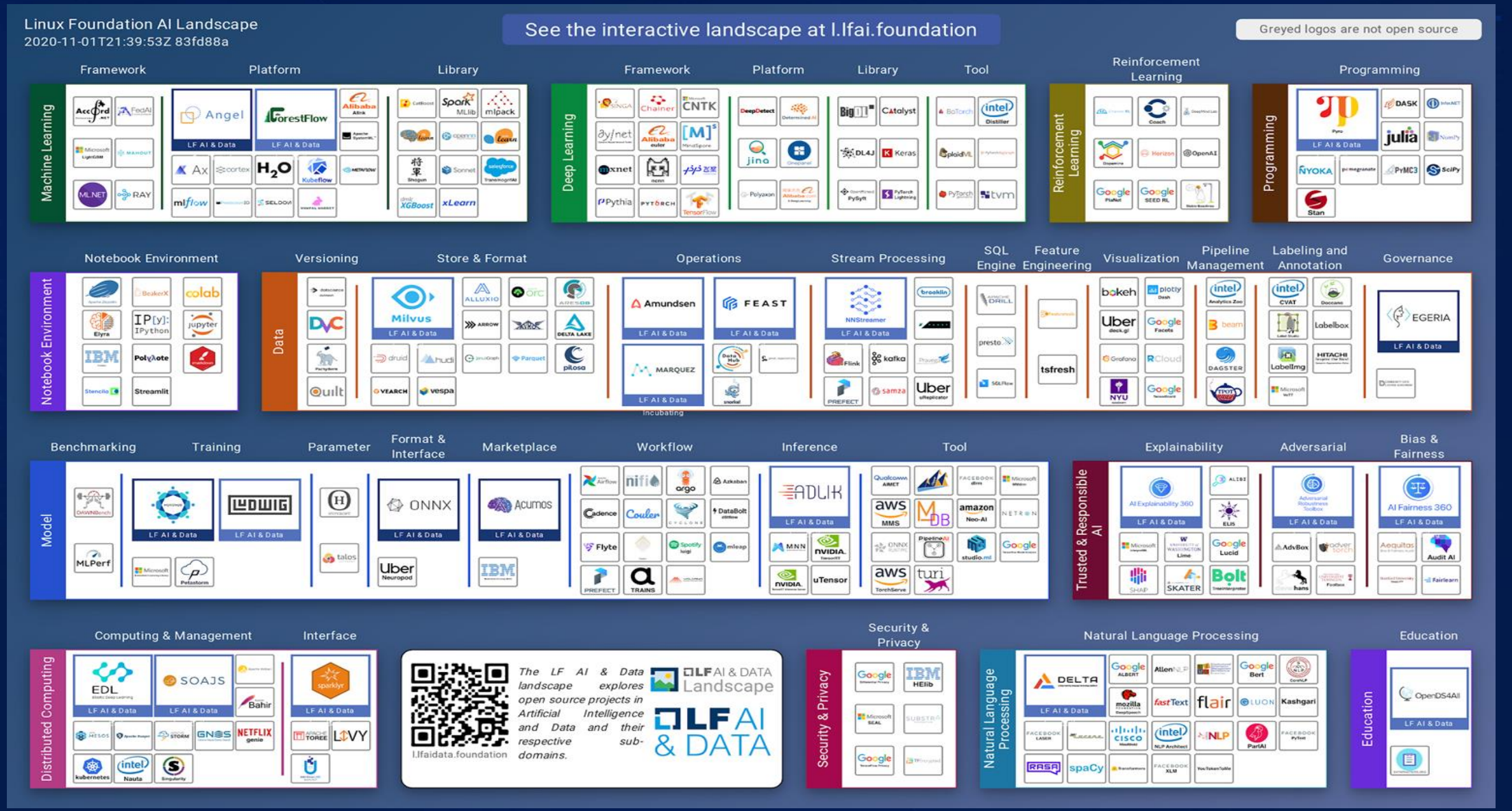
ML Landscape



Vinicius F. Caridá

https://landscape.lfai.foundation/

source: https://ml-ops.org/

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Flexible End-to-End ML Platform

Best practices	Libraries	Binaries	Components	Pipelines
ML is hard; doing it well is even harder	“Vanilla” as well as Data Parallel libraries	Optimized packaging of libraries with APIs	Pluggable binaries / UIs conforming to Artifacts APIs	Task-driven and data-driven pipelines of components

Platform

Seamlessly Integrated

Interoperable

Extensible

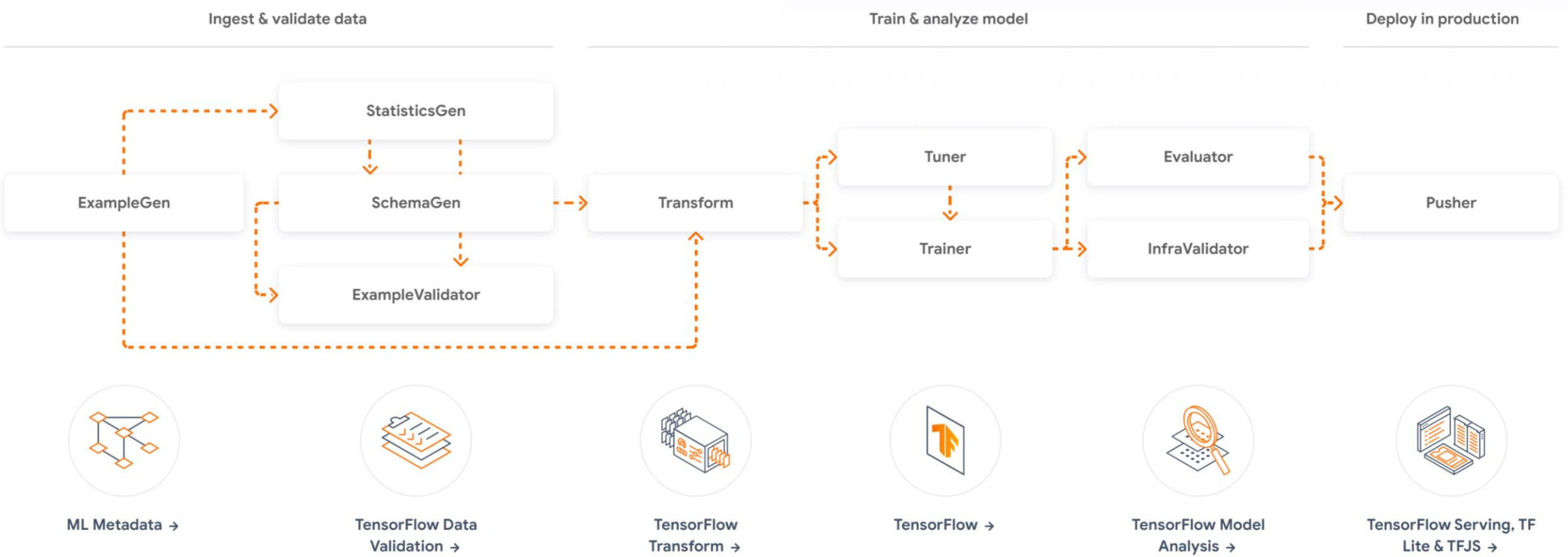
Evolving

Supported

Service-able and Service-ed

TensorFlow Extended (TFX)

Flexible End-to-End ML Platform



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Define problem | Construct and prepare data | Build and train model | Evaluate model | Deploy and monitor

Who is my ML system for?

The way actual users experience your system is essential to assessing the true impact of its predictions, recommendations, and decisions. Make sure to get input from a diverse set of users early on in your development process.

https://www.tensorflow.org/resources/responsible-ai

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Step 1

Define problem

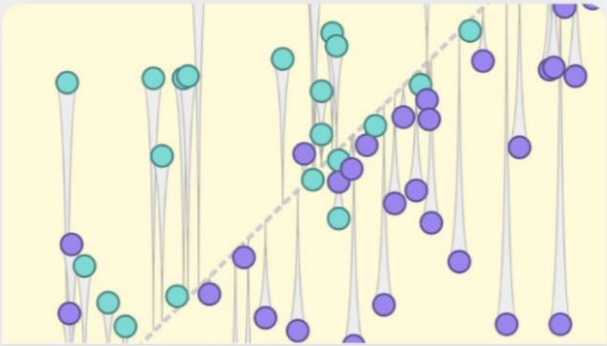
Use the following resources to design models with Responsible AI in mind.

People + AI Guidebook

People + AI Research (PAIR) Guidebook

Learn more about the AI development process and key considerations.

Learn more ↗



PAIR Explorables

Explore, via interactive visualizations, key questions and concepts in the realm of Responsible AI.

Learn more ↗

https://www.tensorflow.org/resources/responsible-ai

Define problem | **Construct and prepare data** | Build and train model | Evaluate model | Deploy and monitor

Am I using a representative dataset?

Is your data sampled in a way that represents your users (e.g. will be used for all ages, but you only have training data from senior citizens) and the real-world setting (e.g. will be used year-round, but you only have training data from the summer)?

Is there real-world/human bias in my data?

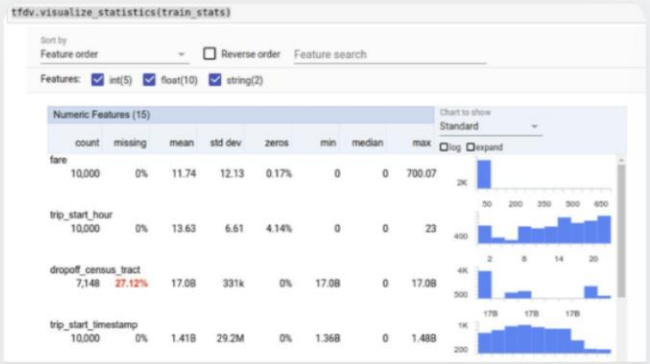
Underlying biases in data can contribute to complex feedback loops that reinforce existing stereotypes.

https://www.tensorflow.org/resources/responsible-ai

Step 2

Construct and prepare data

Use the following tools to examine data for potential biases.



TF Data Validation

Analyze and transform data to detect problems and engineer more effective feature sets.

Learn more →

Data Cards

Create a transparency report for your dataset.

Learn more ↗

https://www.tensorflow.org/resources/responsible-ai

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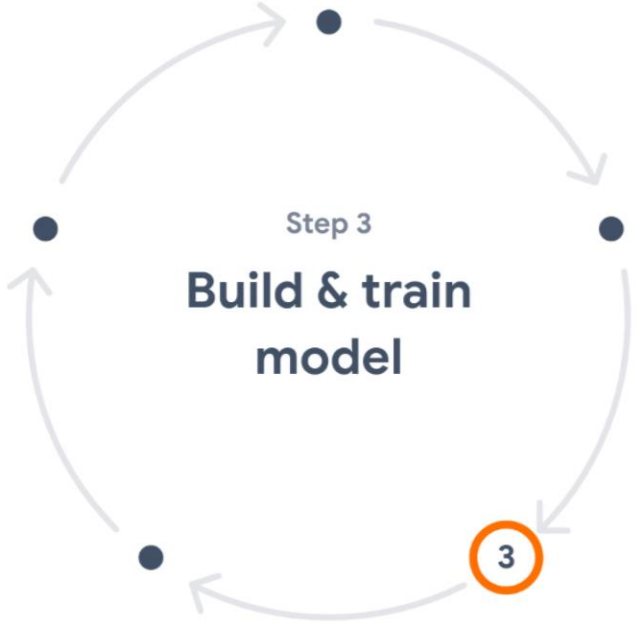
Define problem | Construct and prepare data | **Build and train model** | Evaluate model | Deploy and monitor

What methods should I use to train my model?

Use training methods that build fairness, interpretability, privacy, and security into the model.



https://www.tensorflow.org/resources/responsible-ai

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Step 3

Build and train model

Use the following tools to train models using privacy-preserving, interpretable techniques, and more.

TF Model Remediation

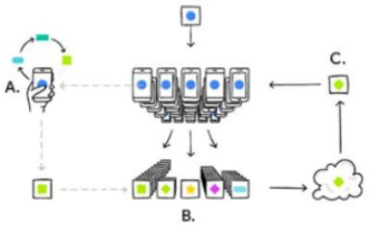
Train machine learning models to promote more equitable outcomes.

Learn more →

TF Privacy

Train machine learning models with privacy.

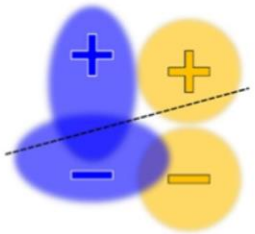
Learn more ↗



TF Federated

Train machine learning models using federated learning techniques.

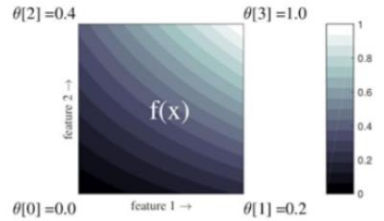
Learn more →



TF Constrained Optimization

Optimize inequality-constrained problems.

Learn more ↗



TF Lattice

Implement flexible, controlled, and interpretable lattice-based models.

Learn more →

https://www.tensorflow.org/resources/responsible-ai

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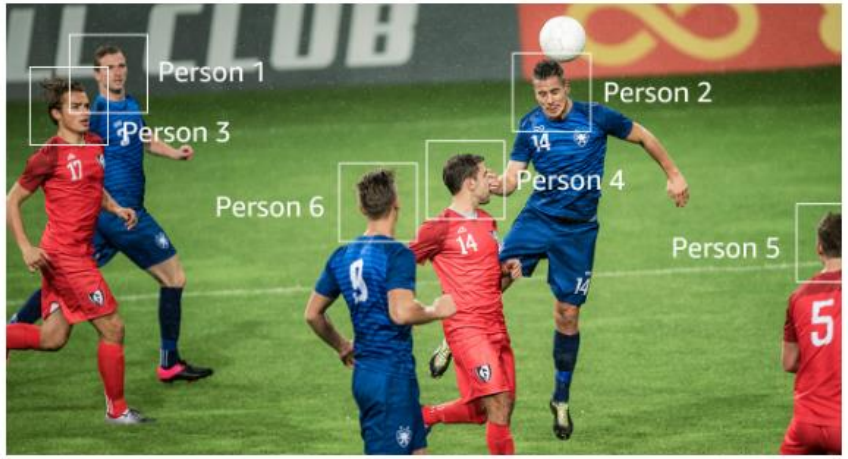
Análise facial



Determinação de caminhos

Detecção de objetos, cenas e atividades

Reconhecimento facial

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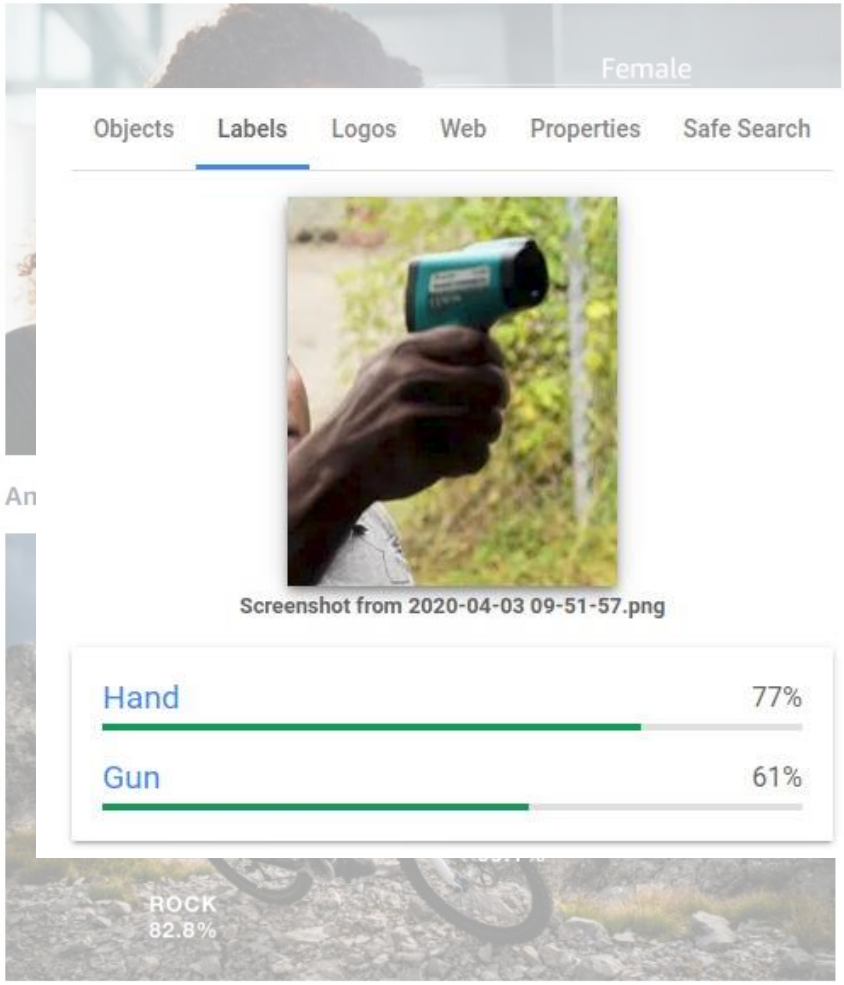
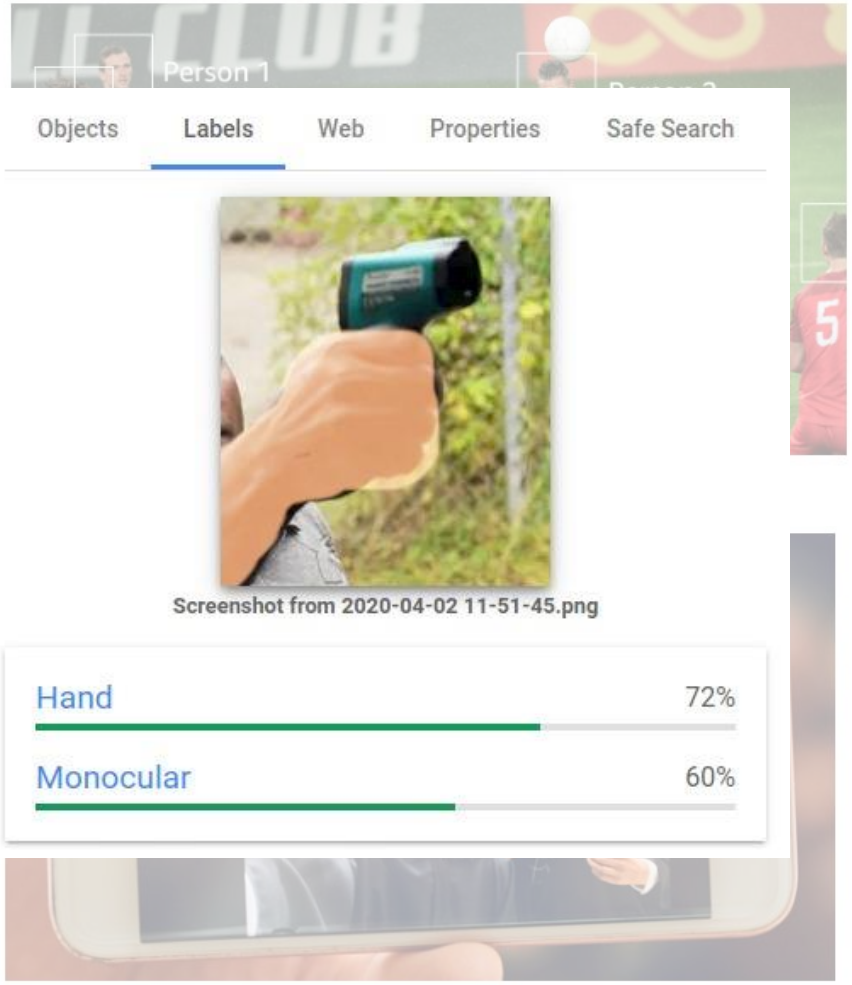


