MLOps: why and how to build end-to-end product teams

Daniël Willemsen

Machine Learning Engineer
At Xebia

DS @ 2023: Building an ML model is easy…

fast.ai

jupyter

APACHE Spark

PyTorch

dmlc XGBoost

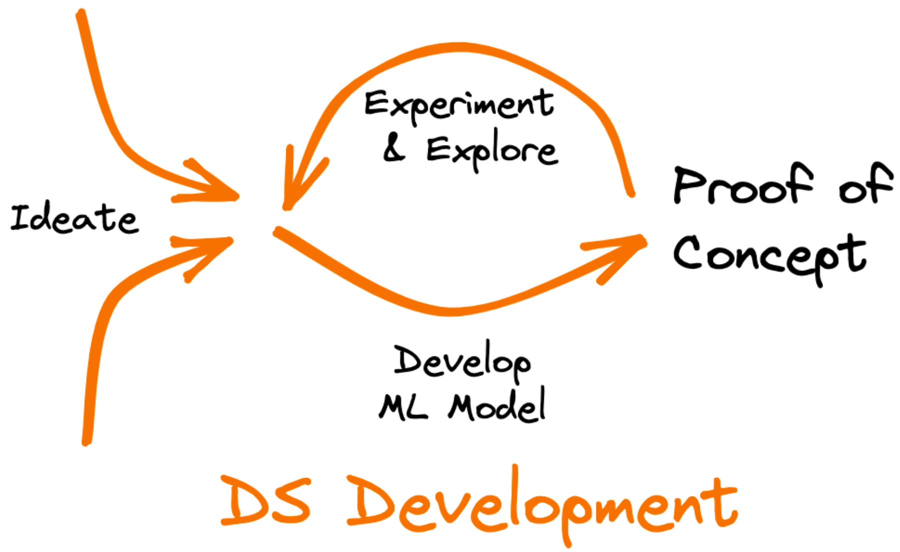
Amazon SageMaker

scikit learn

tidyverse

But many ML products get stuck before prod!

The machine learning lifecycle



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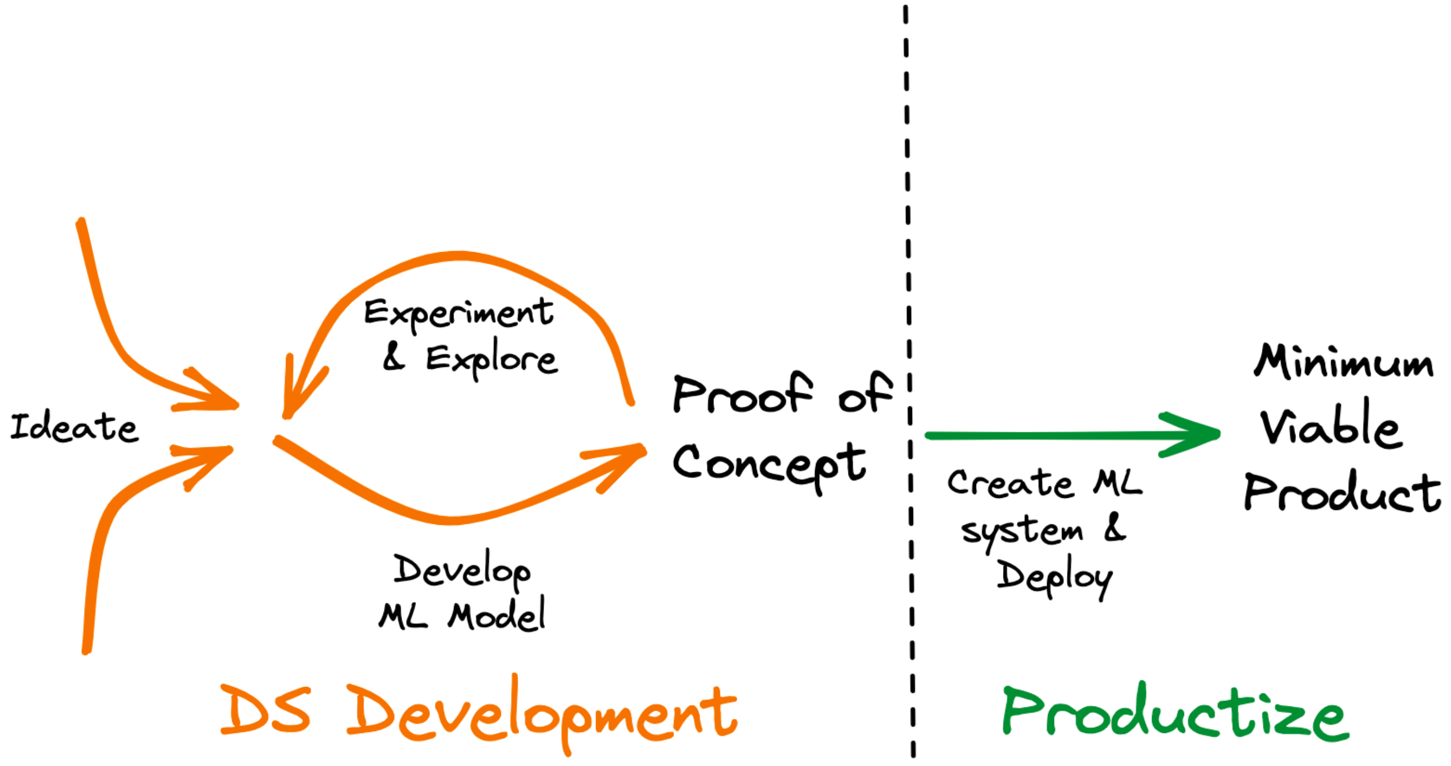

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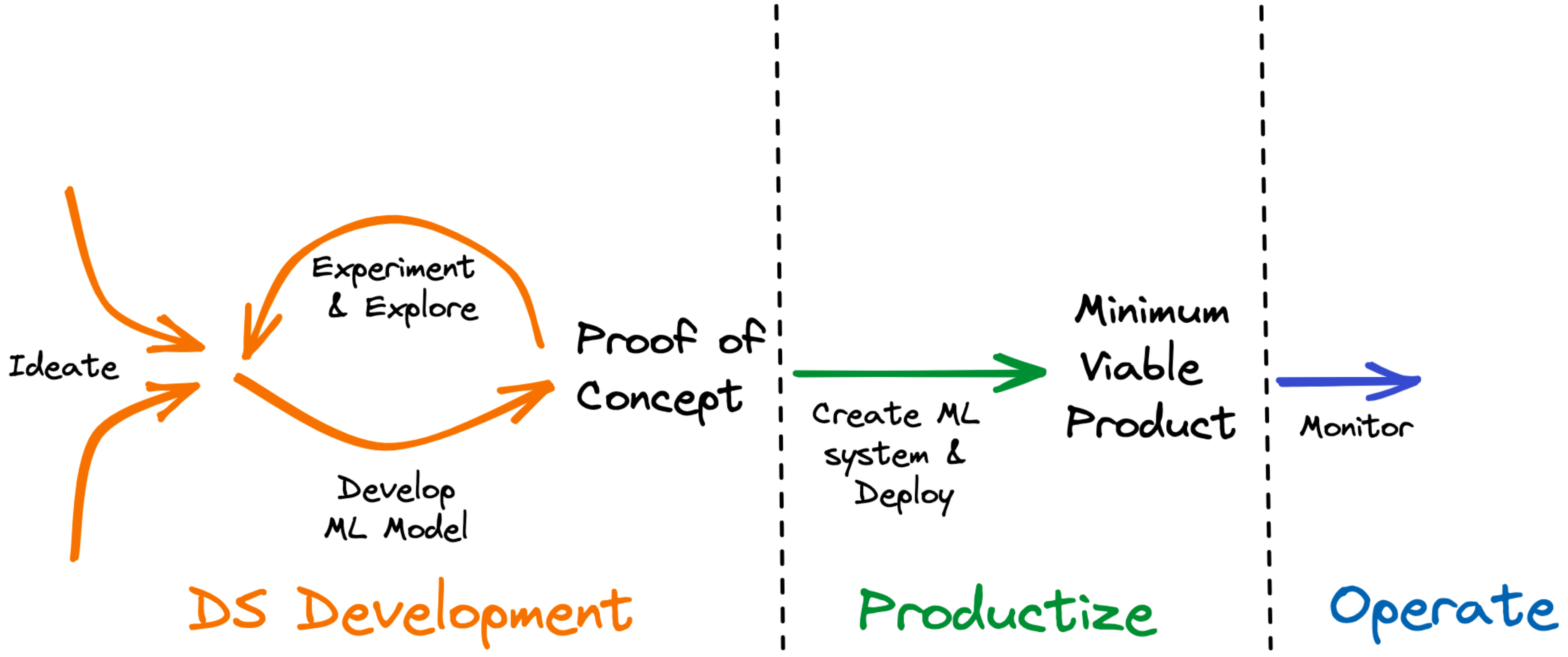

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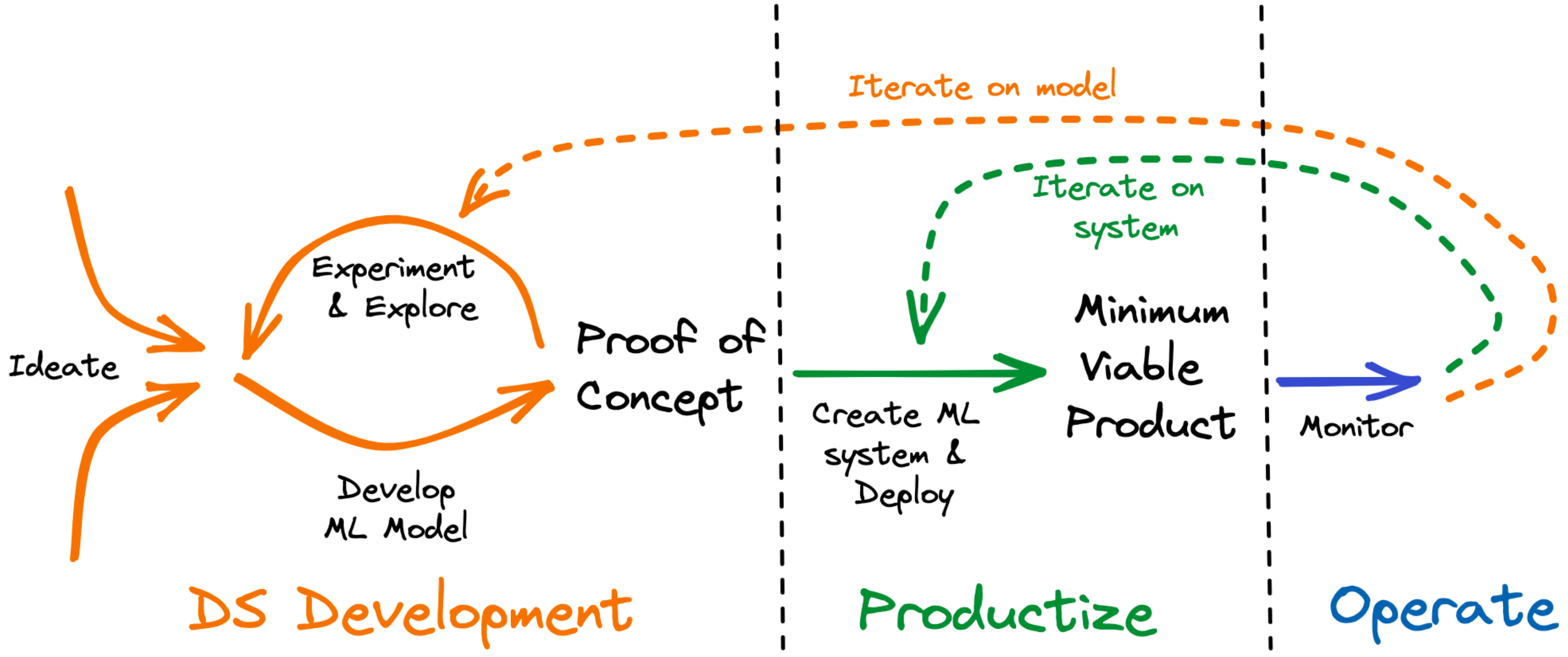


Machine learning in production is hard…

Why Production Machine Learning Fails — And How To Fix It

Source: Monte Carlo

Sponsored

Why do 87% of data science projects never make it into production?

