



# AI4Business

## Developing AI tools



# Roadmap AI4Business



Introduction to AI



Developing AI tools



Data and Value



Deploying AI



Monitoring



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2. Project stages
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# 1 Typical AI team



# AI team members

## Core team

- Data Science Team Lead
- Data Scientist
- Data Engineer

## Supporting roles

- Business Intelligence Analyst
- Database Administrator
- DevOps / MLOps



# Data Science Team Lead

**Role:**

Manages the data science team and plan projects

**Goal:**

Make sure business goal are aligned with data vision to create value

**Toolkit:**

SQL, Python

**Skills:**

- Leadership and project management
- Interpersonal communication
- Data analysis + visualization
- Predictive modeling
- Business mindset



# Data Scientist

**Role:**

Collects, analyzes and interprets the data to propose business decisions

**Goal:**

Construct the means for extracting business-focused insights from data

**Toolkit:**

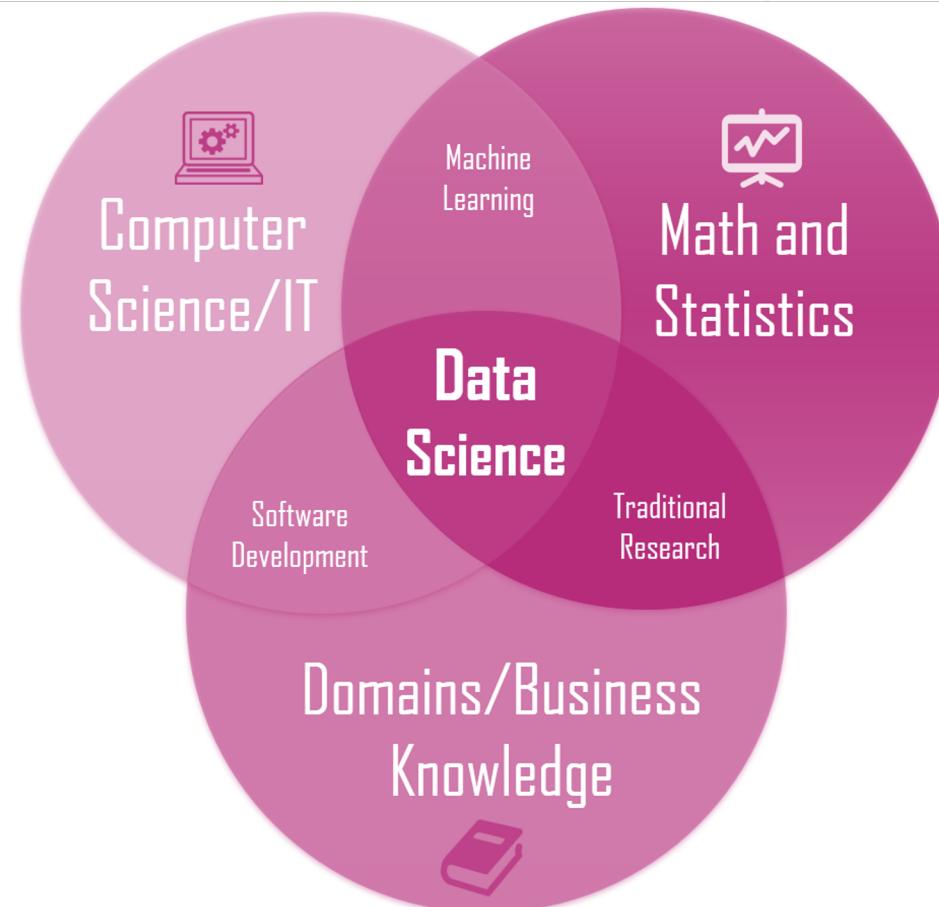
Python, Scikit-learn, Pandas, Numpy, Tensorflow, SQL

**Skills:**

Predictive modeling  
Data visualization and storytelling  
Maths and Stats  
ML and DL algorithms



# Data Scientist





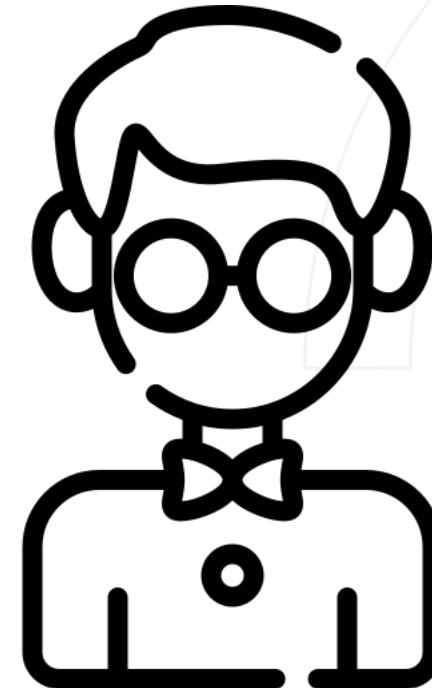
# Data Engineer

**Role:**

Design, build and implement the data infrastructure that fuels machine learning and AI analytics

**Goal:**

Integrate and manage data from various sources to support data scientists with systems to build predictive pipelines

**Toolkit:**

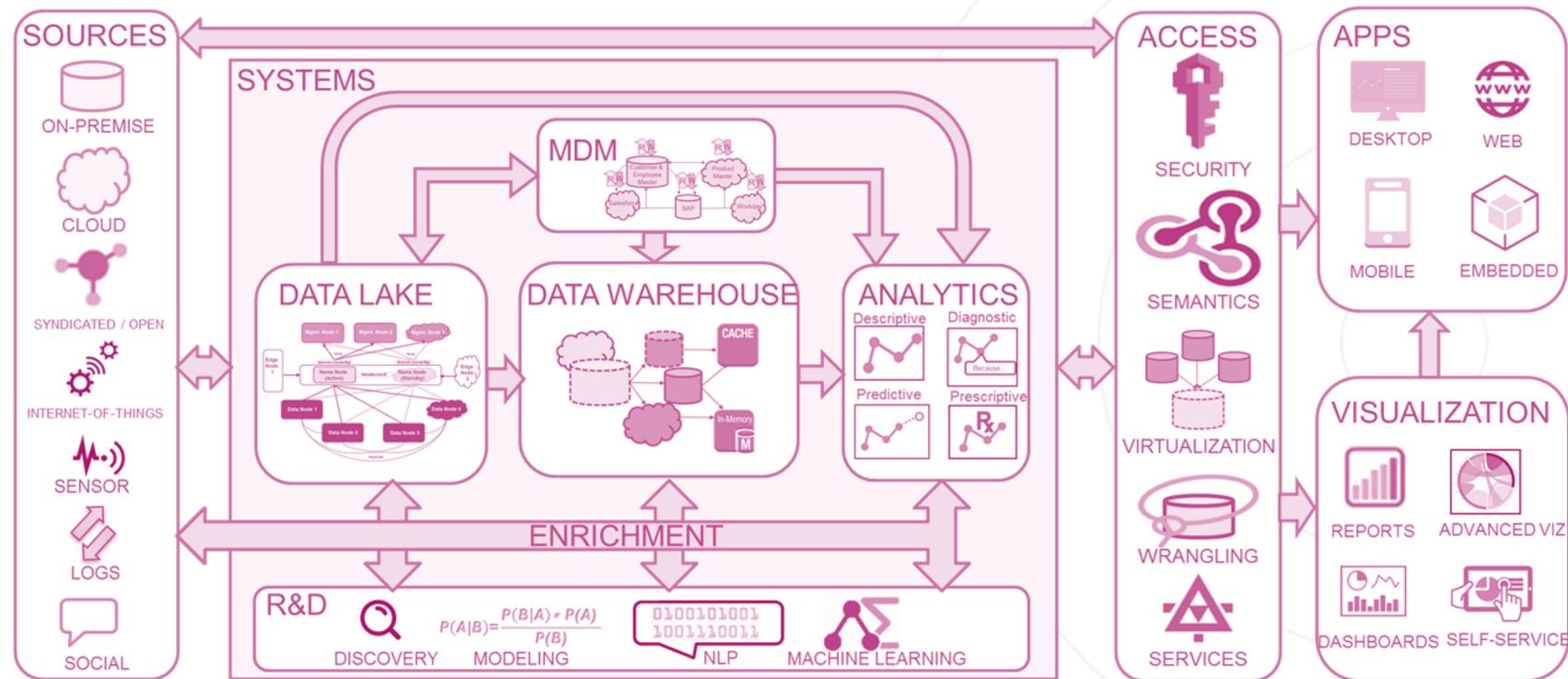
Python, SQL, ETL tools

**Skills:**

Data warehousing solutions  
Database systems  
Data modeling  
Data APIs

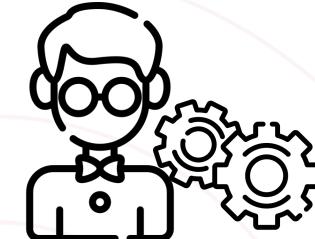


# Data Engineer





# Supporting roles



	<b>Business Intelligence Analyst</b>	<b>Database Administrator</b>	<b>DevOps / MLOps</b>
<b>Role</b>	Improves business processes via data; intermediary between DS team and department	Ensures data availability to a DS team	Integrates ML solutions into existing system
<b>Skills</b>	Data modeling Data visualization tools Communication skills Business understanding	Backup & Recovery Data modeling and design Distributed Computing Data security	Cloud Infrastructure Virtualization Knowledge of CI/CD systems
<b>Department</b>	Every department	IT Department	IT Department



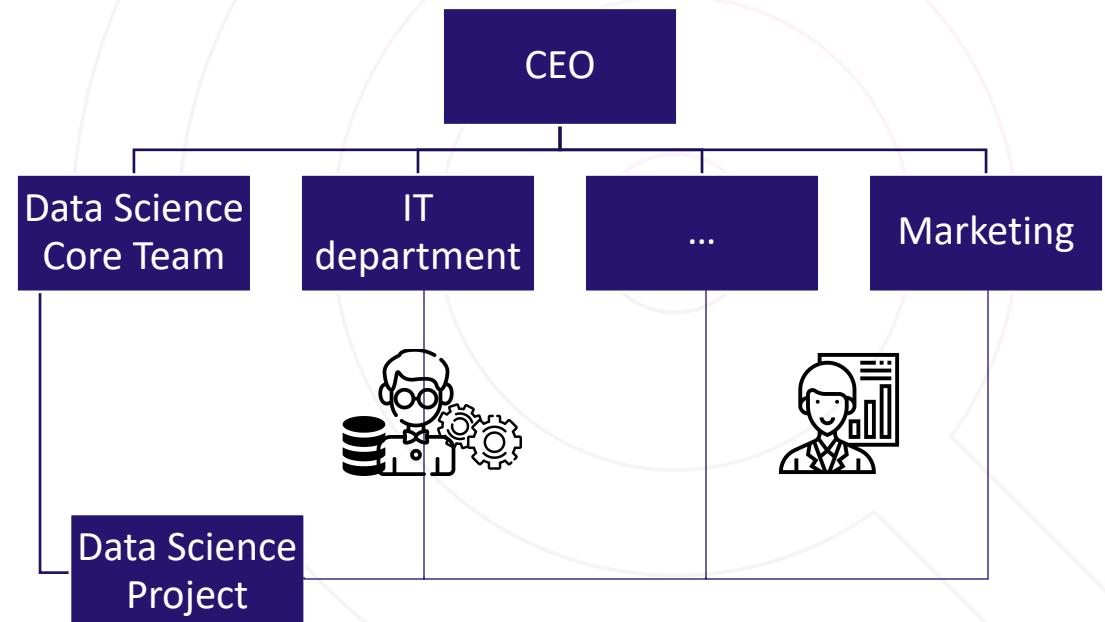
# Business Intelligence Analyst





# Organizational structure

- Data Science Team is
  - a separate organizational unit
  - reporting directly to CEO
- One team serves the whole organization in a variety of projects
- Supported by:
  - Database Administrators + MLOps from IT
  - BI Analysts at a departmental level
- Data Science Team should participate in activities of business units





# Exercise

## Who said what?

- My dashboard shows that sales are down every April in the past 4 years
- My model predicts that sales in November will go up
- I created a way for you to access sales data on a monthly level
- You are assigned to this sales project based on your retail experience
- Your ML model will be up and running in the application by tomorrow

## Role

- ...
- ...
- ...
- ...
- ...



