Why you need to monitor your model

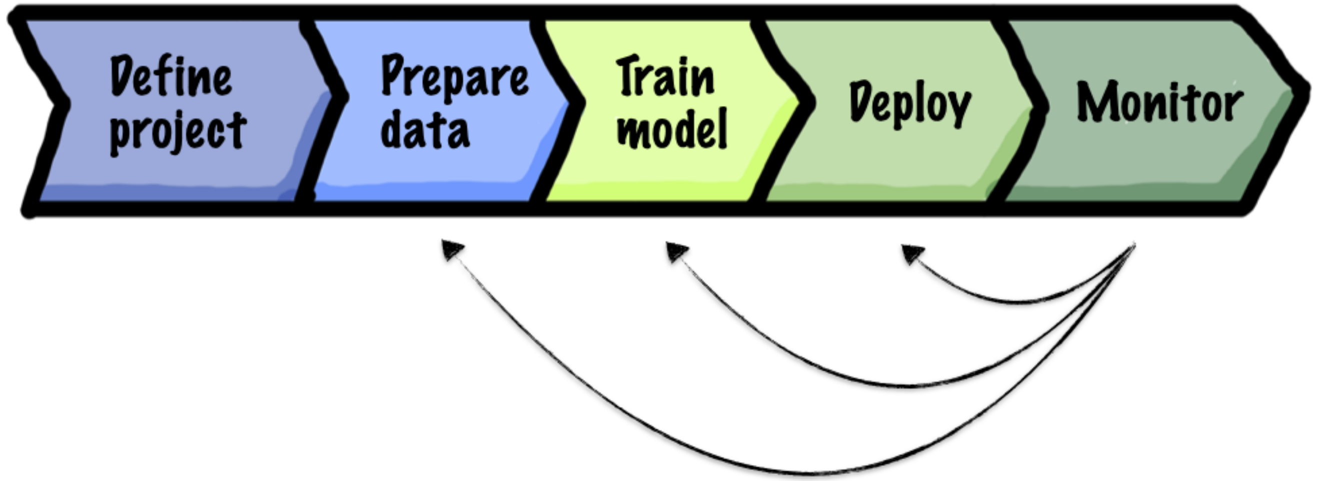
MONITORING MACHINE LEARNING CONCEPTS

Hakim Elakhrass
Co-founder and CEO of NannyML

Machine learning in production

Typical development process

After deployment



Reducing risk of failure

Zillow's case

Reasons for model to fail:

- Software issues
- Drifts in the input data
- Changes in relationship between features and targets

Maximizing business impact

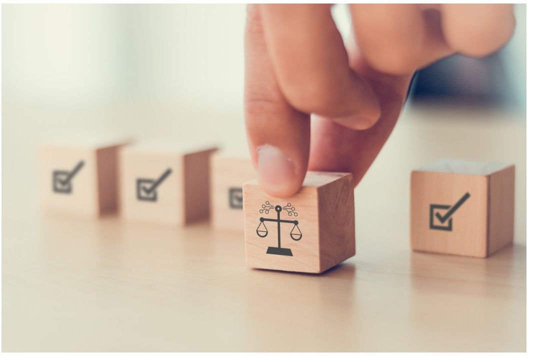
- Optimizing the model in relation to business goals

- Reducing cloud costs

Improving AI safety

Three safety problems:

- Bias - fair output for different groups of users



- Adversarial attacks - detect malicious manipulation of input data

- Lack of explainability - understanding of how the model makes decisions

Changing the world with data

The automatization process

Let's practice!