Source: Venturebeat

Ari Joury, PhD

Nov 8, 2020 · 8 min read · Member-only ·

OPINION

Why 90 percent of all machine learning models never make it into production

Source: Towardsdatascience

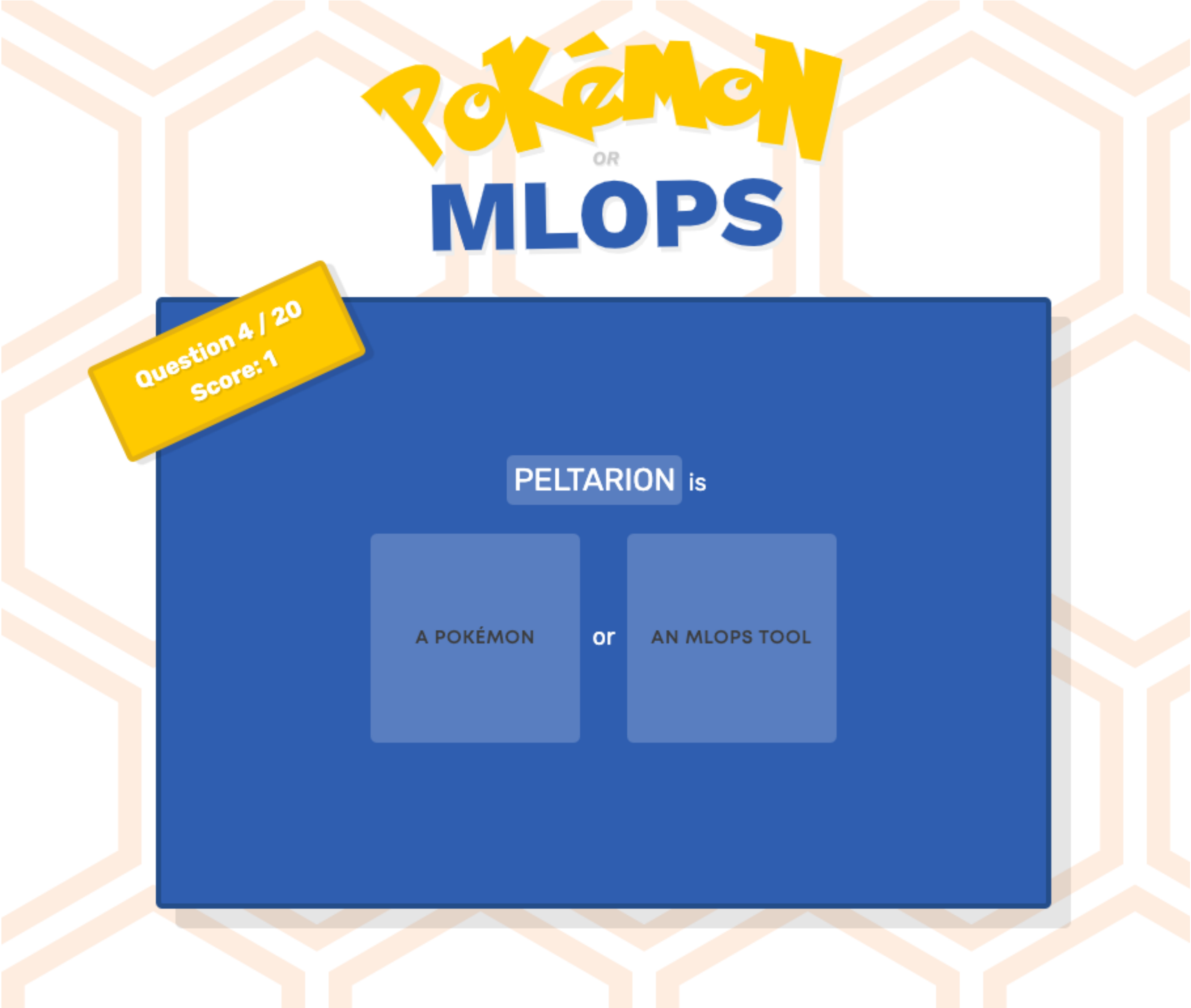
But MLOps is here to save us!

MLOps *is a set of practices that aims to deploy and maintain machine learning models in production reliably and efficiently.*

MLOps is overwhelming…

MLOps is overwhelming… In tools

MLOps is overwhelming... In tools



Source: https://valohai.com/mlops-or-pokemon/

Pokémon

OR

MLOPS

Question 1 / 20
Score: 1

Yay! The Peltarion Platform empowers anyone to design & deploy AI without a single line of code

NEXT QUESTION!


Pokémon
OR
MLOPS
Question 1 / 20
Score: 0
ONIX is
A POKÉMON
or
AN MLOPS TOOL

Pokémon

OR

MLOPS

Question 1 / 20
Score: 1

😎

Yay! Onix is a dual rock/ground type Pokémon composed of a giant chain of gray boulders that become smaller towards the tail. Its length makes it the tallest Rock-type Pokémon.

NEXT QUESTION!

Pokémon

OR

MLOPS

Question 1 / 20
Score: 1

ONNX

Yay! Onix is a dual rock/ground type Pokémon composed of a giant chain of gray boulders that become smaller towards the tail. Its length makes it the tallest Rock-type Pokémon.

NEXT QUESTION!

MLOps is overwhelming….. In concepts

Experiment tracking

Data versioning

CI/CD

Logging

Model governance

ML Metadata

Model versioning

Orchestration

Continuous training

Deployment

Automated Machine Learning Pipelines

Drift monitoring

Data Validation

MLOps is overwhelming…

… where do you start?

Let’s look at Data Scientist Daisy’s work

Daisy Data Scientist @ GoDataMarkets

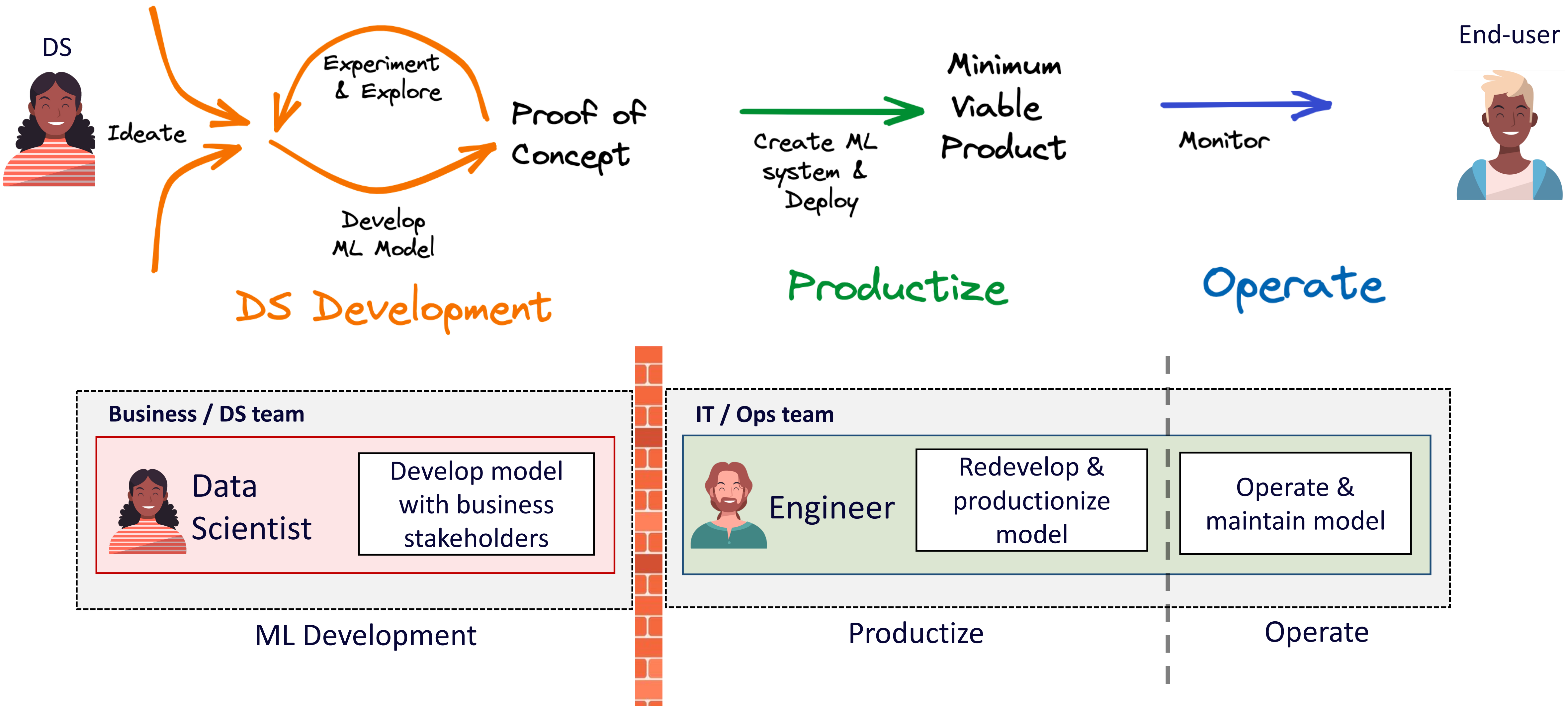
Tasked with helping the business improve their sales forecasts for supply-chain reasons.

Ideate with business to define use case & value → Explore data to find possible relationships → Create predictive model in a notebook → Now what?

“We often have too few or too many umbrellas in stock, resulting in $1M lost sales or overfull warehouses”

Weather forecasts might be a good predictor of umbrella sales!

