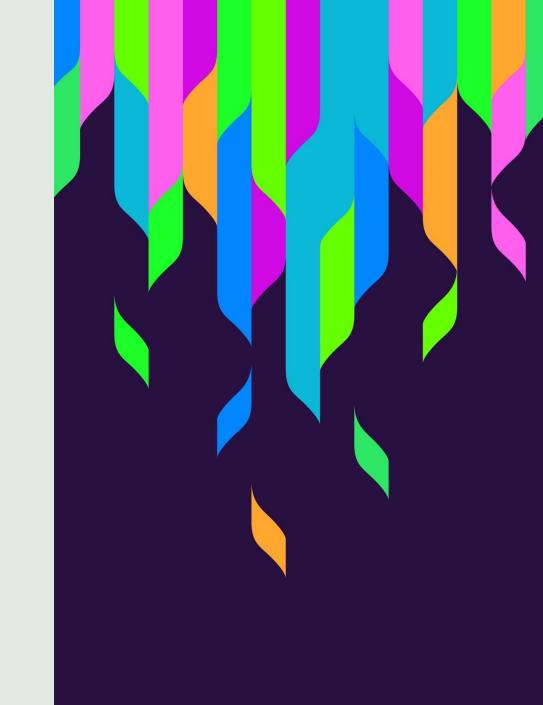
DEPLOYMENT AND INTEGRATION: DEPLOYING AI MODELS IN REAL-WORLD SETTINGS. INTEGRATION WITH EXISTING SYSTEMS AND APPLICATIONS. CONTINUOUS MONITORING AND UPDATES



Problem Identification

STAGES
OF THE
AI
PROJECT
LIFECYCL
E

Monitoring and Maintenance

**Problem Scoping** 

Deployment and Integration

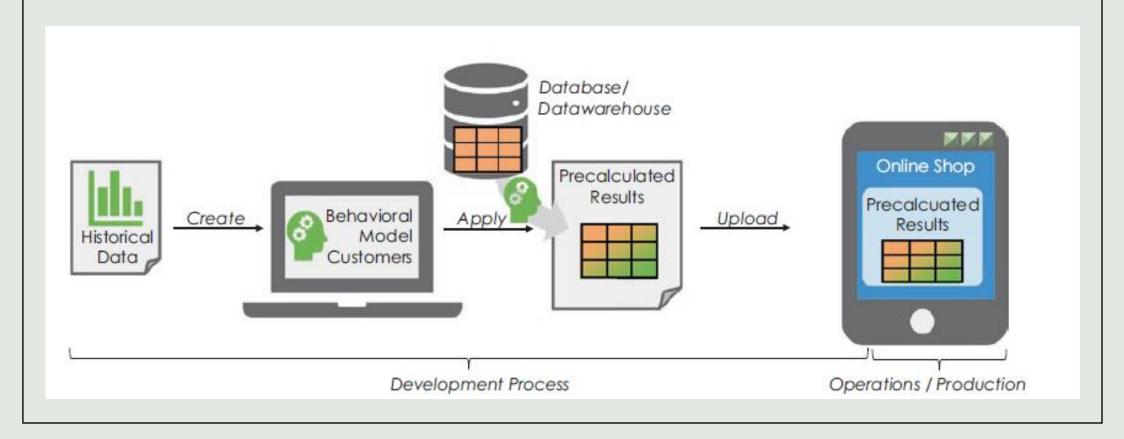
**Data Collection** and **Preparation** 

Model Development

# AI MODEL DEPLOYMENT AND INTEGRATION

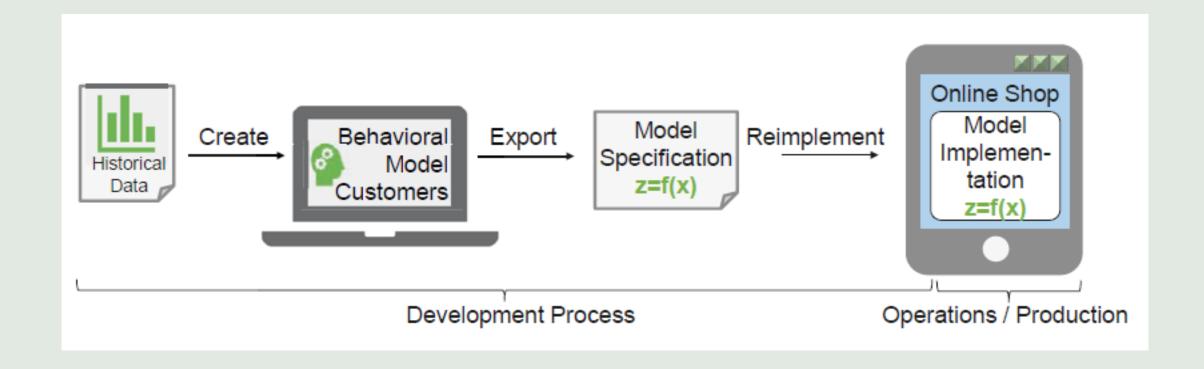
- Model deployment –
  moving/transitioning machine learning
  models into production, enabling their
  predictions to be accessible to users,
  developers, or systems. This allows for
  data-driven business decisions,
  application interactions (such as facial
  recognition), and more.
- 3 patterns of deployment and integration
   [1]
  - Precalculation
  - o Reimplementation
  - o Encapsulated Al component
- https://www.ibm.com/blog/ai-modellifecycle-management-deploy-phase/