# Exercise

## Who said what?

- My dashboard shows that sales are down every April in the past 4 years
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- I created a way for you to access sales data on a monthly level
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## Role

- BI analyst
- Data scientist
- Data engineer
- Team lead
- MLOps engineer

## 2 Project stages

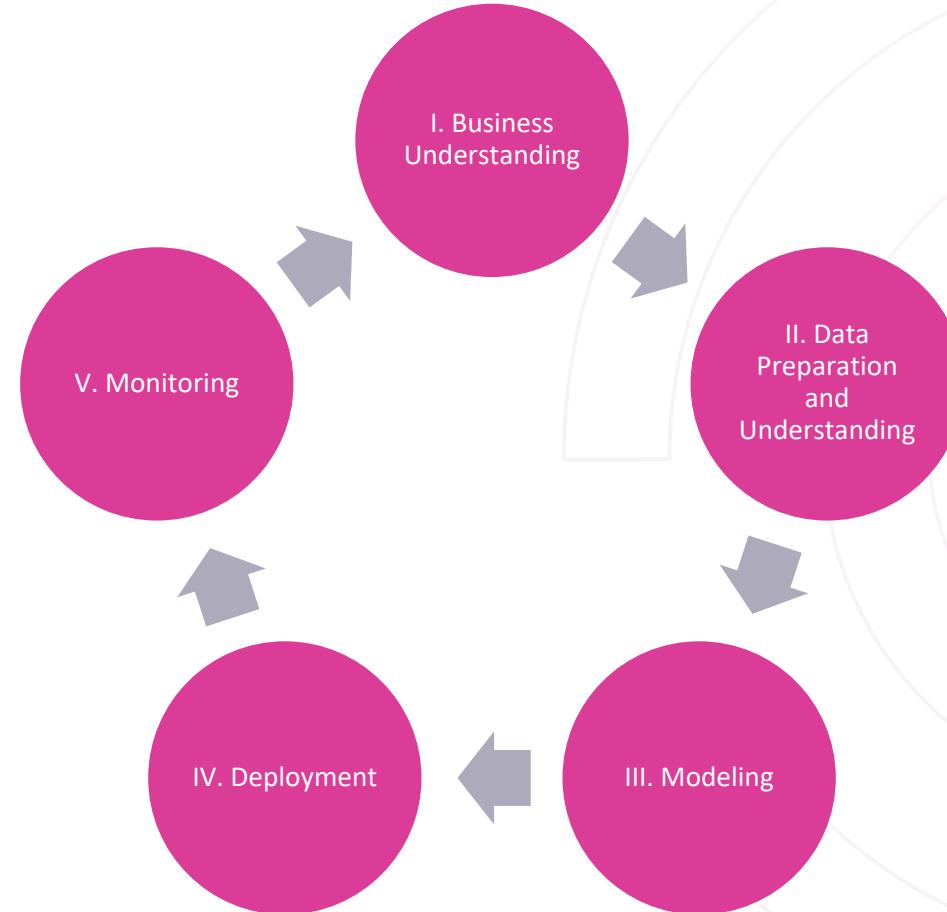


# Three lenses of due diligence

- Due diligence **before** the start of any project:
- Business **viability**: positive value creation
  - increase revenue, lower cost, boost efficiency or launch new business
- Technical **feasibility**: AI system can be built
  - meet desired performance, data availability, engineering timeline, etc.
- Human **desirability**: project is really wanted and ethically ok
  - AI developed/used by people



# Data Science Life Cycle





# I. Business Understanding

- Identify an opportunity to **create value**
  - Which part of your company process workflow can benefit from AI?
- How can AI help us?
  - **Automate** existing processes and facilitate human-machine collaboration
  - **Improve** existing algorithms to become more accurate or reliable
  - **New** business opportunities
- Pin down the project's **goals**
  - How is AI going to solve the problem?



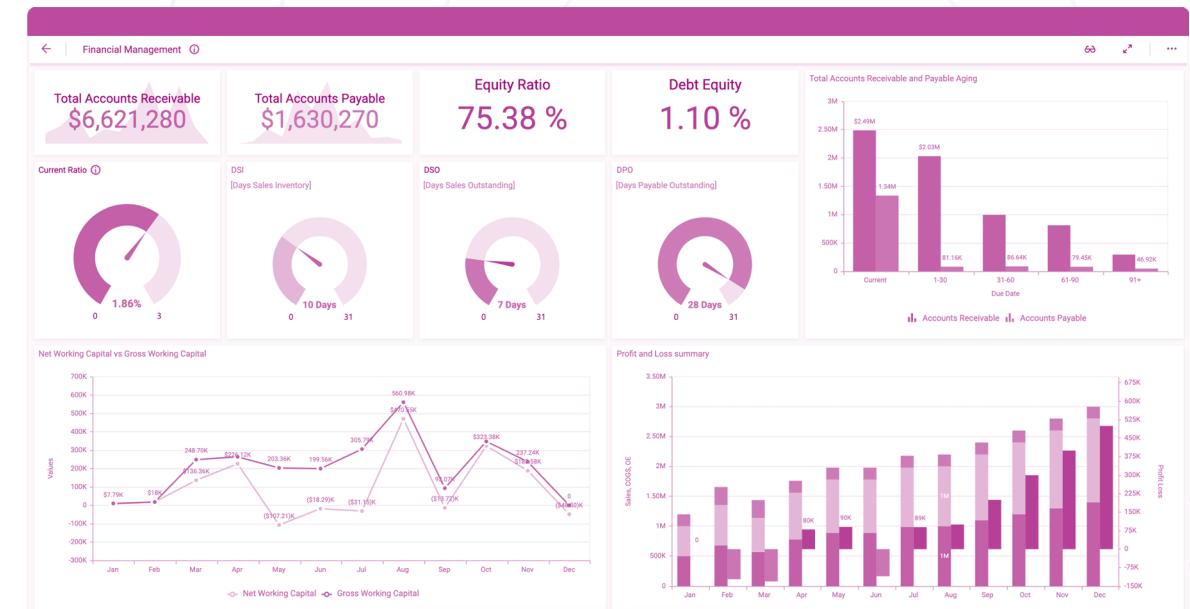
## II. Data Preparation

- Data **collection**
  - Internal & external data sources to acquire relevant and comprehensive data
  - Focus on data quality
- Data **processing**
  - Cleaning to deal with missing and inconsistent data
  - Preparation for modeling phase
  - Can be very time consuming
- Need a structured way to deal with data and **centralize** data flow



## II. Data Understanding

- Summarize the main **characteristics** of the data set
- Represent dataset visually in a **dashboard**
- Understanding the **patterns** and bias in the data
- Gain **insight** into the data
- Assesses **quality** of the data





# Key questions regarding data

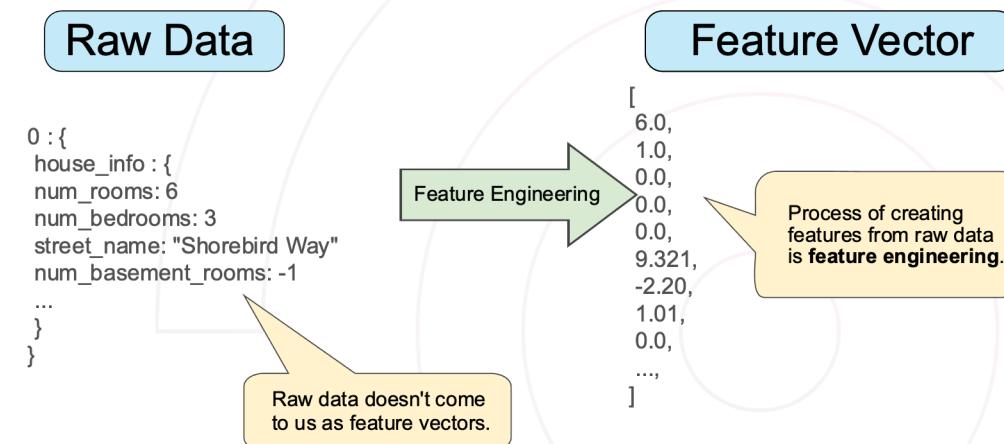
- What kind of data do I have available?
- Where can I find it in my organization?
- Who owns the data and am I allowed to use it?
- What is the format/quality of the data?
- Can I trust my data?
- Possible to enrich own data with external data?
- Is this the right data to solve my business problem at hand?



# III. Modeling – Feature Engineering

- Transform raw data into usable **features**:

- [Google – ML Crash Course](#)



- Feature **construction**

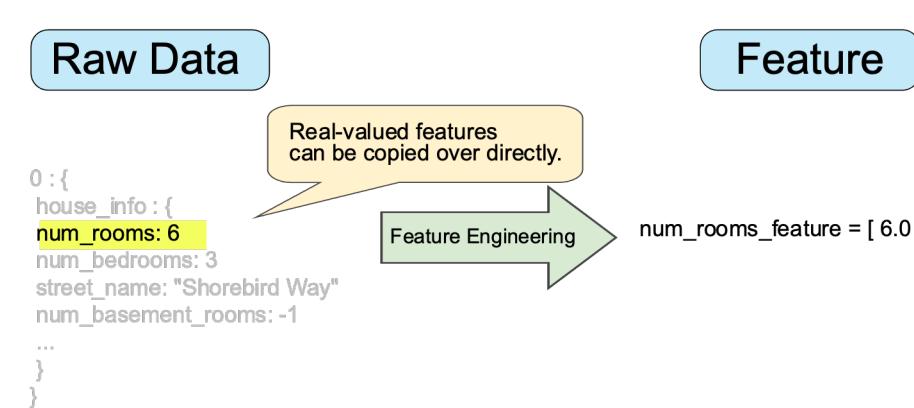
- creating new features from the ones that you already have

- Feature **selection**

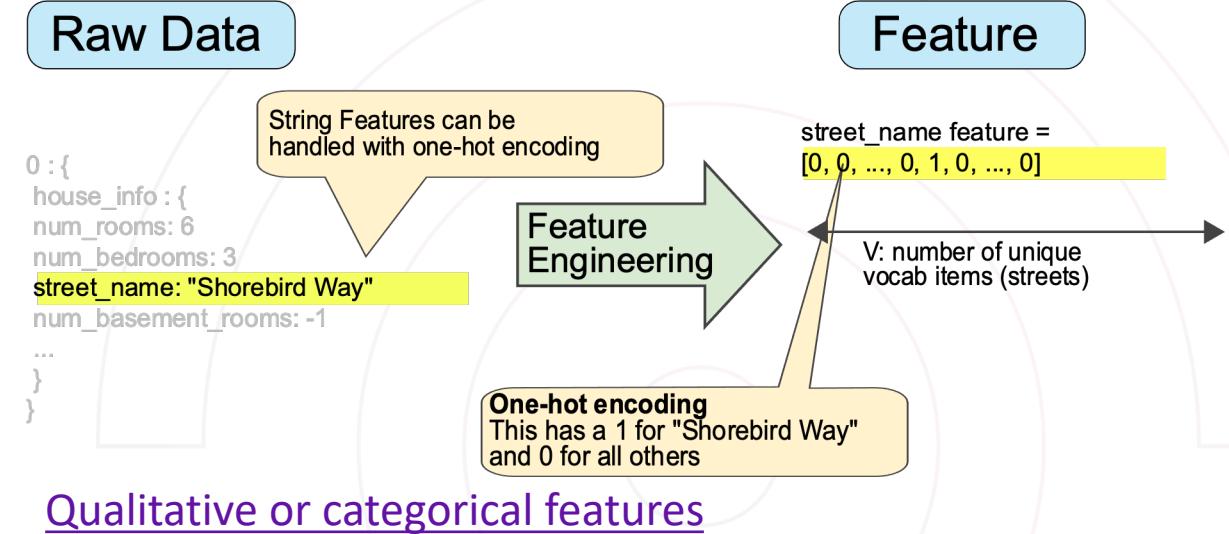
- Remove irrelevant features that add more noise than information