Processing the weather data & using the rain feature as input for a simple regression results in better forecasts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Minimum Viable Product
Productize
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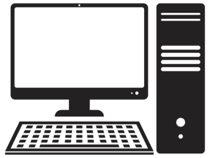
End-user
Business / DS team
Data Scientist
Develop model with business stakeholders
ML Development
IT / Ops team
Engineer
Redevelop & productionize model
Operate & maintain model
Productize
Operate

Let’s look at Engineer Eddy’s work

Eddy Engineer in IT Ops team @GoDataMarkets

Tasked with bringing Daisy’s predictive model into production & operating it

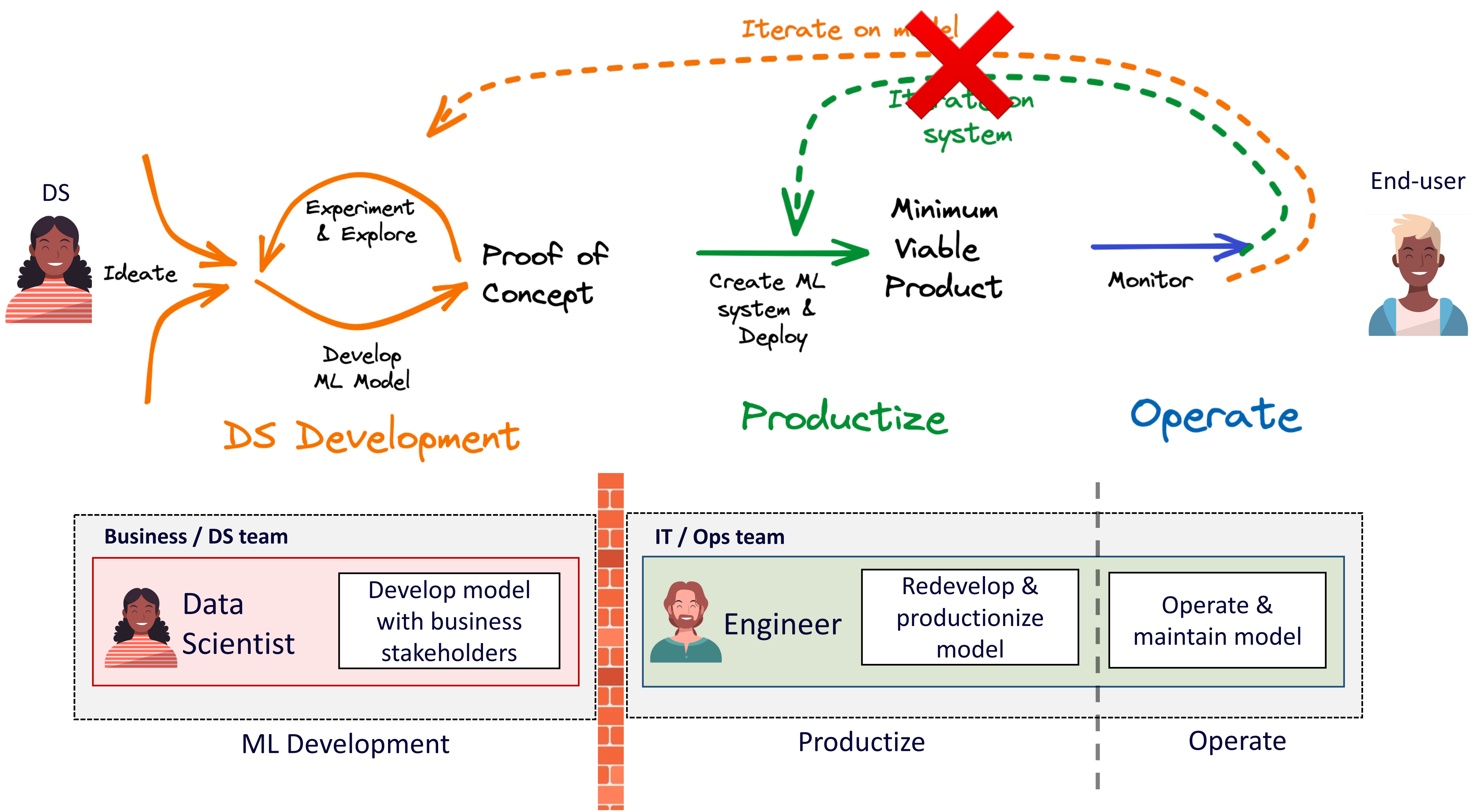


Rewrite Daisy’s code into a java application, loading in her trained model

Deploy the code into production

Model performance starts to become worse

Now what?



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Handovers are a guarantee for headaches

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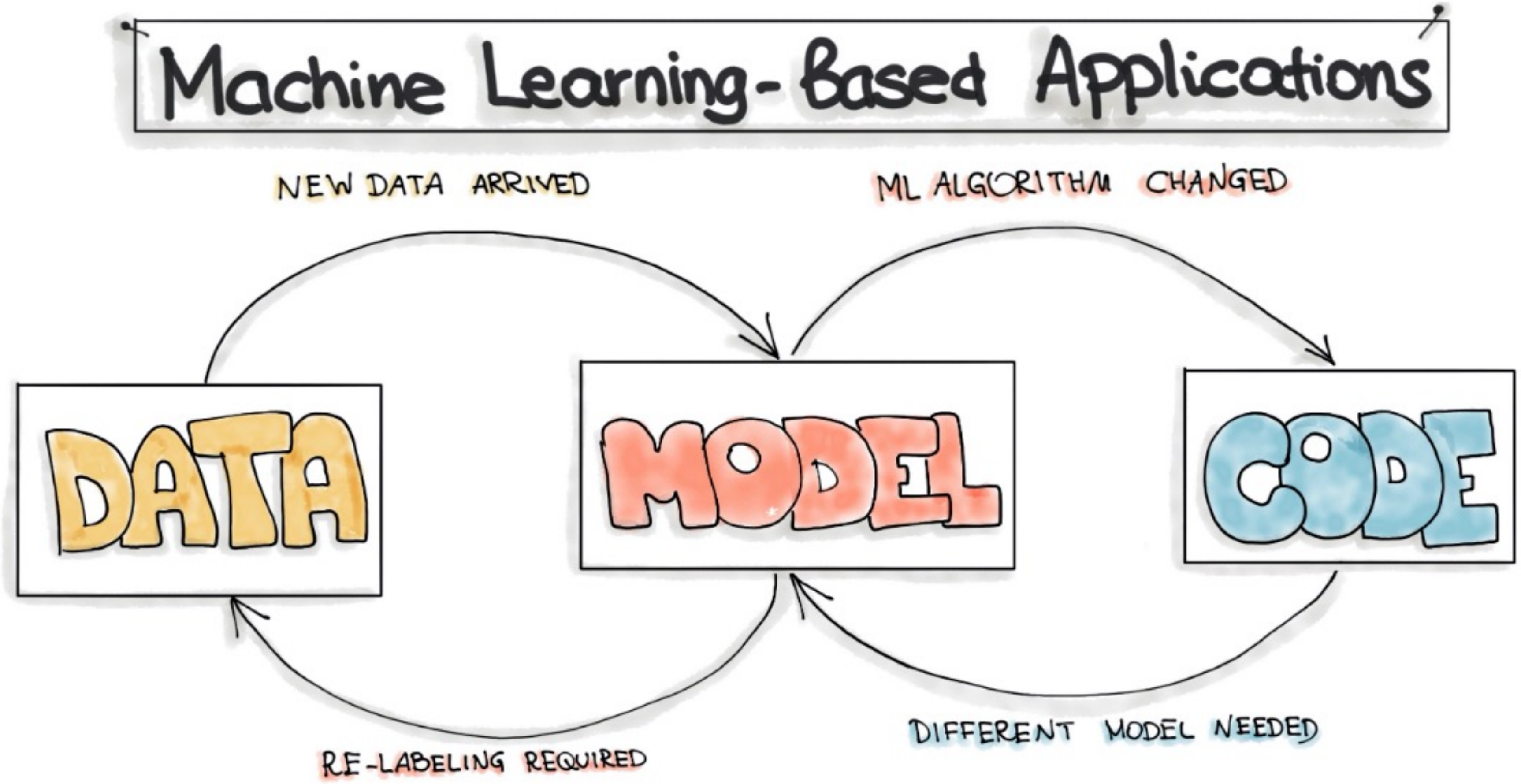
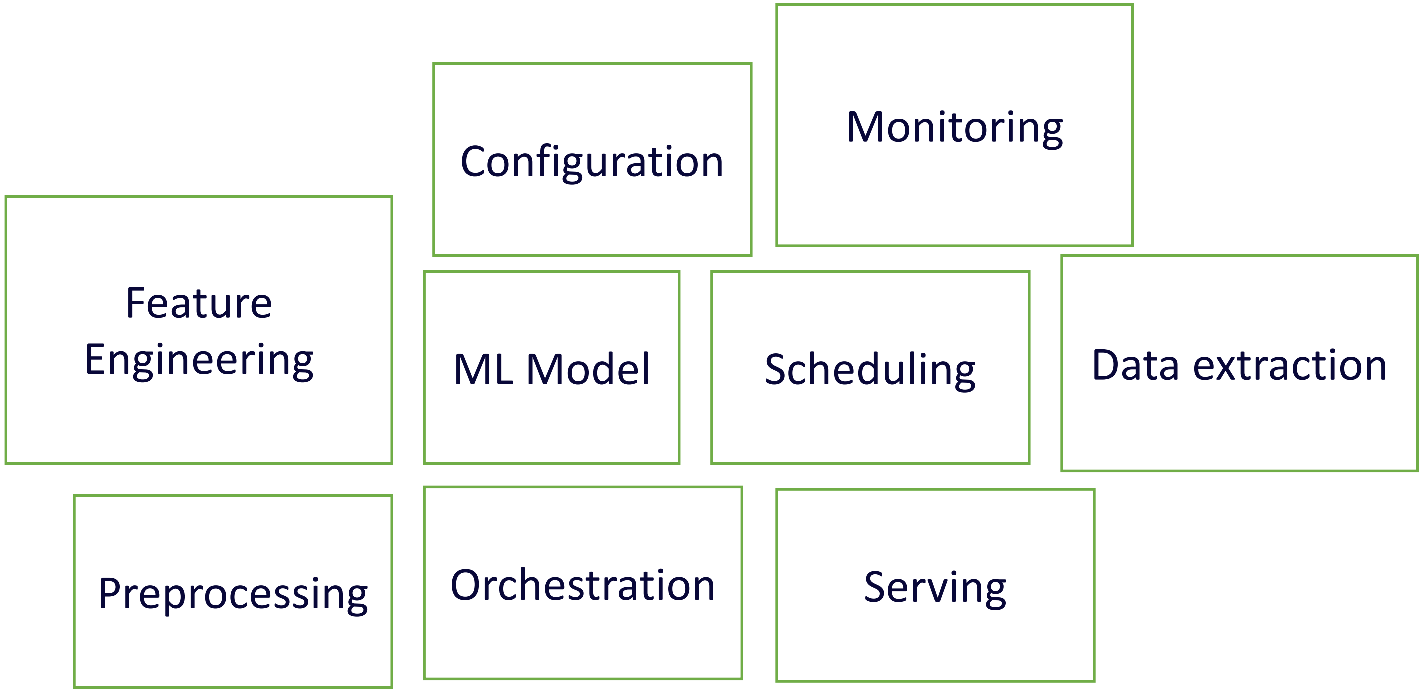
1. Machine learning systems are complex

