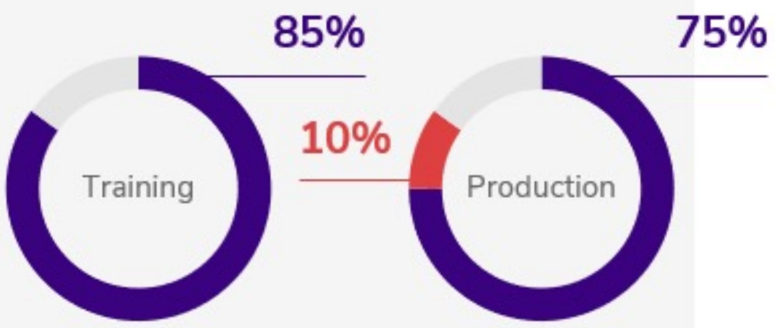
6 Monitoring

AI algorithms deteriorate over time

AI performance drop



The first results after having deployed an AI model, might not live up to the expected training performance. Besides modeling mistakes like overfitting etc., **under specification** or **data shift** might have caused the AI models to fail instantly when put in production.

AI performance decay

It is also possible that AI models only start failing after being deployed for while. This might be caused by **data drift**, where the statistical properties of the model input change. Or **concept drift** where the statistical properties of the outcome AI models are trying to predict fundamentally change over time.

Business impact decline

Often business decisions are taken based on AI generated output. Hence, AI misjudgements, might **cascade** and lead to orders of magnitude more business value lost. It might even lead to AI destroying more value than it was anticipated to bring. On top, making sure business KPIs and technical metrics stay aligned is a challenge. As they can start **diverging** over time.

Monitoring Performance

Track general model performance metrics

- Make sure a ground truth is established, then track model validation metrics

Use granular behavioural metrics

- Go beyond typical performance metrics and also track the behaviour of your model