### III. Modeling- Feature Engineering



## Quantitative or numerical features

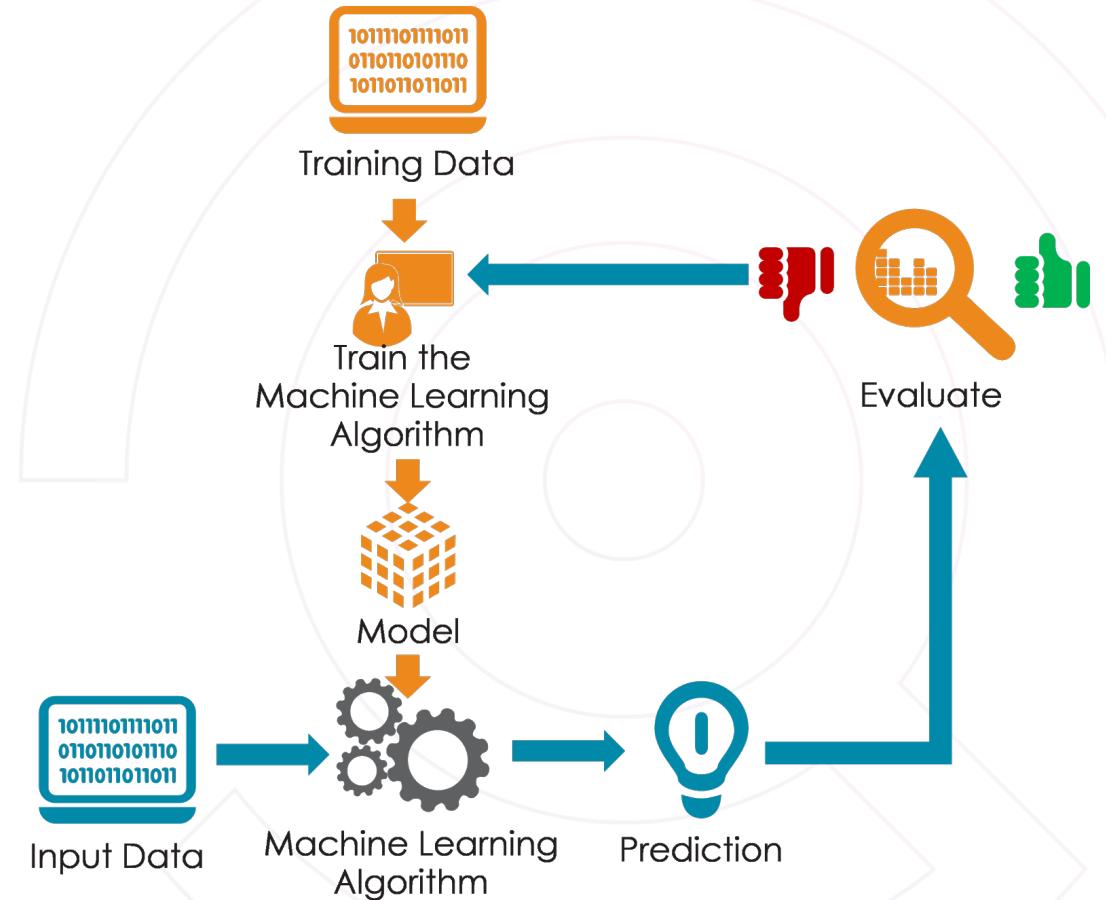


Street	Feature vector
Charleston Road	[1,0,0,0]
North Shoreline Boulevard	[0,1,0,0]
Shorebird Way	[0,0,1,0]
Rengstorff Avenue	[0,0,0,1]



# III. Modeling – Machine Learning

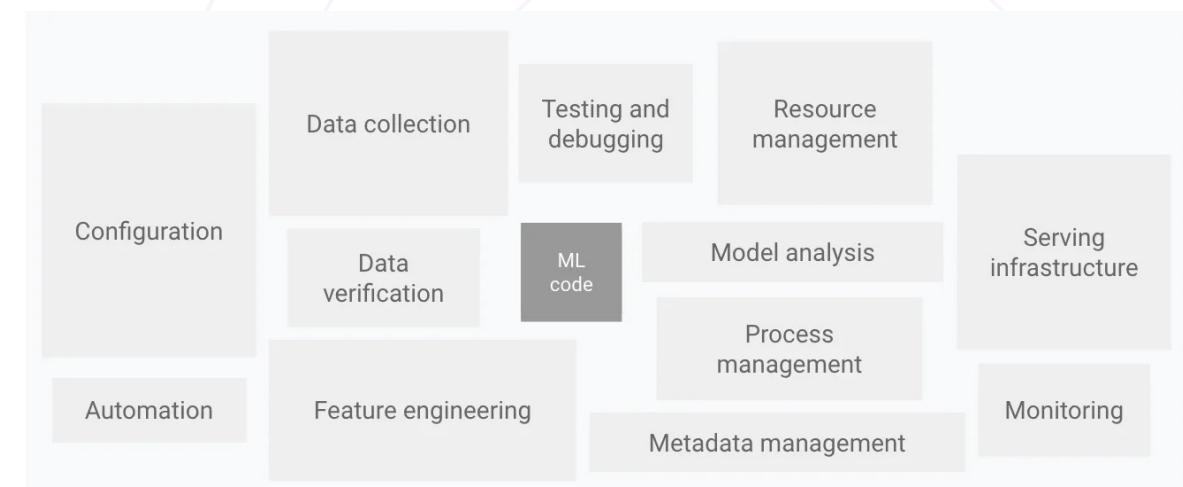
- Train various algorithms to develop models
- Evaluate model performance on new unseen data samples
- Ensure that the outcomes make sense and are significant
- Typically iterative process
  - Review model
  - Review data





# IV. Deployment

- Integration of the ML model into an existing **production environment**
  - ML code only constitutes a tiny part of the full production architecture



- Done by **MLOps** engineer

- Proof of Concept (PoC) to production **gap**
  - Many researched ML solutions don't see daylight

Google Cloud - MLOps



# V. Monitoring

- The real world is constantly **changing**
  - **Data drift**: the distribution of input features changes (e.g., houses become smaller over time because of space scarceness)
  - **Concept drift**: the mapping from features to target changes (e.g., popularity for small houses makes these more expensive)
- Ensure that algorithms **keep doing a good job** once deployed
  - Constantly evaluate their performance with regard to a baseline
  - Identify degrading solutions early on
- Brainstorm **statistics/metrics** to track over time
  - Visualize in a dashboard
  - Set thresholds for alarms
  - Iterative process: adjust metrics + thresholds over time

# 3 The big picture



# Problem definition

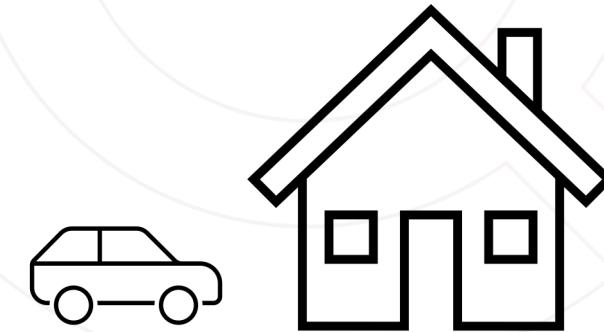
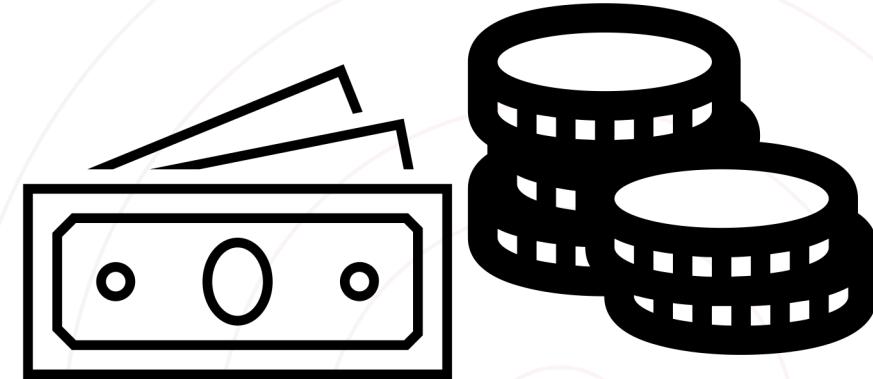
- Automatic feeding system for chickens
- Deciding how much each chicken should get?
- Problem
  - ✓ Roosters and hens look almost the same
  - ✓ Roosters are bigger and require more nutrition





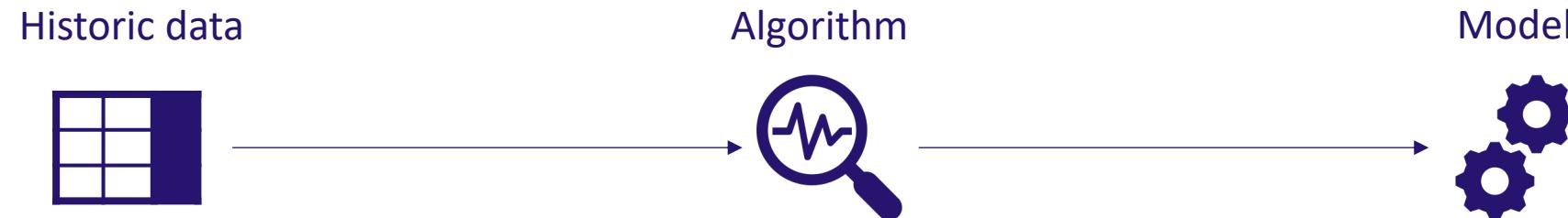
# Problem definition

- Default prediction for bank loans
- Who will be able to repay the loan amount?
- Problem
  - ✓ Default causes big losses for the bank
  - ✓ Find good profiles to grant a loan and avoid risky profiles