ML Systems are complex



Source: MLOps.org

ML Systems are complex



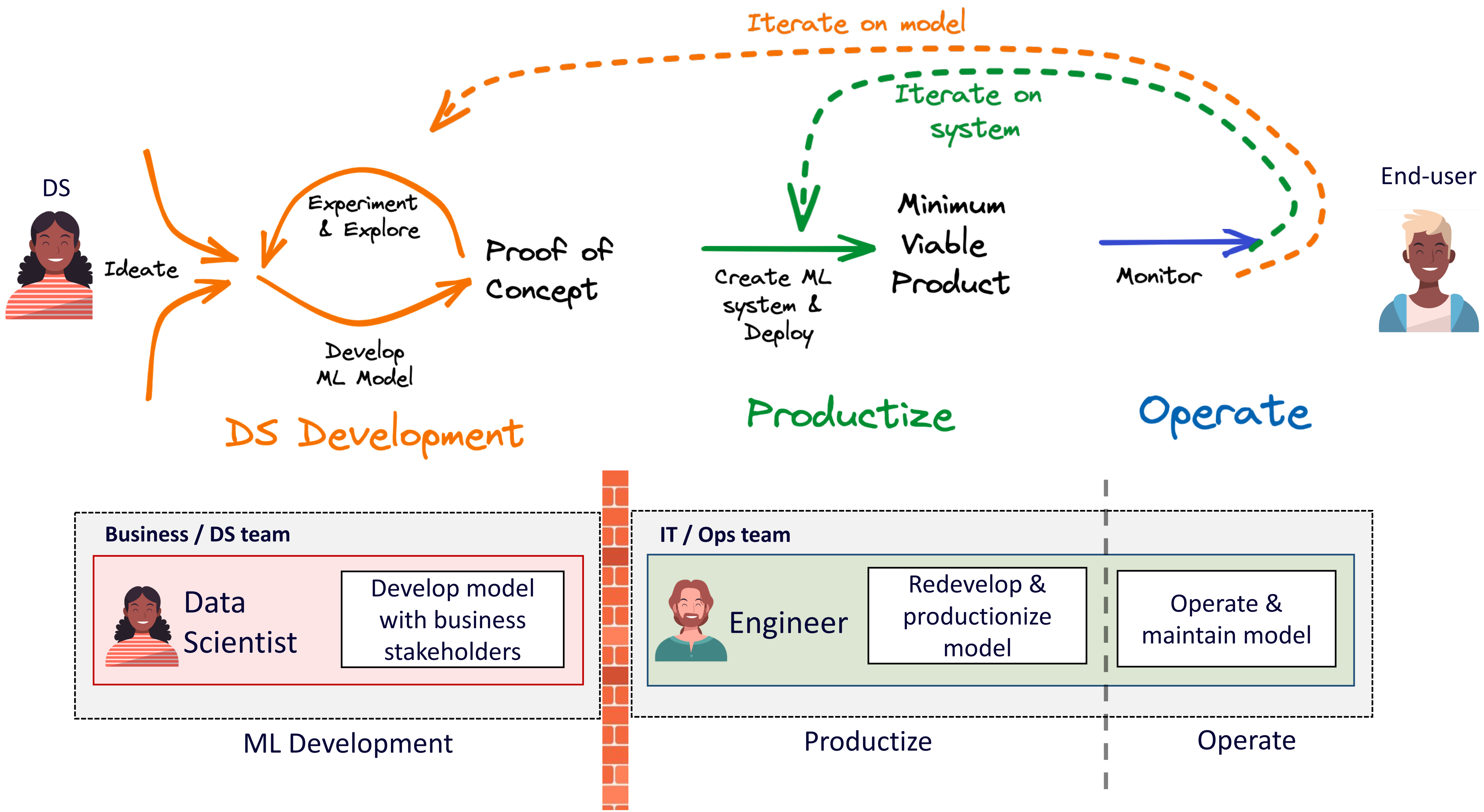
Handovers are a guarantee for headaches

1. Machine learning systems are complex

Handovers are a guarantee for headaches

1. Machine learning systems are complex

2. Machine learning product is immature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Handovers are a guarantee for headaches

1. Machine learning systems are complex

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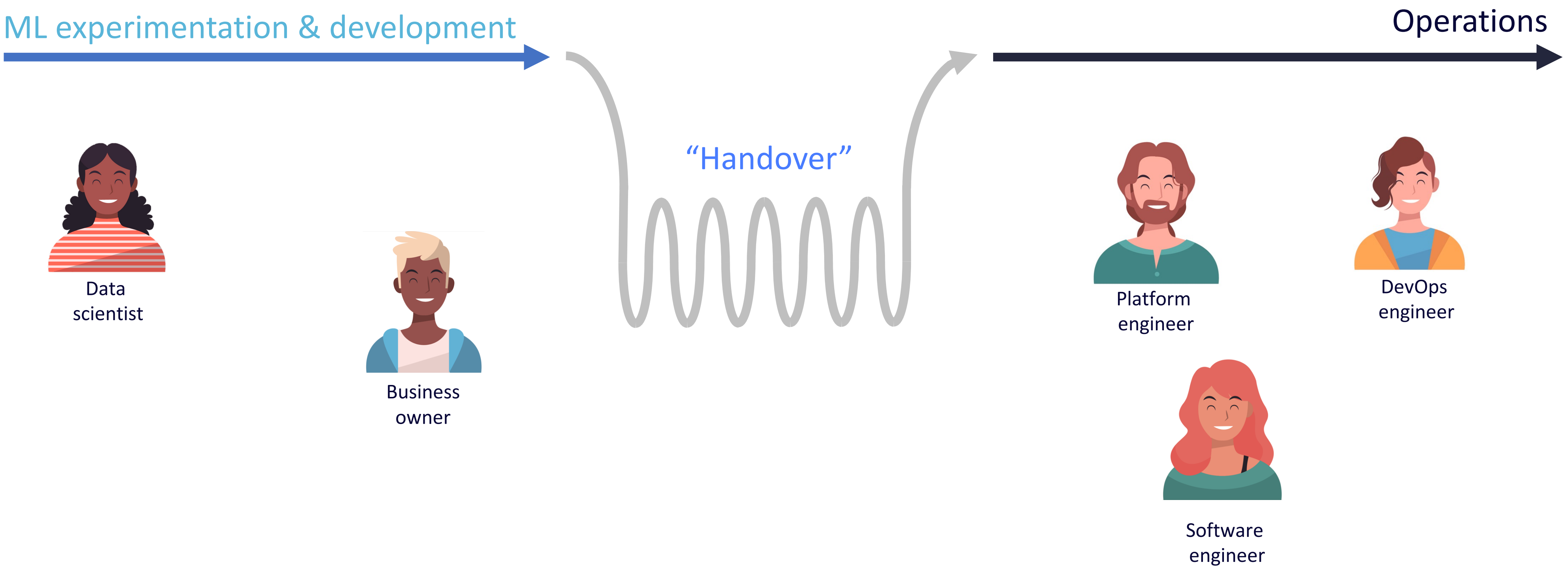
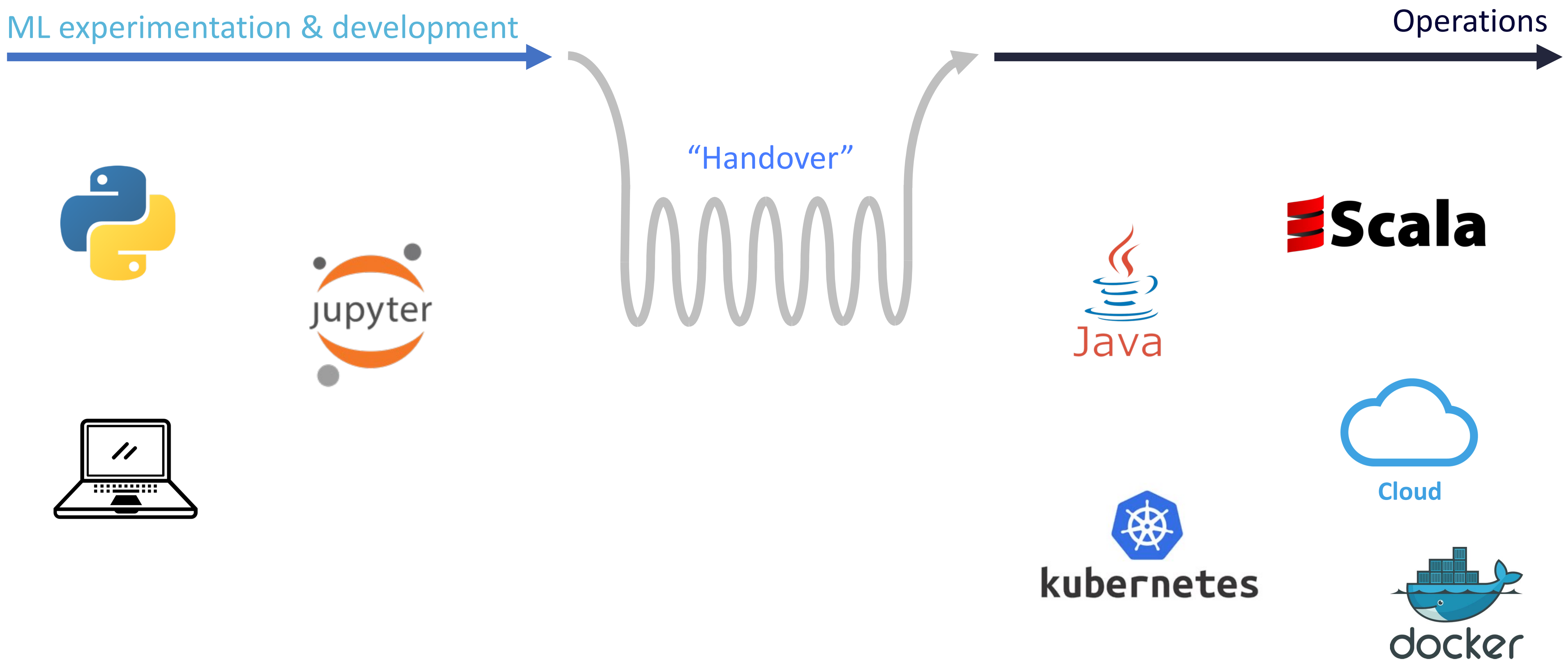
3. Two sides of the handover speak different languages