Detecção de objetos, cenas e atividades



Reconhecimento facial

Remediation:
Smile Detection on CelebA using TF Constrained Optimization

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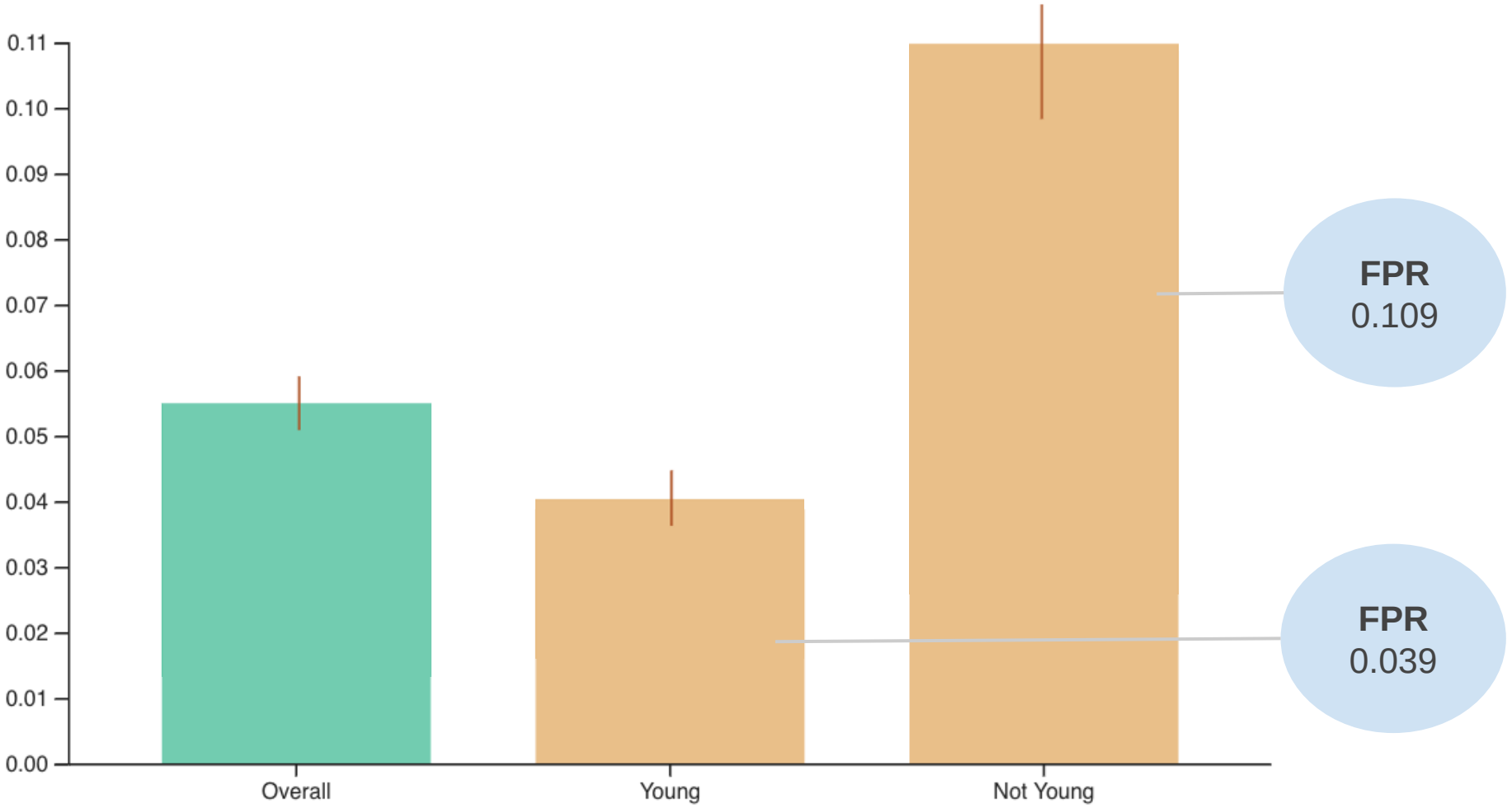
Results: Unconstrained tf.keras.Sequential model



Remediation: CelebA example using TFCO

1. Define subsets of interest

```
context = tfco.rate_context(predictions, labels=lambda:labels_tensor)
context_subset = context.subset(lambda:groups_tensor < 1)
```

https://github.com/google-research/tensorflow_constrained_optimization

Remediation: CelebA example using TFCO

1. Define subsets of interest

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context = tfco.rate_context(predictions, labels=lambda:labels_tensor)
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```

2. Set constraints on subset using rate helpers

```
constraints = [tfco.false_positive_rate(context_subset) <= 0.05]
```

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Remediation: CelebA example using TFCO*

1. Define subsets of interest

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context = tfco.rate_context(predictions, labels=lambda:labels_tensor)
context_subset = context.subset(lambda:groups_tensor < 1)
```

2. Set constraints on subset using rate helpers

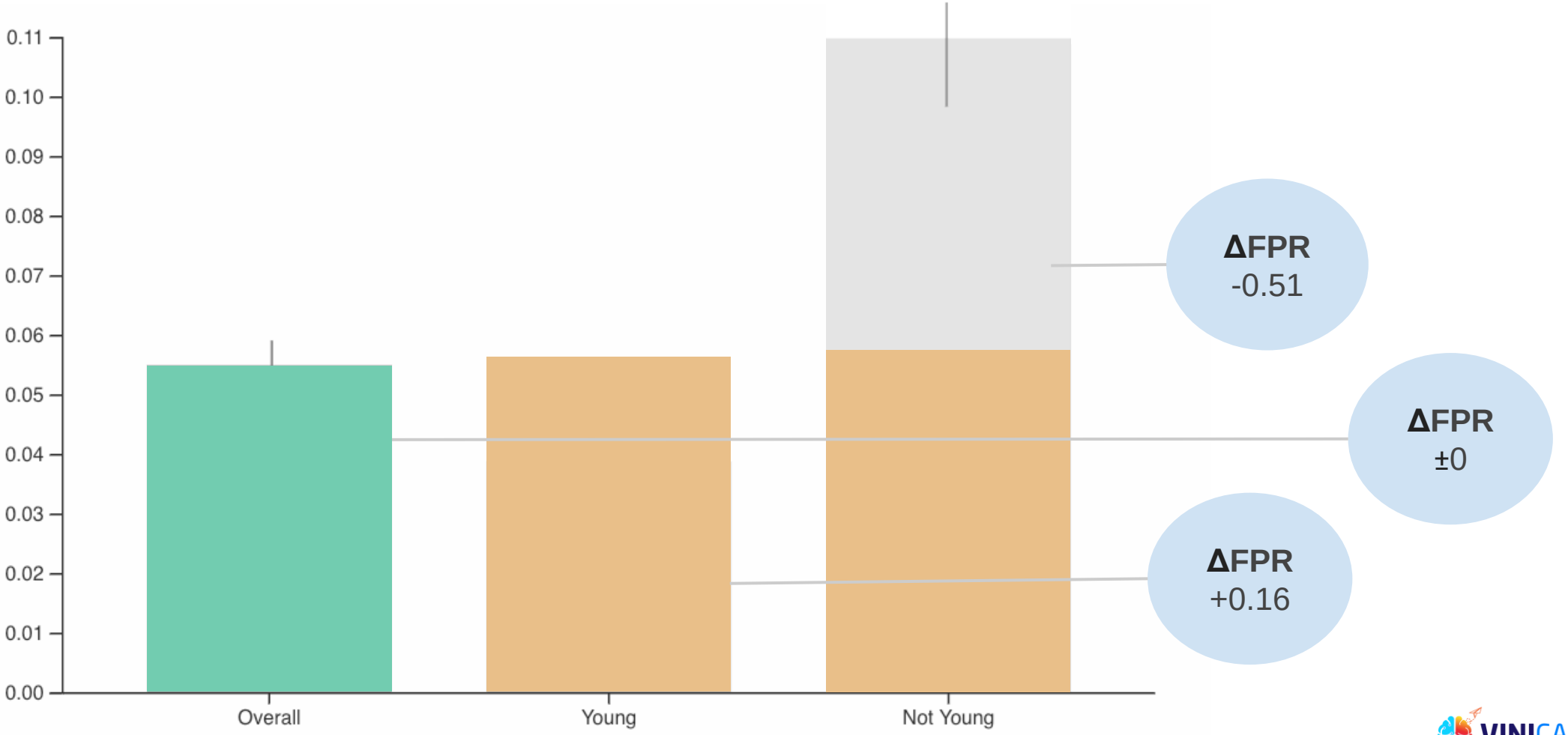
```
constraints = [tfco.false_positive_rate(context_subset) <= 0.05]
```

3. Define optimizer and train