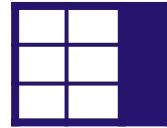
# From data to model





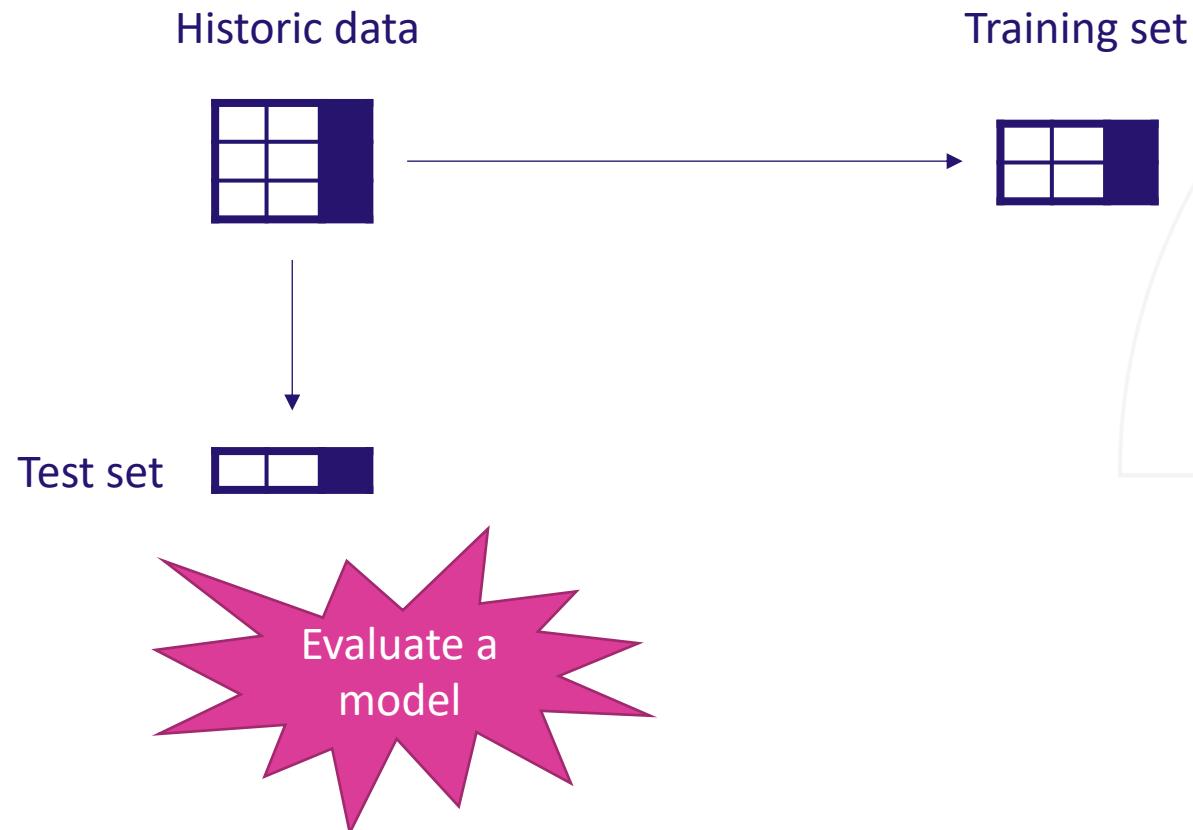
# Complete dataset

Historic data



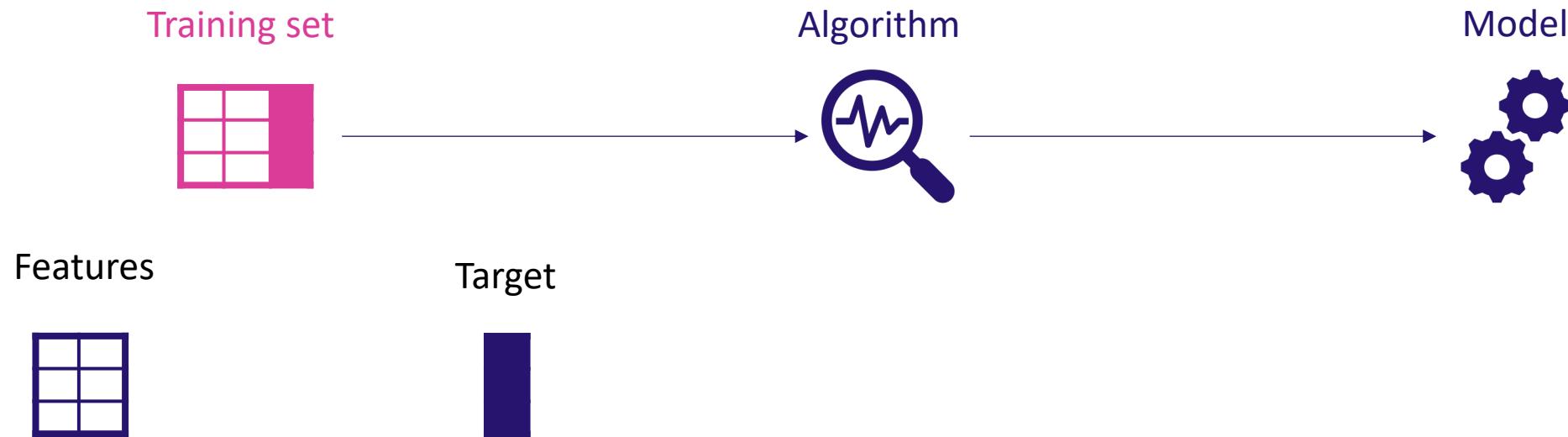


# Data partitioning



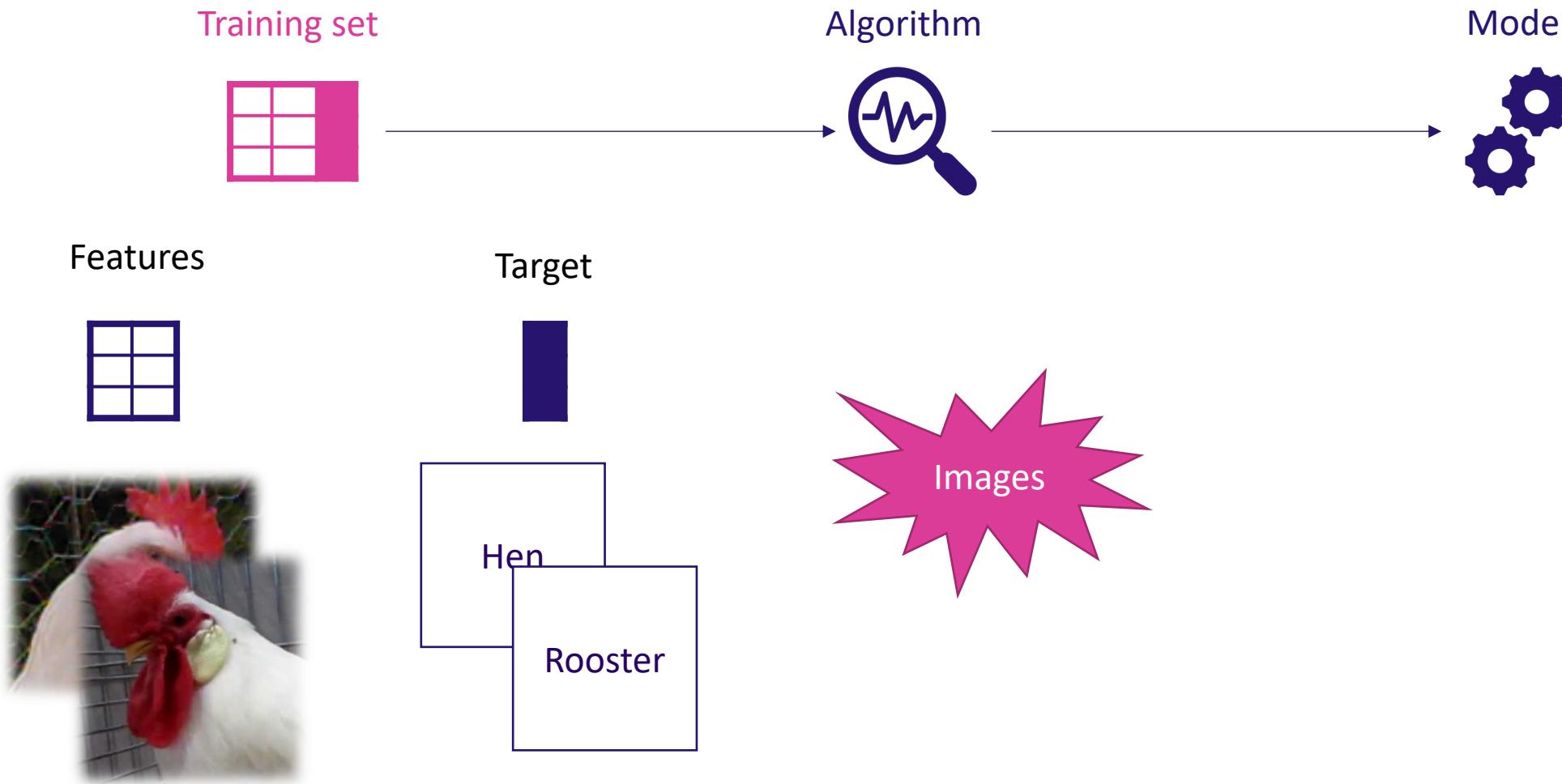


# Training data





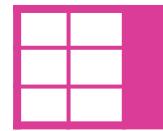
# Unstructured data





# Structured data

Training set



Algorithm



Model



Customer Name	Age	Education	Gender	Default
Joris Maes	62	Low	Male	Yes
Pieter Claes	32	High	Male	No
Nina Peters	25	Low	Female	No

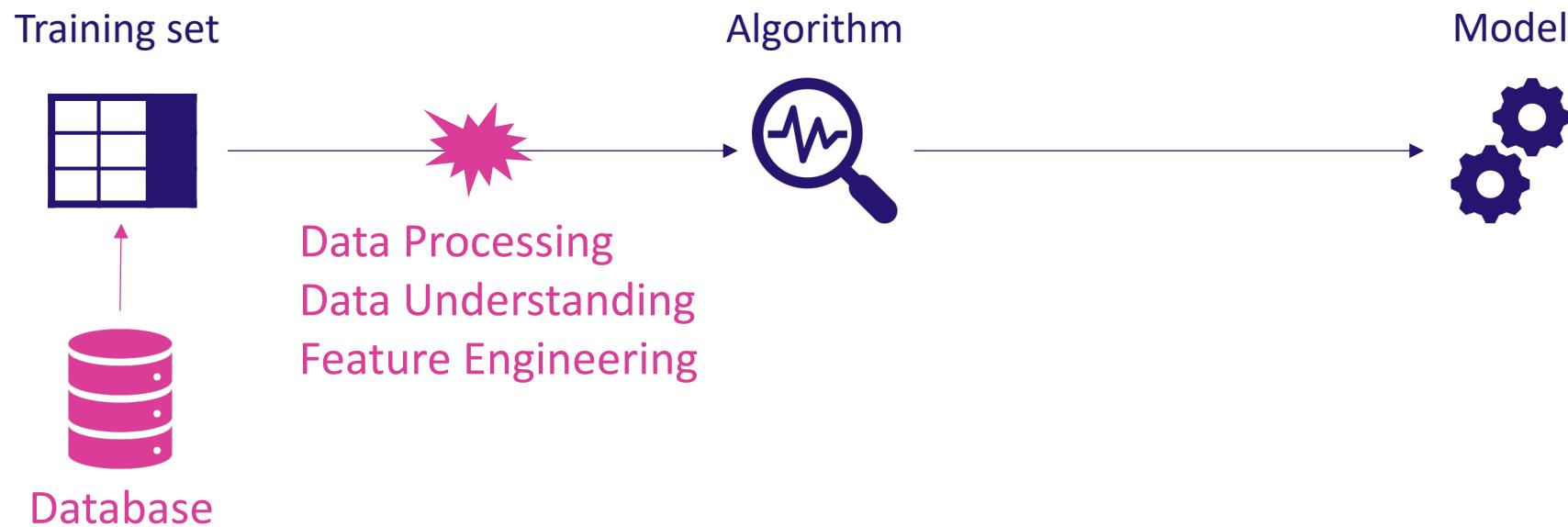
Features

Target



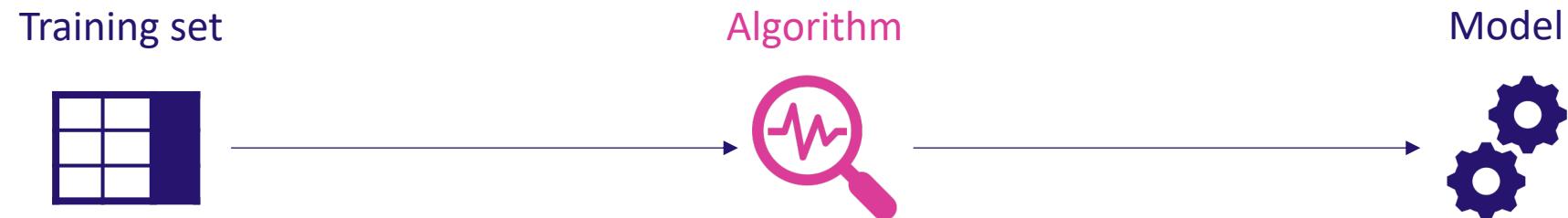


# Data preparation





# Machine learning

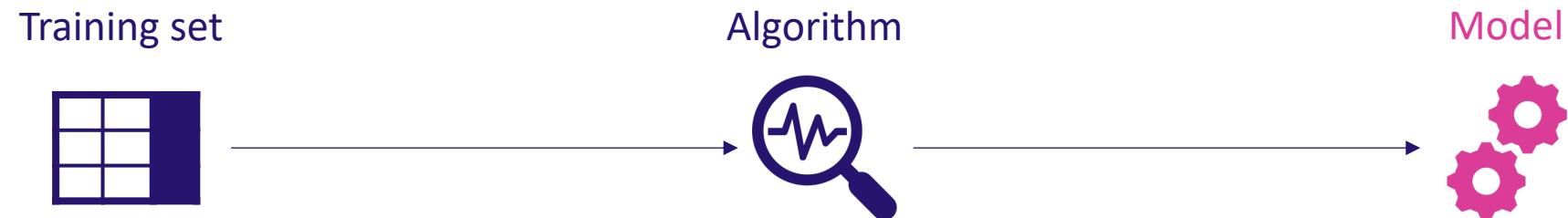


Look for **patterns** that map features to the target

Customer Name	Age	Education	Gender	Default
Joris Maes	62	Low	Male	Yes
Pieter Claes	32	High	Male	No
Nina Peters	25	Low	Female	No
Features				Target