### PRECALCULATION



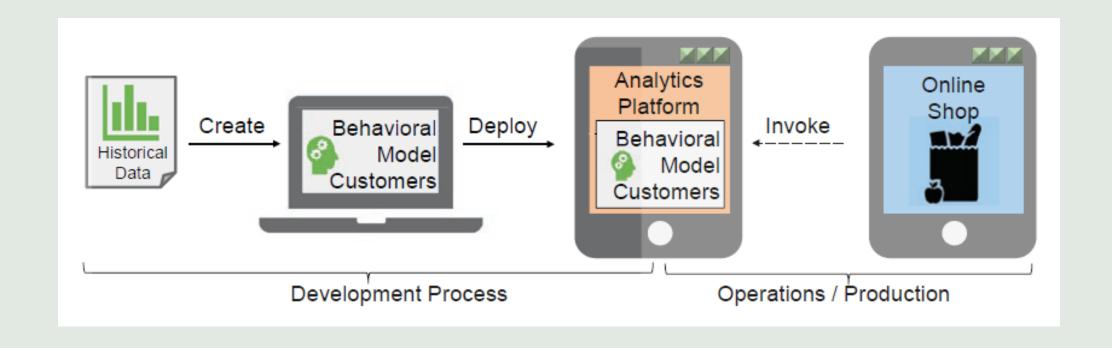
Klaus Haller. Managing AI in the Enterprise

#### REIMPLEMENTATION



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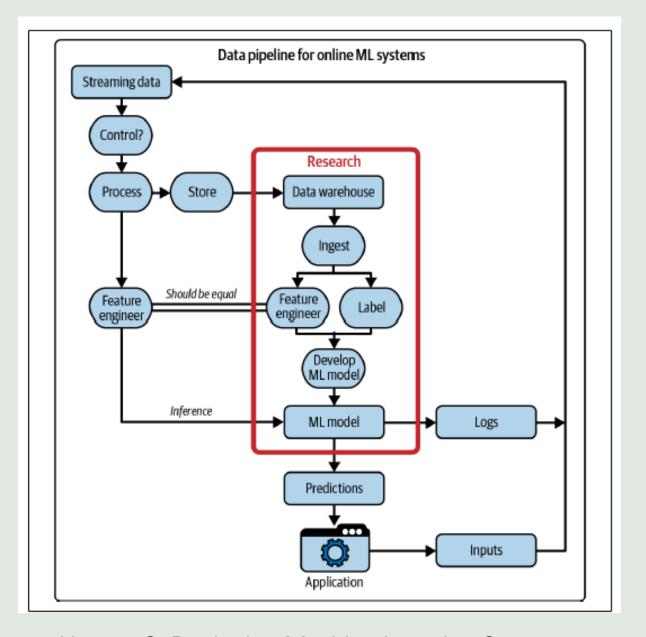
### ENCAPSULATED ANALYTICS



Klaus Haller. Managing Al in the Enterprise

#### DEPLOYMENT STRATEGIES

- Answer a question how does your model generates and gives its predictions to end users?
- Batch Prediction vs Online Prediction/Real-time prediction [2]
  - Batch prediction only batch features
  - Online prediction with only batch features
  - Online prediction batch + streaming features (Streaming prediction)
- https://medium.com/mlops-republic/mlops-batch-vs-online-ml-system-cbacee834837
- https://developers.google.com/machine-learning/crash-course/production-mlsystems/static-vs-dynamic-inference



Huyen, C. Designing Machine Learning Systems

#### DEPLOYMENT STRATEGIES

- On-Premises, Cloud, and Edge Deployment
  - On-premises computations are done within the company / using own resources
  - On the cloud a large amount of computations are done on the cloud (public clouds or private clouds)
  - Edge deployment a large amount of computations are done on consumer devices
- <a href="https://medium.com/@cprasenjit32/deployment-of-machine-learning-models-on-premises-and-in-the-cloud-39b021efba97">https://medium.com/@cprasenjit32/deployment-of-machine-learning-models-on-premises-and-in-the-cloud-39b021efba97</a>
- https://www.trek10.com/blog/ml-on-premise-vs-ml-cloud
- https://www.vector8.com/en/articles/mlops-in-on-prem-environments

# COMPILING AND OPTIMIZING MODELS FOR EDGE DEVICES

- Framework has to be supported by the hardware vendor
- Model optimization
  - Vectorization
  - Parallelization
  - Loop tiling
  - Operator fusion
  - o Using ML to optimize ML models
- ML in Browsers
  - TensorFlow.js
  - Synaptic,
  - Brain.js
  - But JS is slow
  - WebAssembly (WASM).

### INTEGRATION

- API-based Integration
- Database and Middleware
- Compatibility.Interfacing with Front-End Applications
- Legacy System Challenges.

# DEPLOYMENT PIPELINES AND CI/CD FOR AI

- Al project always has an artifact called an ML pipeline
- The ML pipeline is a software artifact that addresses several considerations in your Al system [3]
- Al system [3]:
  - Al algorithms operate on the data (Storage questions)
  - Data quality
  - Different sources
  - o Results must be presented to end user or ensure that the AI system follows some business and safety rules that are specific to domain

# DEPLOYMENT PIPELINES AND CI/CD FOR AI (CHALLENGES)

- Real-world ML pipelines are complex
- No universal solution
- Codification of the technical AND business decisions
- The cost of maintenance of the ML pipeline

### WHY USE CI/CD

Automation of the pipeline Catching errors early Reproducibility Testing and monitoring Faster iteration Scalability

### TOOLS AND TECHNOLOGIES

- Deployment tools:
  - AWS SageMaker
  - Azure ML
  - TensorFlow
  - Serving
- Monitoring tools:
  - Prometheus (Open source)
  - Grafana
- Version Control:
  - DVC
  - MLflow