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The ideal monitoring workflow

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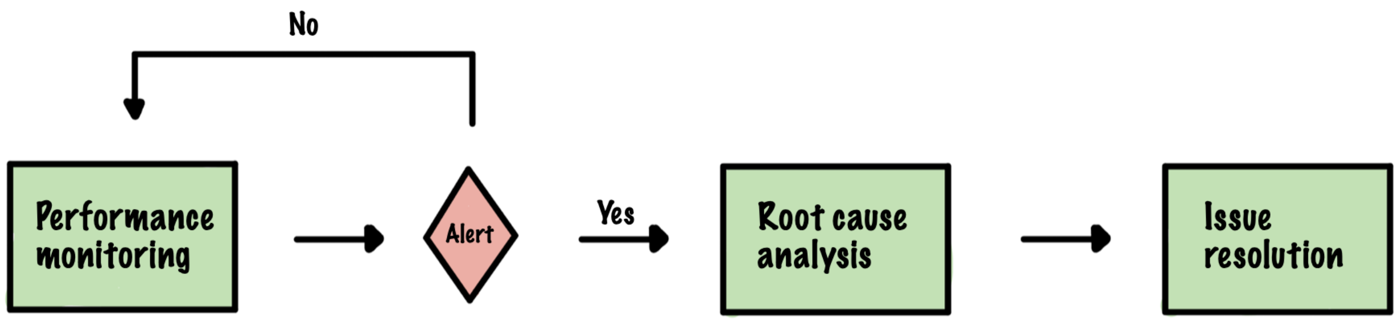
Monitoring workflows

Traditional monitoring workflow

- Calculate technical performance
- Alert based on drifts in the input data
- Results in many false alerts

Ideal monitoring workflow

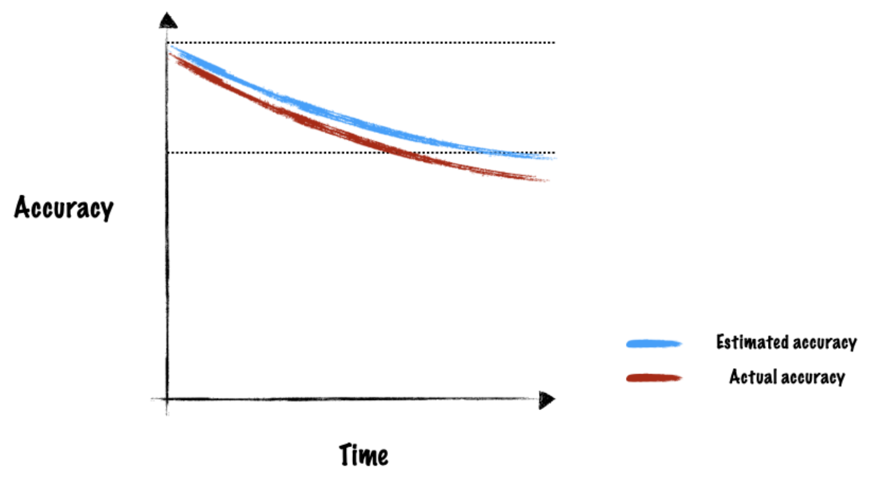
- Technical performance monitoring
  - Calculate and estimate performance
- Root cause analysis
  - Allows to link drifts with drops in performance

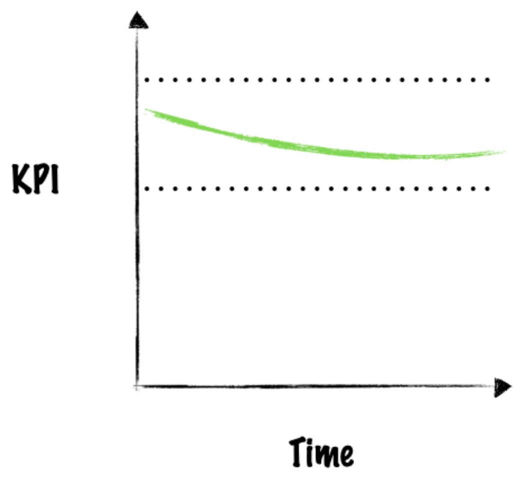


Monitoring performance

Involves:

- Calculating performance - for technical metrics like accuracy
- Estimating performance - if ground truth is not available
- Measuring business impact - monitor key performance indicators