# Model predictions



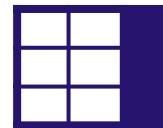
Customer Name	Age	Education	Gender	Default
Joris Maes	62	Low	Male	Yes
Pieter Claes	32	High	Male	No
Nina Peters	25	Low	Female	No

Erica Maes	27	Low	Female	???
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# Model candidate #1

Training set



Algorithm



Model



Customer Name	Age	Education	Gender	Default
Joris Maes	62	Low	Male	Yes
Pieter Claes	32	High	Male	No
Nina Peters	25	Low	Female	No

IF Customer Young & Female  
Then Default No

Erica Maes	27	Low	Female	No
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# Model candidate #2

Training set



Algorithm



Model



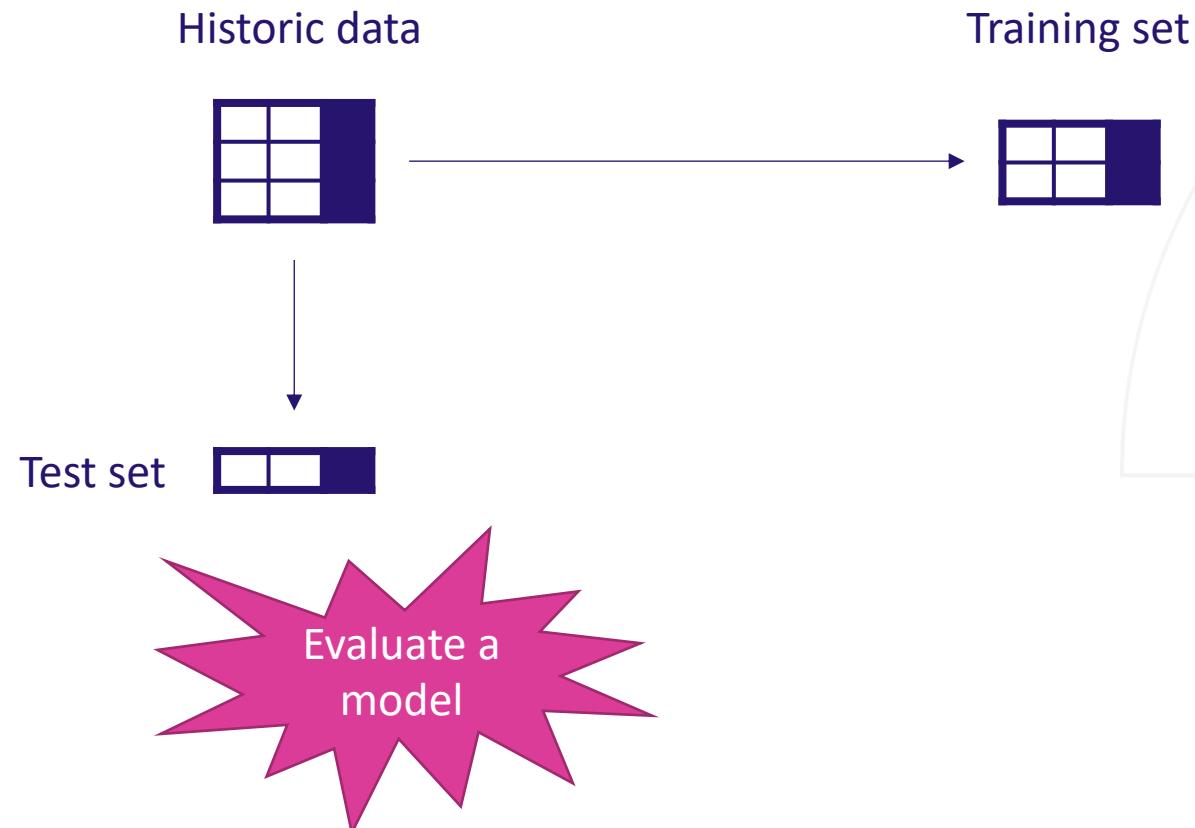
Customer Name	Age	Education	Gender	Default
Joris Maes	62	Low	Male	Yes
Pieter Claes	32	High	Male	No
Nina Peters	25	Low	Female	No

IF Customer Name "Maes"  
Then Default Yes

Erica Maes	27	Low	Female	Yes
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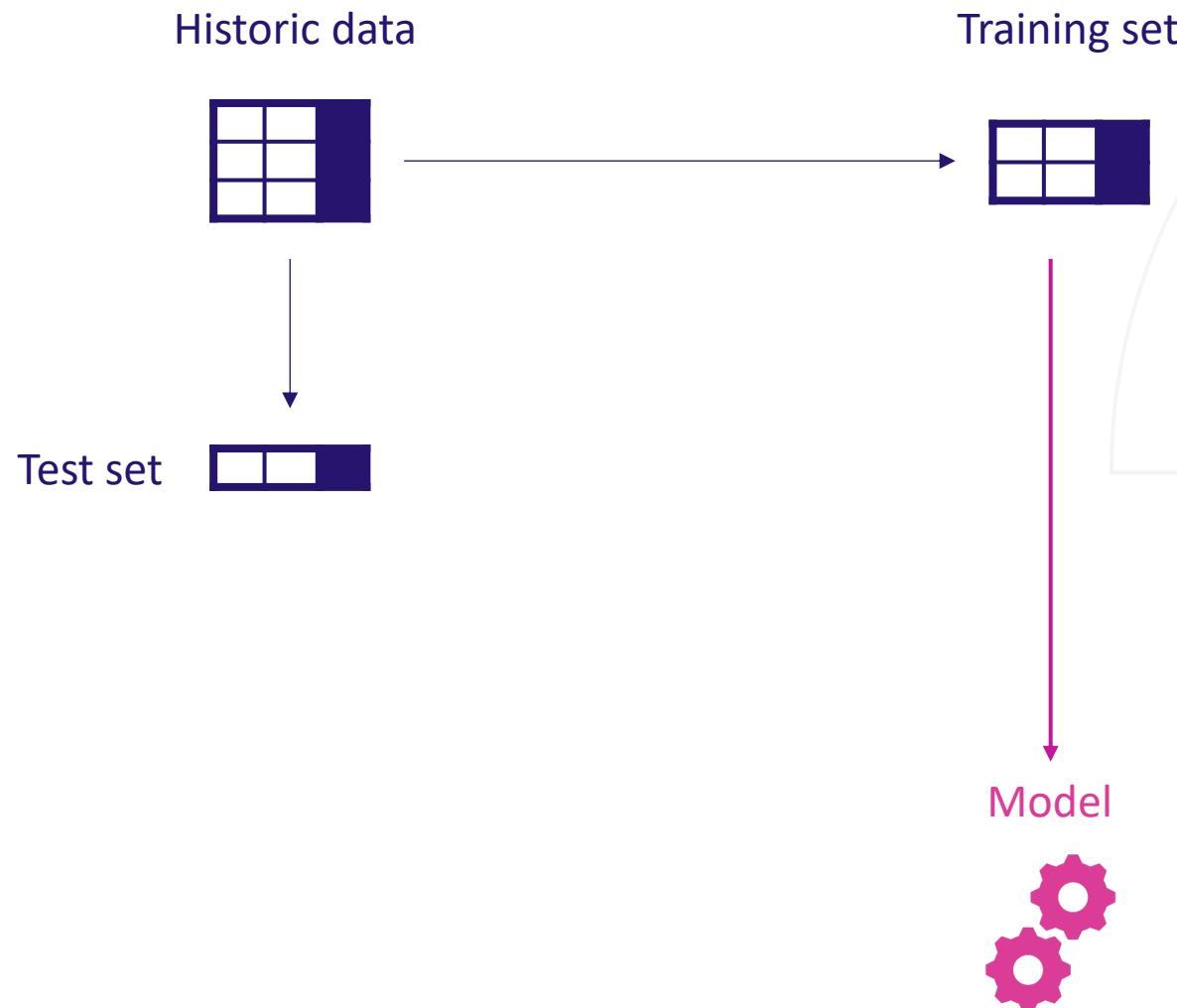