```
problem = tfco.RateMinimizationProblem(tfco.error_rate(context), constraints)
optimizer = tfco.ProxyLagrangianOptimizerV2(
      optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
      constraint_optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
      num_constraints=problem.num_constraints)
```

https://github.com/google-research/tensorflow_constrained_optimization

Results: Constrained tf.keras.Sequential model



Define problem | Construct and prepare data | Build and train model | **Evaluate model** | Deploy and monitor

How is my model performing?

Evaluate user experience in real-world scenarios across a broad spectrum of users, use cases, and contexts of use. Test and iterate in dogfood first, followed by continued testing after launch.

https://www.tensorflow.org/resources/responsible-ai

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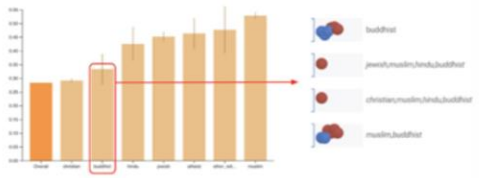
Step 4

Evaluate model

Debug, evaluate, and visualize model performance using the following tools.



Fairness Indicators

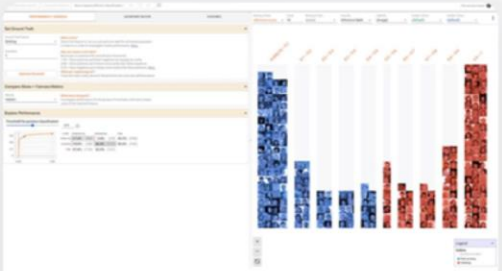
Evaluate commonly-identified fairness metrics for binary and multi-class classifiers.

Learn more →

TF Model Analysis

Evaluate models in a distributed manner and compute over different slices of data.

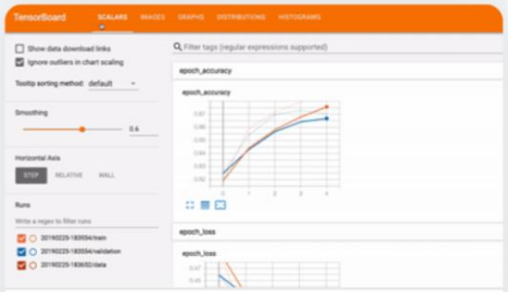
Learn more →



What-If Tool

Examine, evaluate, and compare machine learning models.

Learn more ↗



TensorBoard

Measure and visualize the machine learning workflow.

Learn more →

Language Interpretability Tool

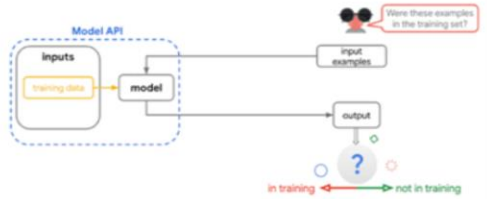
Visualize and understand NLP models.

Learn more ↗

Explainable AI

Develop interpretable and inclusive machine learning models.

Learn more ↗



TF Privacy Tests

Assess the privacy properties of classification models.

Learn more →

https://www.tensorflow.org/resources/responsible-ai

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Define problem | Construct and prepare data | Build and train model | Evaluate model | **Deploy and monitor**

Are there complex feedback loops?

Even if everything in the overall system design is carefully crafted, ML-based models rarely operate with 100% perfection when applied to real, live data. When an issue occurs in a live product, consider whether it aligns with any existing societal disadvantages, and how it will be impacted by both short- and long-term solutions.

https://www.tensorflow.org/resources/responsible-ai

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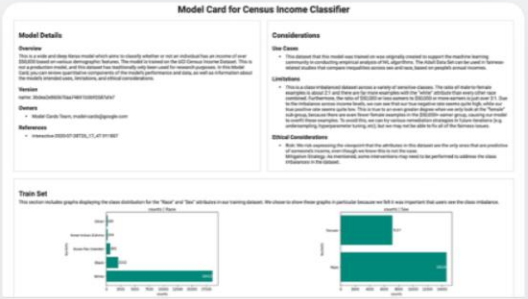
Step 5

Deploy and monitor

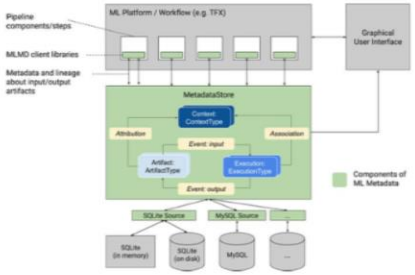
Use the following tools to track and communicate about model context and details.



Model Card Toolkit

Generate model cards with ease using the Model Card toolkit.

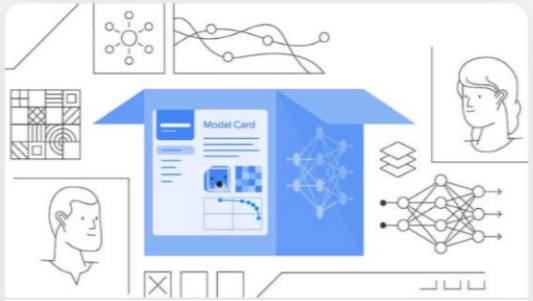
Learn more →



ML Metadata

Record and retrieve metadata associated with ML developer and data scientist workflows.

Learn more →



Model Cards

Organize the essential facts of machine learning in a structured way.

Learn more ↗

https://www.tensorflow.org/resources/responsible-ai

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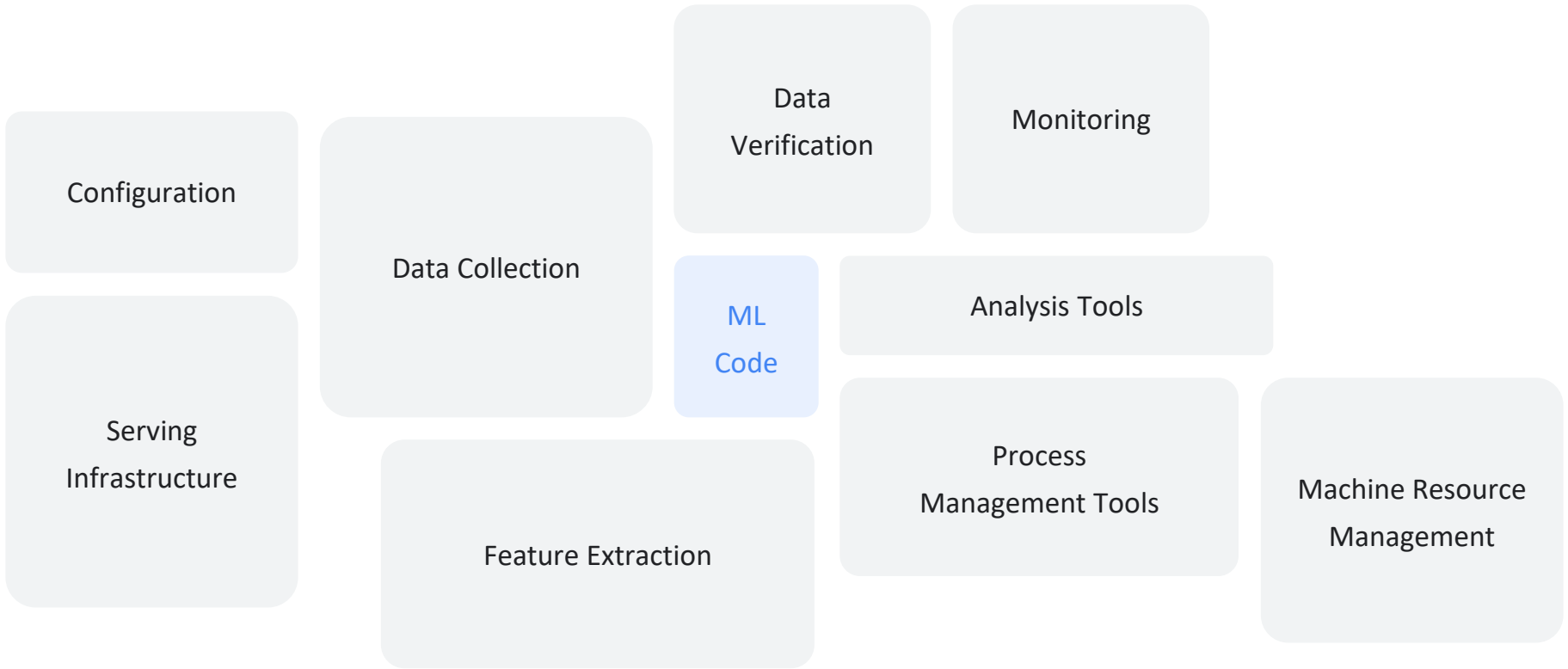

Hidden Technical Debt in Machine Learning Systems, NeurIPS 2015

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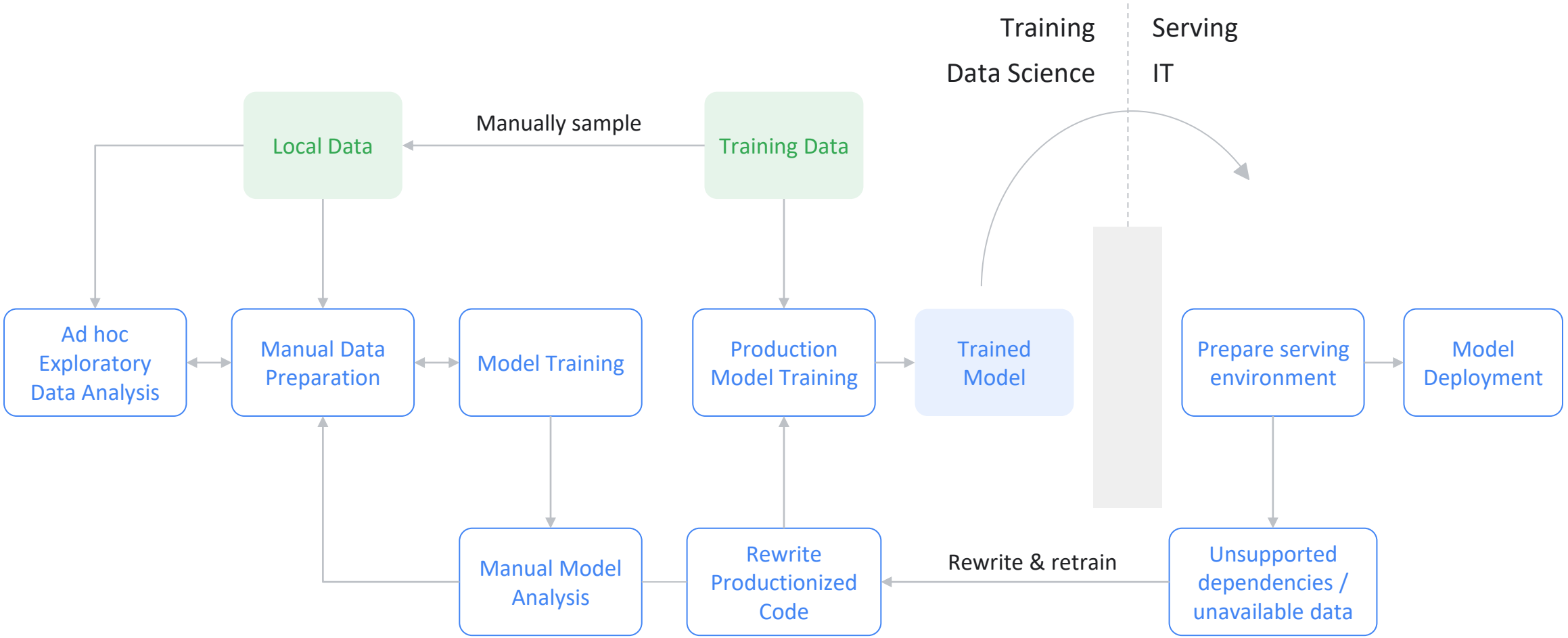
What's happening today: Data Science and IT (Ops) are isolated



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A platform for all users and intents throughout the ML lifecycle

Product Manager

Insights and objectives

- Interactive BI
  Looker
- EDW in a Spreadsheet
  Connected Sheets
- Natural Language Query
  Data QnA

Data analyst

Query and analyze

- Endless EDW
  BigQuery
- Self-managed data pipelines
  Data Fusion, Dataflow
- Data models, catalog
  Looker, Data Catalog
- Machine learning in SQL
  BigQuery ML

Data engineer

Get clean, useful data

- Self-driving infra
  BigQuery, Dataflow, Composer
- Broad choice of tools/language
  Dataproc, Dataflow
- Data quality /lineage
  AI Platform, BigQuery, Dataflow
- Real-time capabilities
  BigQuery, Dataflow

Data scientist

Models that work

- Portable notebooks
  AI Platform Notebooks
- Model eval and selection
  Explainable AI, Experiments
- Point-and-click dev
  AutoML
- Collaboration
  Feature Store, AI Platform Pipelines

ML developer

Intelligent apps

- Images, videos
  Vision, Video Intelligence
- Sentiment analysis, entity extraction
  NL, Translation
- Chatbots, voice commands
  Conversation
- Fleet routing, forecasting
  Optimization

ML engineer

Models in production

- Scalable model hosting
  AI Platform Prediction
- ML CI/CD and orchestration
  AI Platform Pipelines
- Provenance and lineage
  ML Metadata Management
- Improvements and retraining
  Continuous Monitoring

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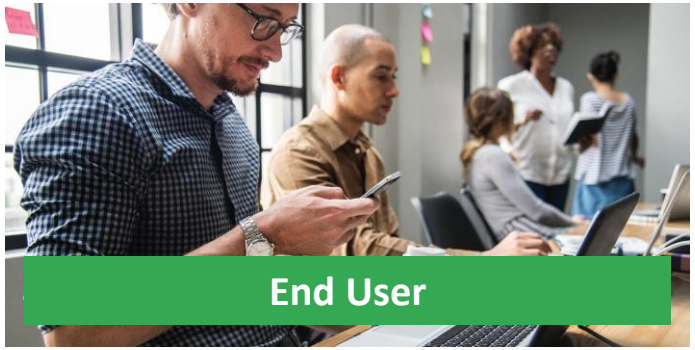
Como conectar usuários para produzir resultados 10x mais impactantes?



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Perfil do Cientista de dados

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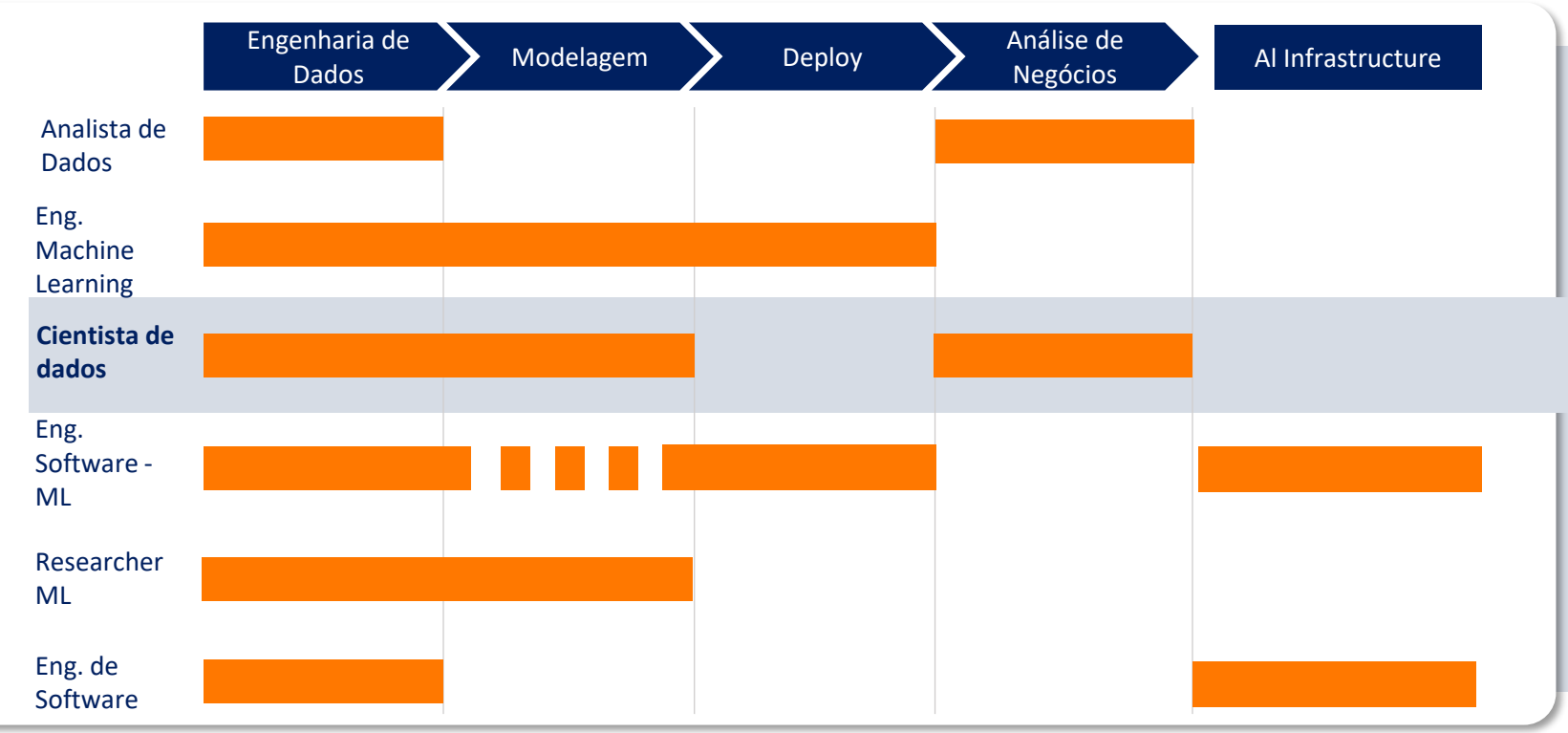
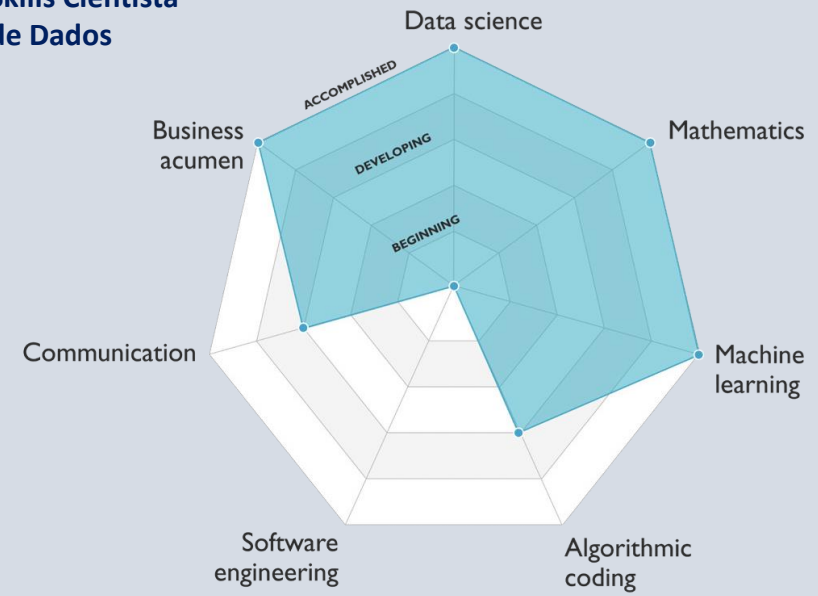
Frentes de trabalho x profissionais , de acordo com texto publicado no Workera:



Skills Cientista de Dados



Profissionais x Skills

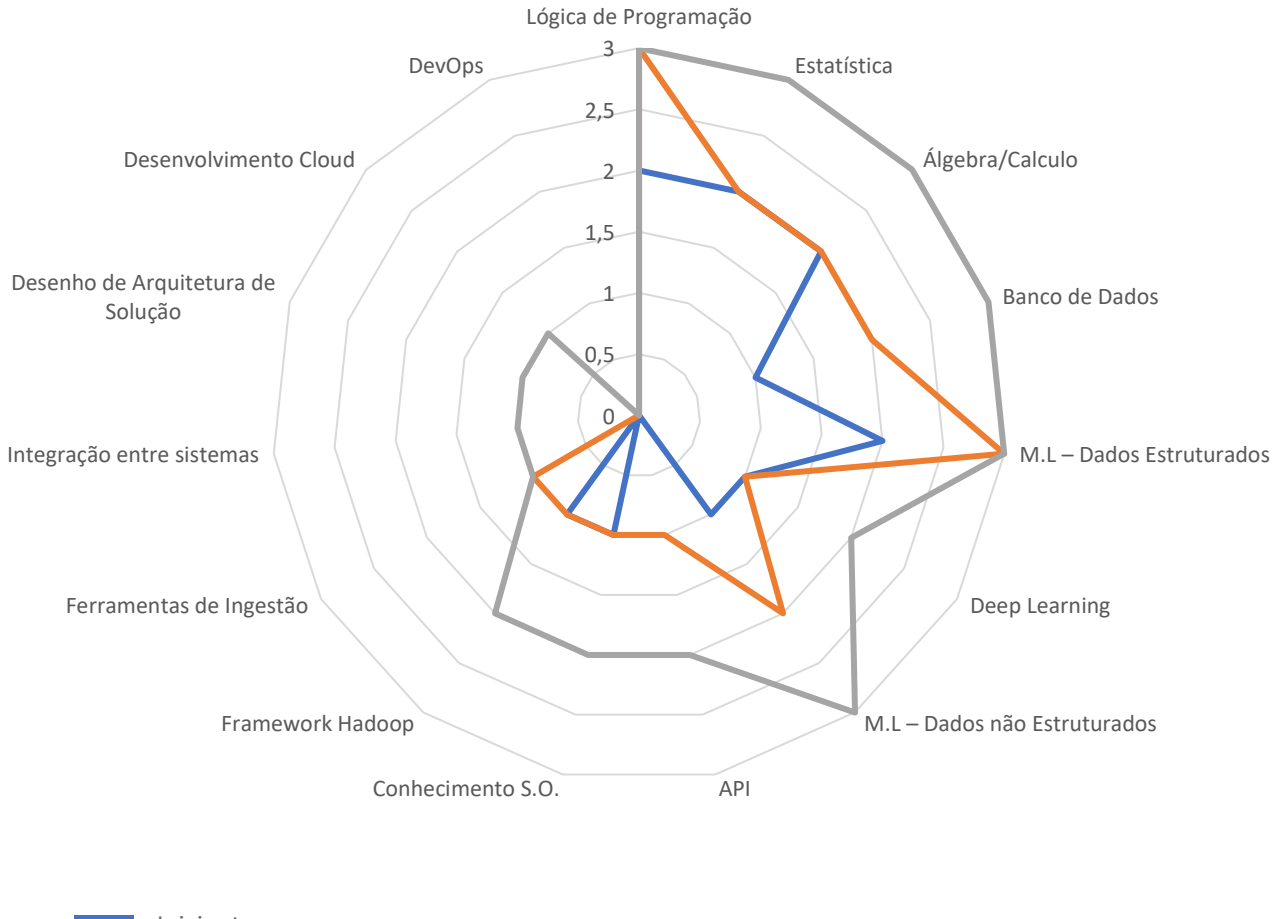
	Data Science	Mathematics	Machine Learning	Algorithmic coding	Software eng.	Communication	Business acumen
Analista de Dados	✓			✓		✓	✓