Differences in people*

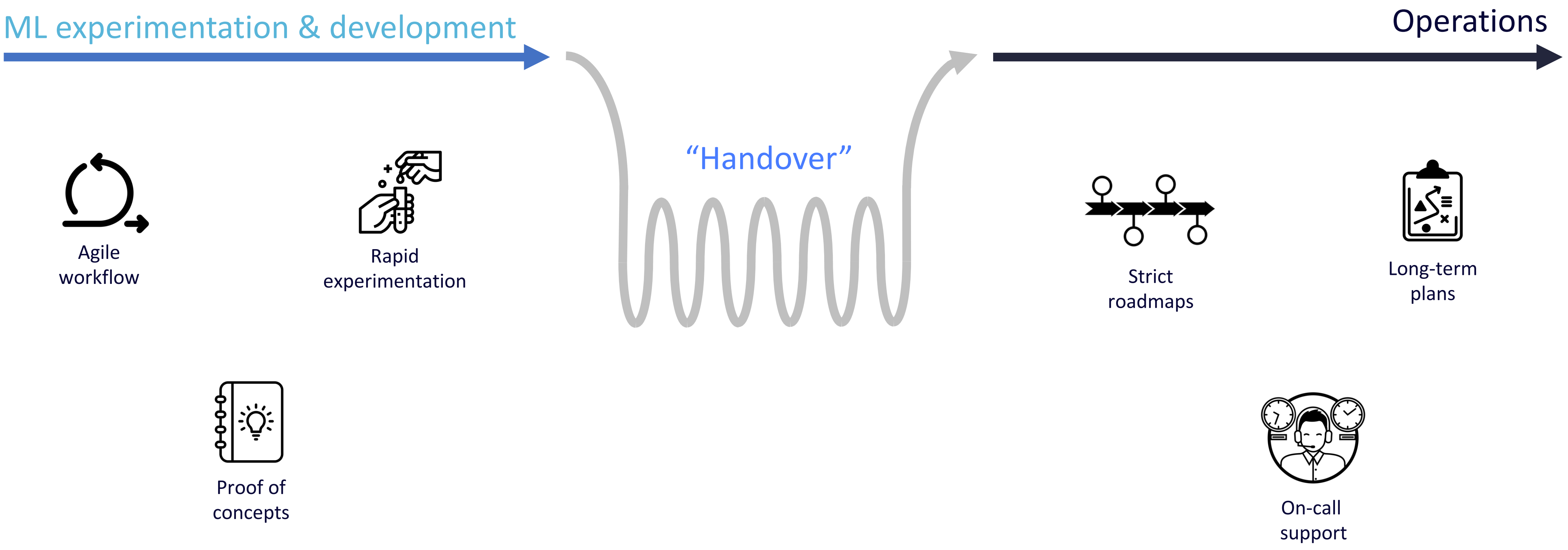


*roles/expertise

Differences in tools



Differences in processes



Handovers are a guarantee for headaches

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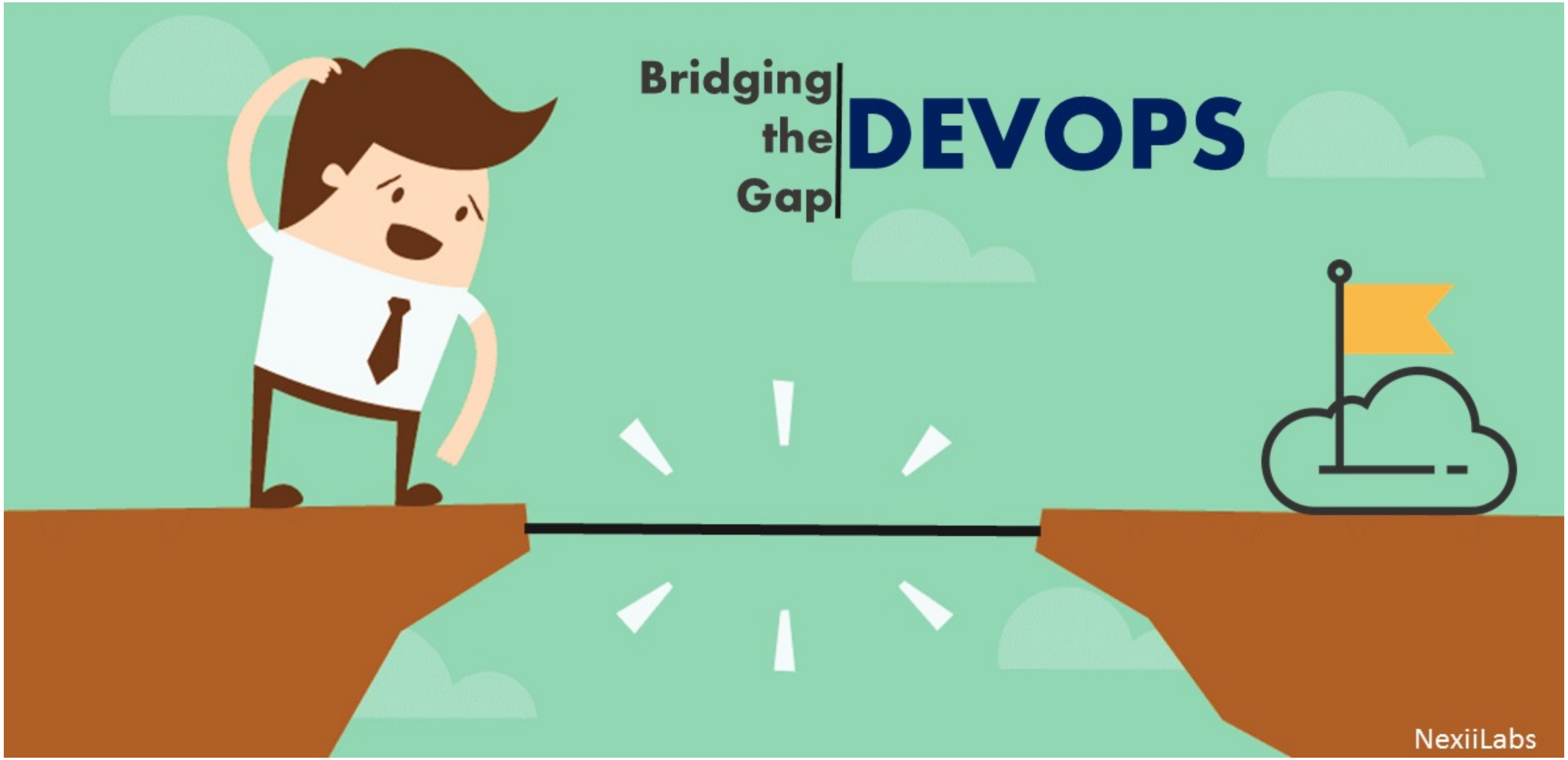
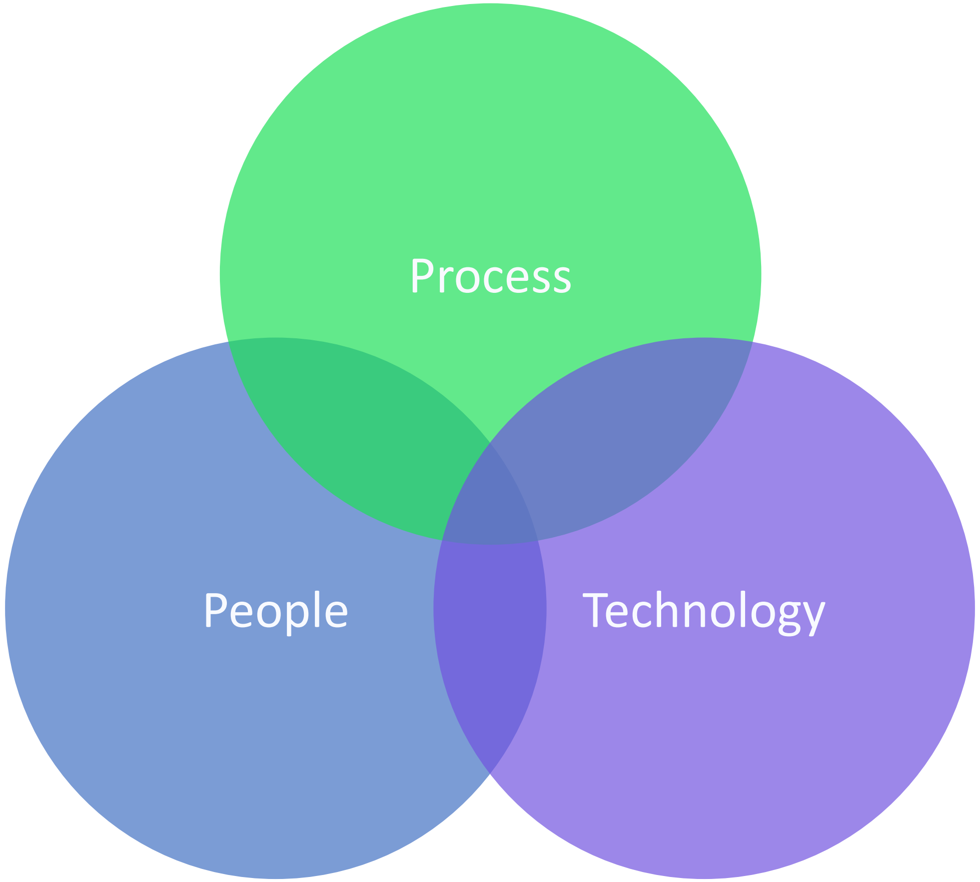
3. Two sides of the handover speak different languages

How to get rid of the handover and close the gap?

We’ve been here before



How do you close the gap?



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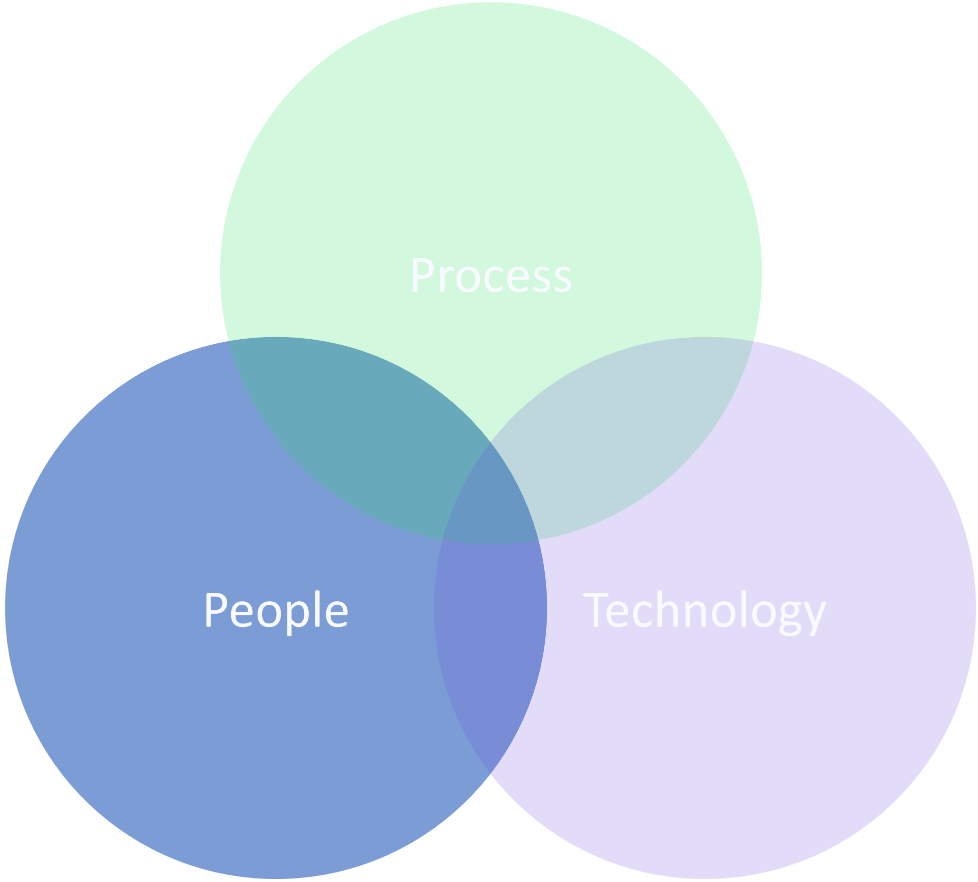


