NOVA IMS
Information Management School

10

EVALUATION AND DEPLOYMENT

Machine Learning for Marketing

Acreditações e Certificações

Instituto Superior de Estatística e Gestão da Informação
Universidade Nova de Lisboa

Summary

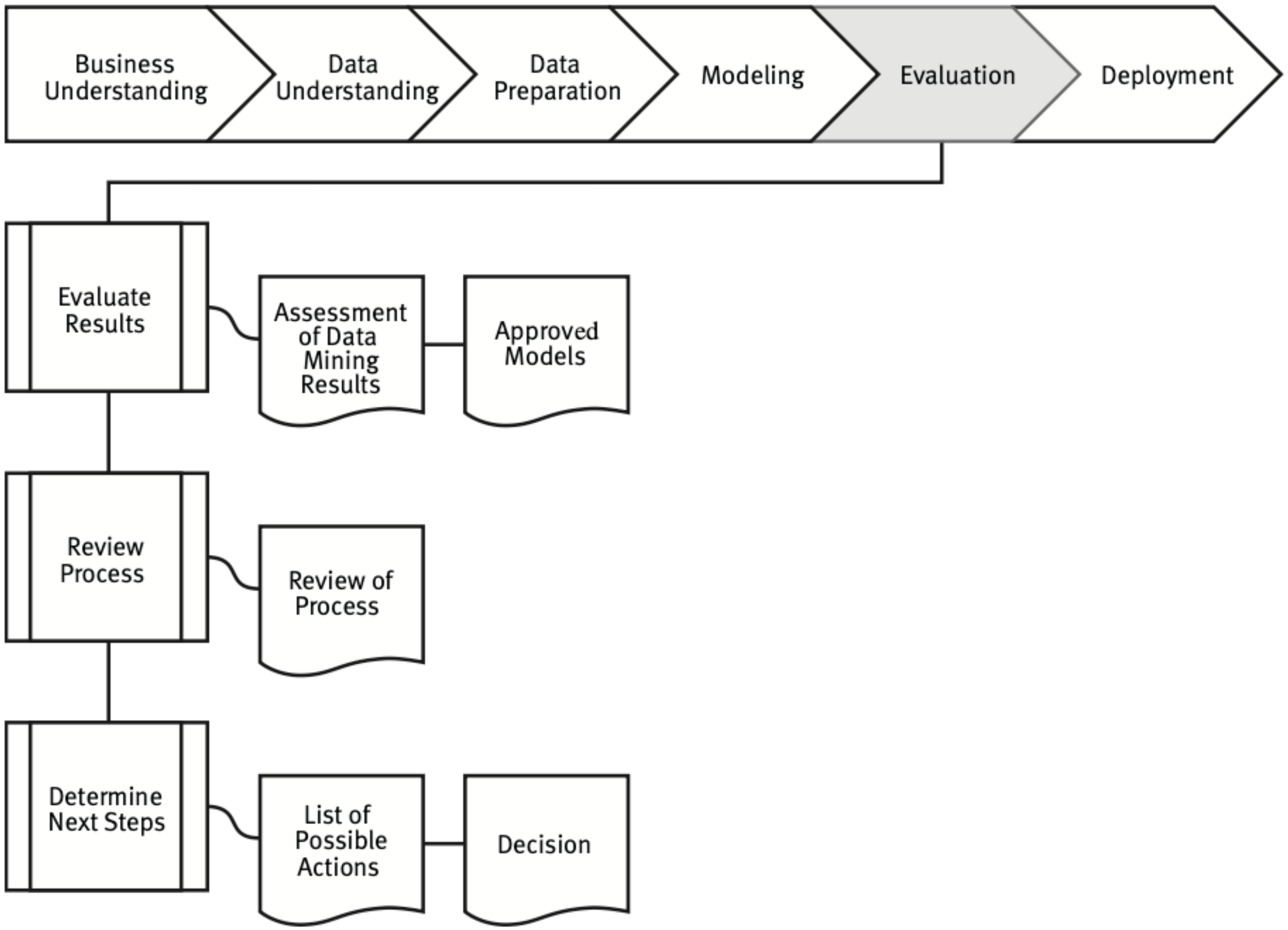
1. Evaluation
2. Deployment

10.1

Evaluation

Evaluation and Deployment

Evaluation


Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Evaluate Results
Assessment of Data Mining Results
Approved Models
Review Process
Review of Process
Determine Next Steps
List of Possible Actions
Decision

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Modeling vs Evaluation results assessment

Modeling

- Done by the modeler according to his/her domain knowledge
- Evaluated against the data mining success criteria and test design
- Only the models are assessed (e.g., not other requirements)
- If multiple models are generated, a comparison/ranking should be done
- Iterations should be done until the best possible models are built

