Chapter 02

Process of Data Science Projects

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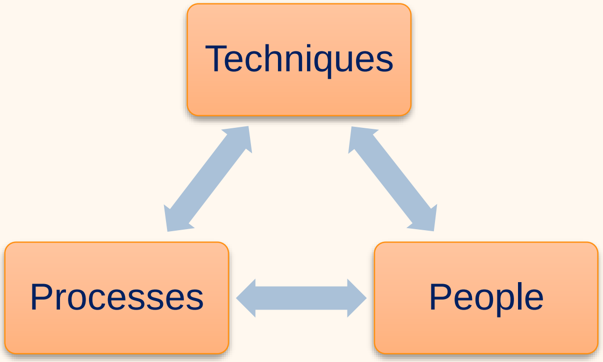
Outline

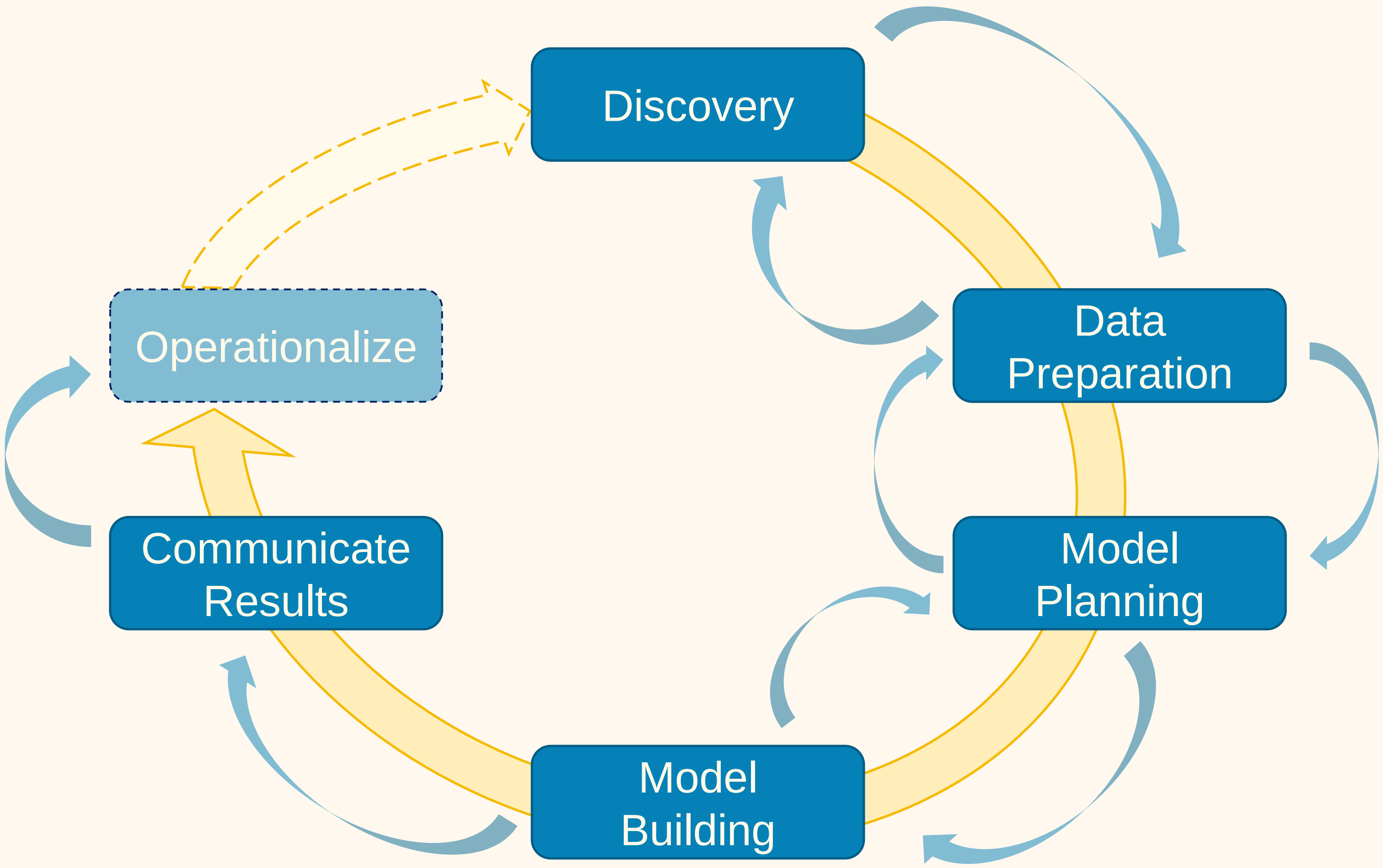
- Generic Process Model
- Roles
- Core Deliverables
- Summary