Eng. Machine Learning	✓	✓	✓	✓	✓		
Eng. Software - ML			✓	✓	✓		
Researcher ML		✓	✓	✓			Research
Eng. de Software				✓	✓		

O Perfil do Cientista de dados

VINICARIDÁ
Human-Centered Data & AI

Para cientista de dados é realizado uma prova com duração de 3 horas e nota de corte 5 e após aprovação na prova existe um entrevista técnica (sabatina), e após aprovação em ambas existe a seleção de perfil por vaga (gestor funcional).

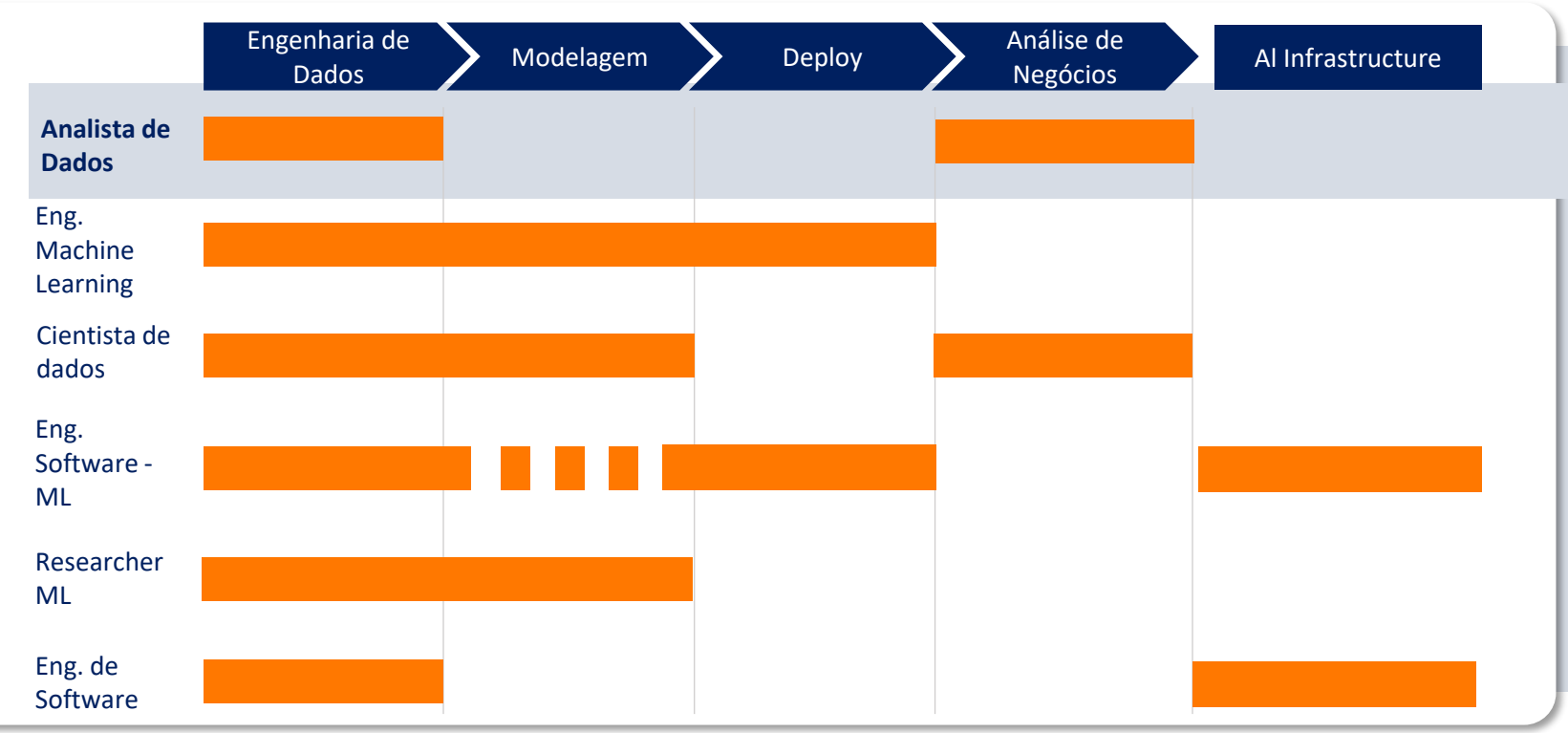
PROCESSOS			
Conhecimento	**Iniciante**	**Intermed.**	**Expert**
Conhecimento Técnicos			
Lógica de Programação	2	3	3
Estatística	2	2	3
Álgebra/Calculo	2	2	3
Banco de Dados	1	2	3
Machine Learning – Dados Estruturados	2	3	3
Deep Learning	1	1	2
Machine Learning – Dados não Estruturados	1	2	3
Construção e Funcionamento de API	-	1	2
Conhecimento S.O.	1	1	2
Framework Hadoop	1	1	2
Ferramentas de Ingestão	-	1	1
Integração entre sistemas	-	-	1
Desenho de Arquitetura de Solução	-	-	1
Desenvolvimento Cloud	-	-	1
DevOps	-	-	-
Habilidades			
Solução de Problemas	2	2	3
Comunicação	1	2	3
Transformação/Inovação	1	2	2
Visão Estratégica e Sistêmica	1	2	3
Influência	-	-	1
Tutoria	-	2	3



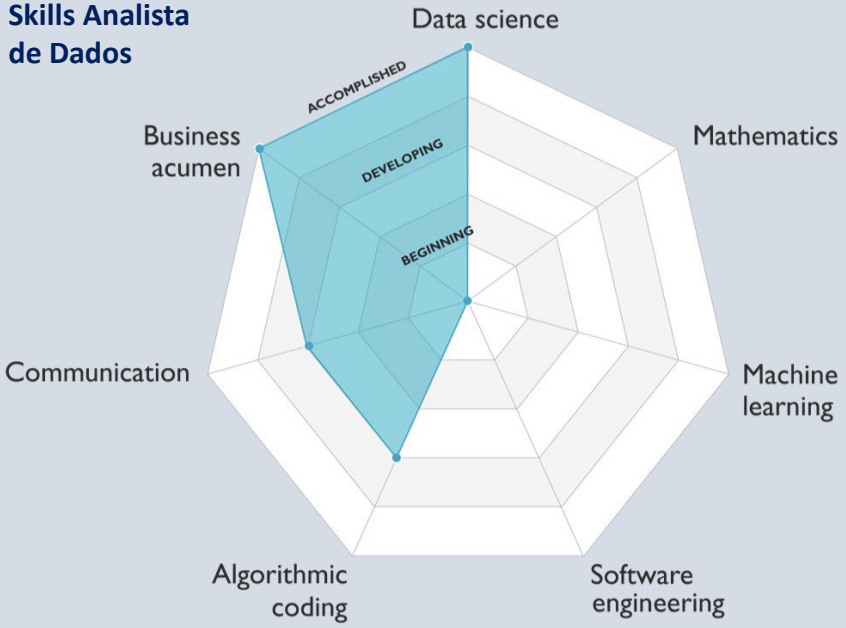
Perfil do Analista de dados

VINICARIDÁ
Human-Centered Data & AI

Frentes de trabalho x profissionais , de acordo com texto publicado no Workera:



Skills Analista de Dados



Profissionais x Skills

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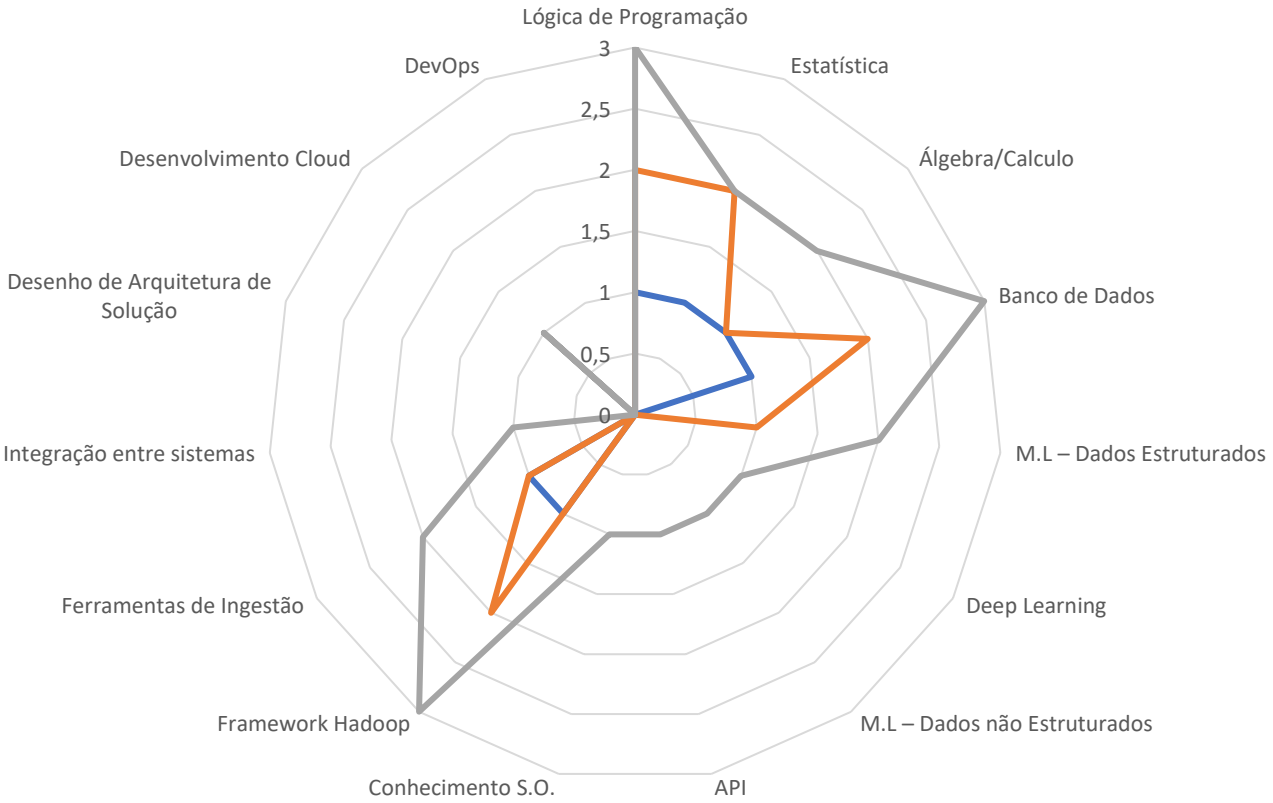
Analista de Dados	✓			✓		✓	✓
Eng. Machine Learning	✓	✓	✓	✓	✓		
Eng. Software - ML			✓	✓	✓		
Researcher ML		✓	✓	✓			Research
Eng. de Software				✓	✓		

O Perfil do Analista de Dados

VINICARIDÁ
Human-Centered Data & AI

O perfil é selecionado em entrevista técnica, análise de portfólio (Github), e seleção de perfil (gestor funcional).

PROCESSOS			
Conhecimento	Iniciante	Intermed.	Expert
Conhecimento Técnicos			
Lógica de Programação	1	2	3
Estatística	1	2	2
Álgebra/Calculo	1	1	2
Banco de Dados	1	2	3
Machine Learning – Dados Estruturados	-	1	2
Deep Learning	-	-	1
Machine Learning – Dados não Estruturados	-	-	1
Construção e Funcionamento de API	-	-	1
Conhecimento S.O.	-	-	1
Framework Hadoop	1	2	3
Ferramentas de Ingestão	1	1	2
Integração entre sistemas	-	-	1
Desenho de Arquitetura de Solução	-	-	-
Desenvolvimento Cloud	-	-	1
DevOps	-	-	-
Habilidades			
Solução de Problemas	1	2	3
Comunicação	1	2	3
Transformação/Inovação	1	2	2
Visão Estratégica e Sistêmica	1	2	3
Influência	-	-	1
Tutoria	-	2	3



alteryx sas tableau

Perfil do Eng. De Machine Learning

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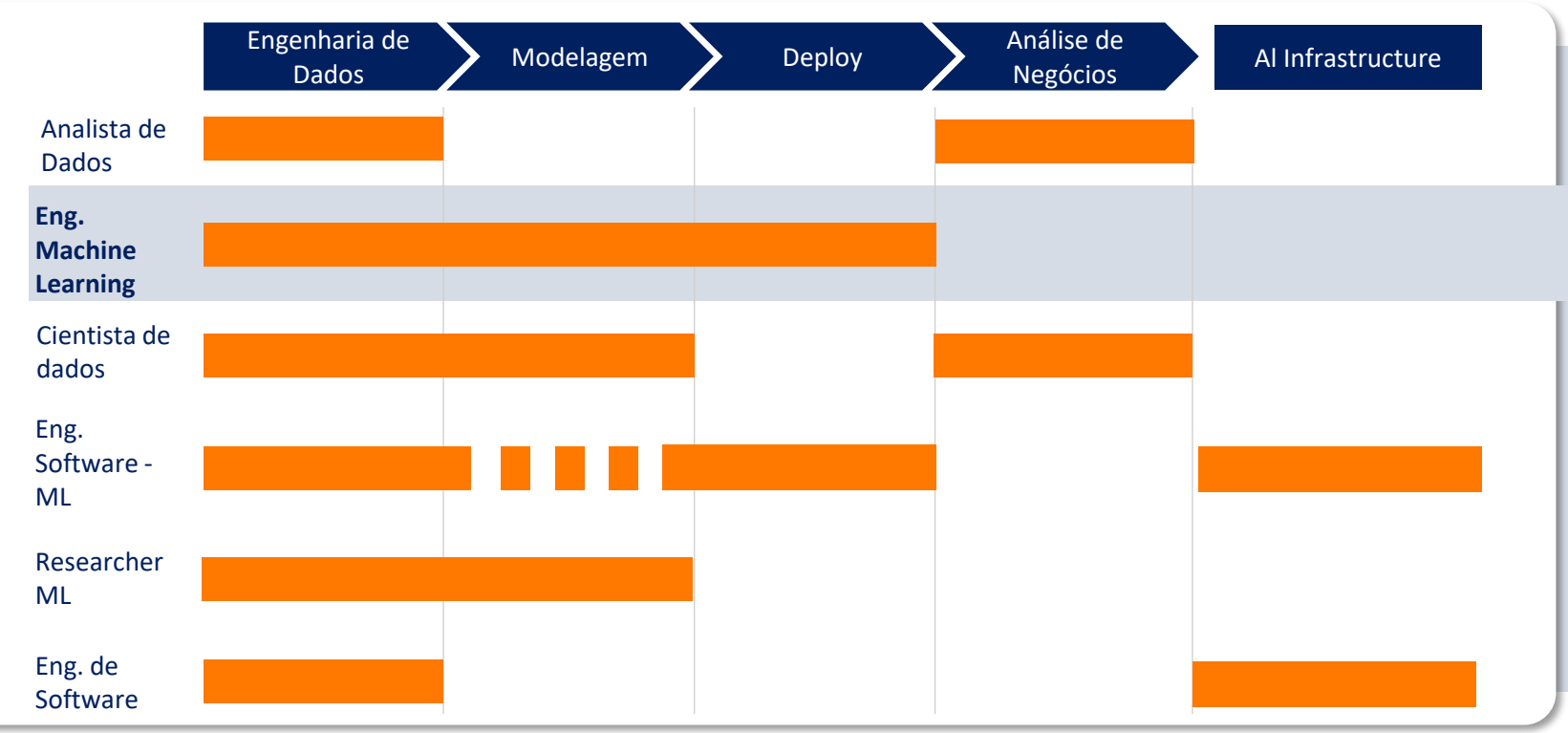
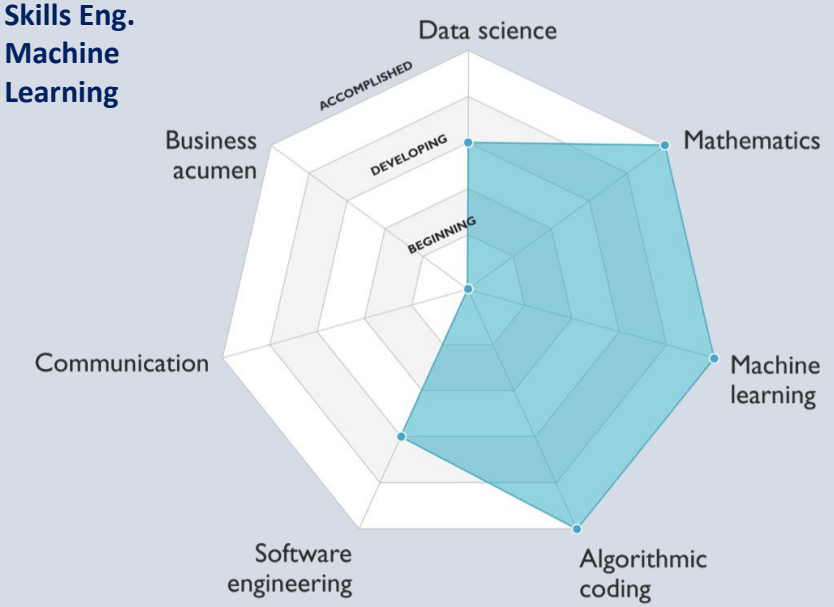
Frentes de trabalho x profissionais , de acordo com texto publicado no Workera:



Skills Eng. Machine Learning



Profissionais x Skills

	Data Science	Mathematics	Machine Learning	Algorithmic coding	Software eng.	Communication	Business acumen
Analista de Dados	✓			✓		✓	✓
Eng. Machine Learning	✓	✓	✓	✓	✓		
Eng. Software - ML			✓	✓	✓		
Researcher ML		✓	✓	✓			Research
Eng. de Software				✓	✓		

O Perfil do Engenheiro de Machine Learning

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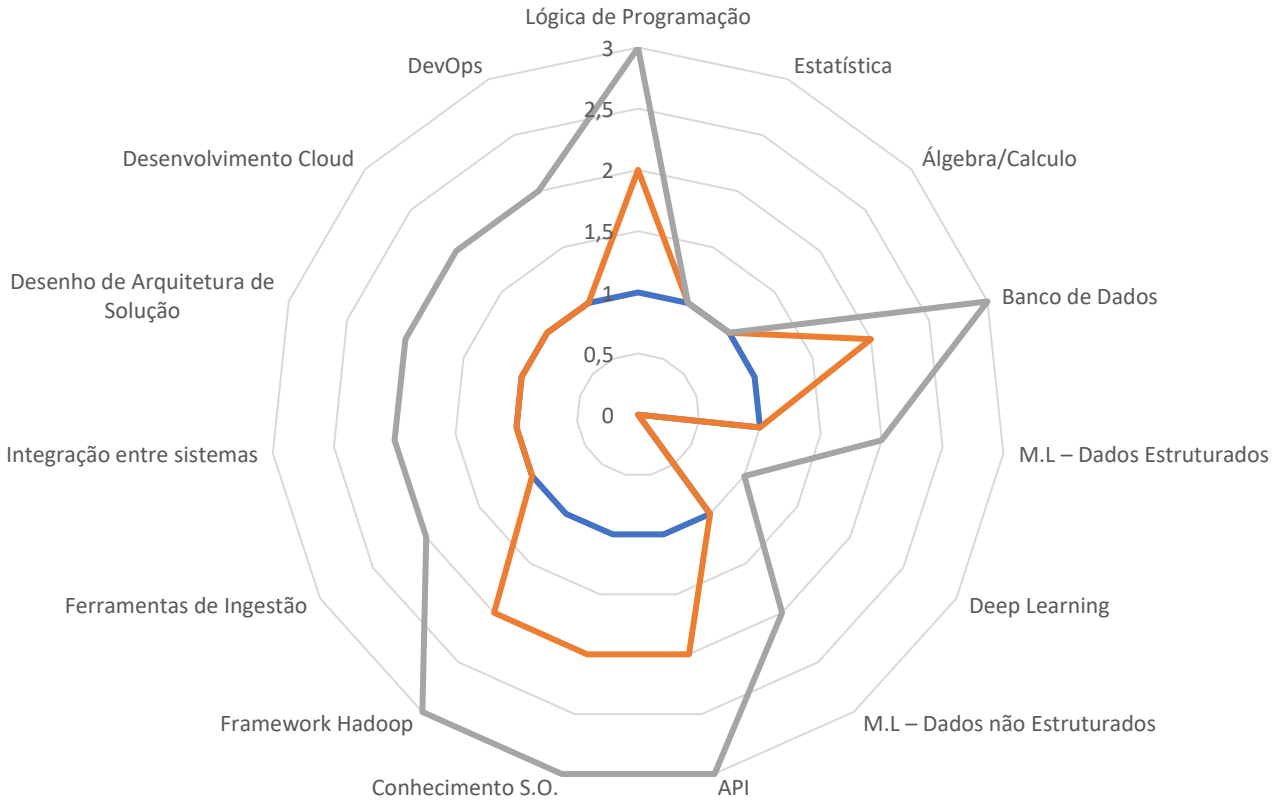
O perfil é selecionado em entrevista técnica, análise de portfólio (Github), e seleção de perfil (gestor funcional).

PROCESSOS			
Conhecimento	**Iniciante**	**Intermed.**	**Expert**
Conhecimento Técnicos			
Lógica de Programação	1	2	3
Estatística	1	1	1
Álgebra/Calculo	1	1	1
Banco de Dados	1	2	3
Machine Learning – Dados Estruturados	1	1	2
Deep Learning	-	-	1
Machine Learning – Dados não Estruturados	1	1	2
Construção e Funcionamento de API	1	2	3
Conhecimento S.O.	1	2	3
Framework Hadoop	1	2	3
Ferramentas de Ingestão	1	1	2
Integração entre sistemas	1	1	2
Desenho de Arquitetura de Solução	1	1	2
Desenvolvimento Cloud	1	1	2
DevOps	1	1	2
Habilidades			
Solução de Problemas	1	2	3
Comunicação	1	2	3
Transformação/Inovação	1	2	2
Visão Estratégica e Sistêmica	1	2	3
Influência	-	-	1
Tutoria	-	2	3



kubernetes docker scikit learn

O Perfil do Engenheiro de Dados

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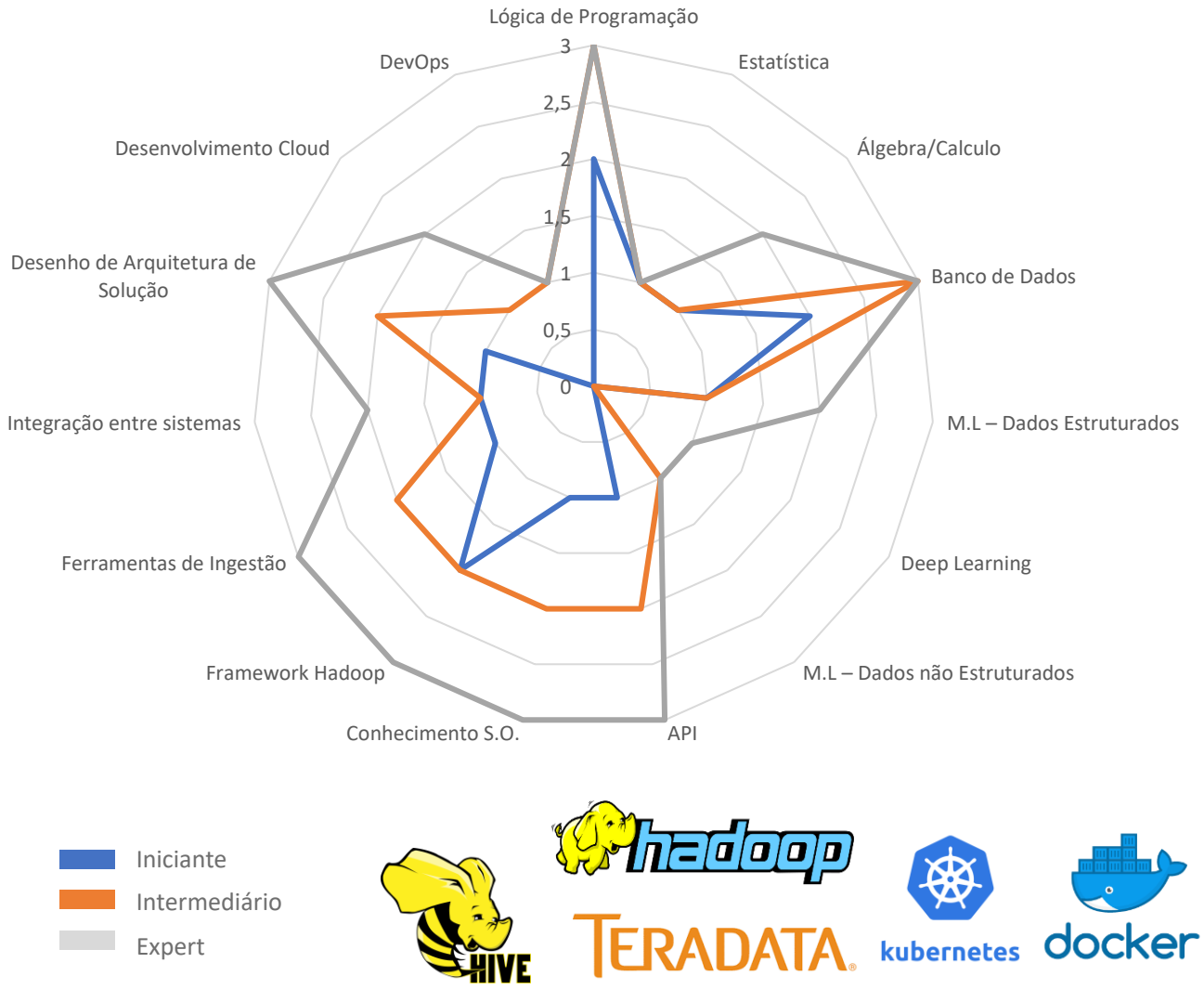
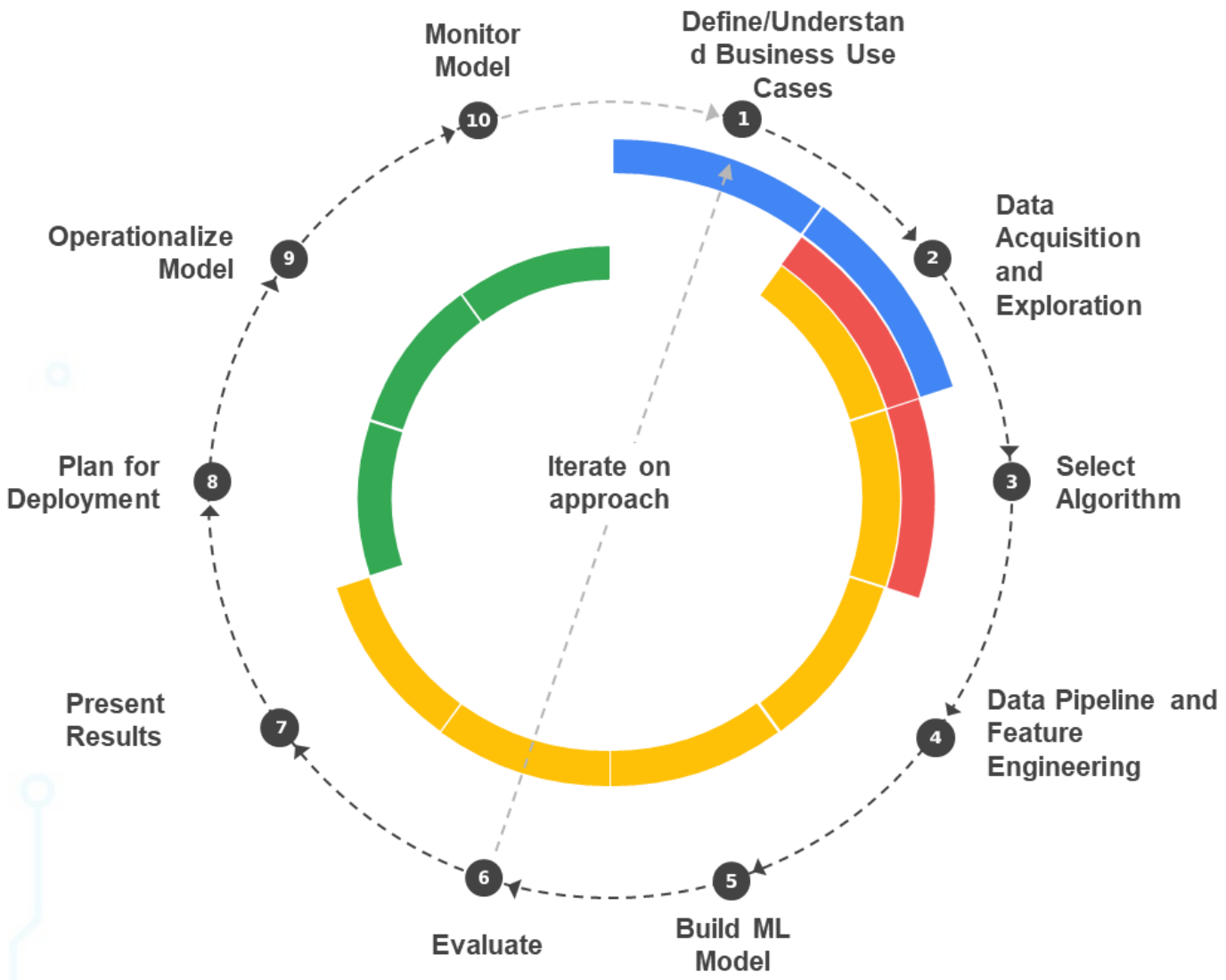
O perfil é selecionado em entrevista técnica, análise de portfólio (Github), e seleção de perfil (gestor funcional).

PROCESSOS			
Conhecimento	Iniciante	Intermed.	Expert
Conhecimento Técnicos			
Lógica de Programação	2	3	3
Estatística	1	1	1
Álgebra/Calculo	1	1	2
Banco de Dados	2	3	3
Machine Learning – Dados Estruturados	1	1	2
Deep Learning	-	-	1
Machine Learning – Dados não Estruturados	-	1	1
Construção e Funcionamento de API	1	2	3
Conhecimento S.O.	1	2	3
Framework Hadoop	2	2	3
Ferramentas de Ingestão	1	2	3
Integração entre sistemas	1	1	2
Desenho de Arquitetura de Solução	1	2	3
Desenvolvimento Cloud	-	1	2
DevOps	-	1	1
Habilidades			
Solução de Problemas	1	2	3
Comunicação	2	2	3
Transformação/Inovação	1	2	2
Visão Estratégica e Sistêmica	1	2	3
Influência	-	1	2
Tutoria	-	2	3




Monitor Model
Define/Understand Business Use Cases
Operationalize Model
Data Acquisition and Exploration
Plan for Deployment
Iterate on approach
Select Algorithm
Present Results
Data Pipeline and Feature Engineering
Evaluate
Build ML Model
1
2
3
4
5
6
7
8
9
10

Modelos em Produção

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Batch

Recomendação de Produtos

Obtém Dados

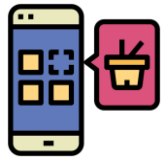
Prevê em máquina local

Gera arquivo com resultados

Envia para a área de negócio

D+1

Insere na aplicação