Track feature behaviour

- Changes in the input data will affect performance of the model

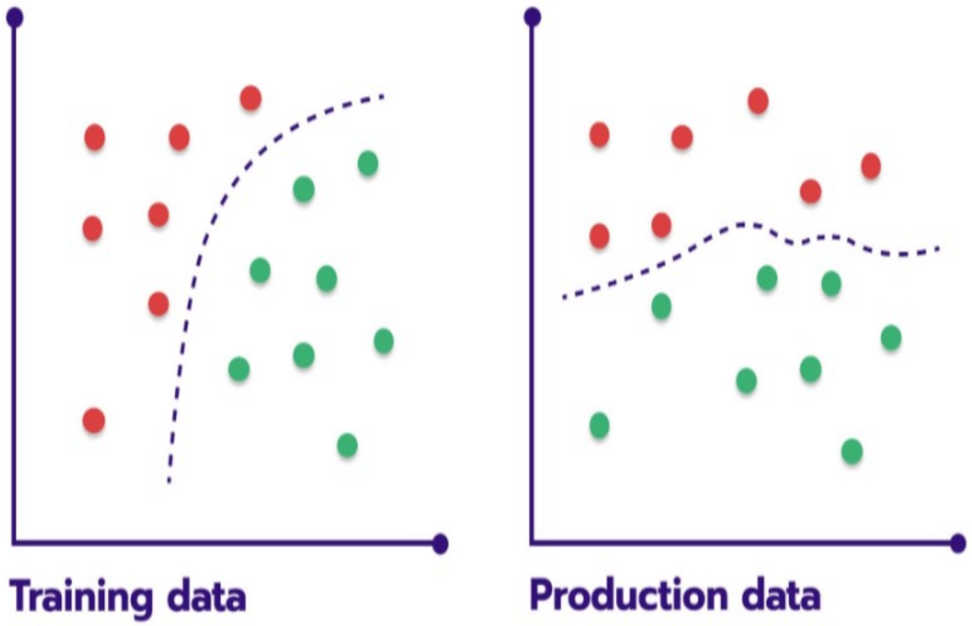
Collect metadata

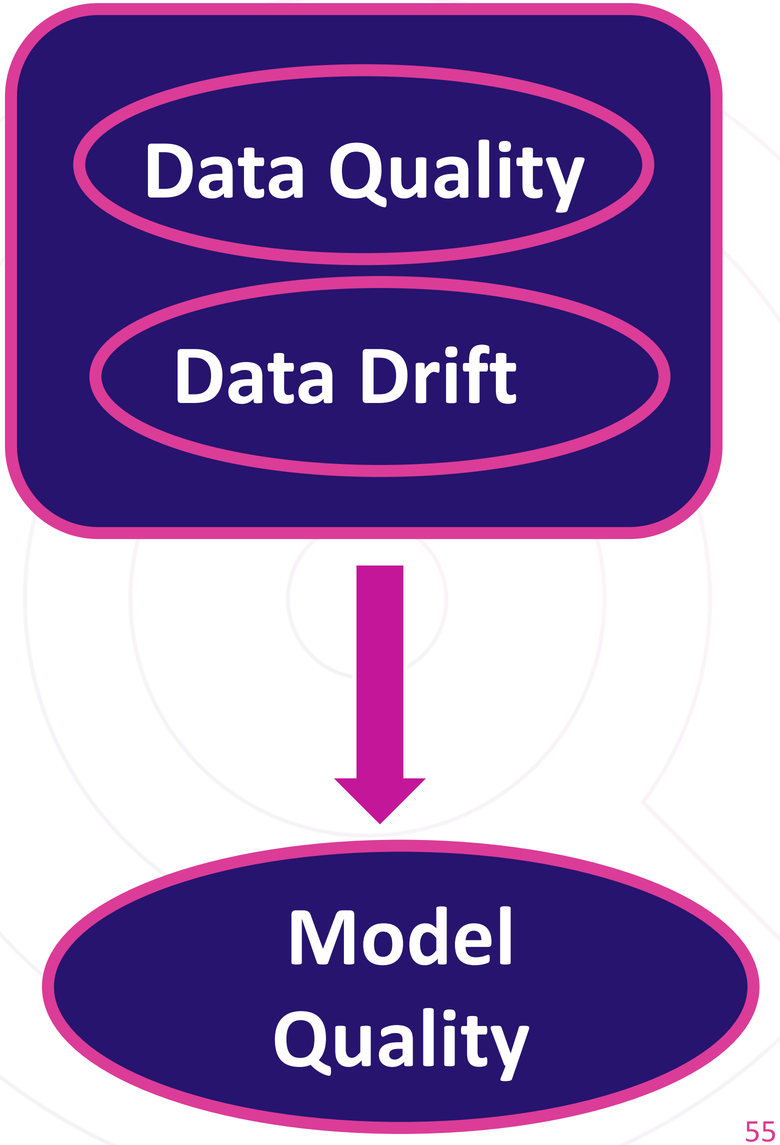
- Use metadata for segmentation of metric’s behaviour

Track data every step of the way

- Understand your data at train, test and prediction time

Data changes





Monitoring data quality

Data processing issues

Model receives incorrect data

- Models receive wrong data or no data at all in production

What can go wrong?

- Wrong source
- Lost access
- Bad queries
- Infrastructure update
- Bad feature code

Data schema change

Model can't deal with severe schema changes

- Models expect the data in certain format

Data catalogue should be part of the designs

- If data changes often, factor it into your design

Changes might be well intended

- Domain experts might see the changes as positive

There must be clear ownership of data

- Especially in large complex organizations

Data loss at source

Data can be lost

- If not replicated, be lost forever

If not tracked it can be hard to identify early

- If no process uses the data, be lost until too late

Data can be corrupted

- Worst case: data can be damaged and still provided

Effects can be local

- Data can partially damaged and harder to identify

Broken upstream models

Model data dependency

- One model's output can be another one's input

Cascade of failing

- If one model fails, all dependant models will fail

Special care is needed

- Linked systems bear an obvious risk.
- Already difficult to monitor one model.