Processes are Important

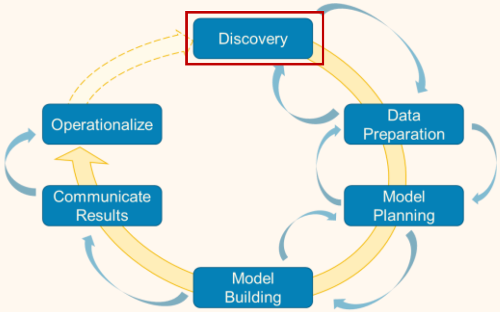
- Techniques
  - Languages, tools, and methods
  - Must be suited for the given problem
- People
  - Require training for the techniques
  - Should be guided through a project by a process
- Process
  - Supports the people
  - Must be accepted by the people
  - Should have a measurable positive effect



Process of Data Science Projects

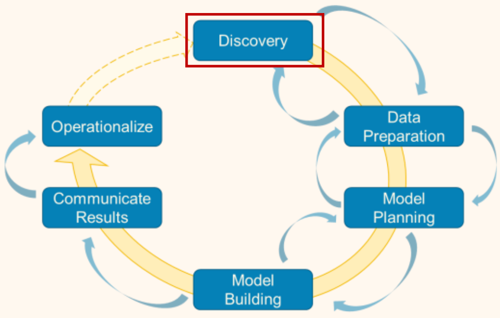


Discovery



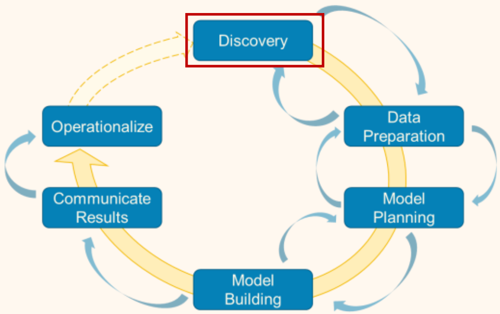
- Initial phase of the project
- Learn the domain
  - Knowledge for understanding the data and the use cases of the project
  - Knowledge for the interpretation of the results
- Learn from the past
  - Identify past projects on similar issues
    - Differences, reasons for failures, weaknesses of past projects
  - Can also be projects of competitors, if reports are available

Discovery



- Frame the problem
  - Framing is the process of stating the data analysis problem to be solved
  - Why is the problem important?
  - Who are the key stakeholders and what are their interests in the project?
  - What is the current situation and what are pain points that motivate the project?
  - What are the objectives of the project?
    - Business needs
    - Research goals
  - What needs to be done to achieve the objectives?
  - What are success criteria for the project?
  - What are risks for the project?

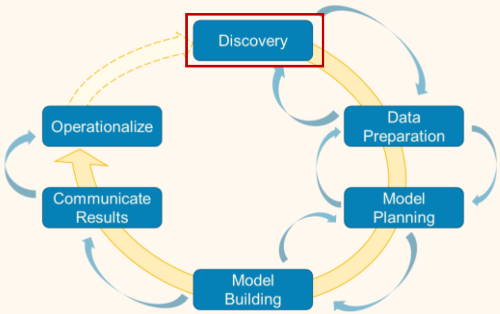
Discovery



- Begin learning the data
  - Get a high-level understanding of the data
    - Maybe even some initial statistics or visualizations of the data
  - Determine requirements for data structures and tools for processing the data

- Formulate hypothesis
  - Part of the „Science“ in „Data Science“
  - Should define expectations
    - „Feature X is well suited for the prediction of …“
    - „The following patterns will be found in the data: …“
    - „Deep learning will outperform …“
    - „Decision trees will perform well and allow insights into …“
  - Should be discussed with stakeholders