# Which model to choose?



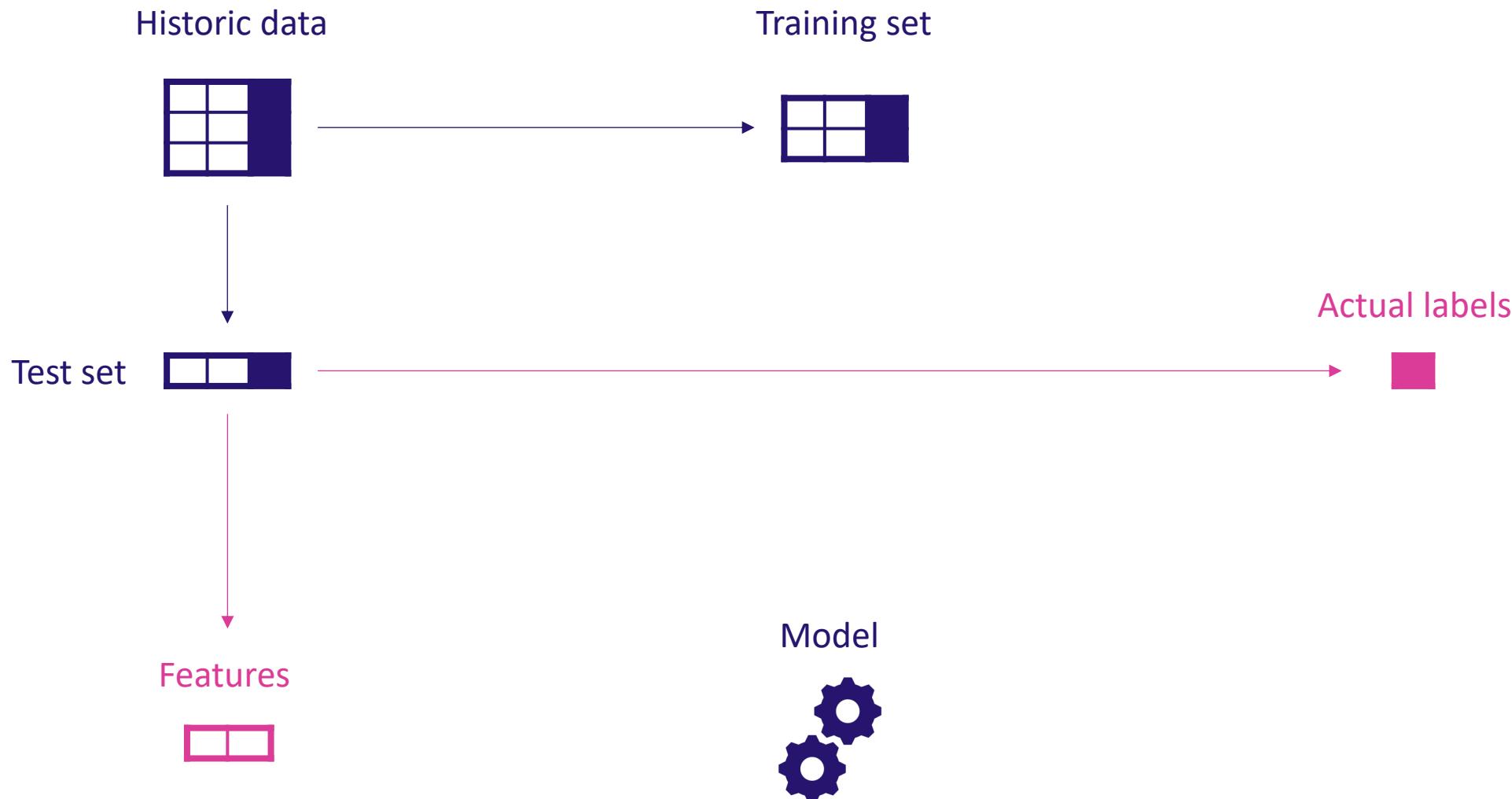


# Trained model



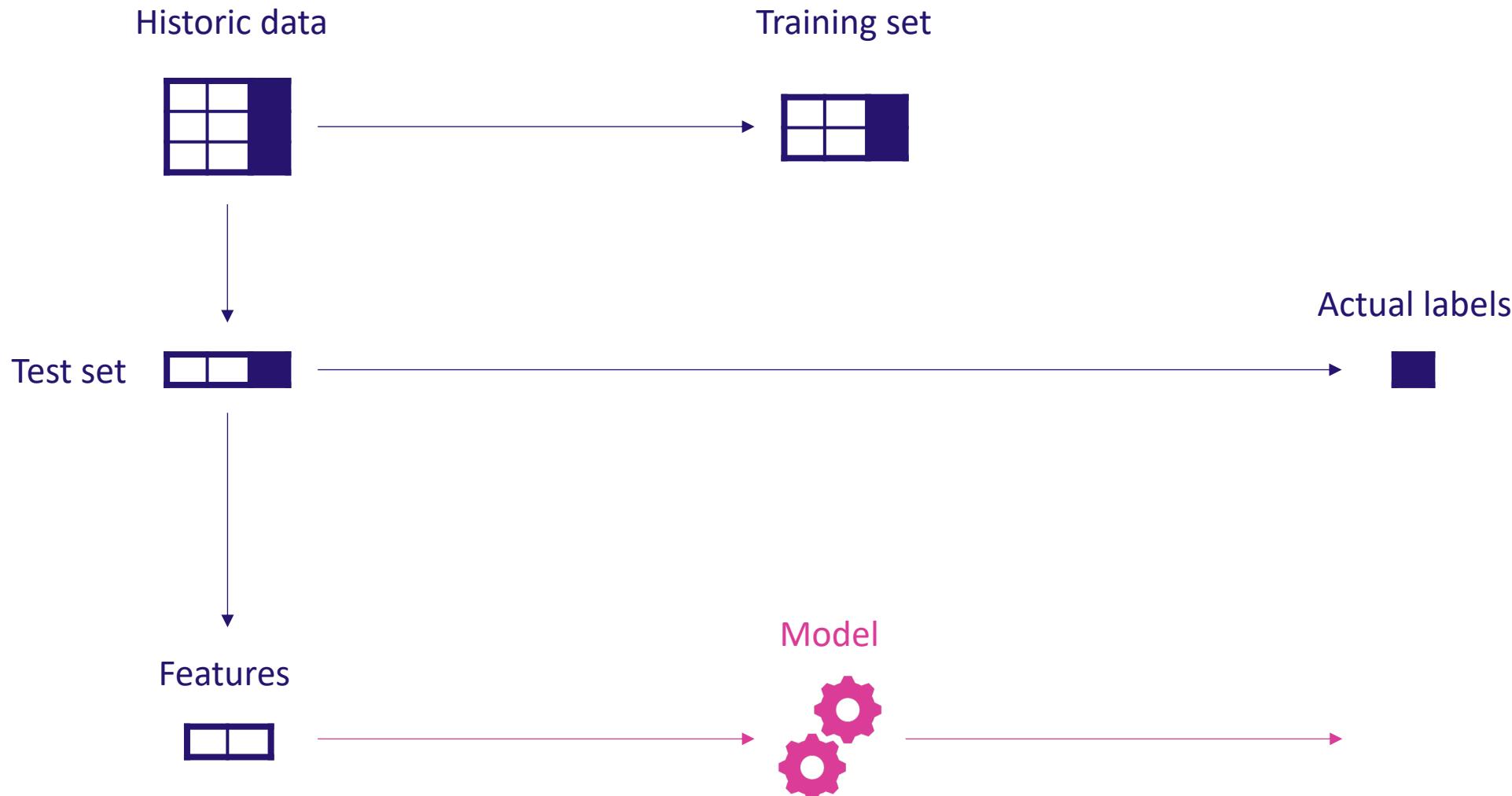


# Evaluating a Model



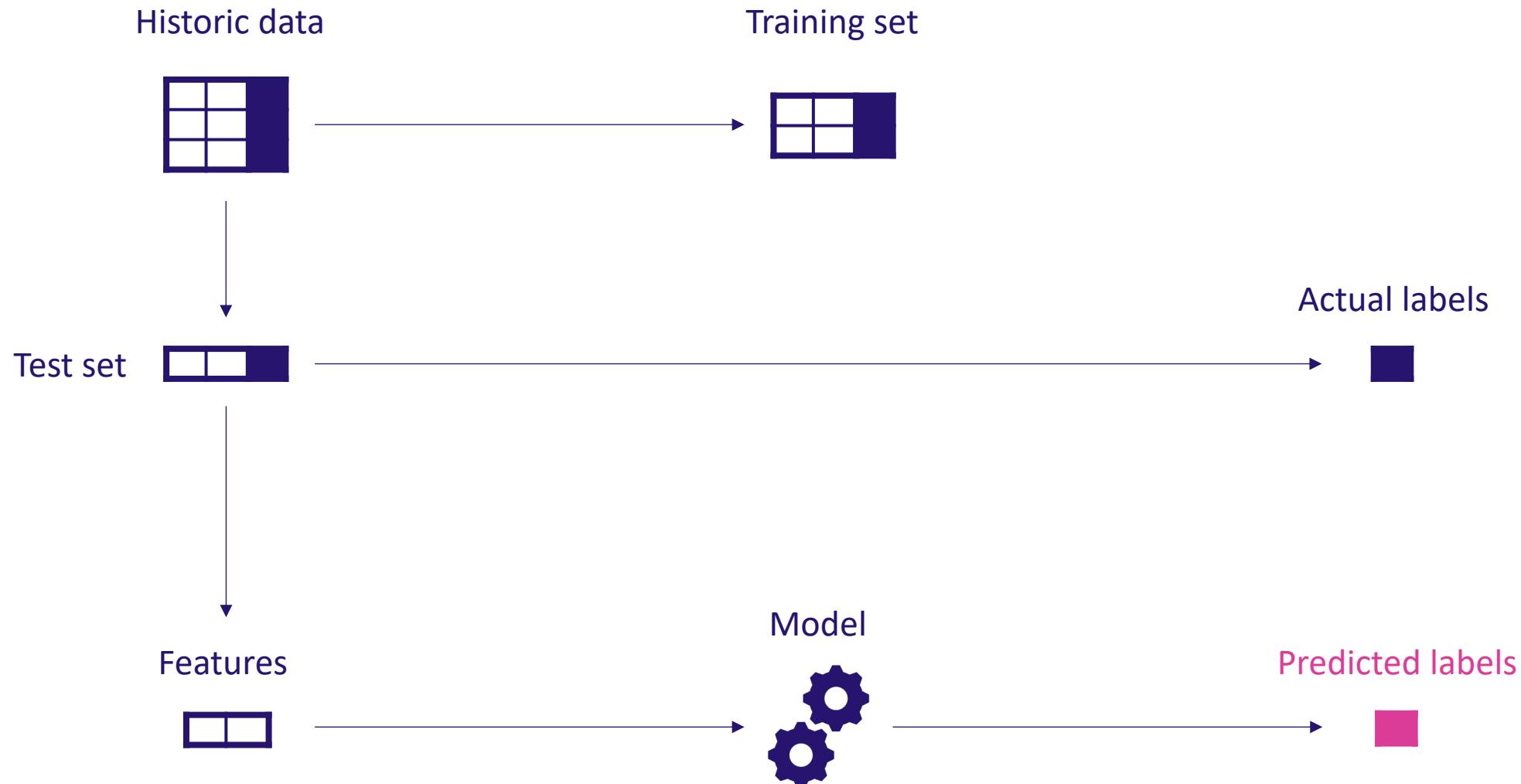


# Evaluating a Model



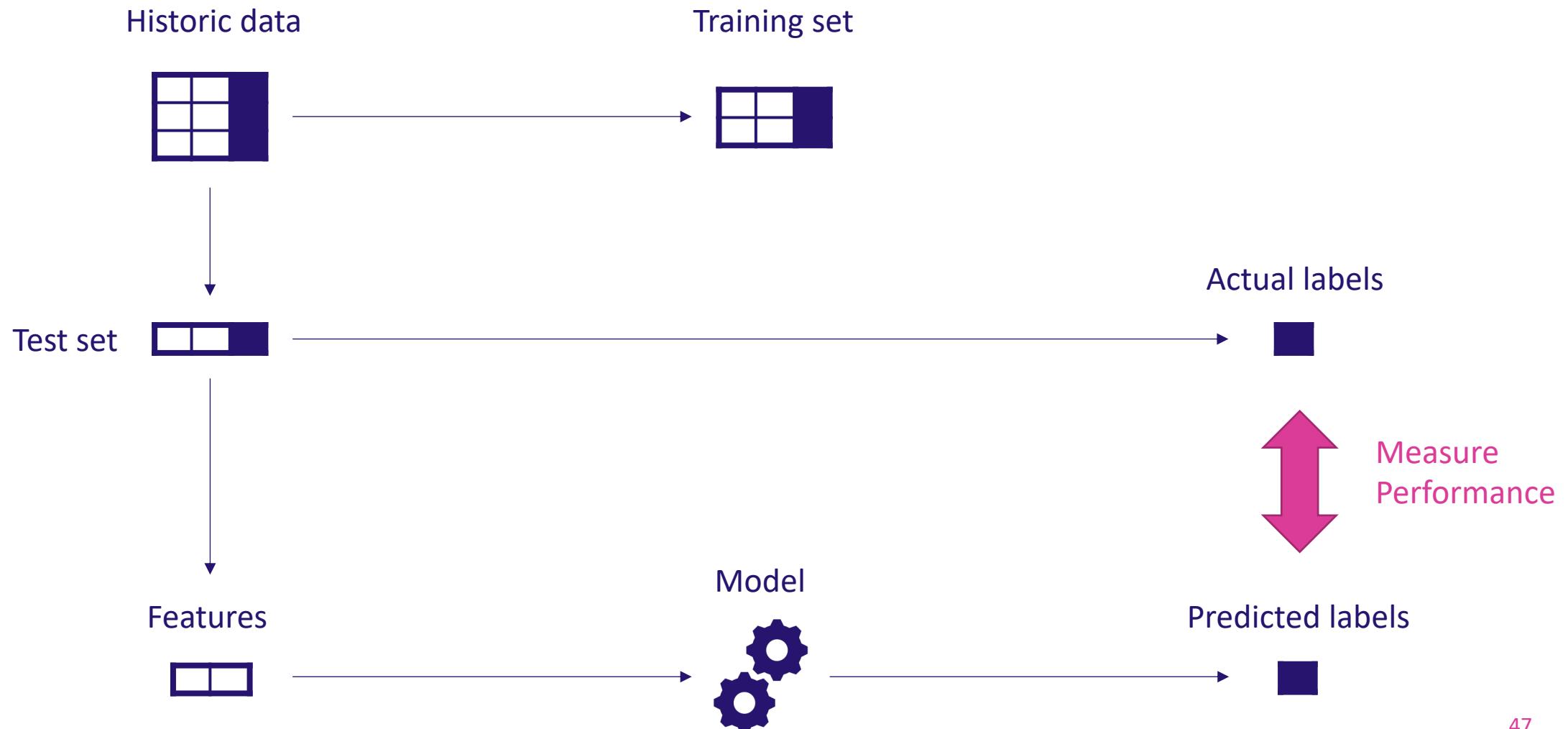


# Evaluating a Model



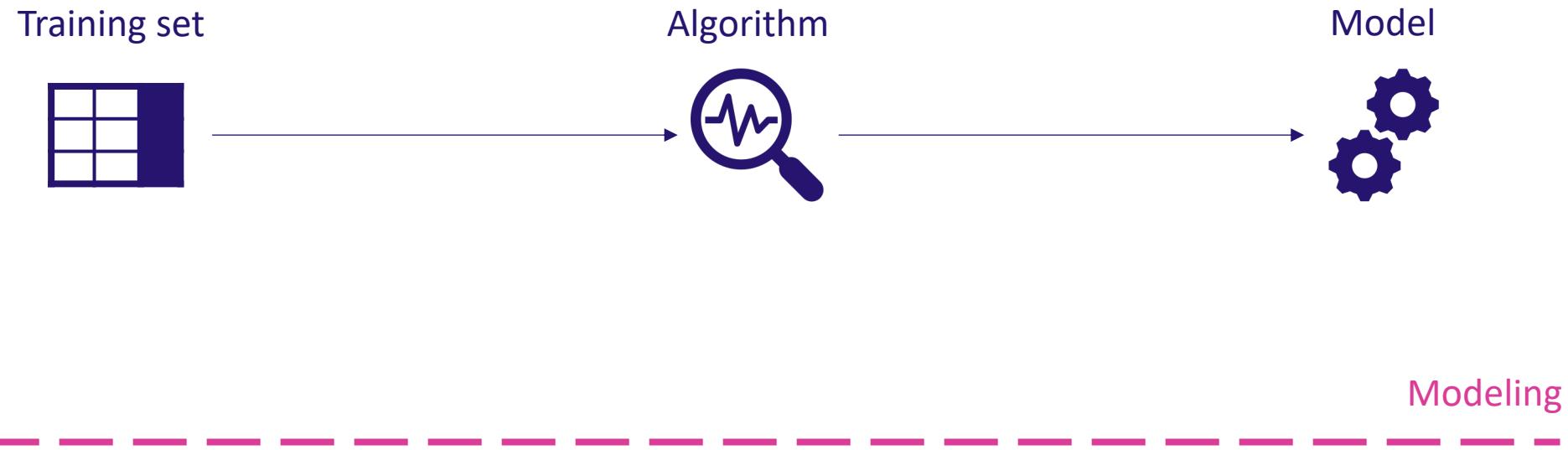


# Evaluating a Model



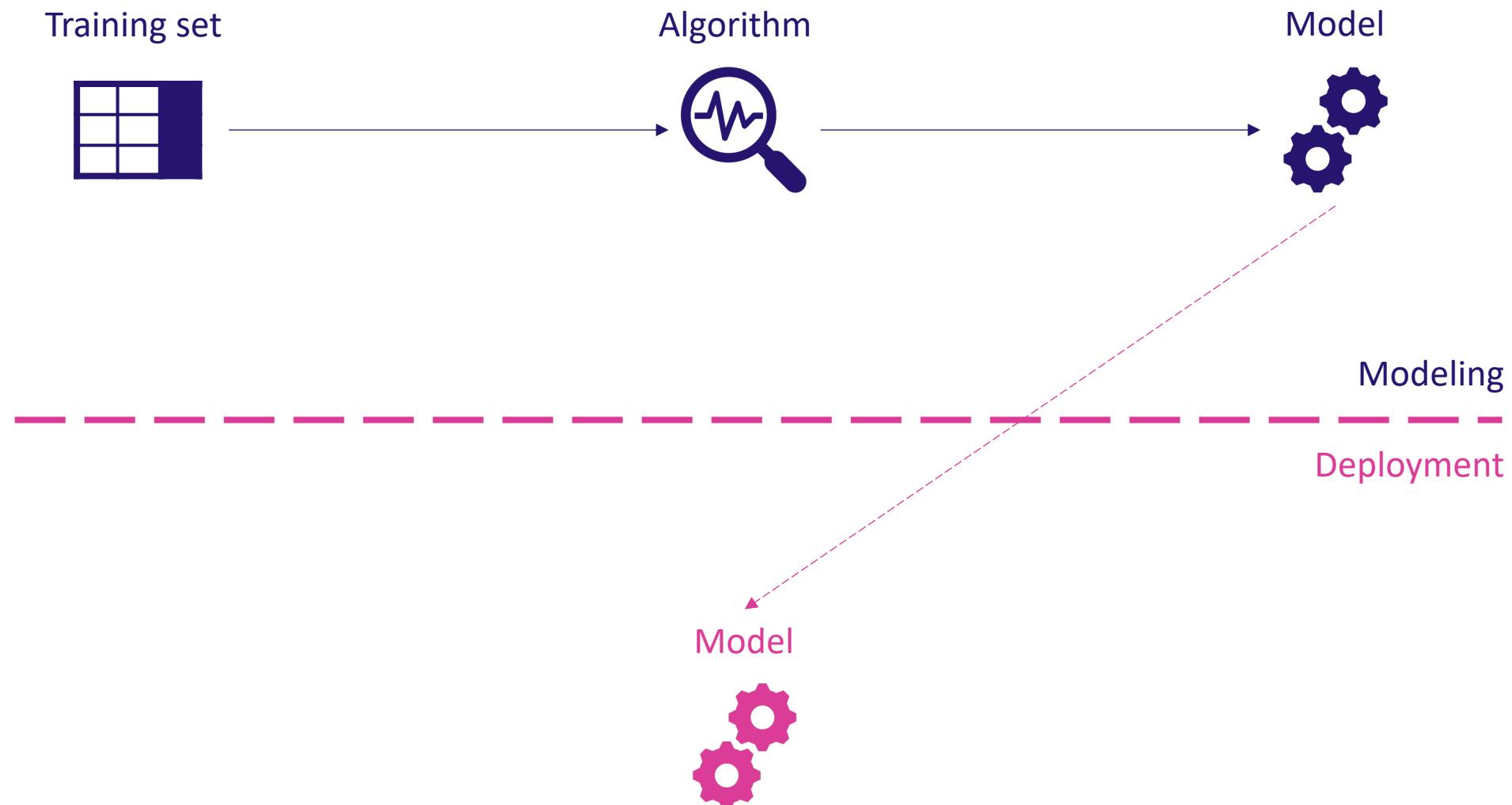


# Modeling



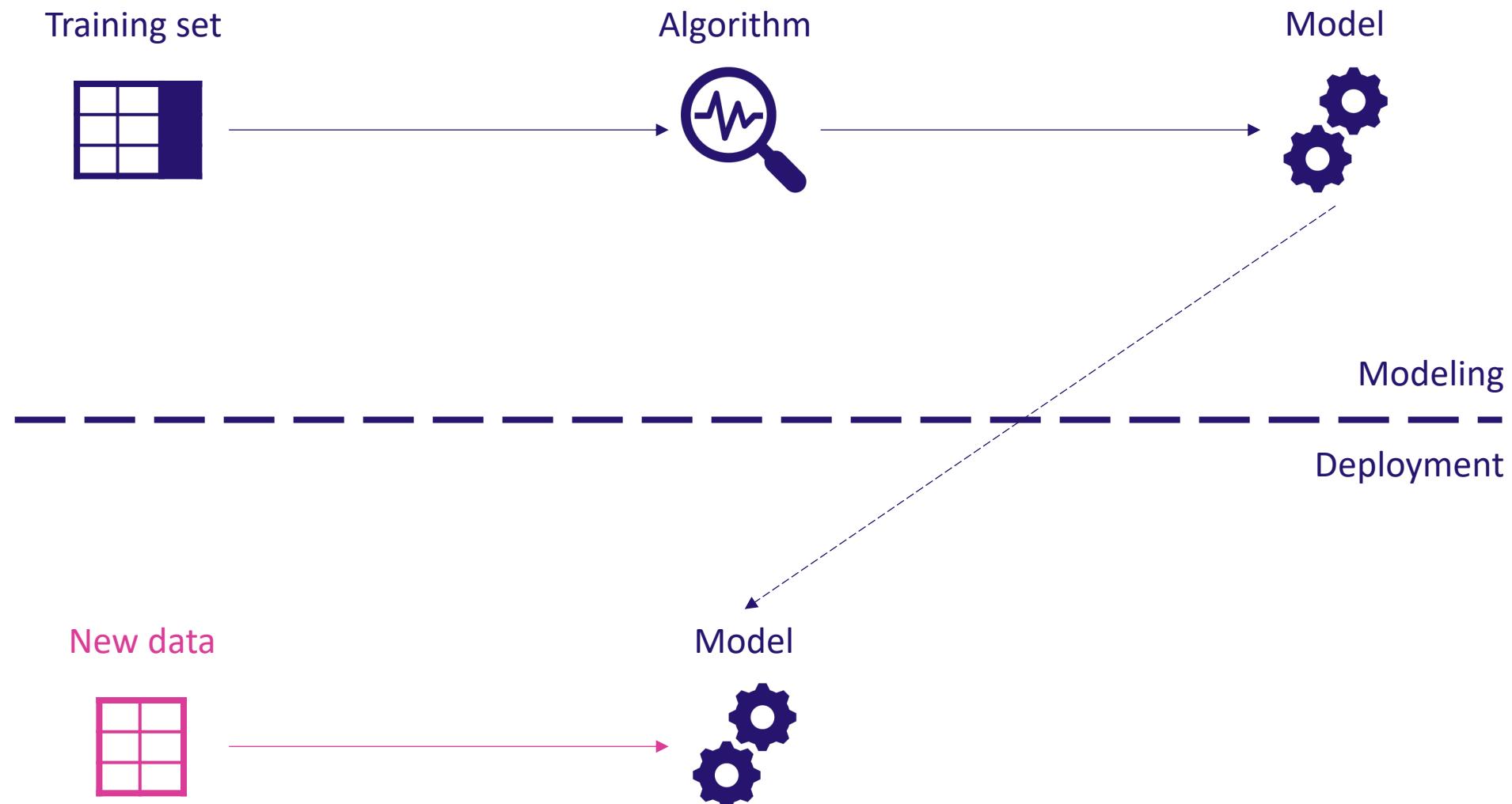


# Deployment



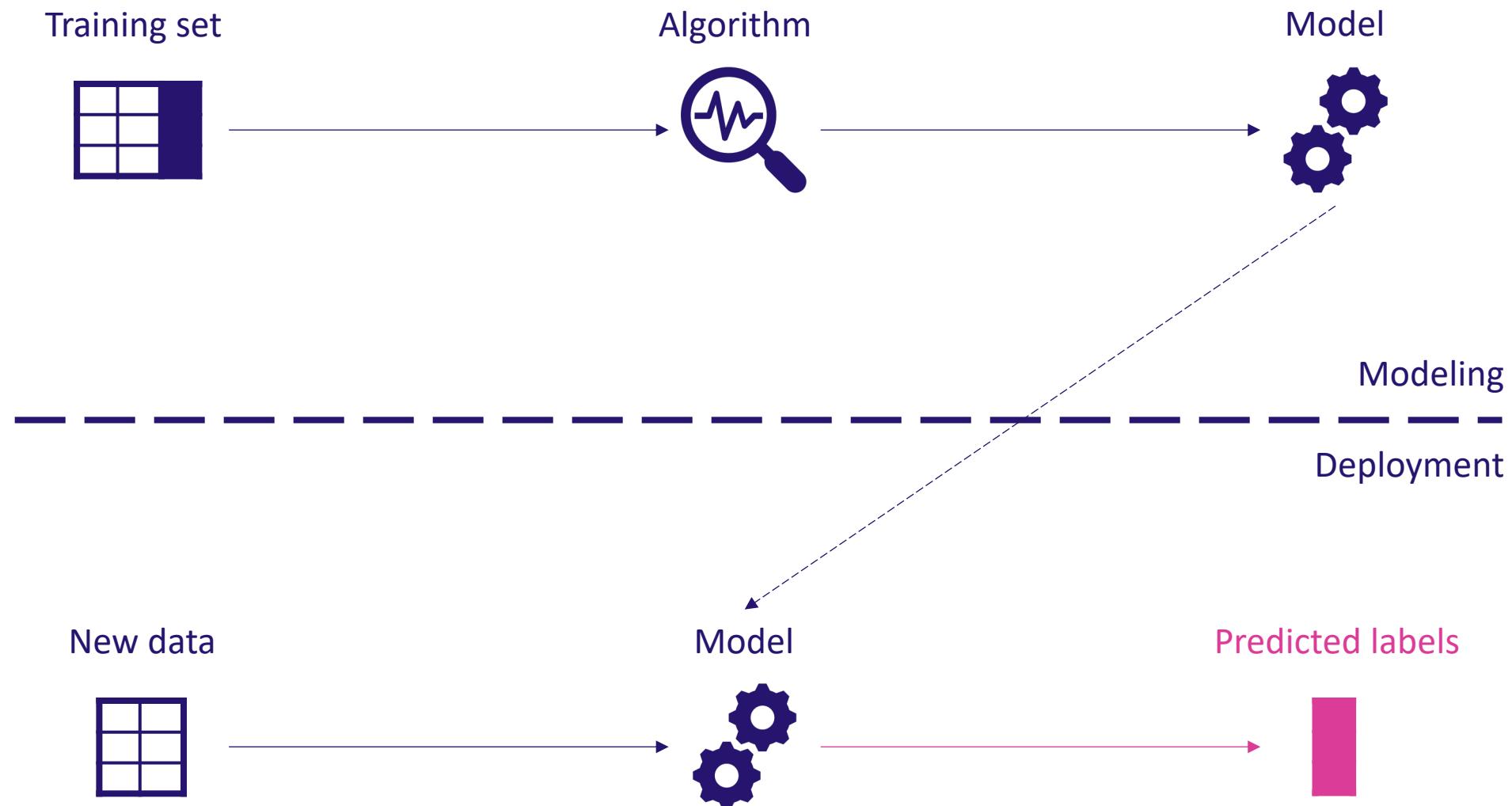


# Deployment



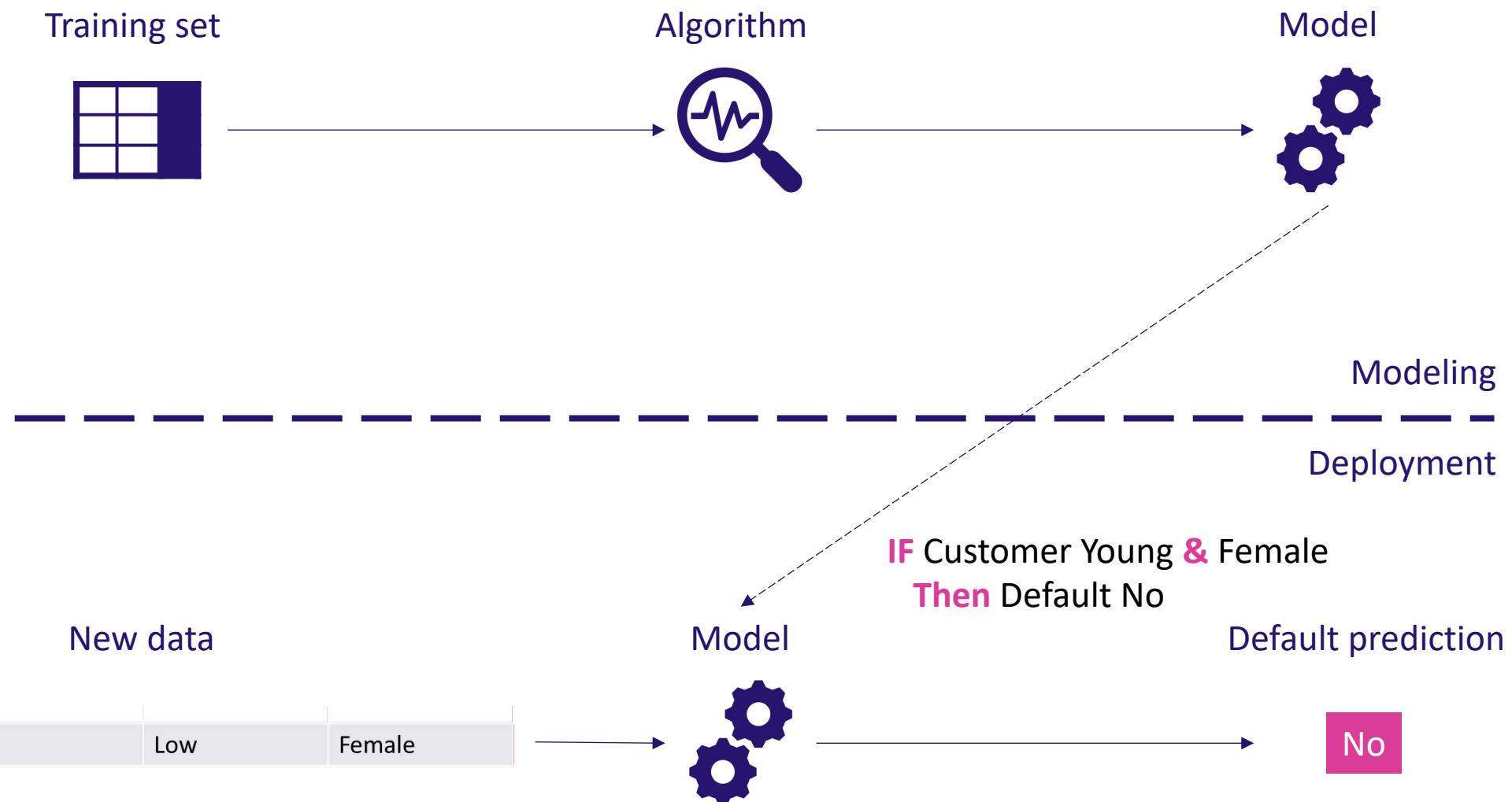


# Deployment





# Deployment



# 4 Evaluating a project



# AI business impact

## Return on investment (ROI)

- Compare **tangible** value and cost
- KPI examples
  - Revenue increase
  - Efficiency gains
  - Implementation costs
  - Risk (investment, acceptance, regulation, cyber, etc.)

## Value on investment (VOI)

- Also consider **intangible** value
- KPI examples
  - Customer satisfaction
  - Employee motivation
  - Brand reputation
  - Intellectual property
  - Partnerships



# How to measure success?

- Project fails if it doesn't meet **predefined objectives**
  - Define goals upfront at start