Ensuring data integrity

Errors happen, but what to do?

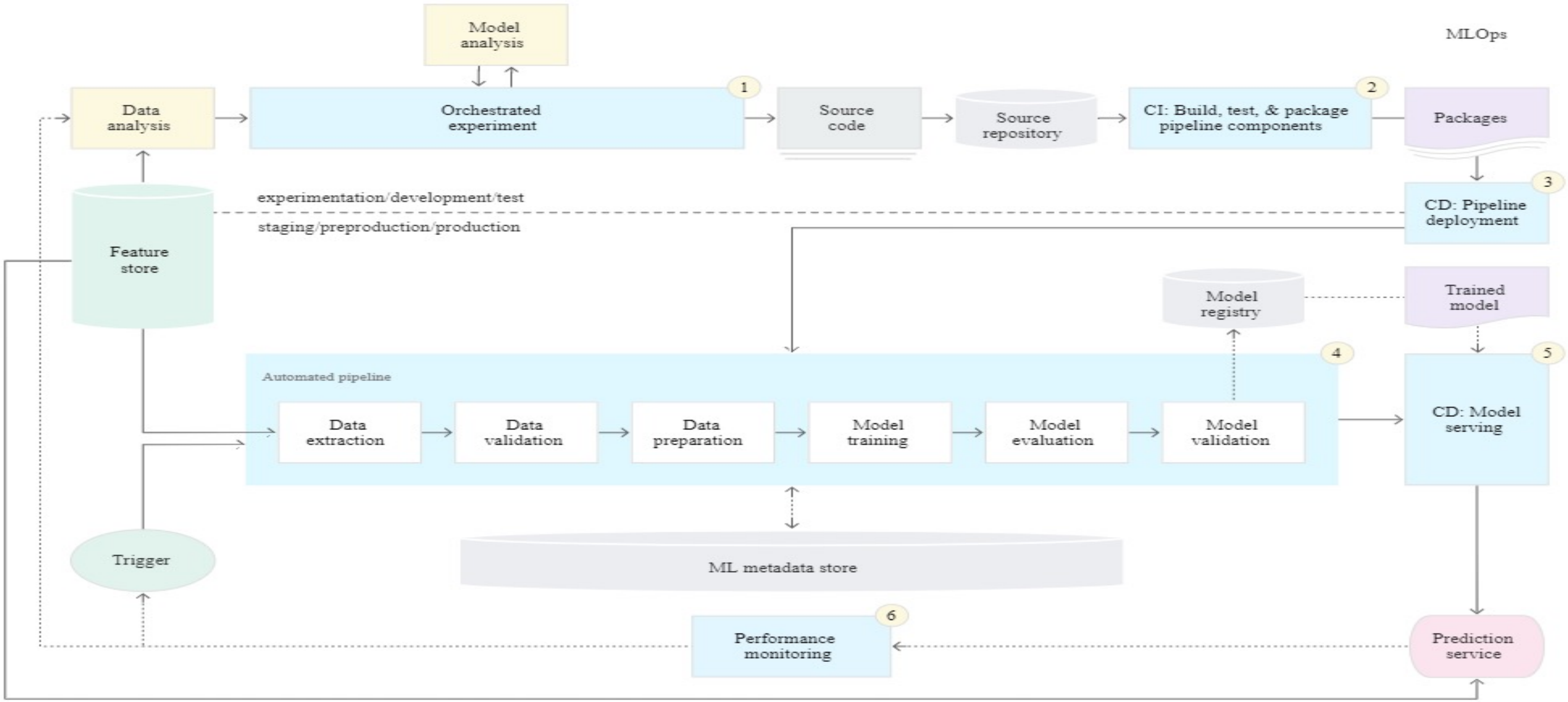
Data schema
- Perform a feature level automated check

Missing data
- Set a combination of monitoring policies to detect and correct

Feature values
- Check if values are abnormal or data shift

Feature processing
- Validate each step of your data's prepossessing journey

MLOps and Monitoring



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