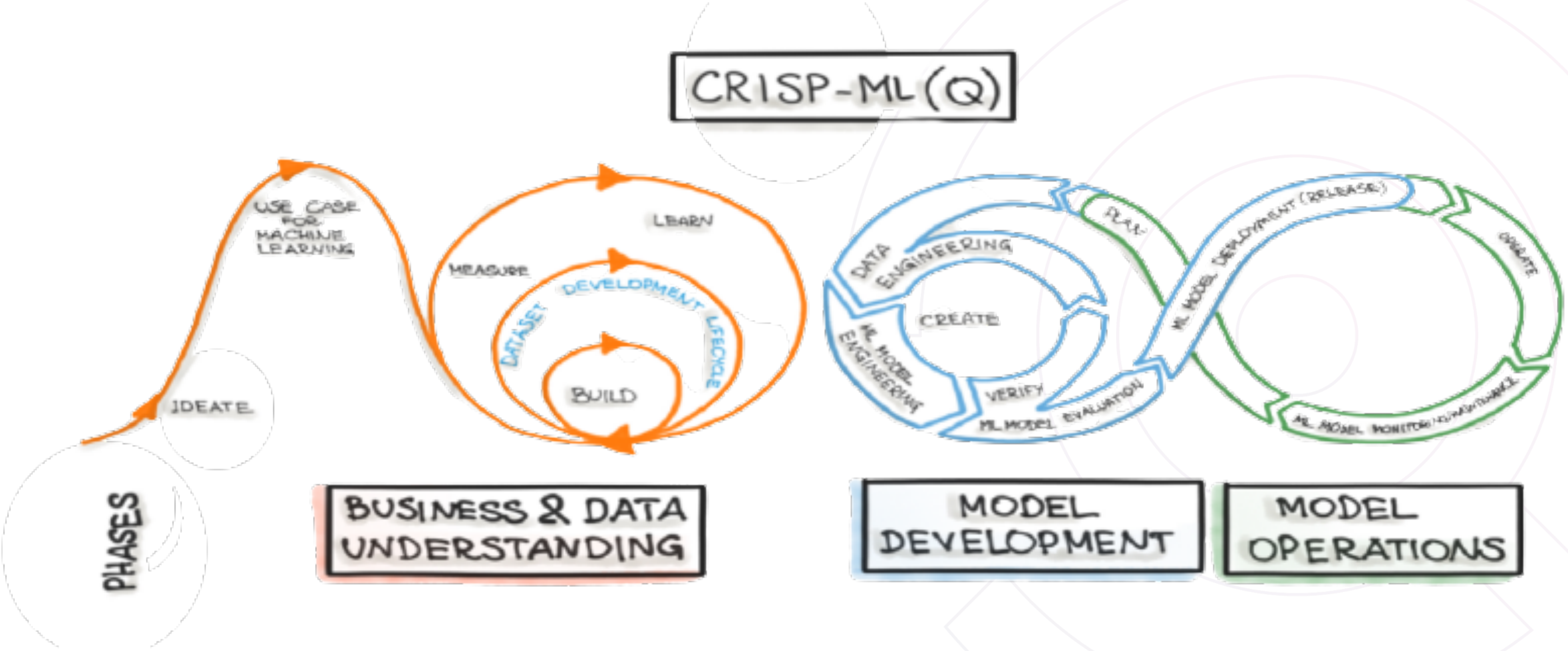
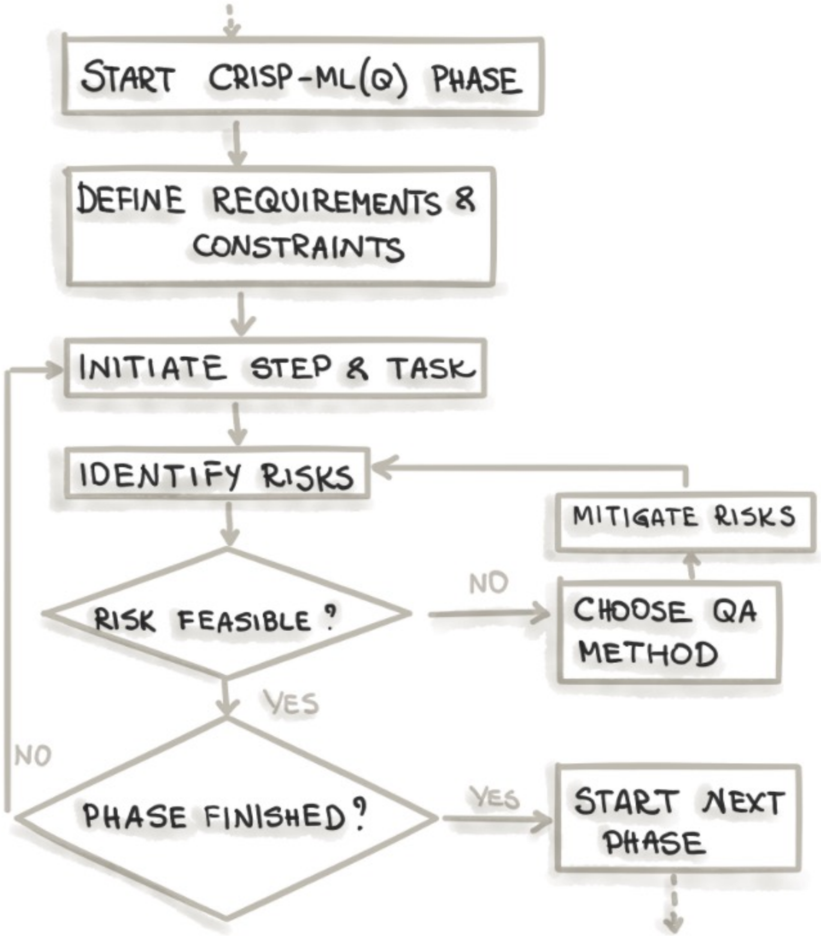
4 CRISP – ML(Q)