  - Well defined, quantifiable and measurable
  - Compare against status-quo benchmark
- Problem definition as a **prediction task**
  - NOT “stop customers from leaving”
  - BUT “predict which customers will churn and primary reasons of churn”
  - Makes it easier to find technical metrics



# Technical vs business metrics

- Always **align** business objectives with technical metrics
  - Not doing so will yield disappointment
- Define **quantifiable** business value
  - Translate it into proper technical metrics
- Choose something **meaningful** to measure in business terms
  - Make their link to the outputs of the AI solution explicit



# Case studies

- Fully automated **image clean-up** for a manufacturing company

- Background removal
  - Time and resource consuming



Time to clean  
an image **0.07s**



Cleaning pixel  
accuracy > **99%**



Man hours saved  
per year > **3500**

- Physical **advertisement impact** prediction

- Assess the effectiveness of ads



3 billion data points  
processed  
in under **10 min**



prediction performance  
**f1 ~0.8**

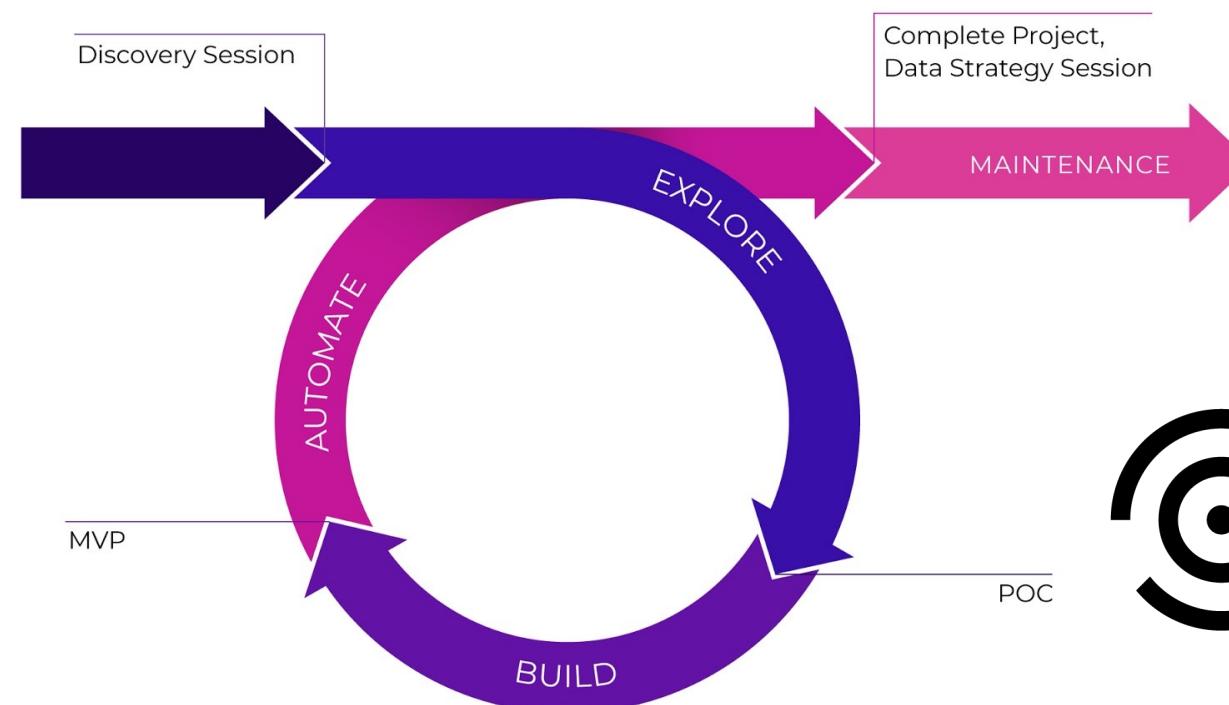


Algorithm used in  
**all reports**

# 5 Practical AI solutions



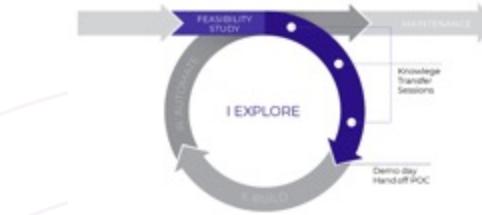