Evaluation

- Done by the modeler and the responsible for validating the business success criteria
- Assesses at what point the model meets the business objectives
- Try to determine if there is some business reason why is the model deficient
- If time and budget allow, define ways to test the model in real application

Outputs

Evaluate results

- Assessment of data mining results against the business success criteria
- Approved models

Review process

- Review of the process

Determine next steps

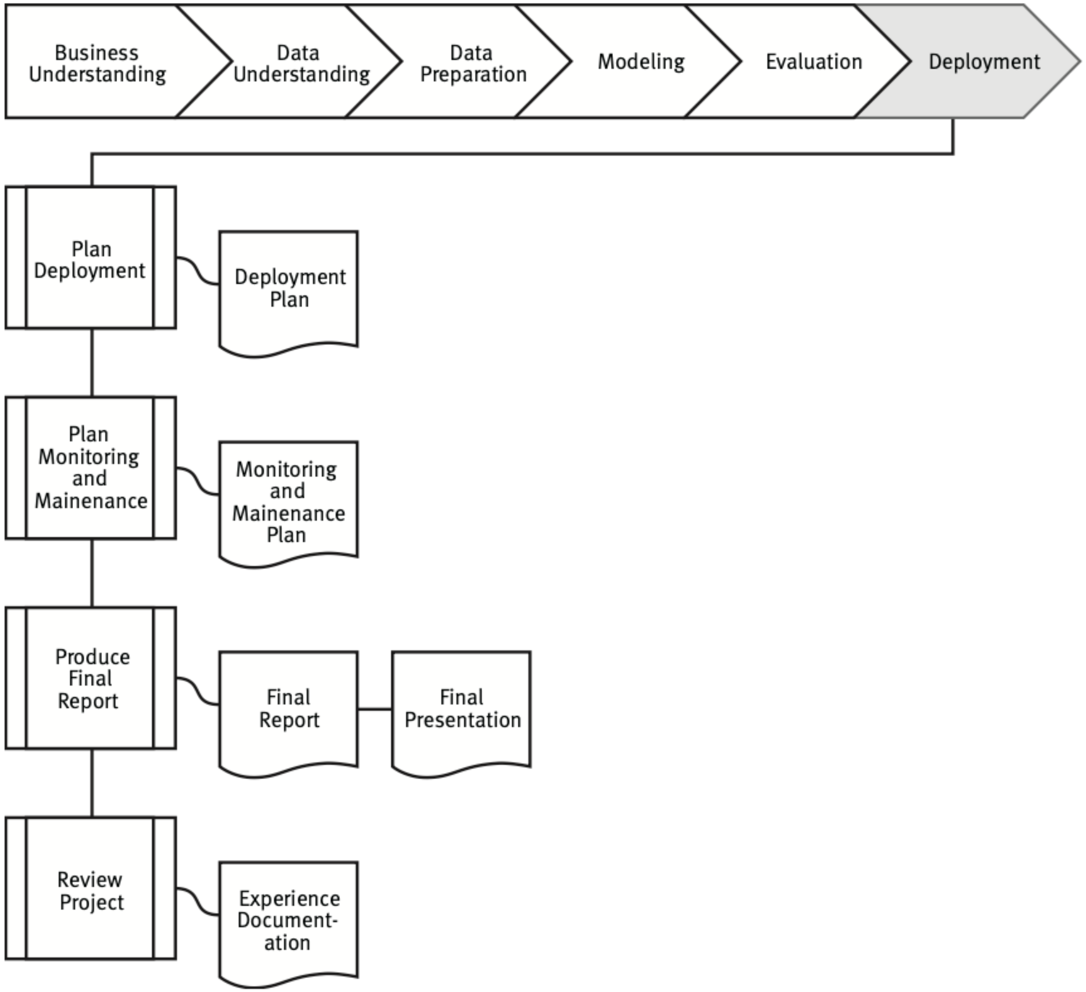
- List of possible actions
- Decision on how to proceed and rationale

10.2

Deployment

Evaluation and Deployment

Deployment


Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Plan Deployment
Deployment Plan
Plan Monitoring and Mainenance
Monitoring and Mainenance Plan
Produce Final Report
Final Report
Final Presentation
Review Project
Experience Document-ation

Deployment plan

- Describe alternative plans for deployment
- Document how knowledge will be propagated to users
- Decide on how to monitor results and measure the benefits (if applicable)
- Establish how the model will be deployed within the organization’s systems
- Identify deployment risks and mitigation measures

Monitoring and maintenance plan

- Specify how to monitor dynamic aspects
- Define how the model performance/accuracy will be monitored
- Define low performance thresholds and what to do when that occurs (e.g., get new data, retrain the model, etc.)
- Define what to do if business objectives changes over time
- Define what tools will be used to monitor the model