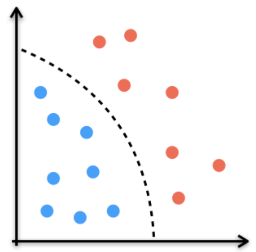


Root Cause Analysis

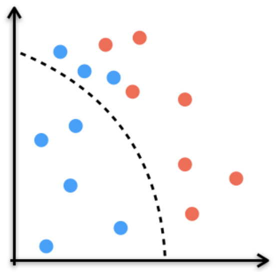
The goal is to investigate:

- Covariate shift - shifts in the input data distribution

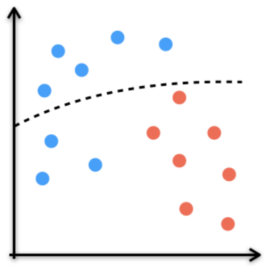
- Concept drift - changes in relationship between features and targets



The original model



Covariate shift

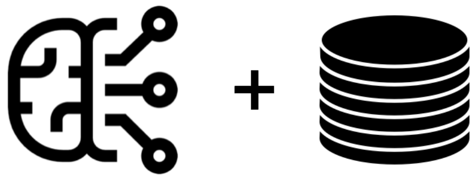


Concept drift

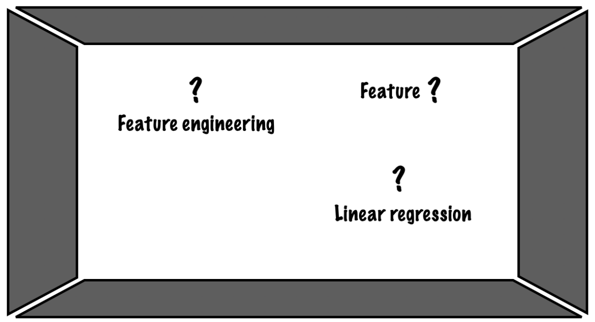
Issue resolution

Possible solutions:

- Retraining - requires additional data and compute



- Refactoring the use case - take a step back and rethink used methods



- Changing the downstream processes - modify processes around the prediction

Let's practice!

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Challenges of monitoring ML models