Faz recomendação

Modelos em Produção

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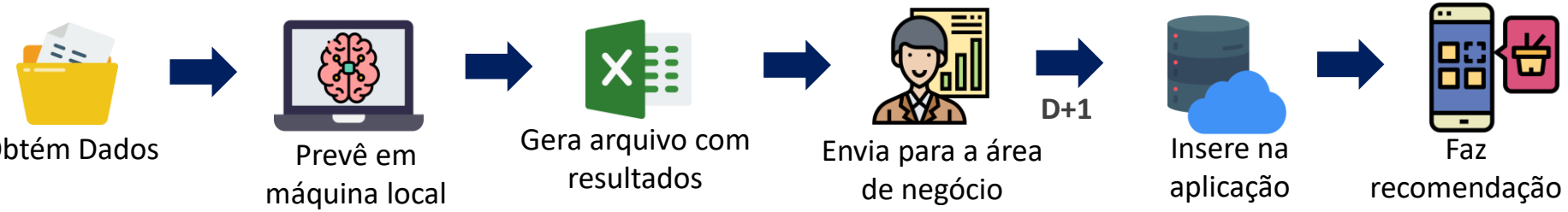
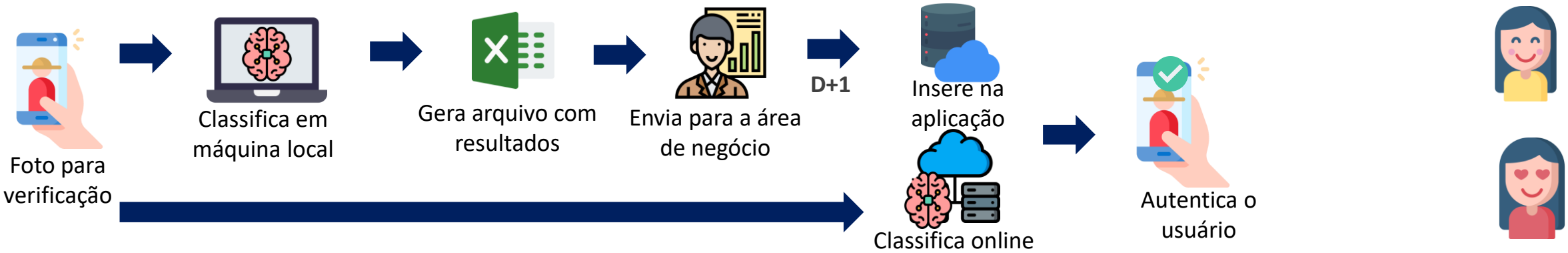
Batch

Recomendação de Produtos



Batch ou Online

Abertura de Contas



Modelos em Produção

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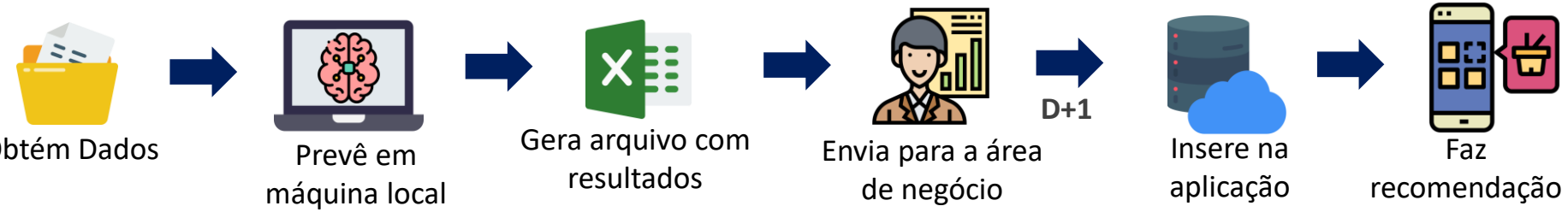
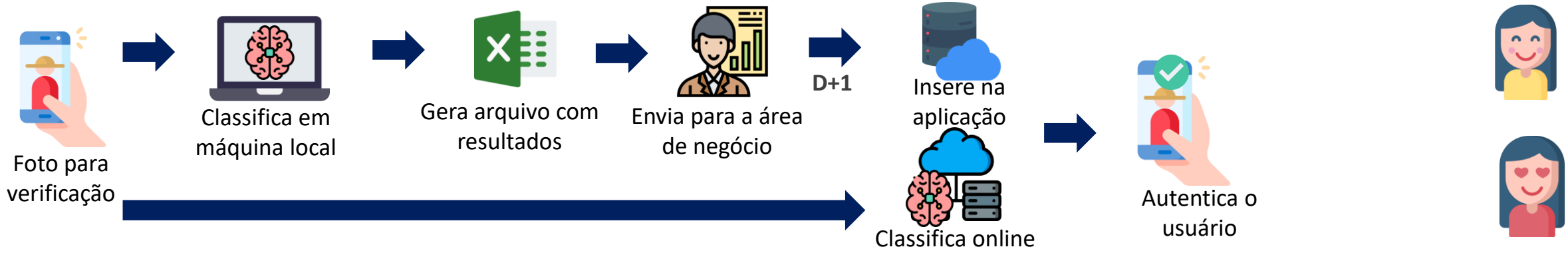
Batch

Recomendação de Produtos



Batch ou Online

Abertura de Contas



Online

Fraude

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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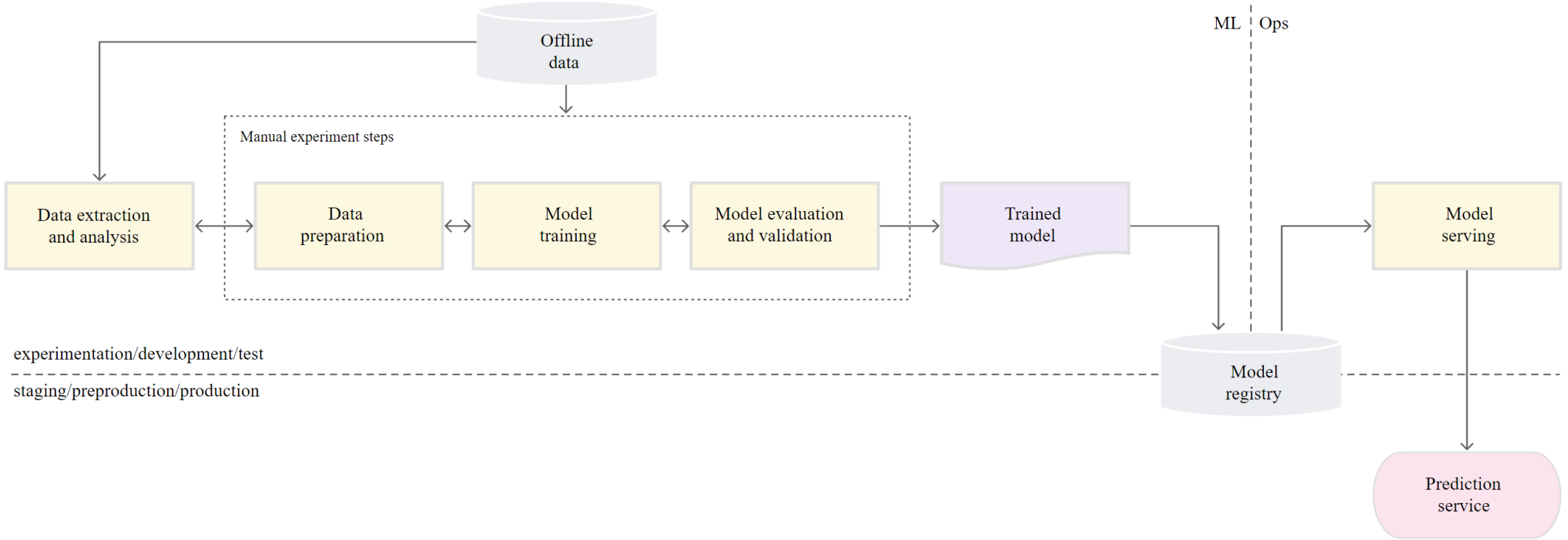
Nível 0 de MLOps: processo manual

Muitas equipes têm cientistas de dados e pesquisadores de ML capazes de criar modelos de última geração, mas o processo de criação e implantação de modelos de ML é totalmente manual. Isso é considerado o nível *básico* de maturidade, ou nível 0

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

Nível 0 de MLOps: processo manual



https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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Nível 0 de MLOps - Desafios

Os MLOps de nível 0 são comuns em muitas empresas que estão começando a aplicar o ML aos casos de uso. Esse processo manual orientado por cientistas de dados pode ser suficiente quando os modelos raramente são alterados ou treinados. Na prática, os modelos costumam falhar quando são implantados no mundo real. Os modelos não se adaptam às mudanças na dinâmica do ambiente ou às alterações nos dados que descrevem o ambiente.

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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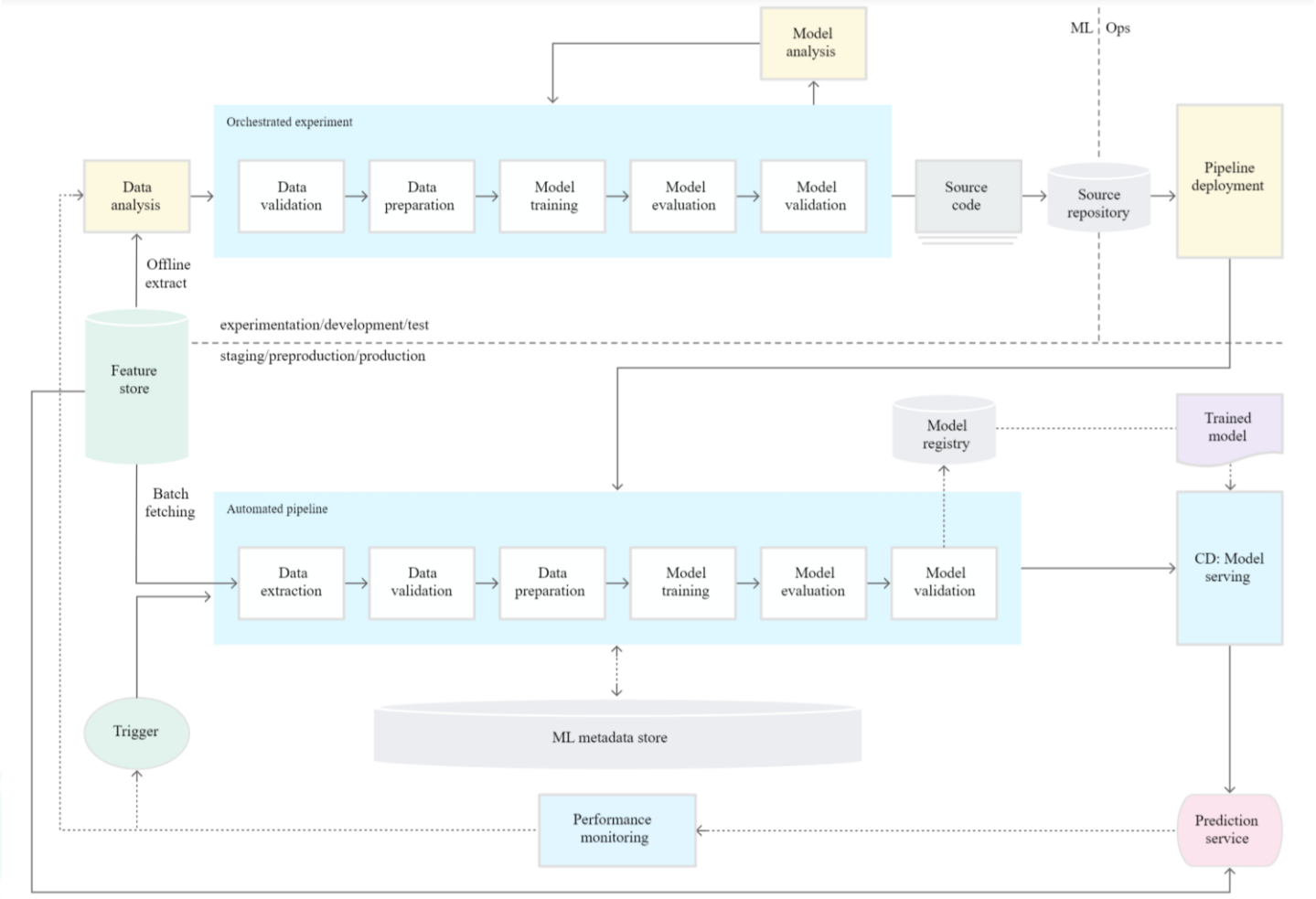
Nível 1 de MLOps: automação de pipeline de ML

O objetivo do nível 1 é realizar o treinamento contínuo do modelo automatizando o pipeline de ML. Isso permite que você alcance a entrega contínua do serviço de predição de modelo. Para automatizar o processo de uso de novos dados para treinar novamente os modelos na produção, é necessário introduzir dados automatizados e passos de validação do modelo, bem como acionadores de pipeline e gerenciamento de metadados.

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

Nível 1 de MLOps: automação de pipeline de ML



MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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Nível 1 de MLOps – Desafios

É preciso testar novas ideias de ML e implantar rapidamente novas implementações dos componentes de ML. Ao gerenciar muitos pipelines de ML na produção, é preciso uma configuração de CI/CD para automatizar a criação, o teste e a implantação de pipelines de ML.

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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Nível 2 de MLOps: automação de pipeline de CI/CD

Para uma atualização rápida e confiável dos pipelines em produção, é preciso ter um sistema de CI/CD robusto automatizado. Um sistema de CI/CD automatizado permite que os cientistas de dados explorem rapidamente novas ideias sobre engenharia de atributos, arquitetura de modelos e hiperparâmetros. É possível implementar essas ideias e criar, testar e implantar automaticamente os novos componentes do pipeline no ambiente de destino.

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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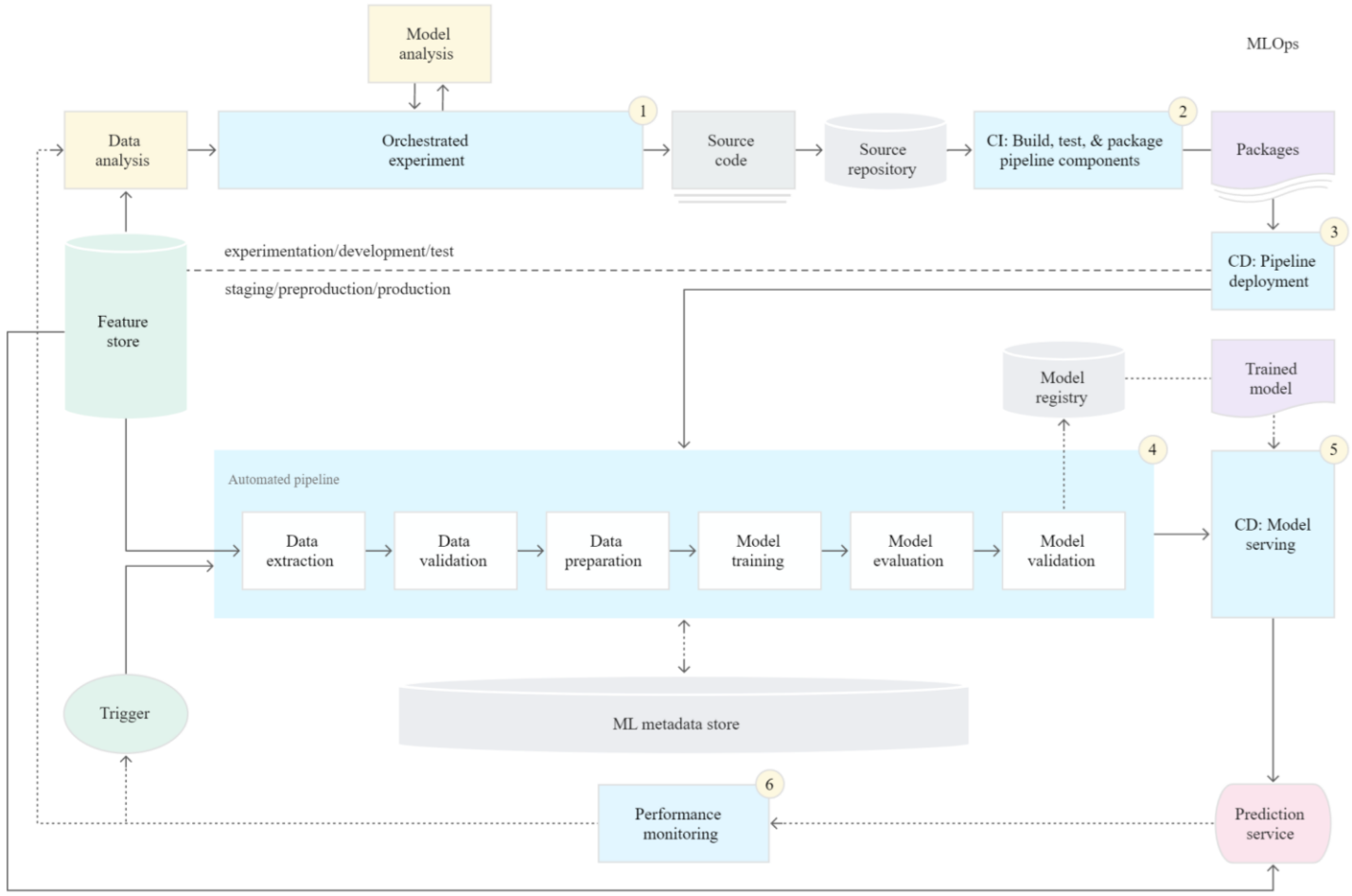
Nível 2 de MLOps: automação de pipeline de CI/CD



MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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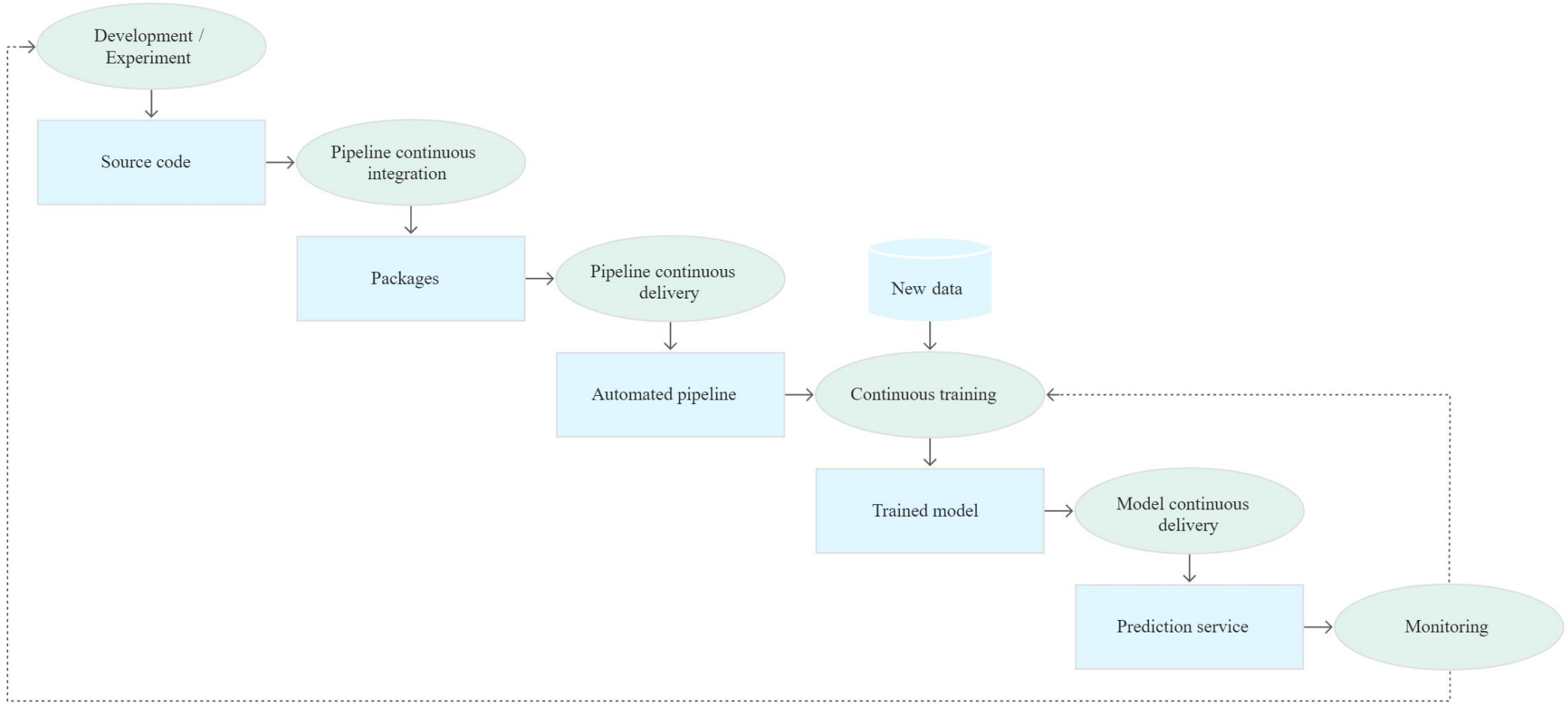
Nível 2 de MLOps: automação de pipeline de CI/CD

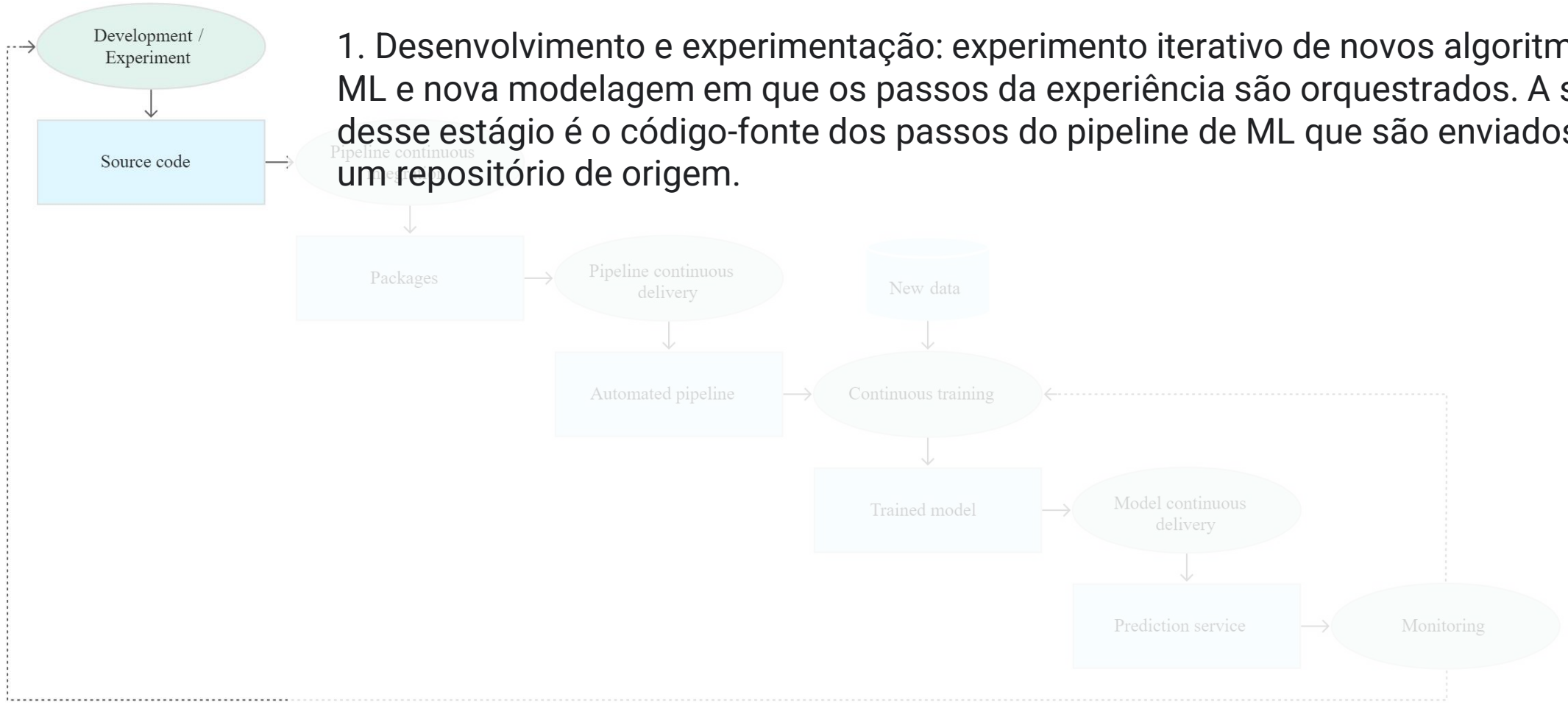
- Controle de origem
- Serviços de teste e criação
- Serviços de implantação
- Registro de modelos
- Armazenamento de recursos
- Armazenamento de metadados de ML
- Orquestrador de pipeline de ML

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

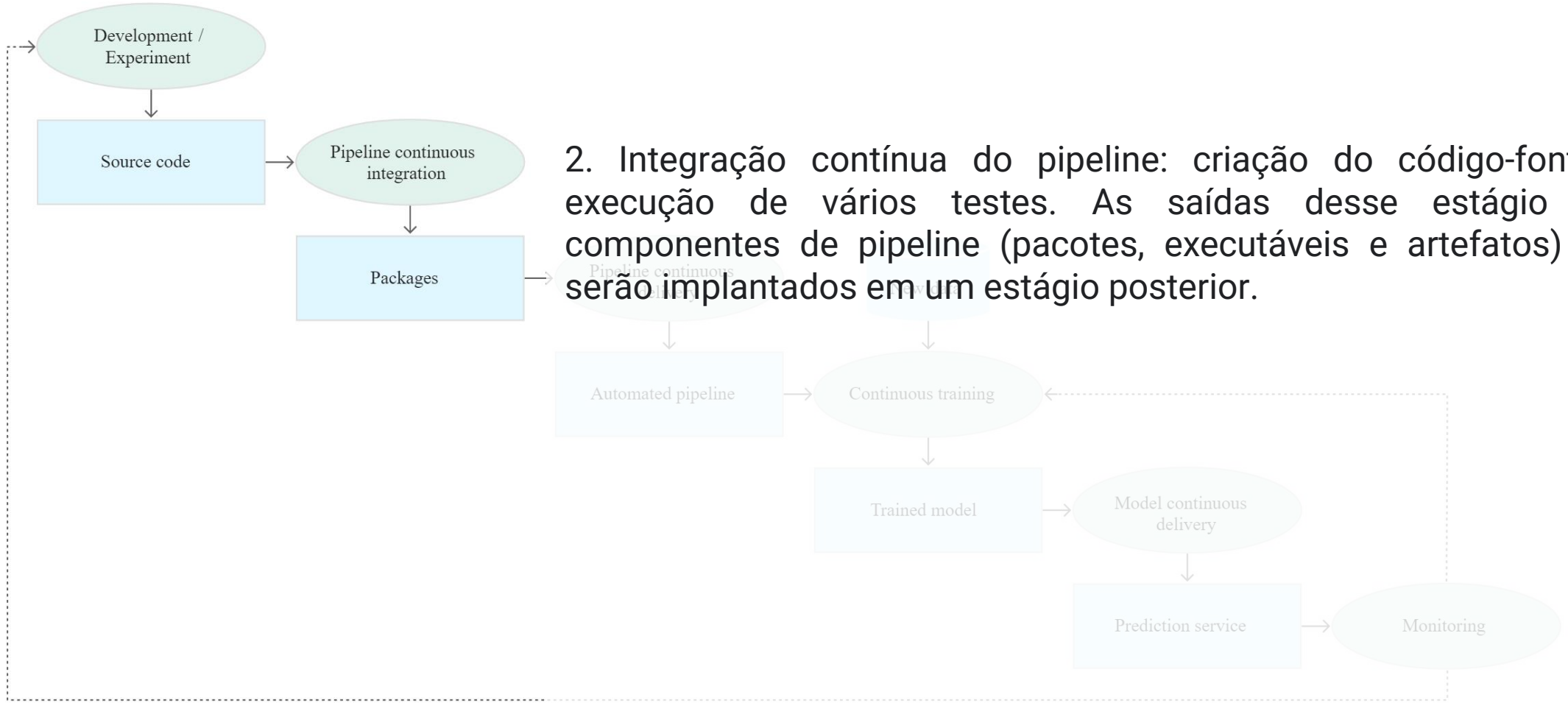


MLOps: pipelines de entrega contínua e automação no aprendizado de máquina



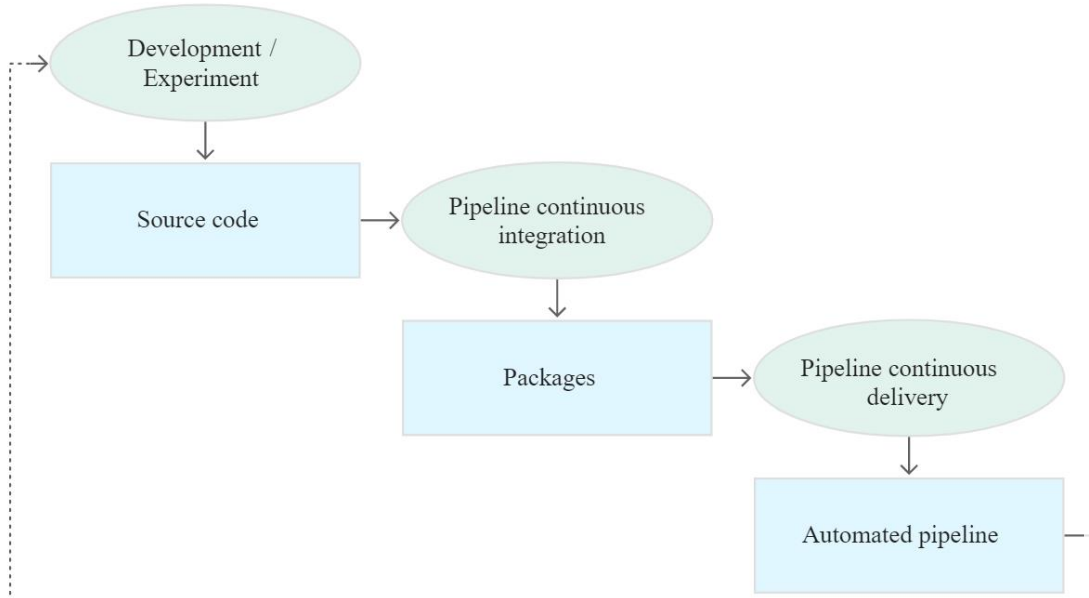
1. Desenvolvimento e experimentação: experimento iterativo de novos algoritmos de ML e nova modelagem em que os passos da experiência são orquestrados. A saída desse estágio é o código-fonte dos passos do pipeline de ML que são enviados para um repositório de origem.

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina



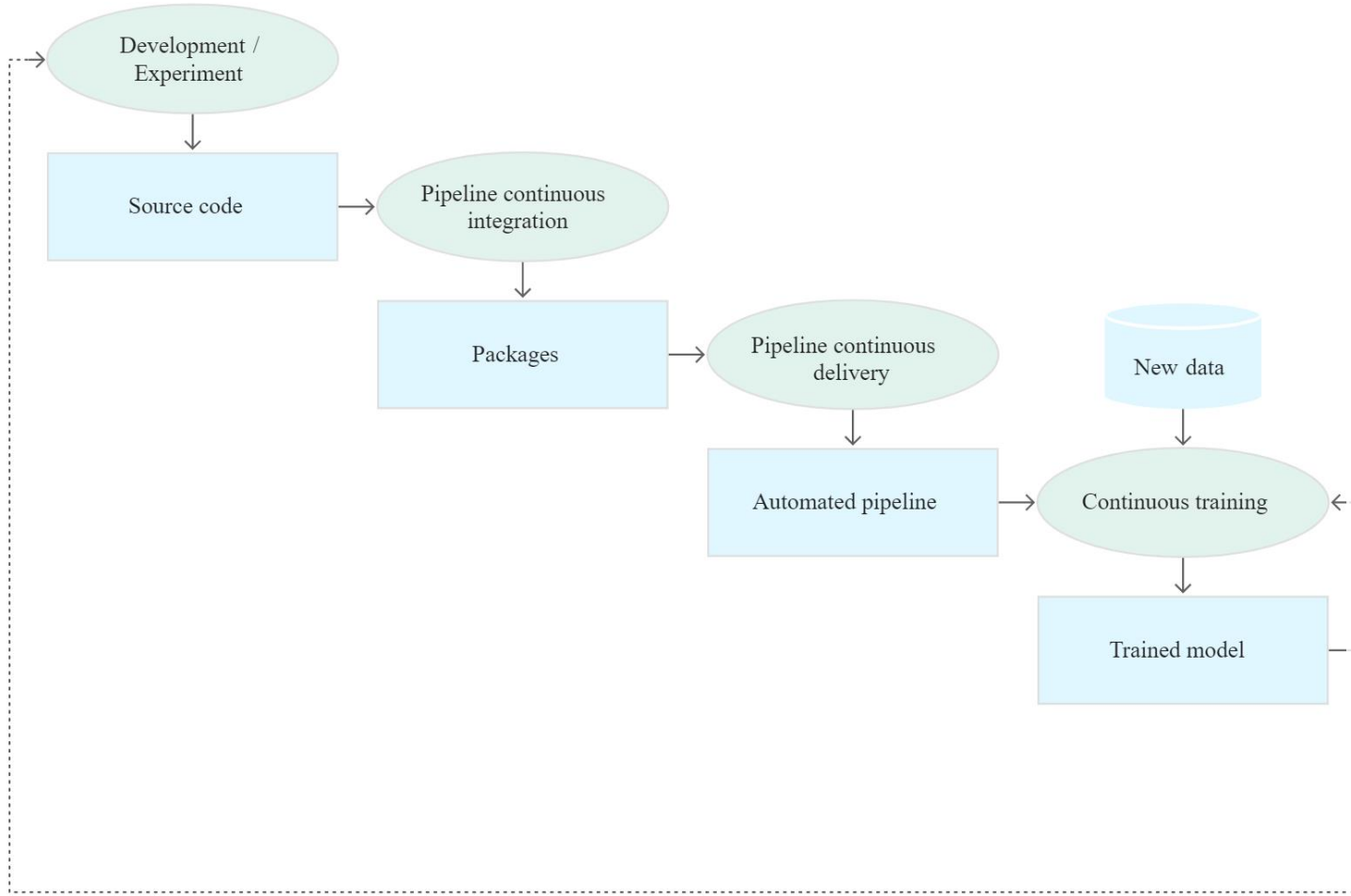
2. Integração contínua do pipeline: criação do código-fonte e execução de vários testes. As saídas desse estágio são componentes de pipeline (pacotes, executáveis e artefatos) que serão implantados em um estágio posterior.

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina



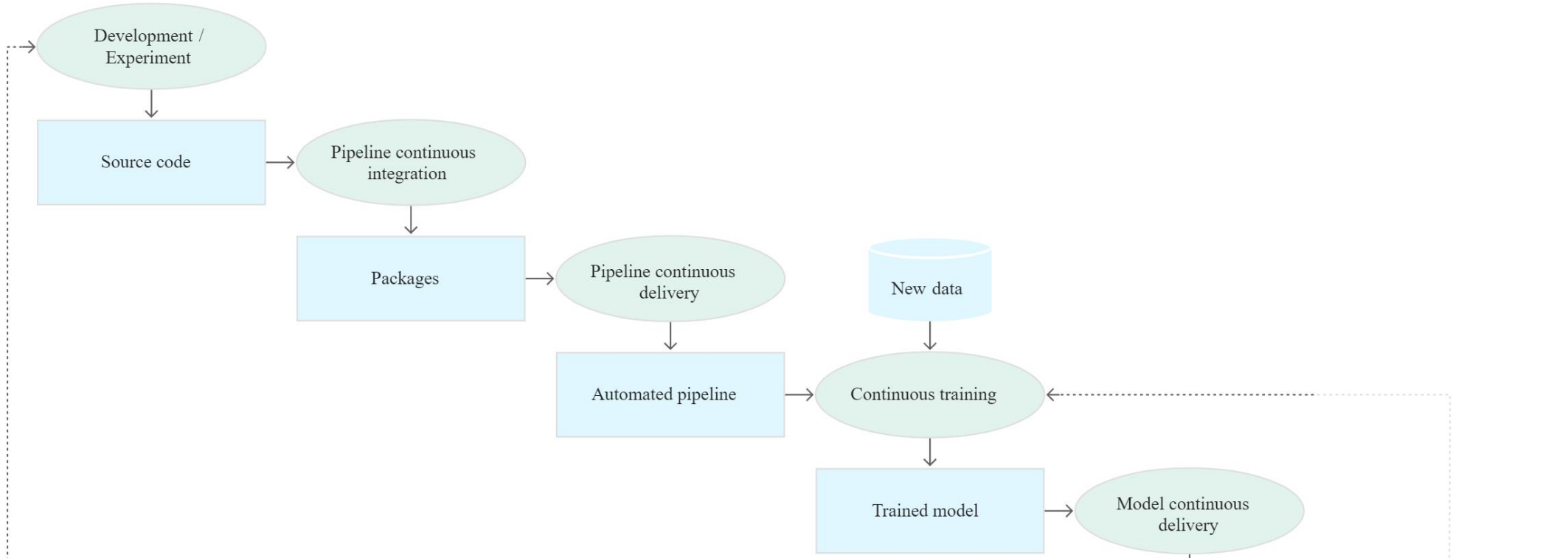
3. Entrega contínua do pipeline: implantação dos artefatos produzidos pelo cenário de CI no ambiente de destino. A saída desse estágio é um pipeline implantado com a nova implementação do modelo.

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina



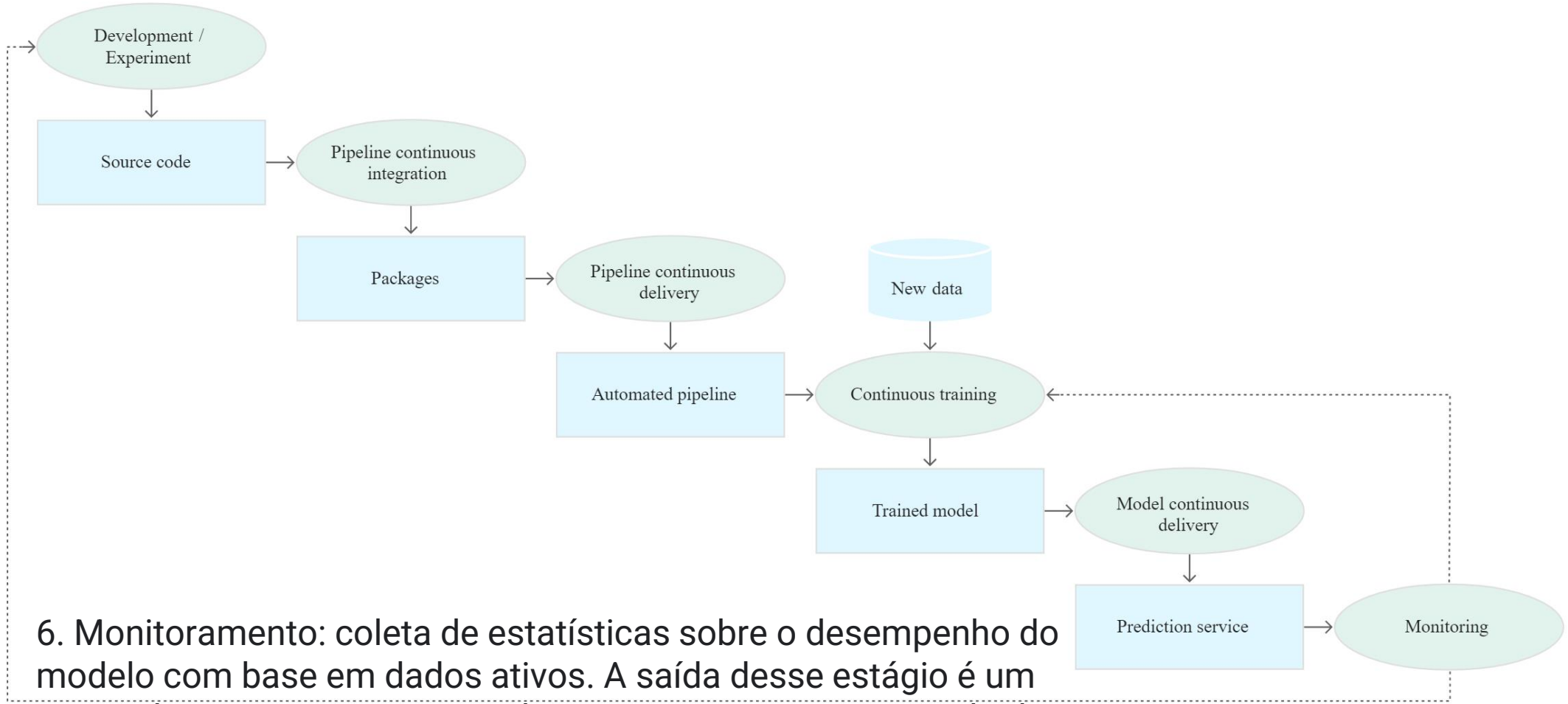
4. Acionamento automatizado: execução automática do pipeline na produção com base em uma programação ou em resposta a um acionador. A saída desse estágio é um modelo treinado que é enviado ao registro de modelos.

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina



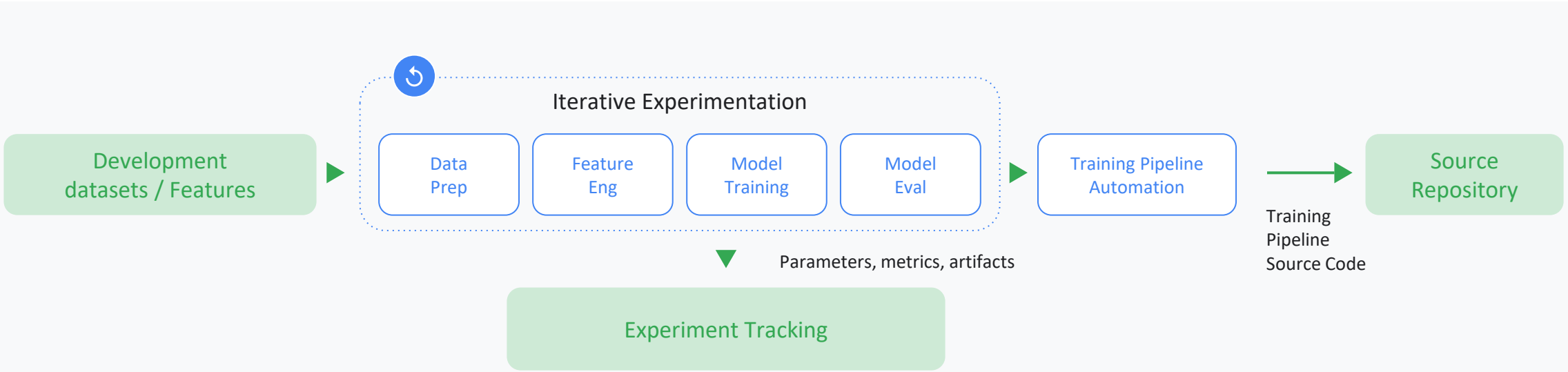
5. Entrega contínua do modelo: exibição do modelo treinado como um serviço de previsão para as previsões. A saída desse estágio é um serviço de previsão de modelo implantado.