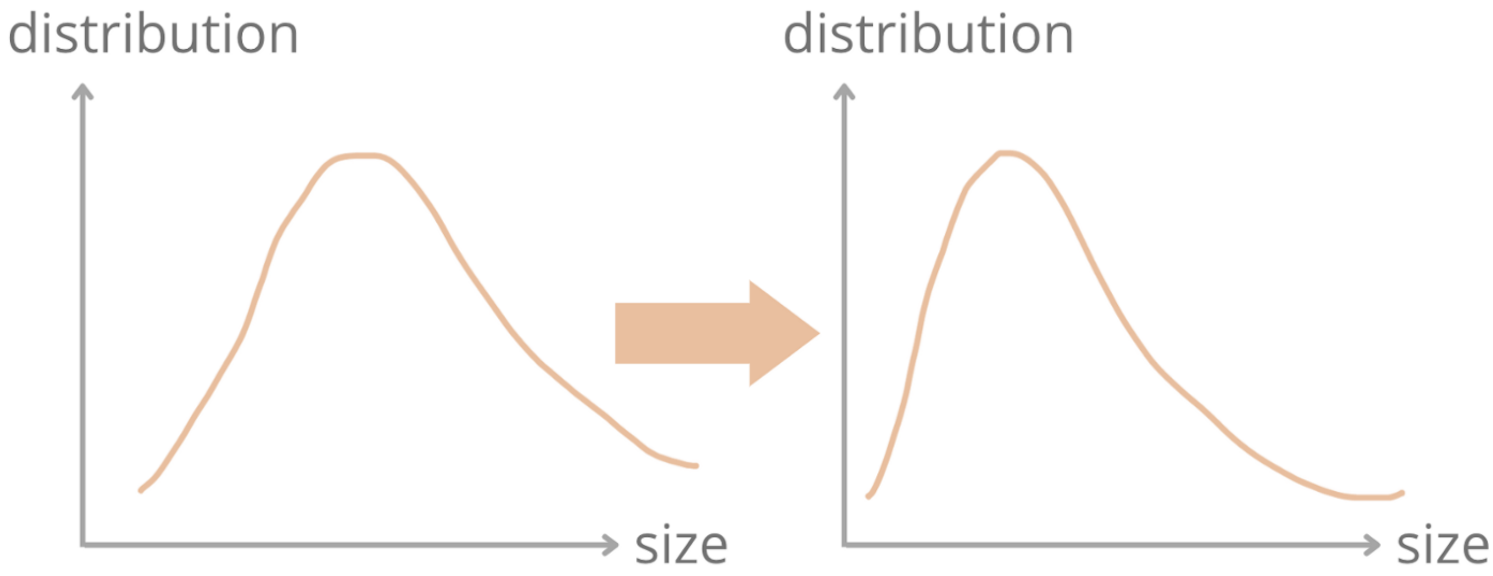
Important! Monitoring for Drift

Drift happens when the model becomes less and less accurate due to changes in the statistical properties of the input features, target variable, or relationships among variables

- Causes for drift:
  - Anomalies
  - Data quality
  - Seasonal effects
- How to monitor drift:
  - Descriptive statistics
  - Distribution changes

Types of drift: Covariate/feature drift

Happens when p(X) changes but p(y|x) remains the same.
The marginal distribution of the input house features changes, but the conditional distribution of house prices given house features stays the same (e.g., model trained with pre-Covid data where there were more houses of larger size in the market)



source: www.towardsdatascience.com

Types of drift: Label drift

Happens when p(y) changes but p(y|x) remains the same.
In the house price prediction example, the house price distribution p(y) could change after when the model was trained previously. For example, the house price has significantly increased during the pandemic, resulting in the house price distribution shifting towards a higher value.

source: www.towardsdatascience.com

Types of drift: Concept drift

Happens when p(y|X) changes but p(X) remains the same.
In the house price prediction example, the conditional probability of housing price given house features p(y|X) could change. Let's reconsider the previous example. Imagine that the distribution of the house sizes does not change. Because people prefer larger houses now, larger houses become more expensive. The conditional probability of housing price given house sizes could change, especially for larger houses.

source: www.towardsdatascience.com

Final report

Should be written according to the target group

- Results obtained (data mining and business)
- Process of building the model
- Costs
- Implementation plans
- Recommendations for future work

Project review

- Summarize experience gained during the project
- Analyze things that worked well, mistakes, lessons learned, etc.
- Generalize aspects that could be helpful in future projects

Tools to help on ML models projects’ lifecycle

- MLflow: https://mlflow.org
- Weights & Biases: https://wandb.ai/site
- Neptune AI: https://neptune.ai
- Comet: https://www.comet.ml/site/
- Valohai: https://valohai.com

Existing models that you can incorporate

- Microsoft cognitive services: https://docs.microsoft.com/en-US/azure/cognitive-services/what-are-cognitive-services
- Google AI services: https://cloud.google.com/products/ai
- Amazon AWS services: https://aws.amazon.com/machine-learning/

Questions?

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