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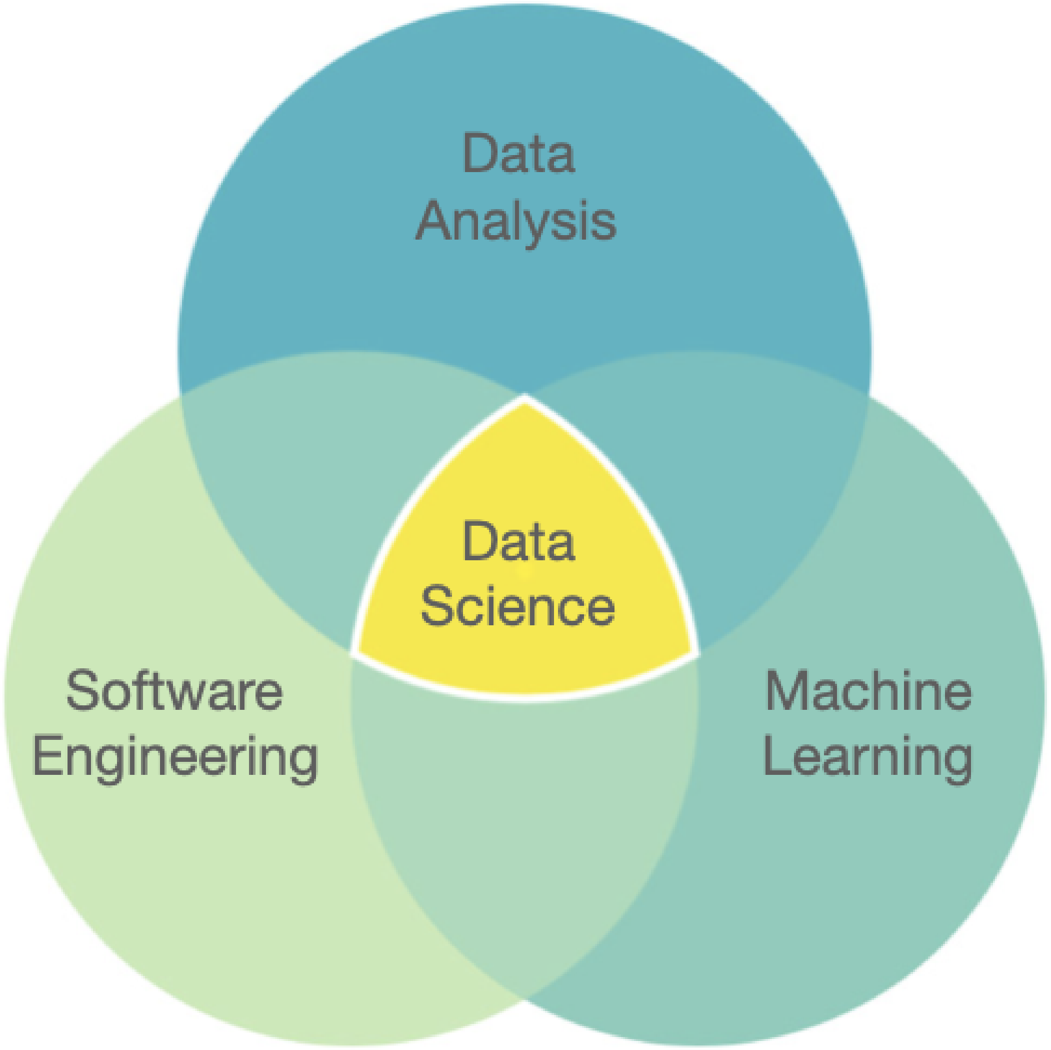
Machine learning project components



The model fails to make predictions

Possible problems :

- Language barriers - combining different programming languages using the "glue" code

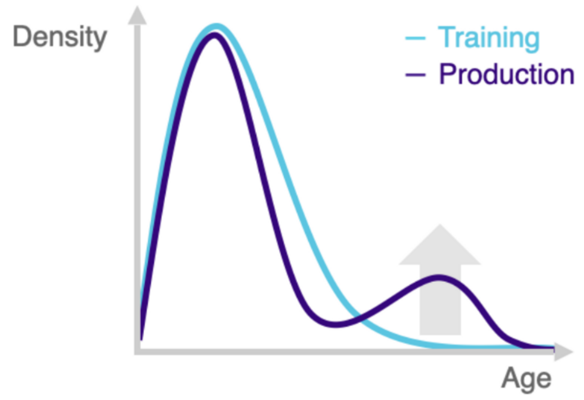
- Code maintenance - compatibility problem of updated dependencies

- Scaling issues - not robust infrastructure to handle more users

The model predictions fail

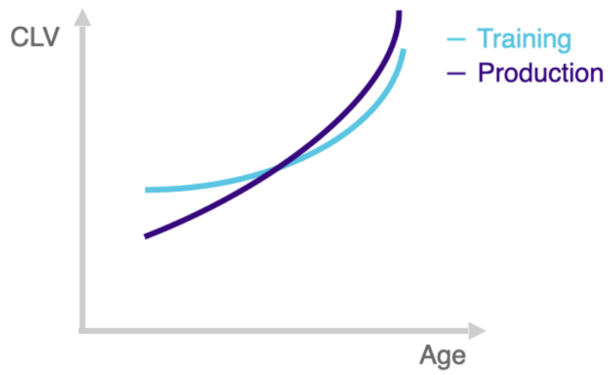
Covariate shift

- Change in the input's distribution
- Possible to detect using statistical methods
- Not every drift impact performance



Concept drift

- Change in the relationship between the input data and targets
- Difficult to detect
- Almost always affects the business impact of the model



Availability of ground truth

Let's practice!

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