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina



6. Monitoramento: coleta de estatísticas sobre o desempenho do modelo com base em dados ativos. A saída desse estágio é um acionador para executar o pipeline ou executar um novo ciclo de experiência

Experimentation management with Vertex Pipelines



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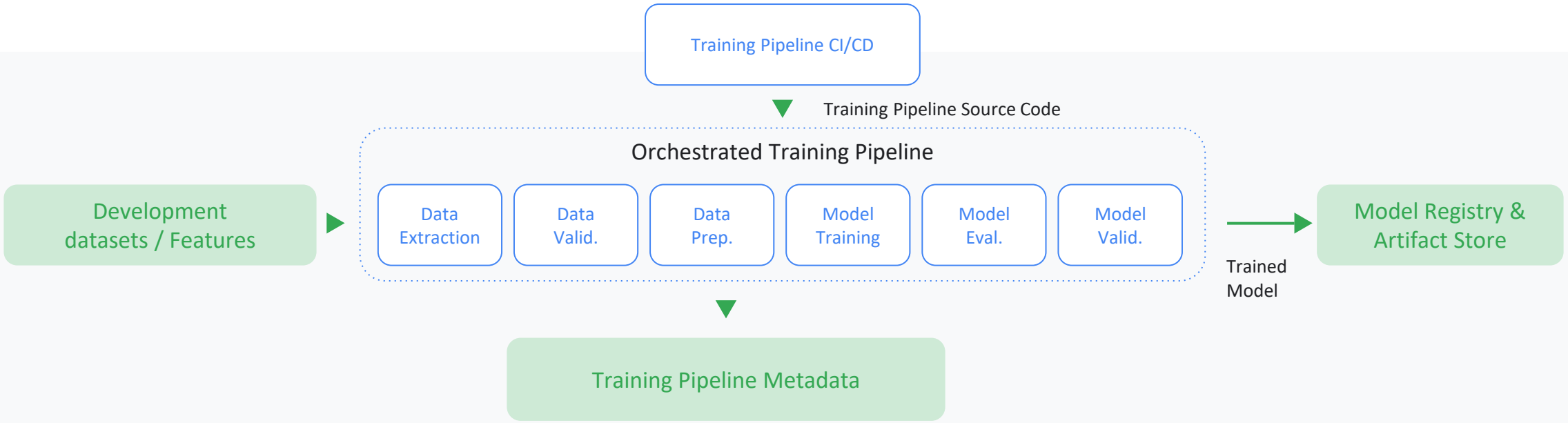
Continuous Training with Vertex Pipelines



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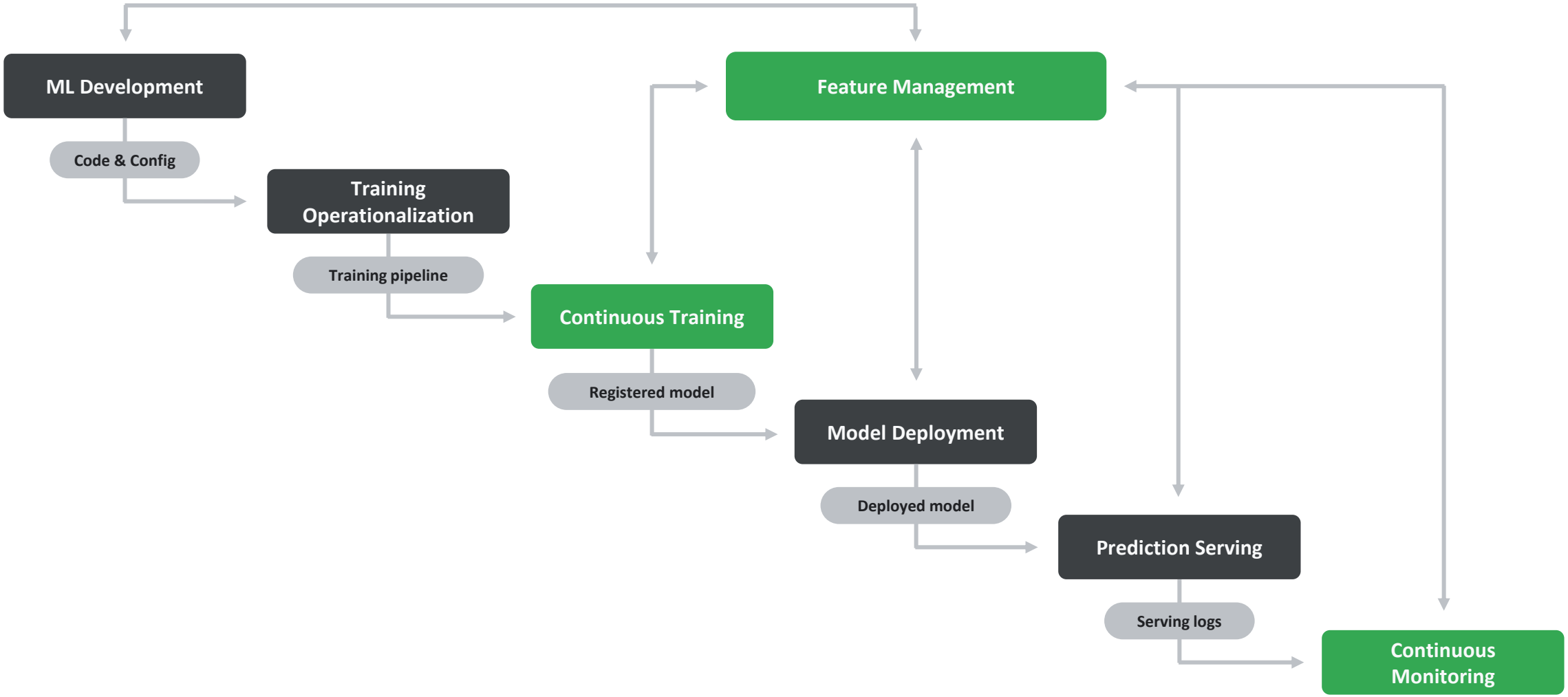
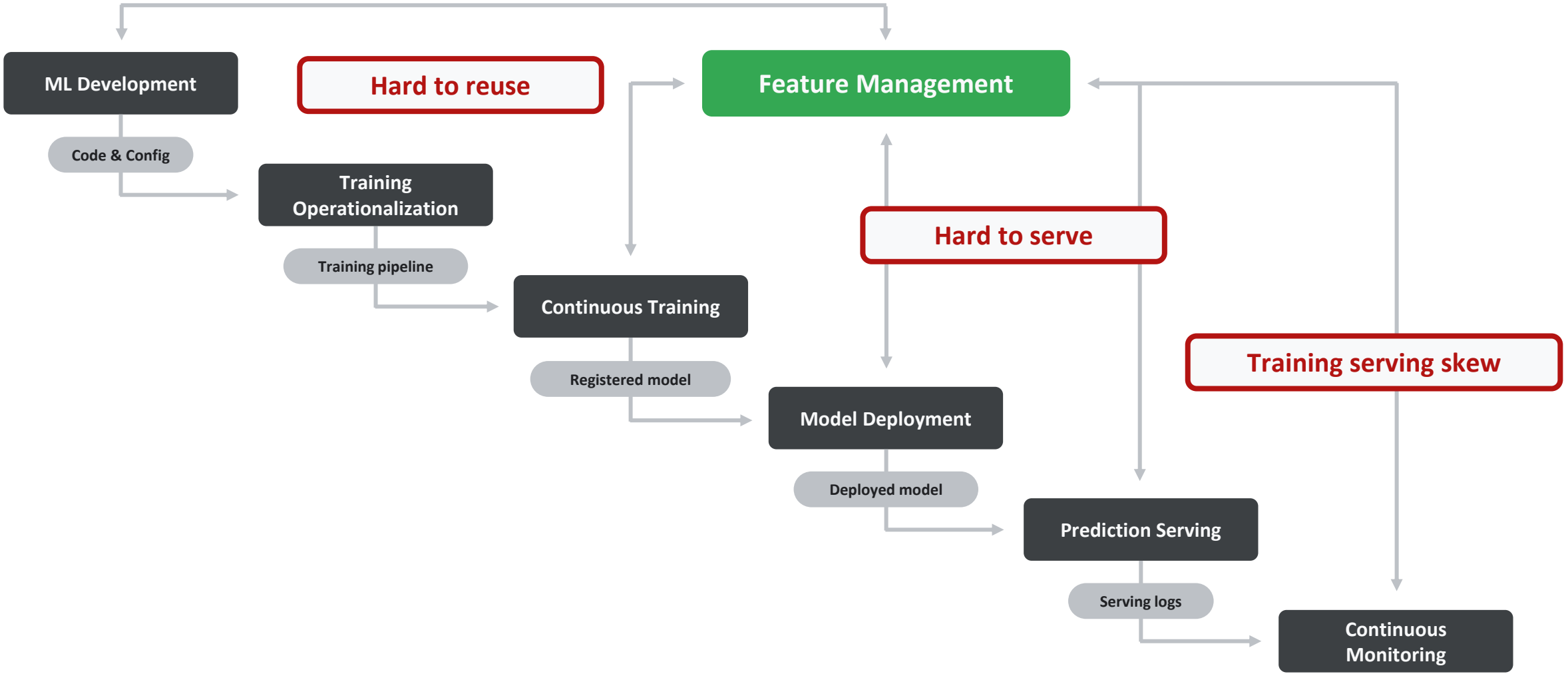
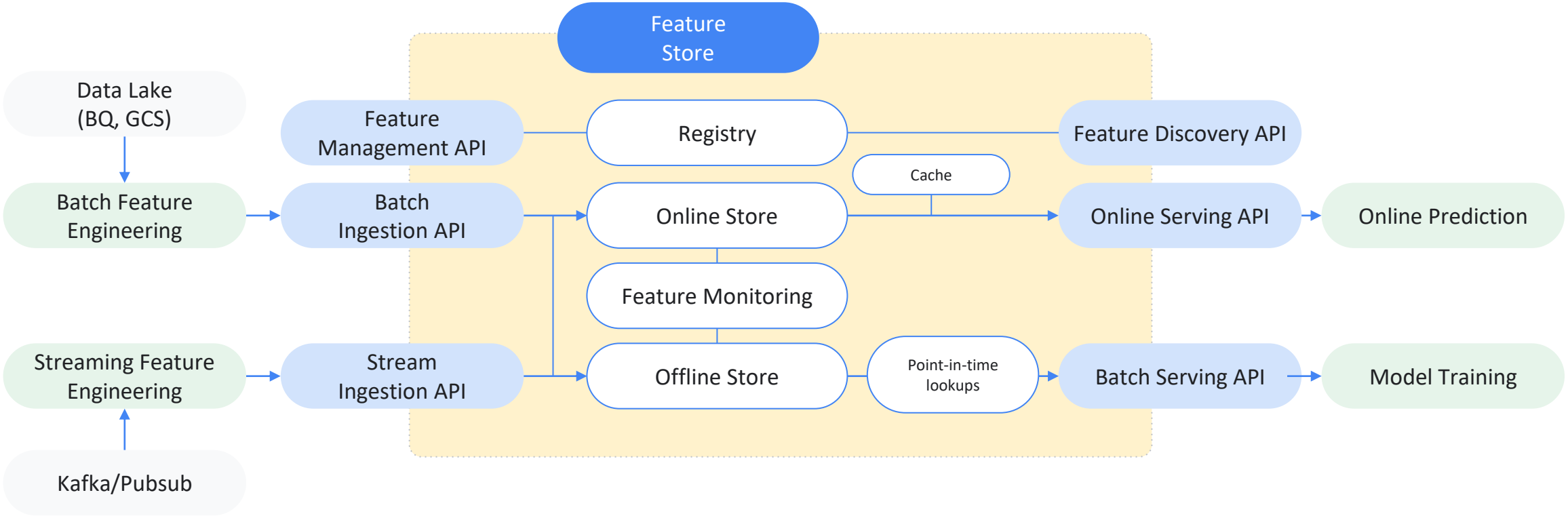
MLOps challenges in ML lifecycle



Feature management pain points

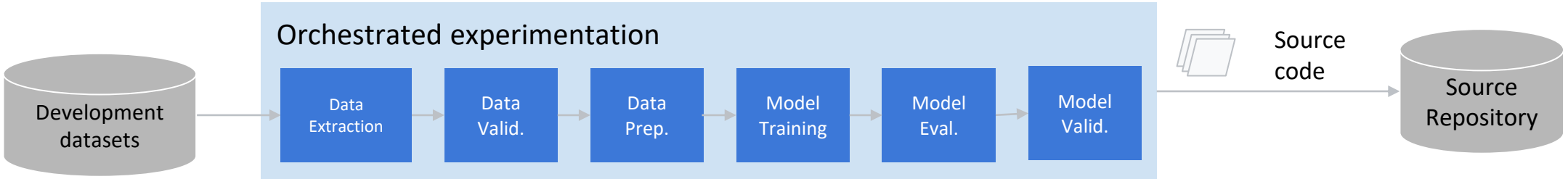


Simple Data Scientist friendly APIs & SDKs abstract away the underlying complexity



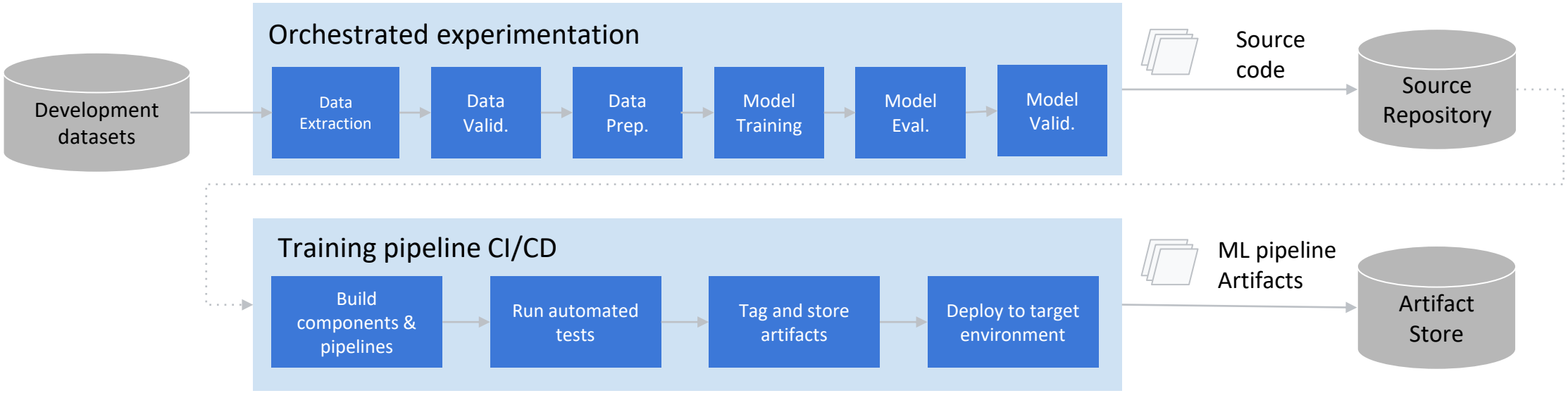
Reliable and repeatable training

Automated E2E Pipelines



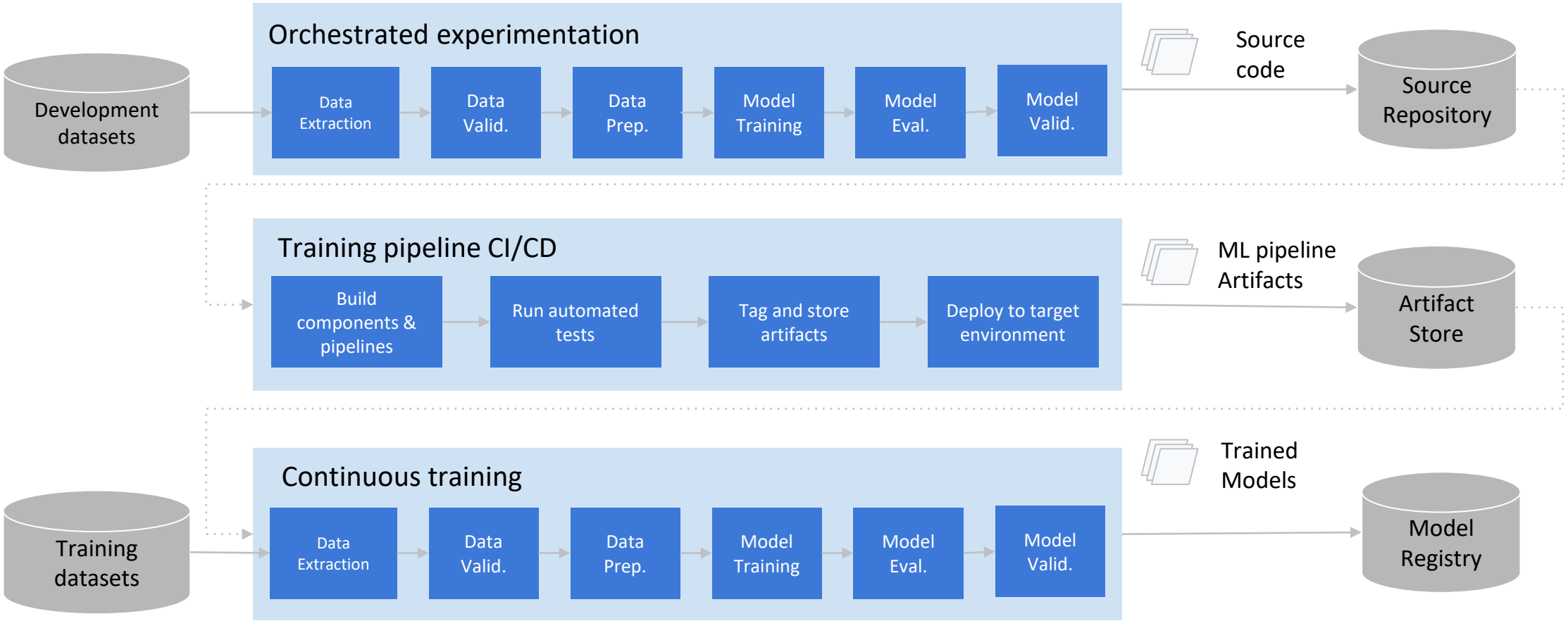
Reliable and repeatable training

Automated E2E Pipelines



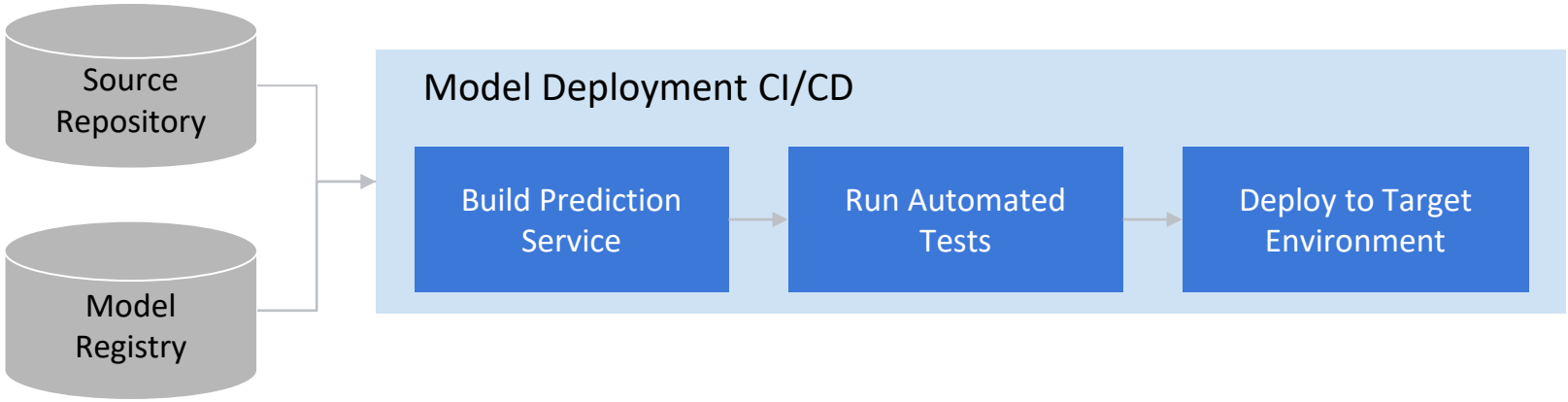
Reliable and repeatable training

Automated E2E Pipelines



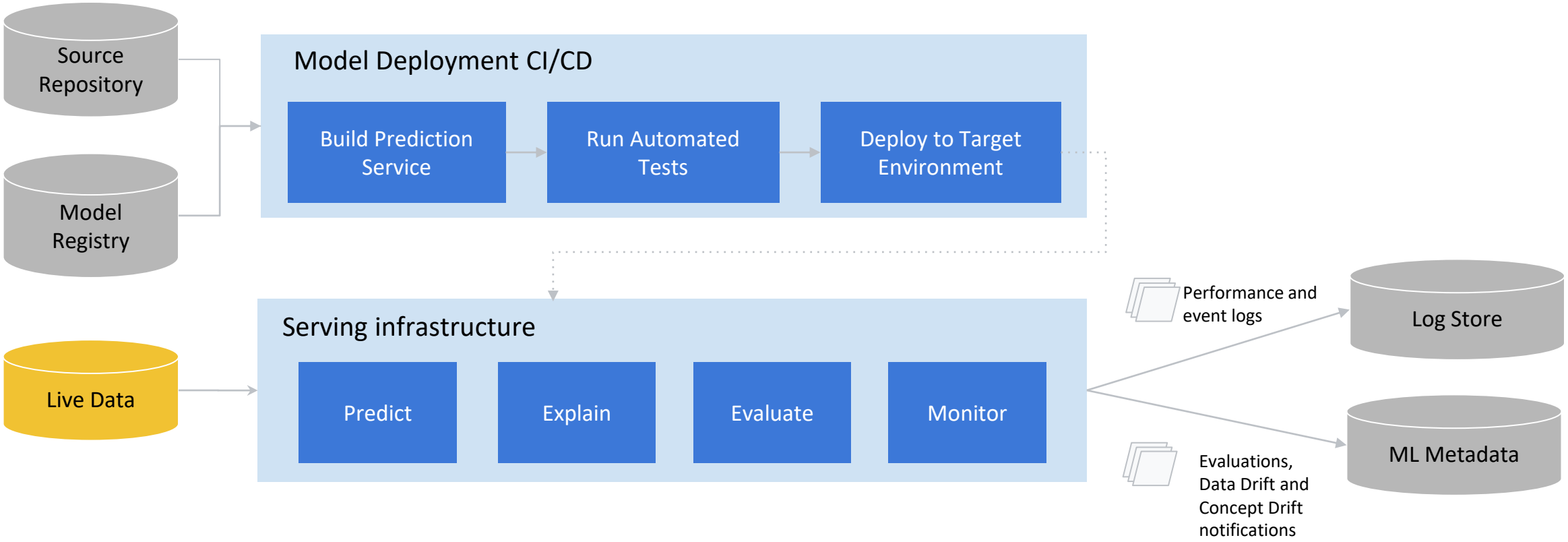
Reliable and monitored serving

Automated E2E Pipelines



Reliable and monitored serving

Automated E2E Pipelines



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Leading ML | Best Practices

Continuous Training for Production ML in the TFX Platform. OpML (2019).
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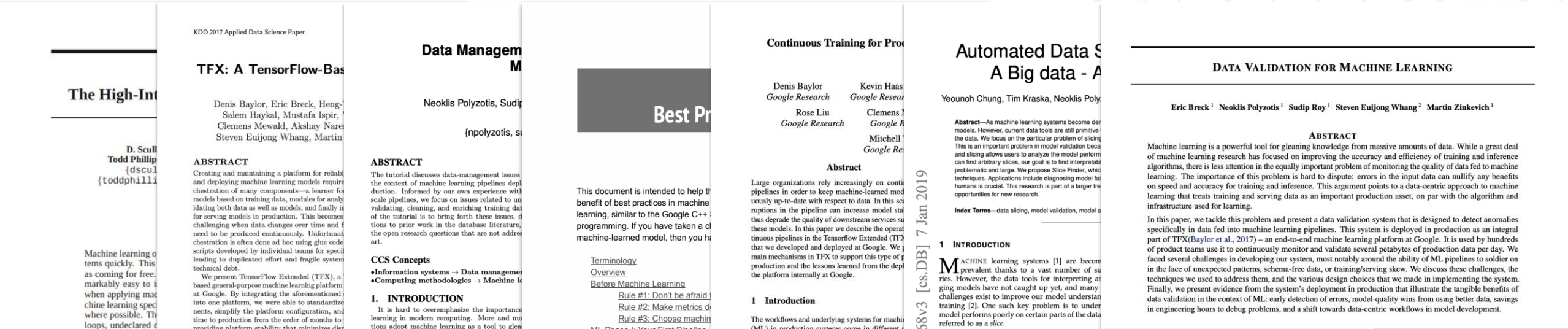

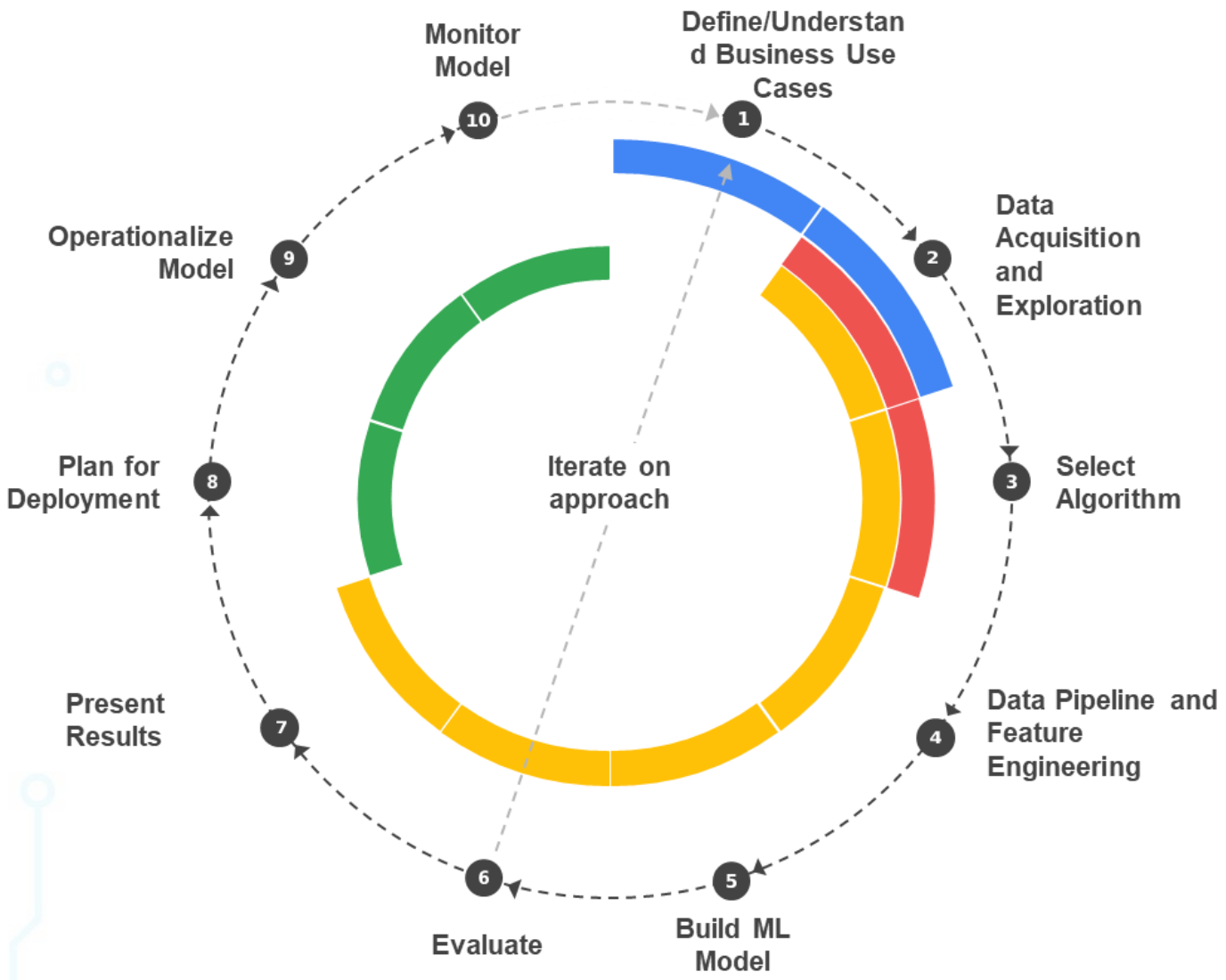
Monitor Model
Define/Understand Business Use Cases
Operationalize Model
Data Acquisition and Exploration
Plan for Deployment
Iterate on approach
Select Algorithm
Present Results
Data Pipeline and Feature Engineering
Evaluate
Build ML Model
1
2
3
4
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6
7
8
9
10

MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

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AutoML

Tools for performing AutoML.

- AutoGluon - Automates machine learning tasks enabling you to easily achieve strong predictive performance.
- AutoKeras - AutoKeras goal is to make machine learning accessible for everyone.
- AutoPyTorch - Automatic architecture search and hyperparameter optimization for PyTorch.
- AutoSKLearn - Automated machine learning toolkit and a drop-in replacement for a scikit-learn estimator.
- EvalML - A library that builds, optimizes, and evaluates ML pipelines using domain-specific functions.
- FLAML - Finds accurate ML models automatically, efficiently and economically.
- H2O AutoML - Automates ML workflow, which includes automatic training and tuning of models.
- MindsDB - AI layer for databases that allows you to effortlessly develop, train and deploy ML models.
- MLBox - MLBox is a powerful Automated Machine Learning python library.
- Model Search - Framework that implements AutoML algorithms for model architecture search at scale.
- NNI - An open source AutoML toolkit for automate machine learning lifecycle.

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CI/CD for Machine Learning

Tools for performing CI/CD for Machine Learning.

- ClearML - Auto-Magical CI/CD to streamline your ML workflow.
- CML - Open-source library for implementing CI/CD in machine learning projects.

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MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

Cron Job Monitoring

Tools for monitoring cron jobs (recurring jobs).

- Cronitor - Monitor any cron job or scheduled task.
- HealthchecksIO - Simple and effective cron job monitoring.

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Data Catalog

Tools for data cataloging.

- Amundsen - Data discovery and metadata engine for improving the productivity when interacting with data.
- Apache Atlas - Provides open metadata management and governance capabilities to build a data catalog.
- CKAN - Open-source DMS (data management system) for powering data hubs and data portals.
- DataHub - LinkedIn's generalized metadata search & discovery tool.
- Magda - A federated, open-source data catalog for all your big data and small data.
- Metacat - Unified metadata exploration API service for Hive, RDS, Teradata, Redshift, S3 and Cassandra.
- OpenMetadata - A Single place to discover, collaborate and get your data right.

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Data Enrichment

Tools and libraries for data enrichment.

•Upgini - Enriches training datasets with features from public and community shared data sources.

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Data Exploration

Tools for performing data exploration.

- Apache Zeppelin - Enables data-driven, interactive data analytics and collaborative documents.
- BambooLib - An intuitive GUI for Pandas DataFrames.
- Google Colab - Hosted Jupyter notebook service that requires no setup to use.
- Jupyter Notebook - Web-based notebook environment for interactive computing.
- JupyterLab - The next-generation user interface for Project Jupyter.
- Jupytext - Jupyter Notebooks as Markdown Documents, Julia, Python or R scripts.
- Polynote - The polyglot notebook with first-class Scala support.

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Data Management

Tools for performing data management.

- Arrikto - Dead simple, ultra fast storage for the hybrid Kubernetes world.