People: Having the right roles & responsibilities

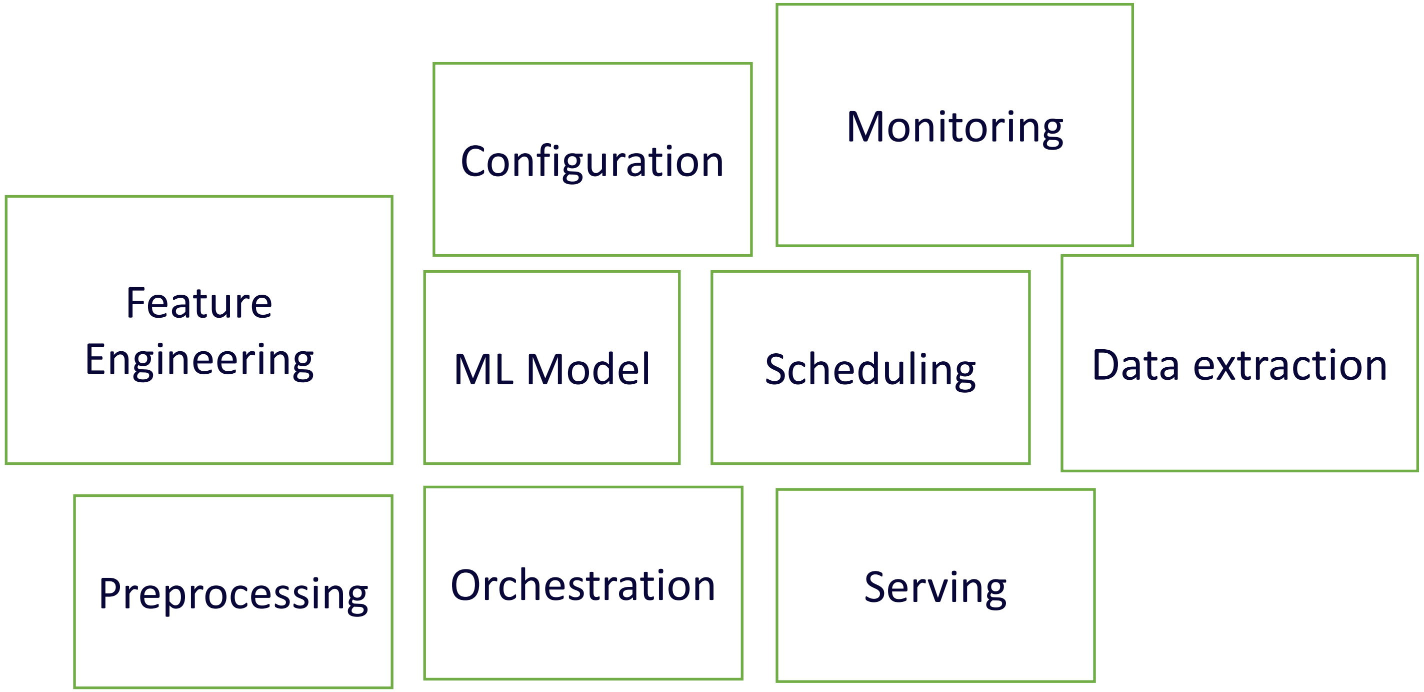
Data Scientist

Collaborates closely with stakeholders to build production-ready ML models that solve key business problems.

ML Engineer

Combines a strong software engineering background with a keen knowledge of ML to support building robust ML systems.

Together, they grasp the entire ML system



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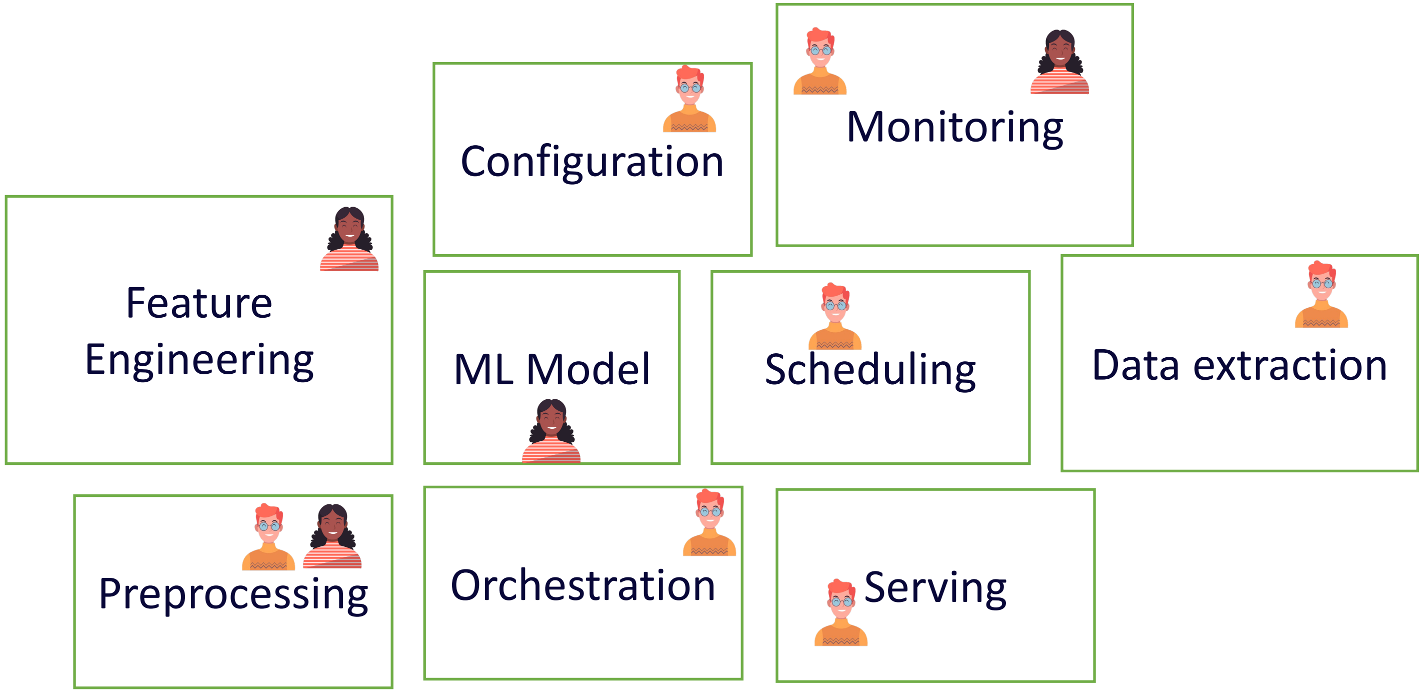

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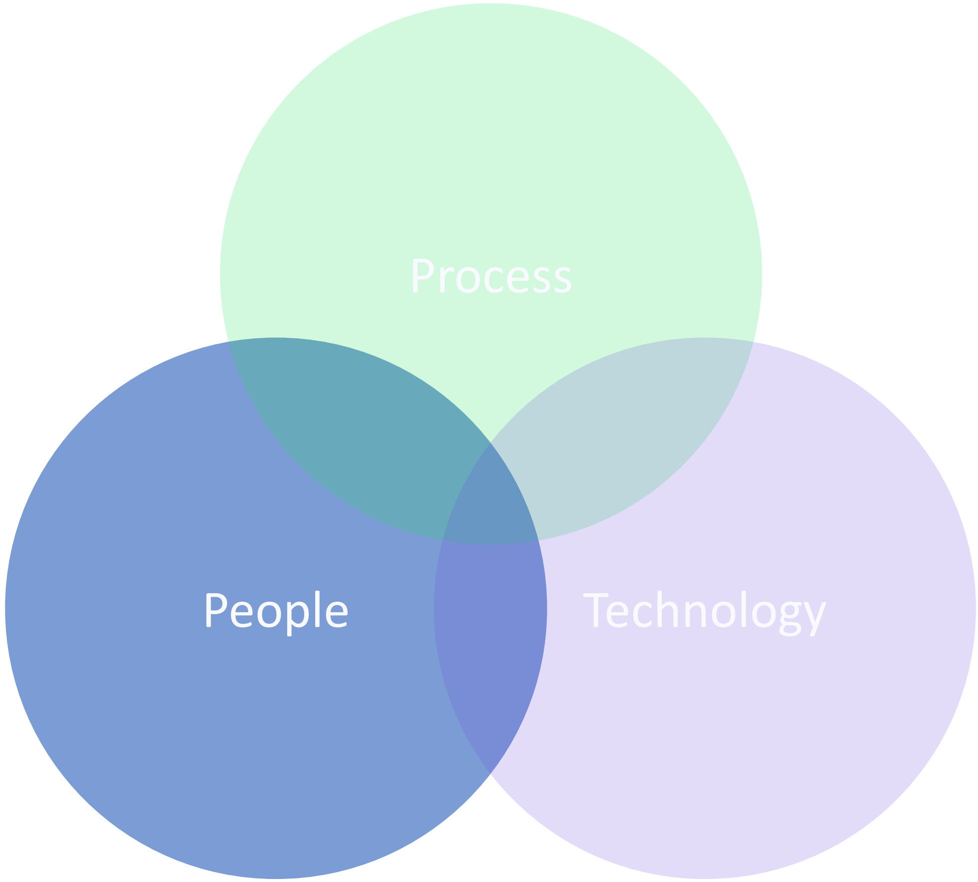