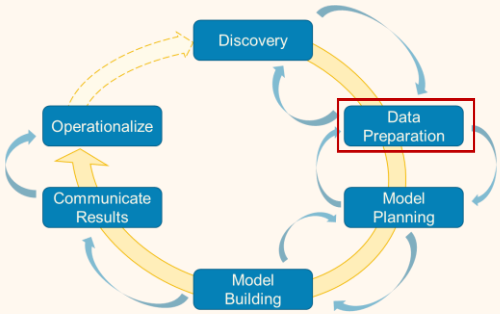
Discovery



- Analyze available resources
  - Technologies
    - Resources for computation and storage
    - Licenses for analysis frameworks
  - Data
    - Is the available data sufficient for the use case?
    - Would other data be required and could the additional data be collected within the scope of the project?
  - Timeframe
    - Scope in calendar time and person months
  - Human resources
    - Who is available for the project?
    - Is the skillset a good match for the tasks of the project?

→ Only start project if the resources are sufficient!

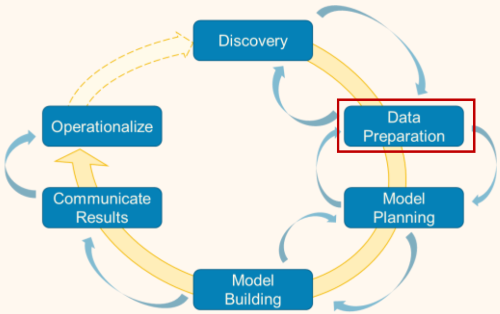
Data Preparation



- Create the infrastructure for the project
  - Usually different from infrastructure in which data is made available to you
  - Warehouse/csv-file/… ←→ distributed storage that enables analysis
    - Could also be simpler, for small data sizes

- Extract – Transform – Load (ETL) the data
  - Define how to query existing database to extract required data
  - Determine required transformations of the raw data
    - Quality checking (e.g., filtering of missing data, implausible data)
    - Structuring (e.g., for unstructured data, differences in data structures)
    - Conversions (e.g., timestamps, character encodings)
  - Load the data into your analysis environment

Data Preparation



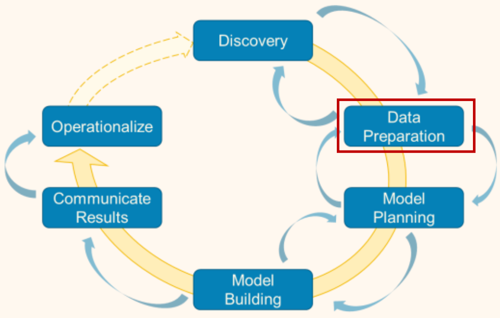
- ELT vs. ETL
  - Transformations can be very time-consuming for big data
  - Might not be possible without using the analysis infrastructure

→ Load raw data, transform afterwards → ELT!

- Also allows more flexibility with transformations
  - E.g., testing the effect of different transformations

- Allows access to raw data

Data Preparation

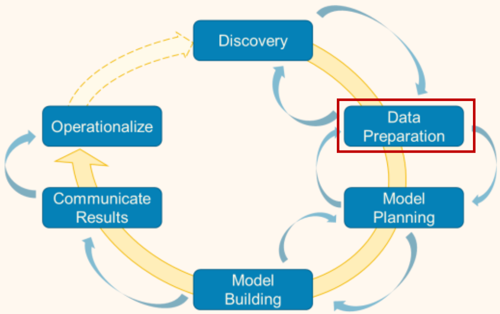


- Get a deep understanding of the data
  - Understand all data sources
  - E.g., what does each column in a relational database contain?
  - How can a structure be imposed on semi-/quasi-/unstructured data?

- Survey and visualize data
  - Descriptive statistics
  - Correlation analysis
  - Visualizations like histograms, density plots, pair-wise plots, etc.