- BlazingSQL - A lightweight, GPU accelerated, SQL engine for Python. Built on RAPIDS cuDF.
- Delta Lake - Storage layer that brings scalable, ACID transactions to Apache Spark and other engines.
- Dolt - SQL database that you can fork, clone, branch, merge, push and pull just like a git repository.
- Dud - A lightweight CLI tool for versioning data alongside source code and building data pipelines.
- DVC - Management and versioning of datasets and machine learning models.
- Git LFS - An open source Git extension for versioning large files.
- Hub - A dataset format for creating, storing, and collaborating on AI datasets of any size.
- Intake - A lightweight set of tools for loading and sharing data in data science projects.
- lakeFS - Repeatable, atomic and versioned data lake on top of object storage.
- Marquez - Collect, aggregate, and visualize a data ecosystem's metadata.
- Milvus - An open source embedding vector similarity search engine powered by Faiss, NMSLIB and Annoy.
- Pinecone - Managed and distributed vector similarity search used with a lightweight SDK.
- Qdrant - An open source vector similarity search engine with extended filtering support.
- Quilt - A self-organizing data hub with S3 support.

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Data Processing

Tools related to data processing and data pipelines.

- Airflow - Platform to programmatically author, schedule, and monitor workflows.
- Azkaban - Batch workflow job scheduler created at LinkedIn to run Hadoop jobs.
- Dagster - A data orchestrator for machine learning, analytics, and ETL.
- Hadoop - Framework that allows for the distributed processing of large data sets across clusters.
- Spark - Unified analytics engine for large-scale data processing.

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Data Validation

Tools related to data validation.

- Cerberus - Lightweight, extensible data validation library for Python.
- Great Expectations - A Python data validation framework that allows to test your data against datasets.
- JSON Schema - A vocabulary that allows you to annotate and validate JSON documents.
- TFDV - An library for exploring and validating machine learning data.

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Data Visualization

Tools for data visualization, reports and dashboards.

- Count - SQL/drag-and-drop querying and visualisation tool based on notebooks.
- Dash - Analytical Web Apps for Python, R, Julia, and Jupyter.
- Data Studio - Reporting solution for power users who want to go beyond the data and dashboards of GA.
- Facets - Visualizations for understanding and analyzing machine learning datasets.
- Lux - Fast and easy data exploration by automating the visualization and data analysis process.
- Metabase - The simplest, fastest way to get business intelligence and analytics to everyone.
- Redash - Connect to any data source, easily visualize, dashboard and share your data.
- Superset - Modern, enterprise-ready business intelligence web application.
- Tableau - Powerful and fastest growing data visualization tool used in the business intelligence industry.

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MLOps: pipelines de entrega contínua e automação no aprendizado de máquina

Feature Engineering

Tools and libraries related to feature engineering.

- Feature Engine - Feature engineering package with SKlearn like functionality.
- Featuretools - Python library for automated feature engineering.
- TSFresh - Python library for automatic extraction of relevant features from time series.

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Feature Store

Feature store tools for data serving.

- Butterfree - A tool for building feature stores. Transform your raw data into beautiful features.
- ByteHub - An easy-to-use feature store. Optimized for time-series data.
- Feast - End-to-end open source feature store for machine learning.
- Feathr - An enterprise-grade, high performance feature store.
- Tecton - A fully-managed feature platform built to orchestrate the complete lifecycle of features.

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Hyperparameter Tuning

Tools and libraries to perform hyperparameter tuning.

- Advisor - Open-source implementation of Google Vizier for hyper parameters tuning.
- Hyperas - A very simple wrapper for convenient hyperparameter optimization.
- Hyperopt - Distributed Asynchronous Hyperparameter Optimization in Python.
- Katib - Kubernetes-based system for hyperparameter tuning and neural architecture search.
- KerasTuner - Easy-to-use, scalable hyperparameter optimization framework.
- Optuna - Open source hyperparameter optimization framework to automate hyperparameter search.
- Scikit Optimize - Simple and efficient library to minimize expensive and noisy black-box functions.
- Talos - Hyperparameter Optimization for TensorFlow, Keras and PyTorch.
- Tune - Python library for experiment execution and hyperparameter tuning at any scale.

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Machine Learning Platform

Complete machine learning platform solutions.

- aiWARE - aiWARE helps MLOps teams evaluate, deploy, integrate, scale & monitor ML models.
- Algorithmia - Securely govern your machine learning operations with a healthy ML lifecycle.
- Allegro AI - Transform ML/DL research into products. Faster.
- Bodywork - Deploys machine learning projects developed in Python, to Kubernetes.
- CNVRG - An end-to-end machine learning platform to build and deploy AI models at scale.