Introducing CRISP - ML(Q)



[Google - CD and automation pipelines in ML]

CRISP-ML(Q) Phases



Six phases:

- Business and Data Understanding
- Data Engineering (Data Preparation)
- Machine Learning Model Engineering
- Quality Assurance for Machine Learning Applications
- Deployment
- Monitoring and Maintenance

Business and Data Understanding

From **Business to ML** objectives

Defining the scope

- Data scientist and Business

Establishing a success criteria

- Business, ML and Economic

Feasibility

- Applicability of ML technology, legal constraints and requirements of the application

Data Collection

- Having the data is required before starting as well as data version control

Data Quality Verification

- Data description + requirements + verification

Data Engineering

Data preparation serves the purpose of producing a data set for the subsequent modelling phase.

Data Selection

- Feature selection, data selection, unbalanced classes

Clean Data

- Noise reduction, data imputation

Construction of Data

- Feature engineering, data augmentation

Standardization of data

- Data format, normalization

Machine Learning Engineering

The goal of the modelling phase is to craft one or multiple models that satisfy the given constraints and requirements

Literature research

- Screen the literature, search for baselines, don’t re-invent the wheel

Quality measures and Model selection

- Use the right measures and models for the problem at hand

Domain knowledge

- Incorporate the domain knowledge available, only if improves performance

Reproducibility

- Method and results reproducibility is non-negotiable

Experimental documentation

- Keep track of the changed model performance

Quality Assurance

Validate performance

- Generalization performance on a test set

Determine Robustness

- Real life data can be noisy

Increase explainability for ML practitioner and end user

- Explainable models are easier to improve and more likely to be accepted

Compare result with success criteria

- If success criteria not met, one should backtrack to previous phases

Deployment

The deployment phase of a ML model is characterized by its practical use in the designated field of application

Select right architecture
- Select right architecture for your models, scalability is paramount

Model evaluation under production conditions
- Production data and environment might widely differ from development

User acceptance and usability
- Model might still be unusable, incomprehensible or susceptible to outliers

Minimize risks of unforeseen errors
- Have a fall back plan in case model fails

Deployment strategy
- Deployment should be incremental

Monitoring and Maintenance

The risk of not maintaining the model is the degradation of the performance over time which leads to false predictions

Data drift over time

- Input data is not always similar to training data

ML systems require monitoring

- ML systems are complex, with many possible points of failure

Models need to be updated

- Performance of model deteriorates over time, so they need to be updated

Is not always about the data

- Technical monitoring is also a must