Having the right roles
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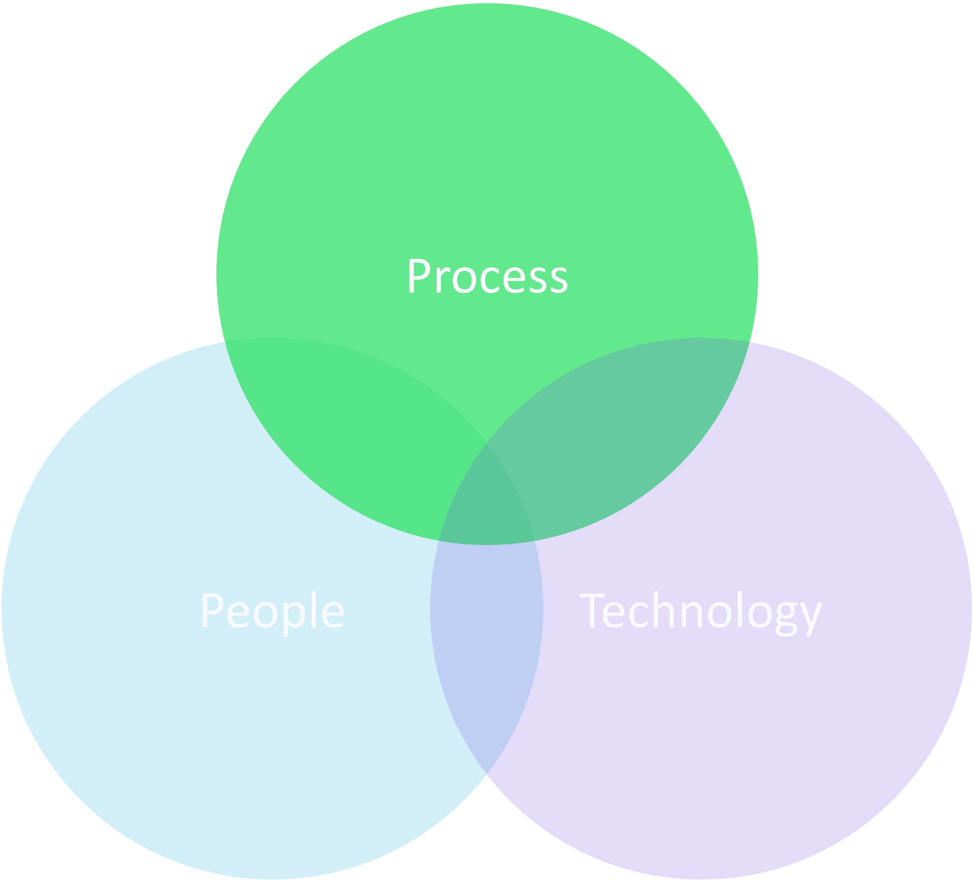
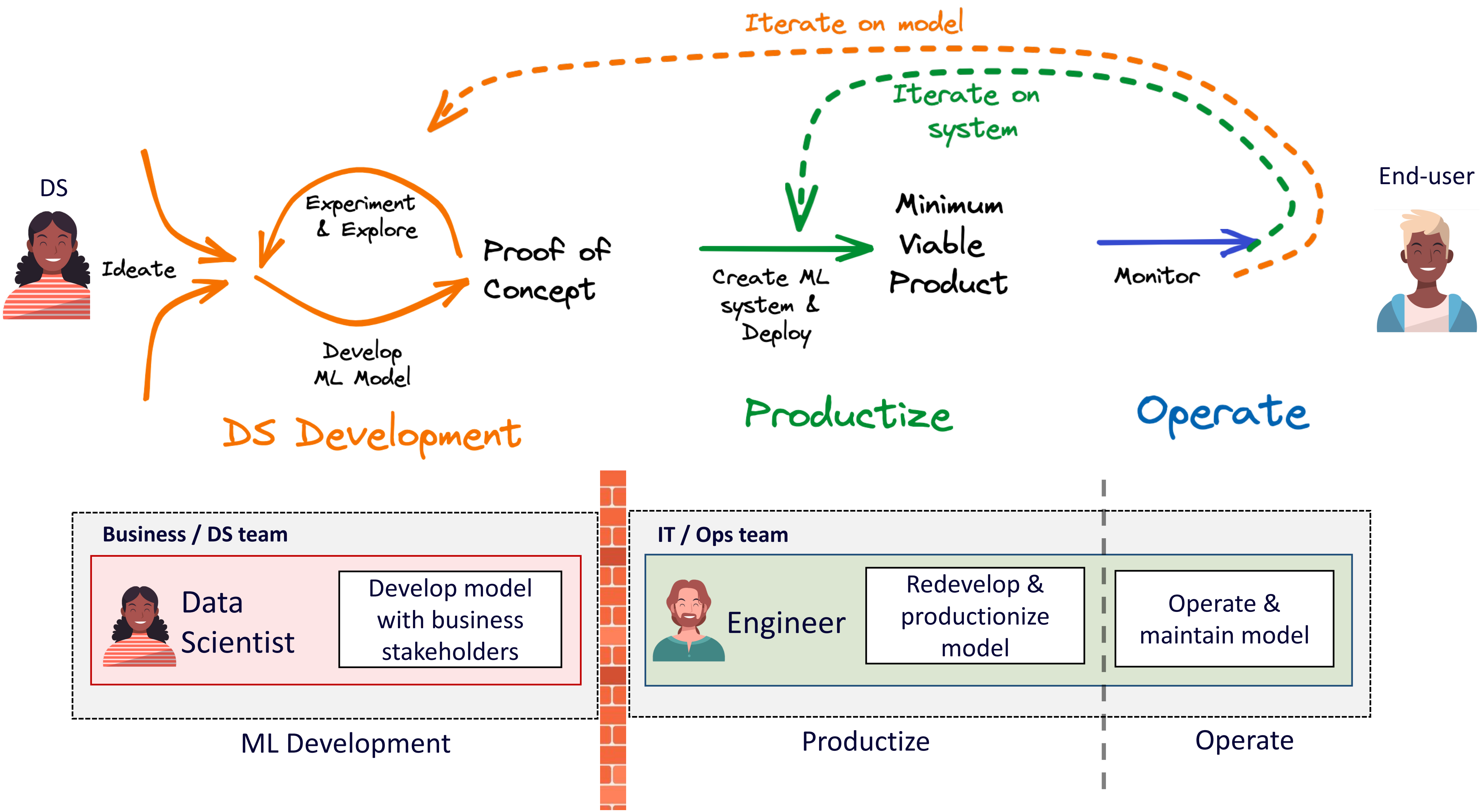
How do you close the gap?

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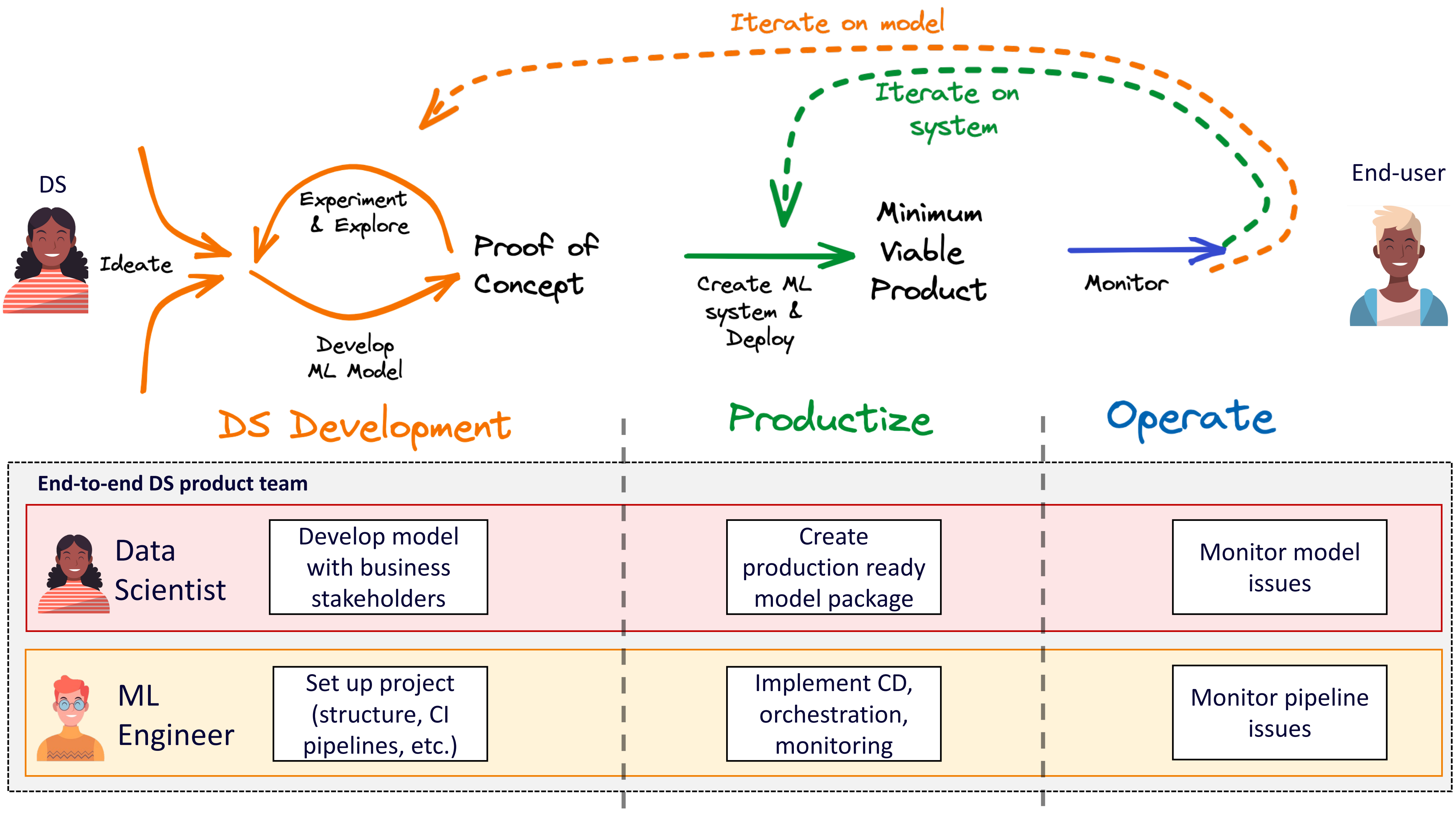
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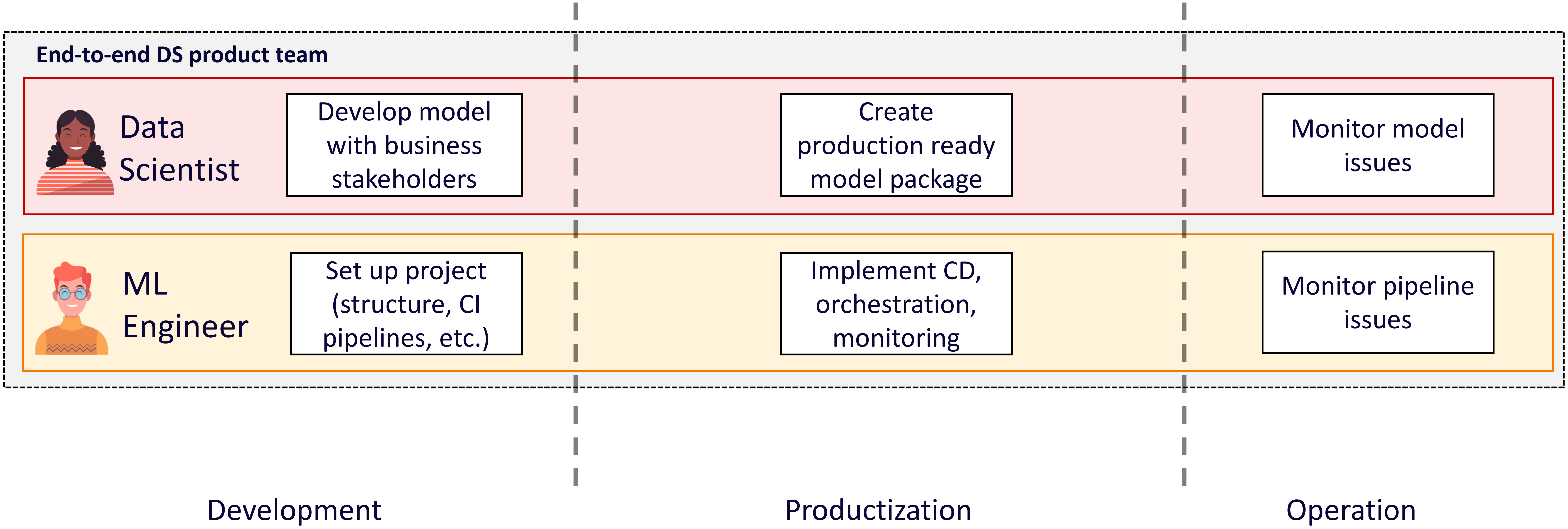
Data Scientist
Develop model with business stakeholders
Create production ready model package
Monitor model issues
ML Engineer
Set up project (structure, CI pipelines, etc.)
Implement CD, orchestration, monitoring
Monitor pipeline issues