- Clean and normalize data
  - Discard data that is not required
  - Normalize to remove scale effects

Data Preparation

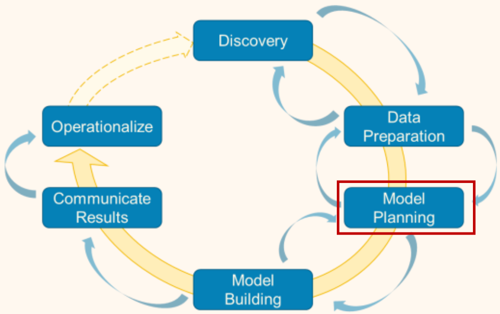


- Clean data
  - Discard data that is not required
  - Can make the difference between a complex infrastructure and a single machine for analysis

  - Example:
    - 100 million measurements
    - 10 floating point features per measurement → 80 Bytes per measurement
    - 3 useful features ≈ 24 Bytes per measurement
    - 7.45 Gigabytes with all features, 2.23 Gigabytes with only useful features

    → Can use my laptop for cleaned data without problems

Model Planning



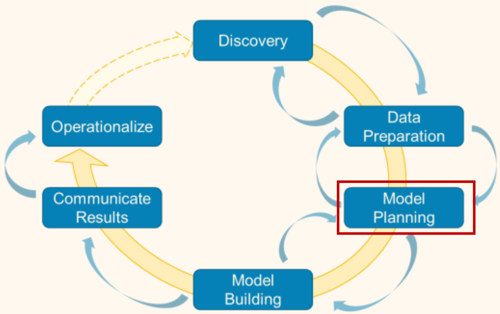
- Determine methods for data analysis

- Should be well-suited to meet objectives
  - Often determines the type of method
    - Classification, regression, clustering, association mining, …
  - Other factors can also restrict the available methods
    - For example, if insight is important, „blackbox“ methods cannot be used

- Should be well-suited for the available data
  - Volume, structure, …

A blackbox method is a method where you only get results, but do not really understand why the output is computed that way.
A whitebox method also explains why the output is as it is.

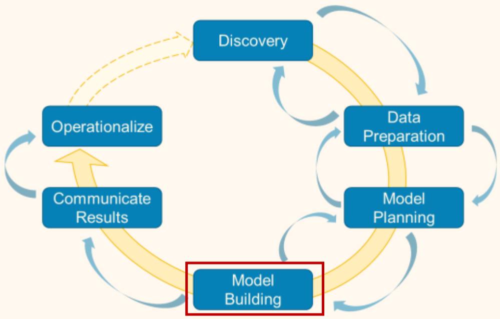
Model Planning



- Methods for data analysis may cover
  - Feature modeling, e.g., for text mining
  - Feature selection, e.g., based on information gain, correlations, etc.
  - Model creation, e.g., different models that may address the use case
  - Statistical methods, e.g., for the comparison of results
  - Visualizations, e.g., for the presentation of results

- Split data into different data sets
  - Training data, validation data, test data
  - „Toy“ data for local use in case of big data
    - Same structure, but very small

Model Building

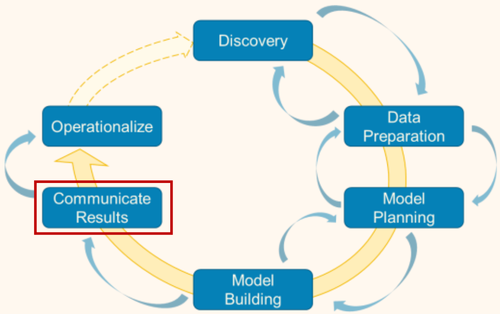


- Perform the analysis using the planned methods
  - Often iterative process!

- Separate phase, because this can be VERY time consuming
  - Use toy examples for model planning
  - Use real big data set with potentially lots of hyper parameters for tuning during model building

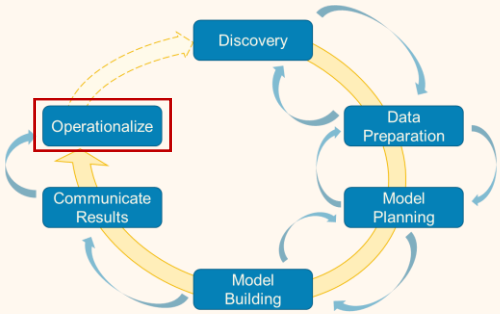
- Includes the calculation of performance indicators

Communicate Results



- Main question: Was the project successful?
- Compare results to hypothesis from the discovery phase
- Identify the key findings
- Try to quantify the value of your results
  - Business value, e.g., the expected Return On Investment (ROI)
  - Advancement of the state of the art
- Summarize findings for different audiences