- DAGsHub - A platform built on open source tools for data, model and pipeline management.
- Dataiku - Platform democratizing access to data and enabling enterprises to build their own path to AI.
- DataRobot - AI platform that democratizes data science and automates the end-to-end ML at scale.
- Domino - One place for your data science tools, apps, results, models, and knowledge.
- Edge Impulse - Platform for creating, optimizing, and deploying AI/ML algorithms for edge devices.
- envd - Machine learning development environment for data science and AI/ML engineering teams.
- FedML - Simplifies the workflow of federated learning anywhere at any scale.
- Gradient - Multicloud CI/CD and MLOps platform for machine learning teams.
- H2O - Open source leader in AI with a mission to democratize AI for everyone.
- Hopsworks - Open-source platform for developing and operating machine learning models at scale.

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Model Fairness and Privacy

Tools for performing model fairness and privacy in production.

- AIF360 - A comprehensive set of fairness metrics for datasets and machine learning models.
- Fairlearn - A Python package to assess and improve fairness of machine learning models.
- Opacus - A library that enables training PyTorch models with differential privacy.
- TensorFlow Privacy - Library for training machine learning models with privacy for training data.

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Model Interpretability

Tools for performing model interpretability/explainability.

- Alibi - Open-source Python library enabling ML model inspection and interpretation.
- Captum - Model interpretability and understanding library for PyTorch.
- ELI5 - Python package which helps to debug machine learning classifiers and explain their predictions.
- InterpretML - A toolkit to help understand models and enable responsible machine learning.
- LIME - Explaining the predictions of any machine learning classifier.
- Lucid - Collection of infrastructure and tools for research in neural network interpretability.
- SAGE - For calculating global feature importance using Shapley values.
- SHAP - A game theoretic approach to explain the output of any machine learning model.
- Skater - Unified framework to enable Model Interpretation for all forms of model.

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Model Lifecycle

Tools for managing model lifecycle (tracking experiments, parameters and metrics).

- Aim - A super-easy way to record, search and compare 1000s of ML training runs.
- Comet - Track your datasets, code changes, experimentation history, and models.
- Guild AI - Open source experiment tracking, pipeline automation, and hyperparameter tuning.
- Keepsake - Version control for machine learning with support to Amazon S3 and Google Cloud Storage.
- Losswise - Makes it easy to track the progress of a machine learning project.
- Mlflow - Open source platform for the machine learning lifecycle.
- ModelDB - Open source ML model versioning, metadata, and experiment management.
- Neptune AI - The most lightweight experiment management tool that fits any workflow.
- Replicate - Library that uploads files and metadata (like hyperparameters) to S3 or GCS.
- Sacred - A tool to help you configure, organize, log and reproduce experiments.
- Weights and Biases - A tool for visualizing and tracking your machine learning experiments.

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Model Serving

Tools for serving models in production.

- Banana - Host your ML inference code on serverless GPUs and integrate it into your app with one line of code.
- BentoML - Open-source platform for high-performance ML model serving.
- BudgetML - Deploy a ML inference service on a budget in less than 10 lines of code.
- Cortex - Machine learning model serving infrastructure.
- Gradio - Create customizable UI components around your models.
- GraphPipe - Machine learning model deployment made simple.
- Hydrosphere - Platform for deploying your Machine Learning to production.
- KFServing - Kubernetes custom resource definition for serving ML models on arbitrary frameworks.
- Merlin - A platform for deploying and serving machine learning models.
- MLEM - Version and deploy your ML models following GitOps principles.
- Opyrator - Turns your ML code into microservices with web API, interactive GUI, and more.
- Rune - Provides containers to encapsulate and deploy EdgeML pipelines and applications.
- Seldon - Take your ML projects from POC to production with maximum efficiency and minimal risk.
- Streamlit - Lets you create apps for your ML projects with deceptively simple Python scripts.
- TensorFlow Serving - Flexible, high-performance serving system for ML models, designed for production.

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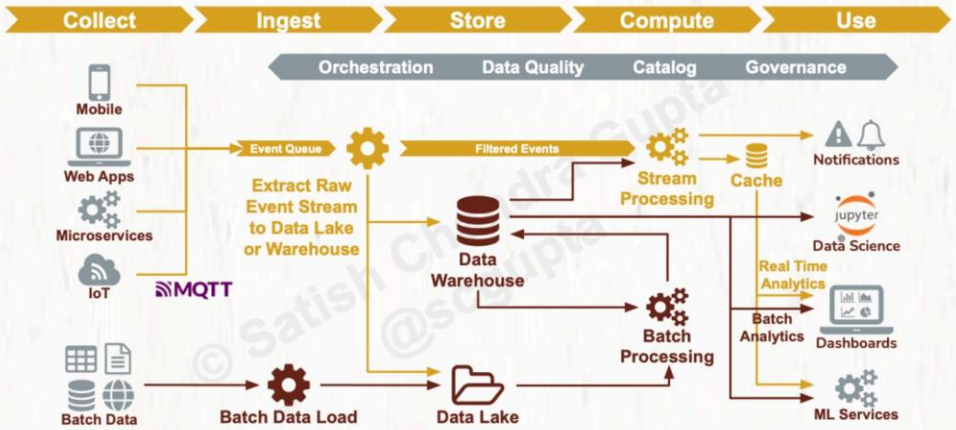
Collect
data from internal & external sources

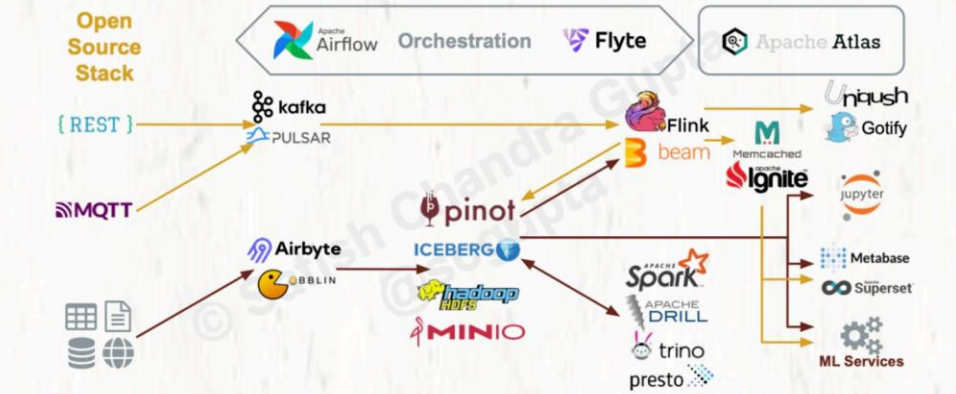
Ingest
data through batch jobs or streams

Store
in Data Lake or Data Warehouse

Compute
analytics aggregations, ML features

Use
it in dashboards, data science, ML





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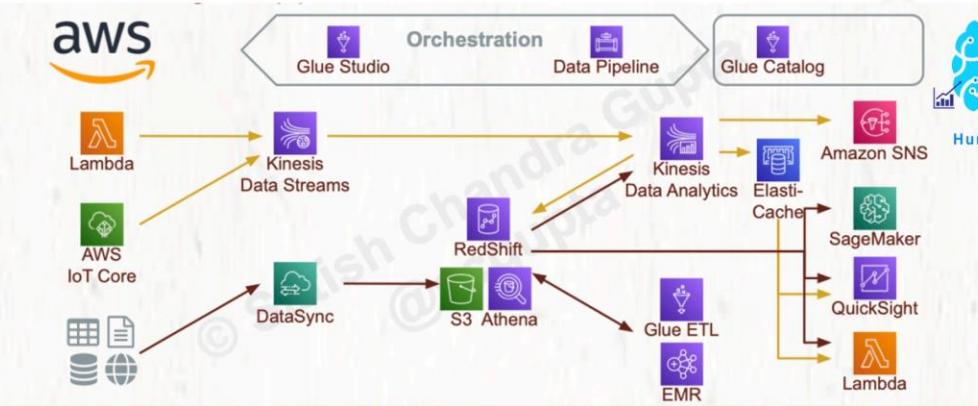

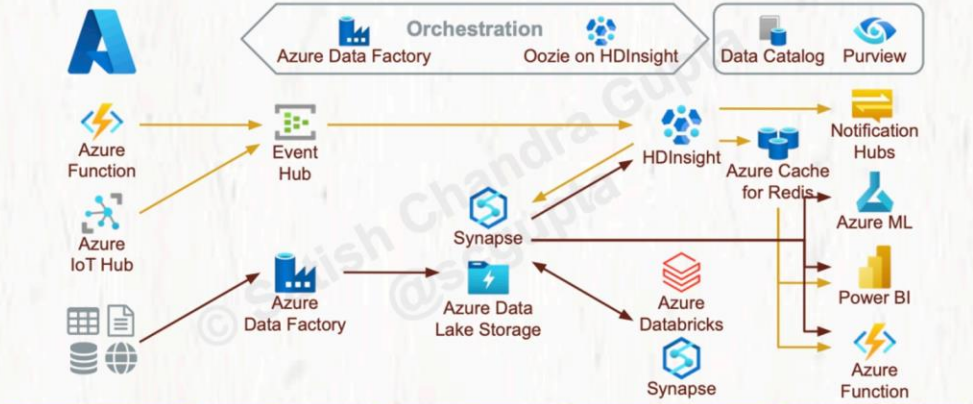

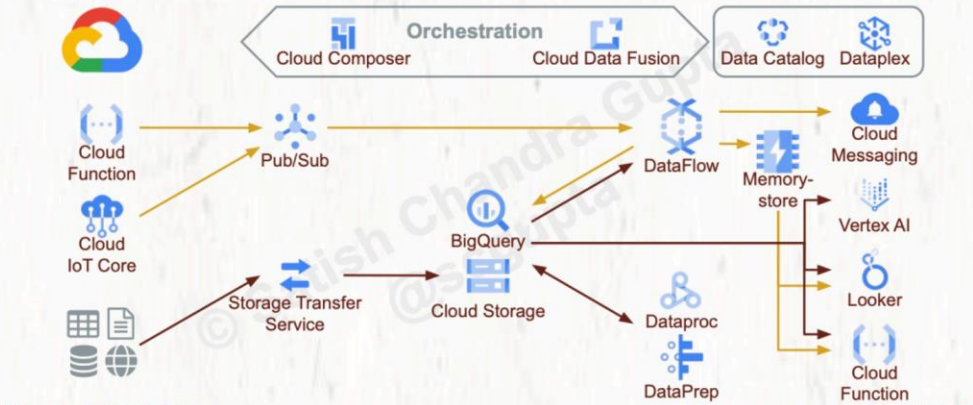

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Thanks !

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O que você achou da aula de hoje?

Questions and Feedback

MBA+

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