Process: Enable ownership over the entire ML life-cycle



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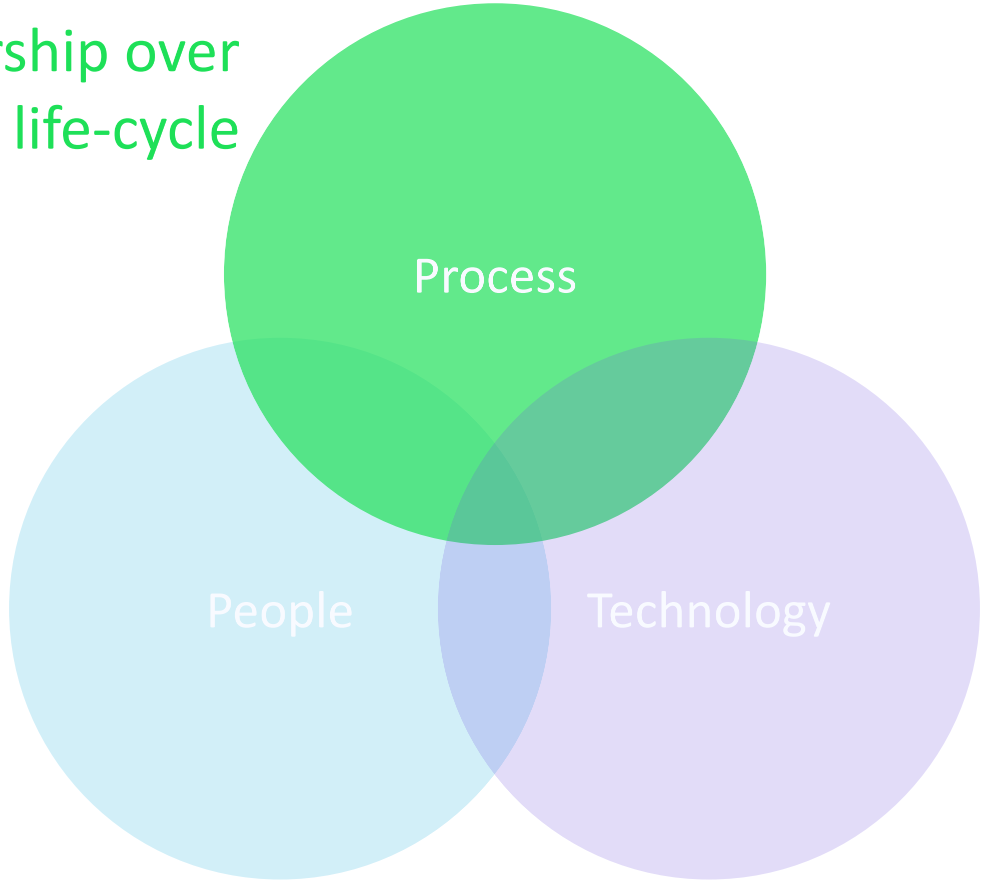

Having the right roles
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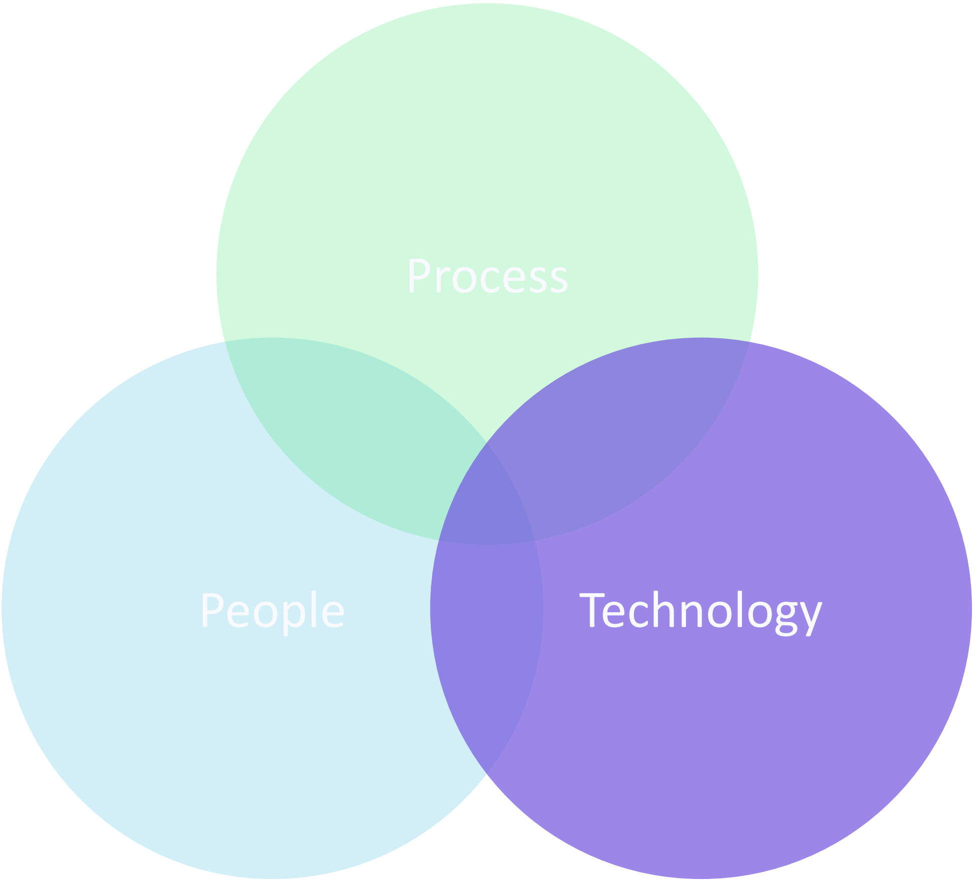

Technology: support the product with the right tools & platform

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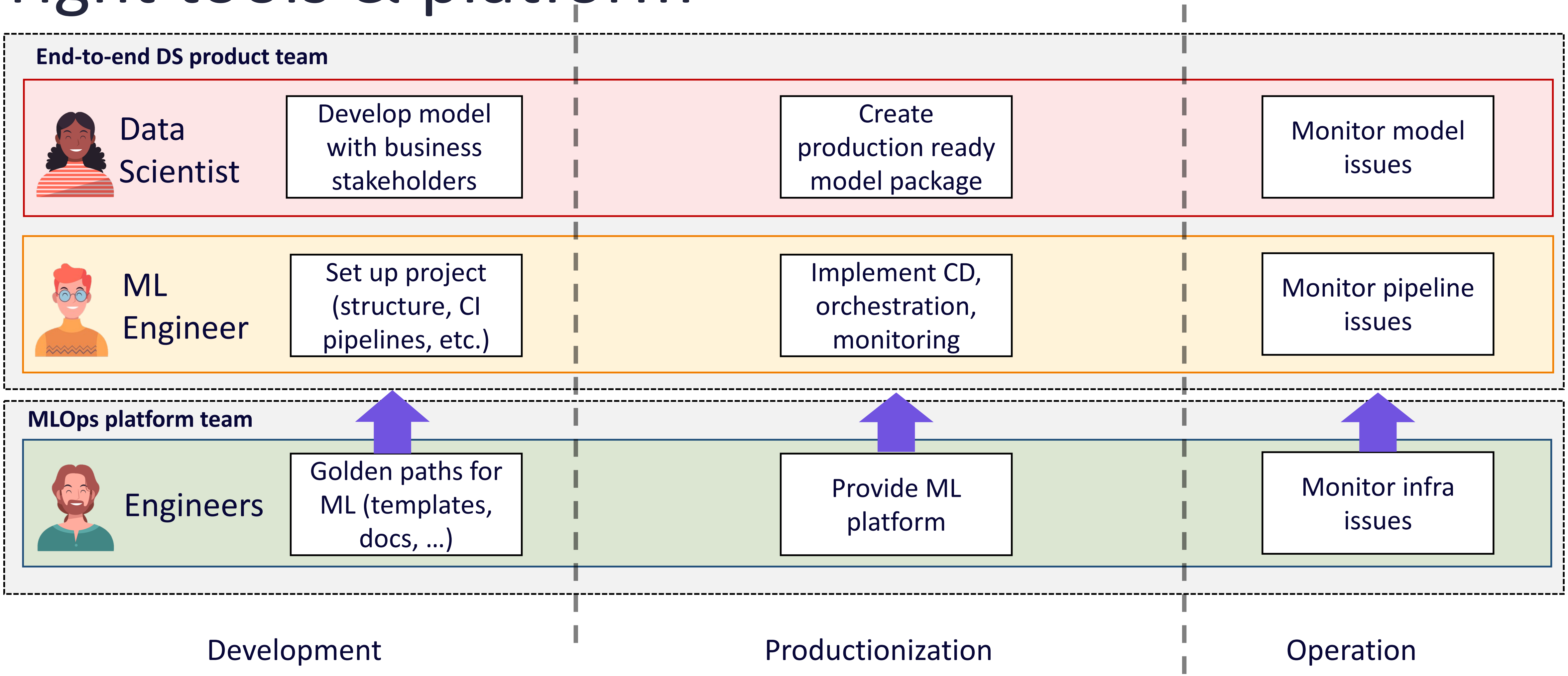

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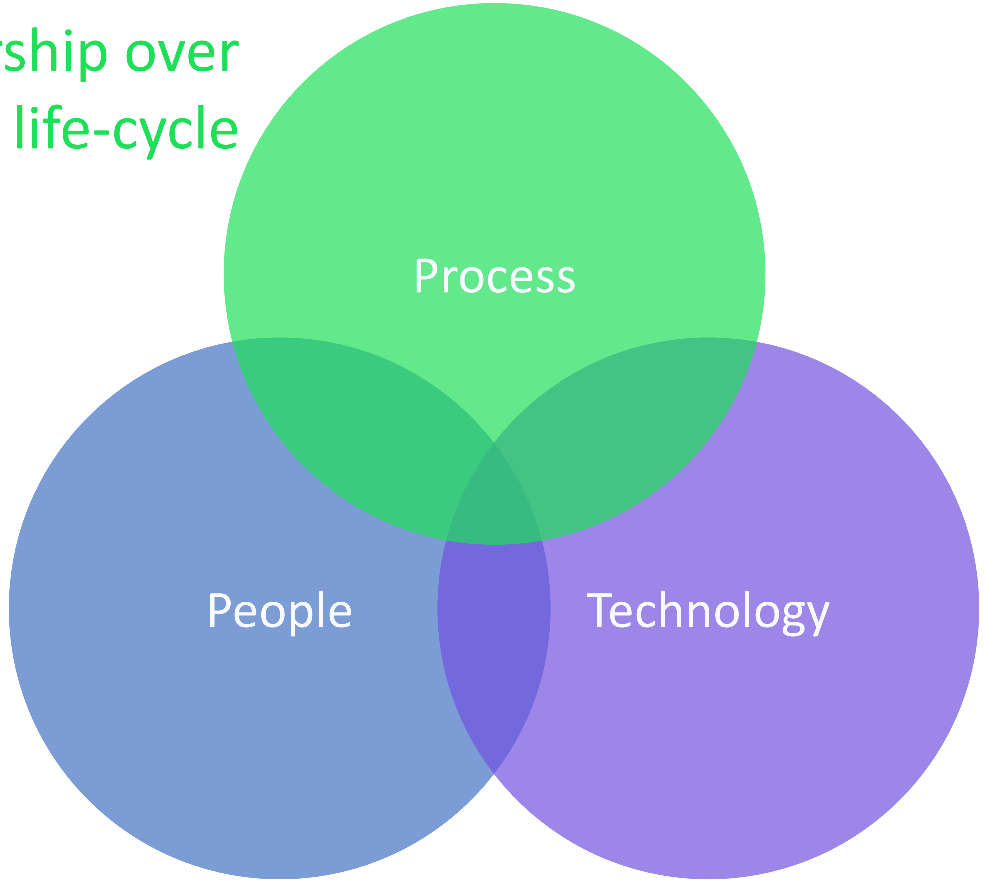

Support the product team with the right tools & platform

Having the right roles & responsibilities

Xebia

MLOps is not *Just* about tooling

Daniël Willemsen

Machine Learning Engineer
Xebia

MLOps is not *Just* about tooling

… it’s about enabling end-to-end responsibility

Daniël Willemsen

Machine Learning Engineer
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