Operationalize



- Implement results in operation
  - Only in case of successful projects
- Should run a pilot first
  - Determine if expectations hold during the practical application
  - All kinds of reasons for failures
    - Rejection by users, shift in data reduces model performance, ...
- Define a process to update and retrain model
  - Data gets older, models get outdated
  - Data driven models should be updated regularly
  - Process is required

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Roles within Projects

- A role is „a function or part performed especially in a particular operation or process” (Merriam-Webster)
- Role ≠ Person
  - One role can be fulfilled by multiple persons
  - One person can fulfill multiple roles
- Roles assign responsibilities within processes
  - In practice, roles are often related to job titles
    - „Software Developer“, „Database Administrator“, „Project Manager“, …

Roles for Data Science Projects

Role	Description
Business User	• Someone who uses the end results • Can consult and advise project team on value of end results and how these will be operationalized
Project Sponsor	• Responsible for the genesis of the project • Generally provides the funding • Gauge the value from the final outputs
Project Manager	• Ensure key milestones and objectives are met on time and at expected quality • Plans and manages resources
Business Intelligence Analyst	• Business domain expertise with deep understanding of the data • Understands reporting in the domain, e.g., Key Performance Indicators (KPIs)
Data Engineer	• Deep technical skills to assist with data management and ETL/ELT
Database Administrator	• Provisions and configures database environment to support the analytical needs of the project
Data Scientist	• Expert on analytical techniques and data modeling • Applies valid analytical techniques to given business problems • Ensures analytical objectives are met

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Deliverables

- A deliverable is a tangible or intangible good or service produced as a result of a project.
  - Are often parts of contracts
  - Should meet stakeholder‘s needs and expectations

- Four core deliverables for data science projects
  - Sponsor presentation
  - Analyst presentation
  - Code
  - Technical specifications

Sponsor Presentation

- „Big Picture“ of the project
- Clear takeaway messages
  - Highlight KPIs
  - Should aid decision making
- Should address a non-technical audience
- Clean and simple visualizations
  - For example, bar charts, line charts, …

Analyst Presentation

- Describe analysis methods and data
  - General approach
  - Interesting insights, unexpected situations
- Details on how results change current status
  - Business process changes
  - Advancement of the state of the art
- May use more complex visualizations
  - For example, density plots, histograms, boxplots, ROC curves, …
  - Should still be clean and not overloaded

Code and Technical Specification

- All available code of the project
  - Often code is prototypical („hacky“) because results are more important than clean code

- Enables operationalization
  - May re-use code as is
  - May adopt code or clean up code
  - May rewrite same functionality in a different language/for a different environment

- Technical specification should be provided as well
  - Description of the environment
  - Description of how to invoke code

Expected Deliverables by Role

Role	Deliverable
Business User	Expects a sponsor presentation: ➢ Are the results good for me? ➢ What are the benefits for me? ➢ What are the implications for me?
Project Sponsor	Expects a sponsor presentation: ➢ What is the impact of operationalizing the results? ➢ What are the risk and what is the potential ROI? ➢ How can this be evangelized within the organization (and beyond)?
Project Manager	• Responsible for the timely availability of all deliverables • Responsible for the sponsor presentations
Business Intelligence Analyst	Expects an analyst presentation: ➢ Which data was used? ➢ How will reporting change? ➢ How will KPIs change?
Data Engineer	• Responsible for data engineering code and technical documentation
Database Administrator	• Responsible for infrastructure code and technical documentation
Data Scientist	• May be the target audience for analyst presentations. • Responsible for data analysis code and technical documentation • Responsible for the analyst presentation • Support of the project management with the sponsor presentation

Data as Deliverable

- Only applicable if new data was collected/generated

- Sharing the data may be very important
  - Especially in research to enable reproducible and replicable research

- Sharing may be internal (industry) or public (research)
  - Use stable links for references to prevent link rot
  - Ideally Digital Object Identifiers (DOIs)

- Should not only contain the data, but also metadata and tools for collecting the data

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Summary

- Generic process for data science projects with six phases
  - Discovery, data preparation, model planning, model building, communication of results, and operationalization
- Different actors in different roles involved in project
  - Expectations depend on role
- Four core deliverables fulfill most stakeholder needs
  - Sponsor presentation, analyst presentation, code, technical specification
- Data may also be a deliverable