# Explore - Build - Automate





# Explore

- Test use case **viability**
  - Worth investing time and money into technological solution?
- Provide minimal solution with a **Proof of Concept (PoC)**
  - Compare different approaches
  - Identify potential problems + efficient solutions
  - Test software, hardware and infrastructure
  - Gain essential experience, skills and confidence
- Convince stakeholders to **invest** in AI solution





# Build

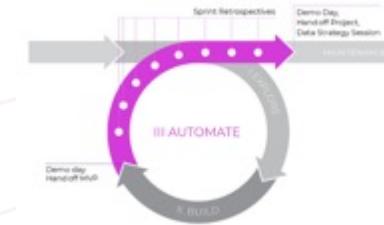
- Develop and deploy a fully functional **Minimal Viable Product (MVP)**
- Provide tangible business **value**
  - Actionable insights, forecasts, optimized processes or automated tasks
- Satisfy all **requirements** with focus on
  - Stability, testing and good code quality
  - Proper infrastructure
  - Scalability if needed





# Automate

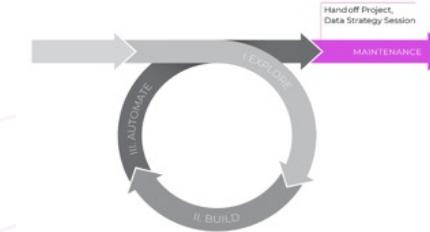
- Make the software operate **autonomously**
  - Minimal human supervision needed
- Integrate the solution in current **infrastructure**
  - Fully scalable and robust





# Maintenance

- Evaluate and **monitor** performance of the model
- Track model quality and predictions over time
- React to **feedback** from deployed models



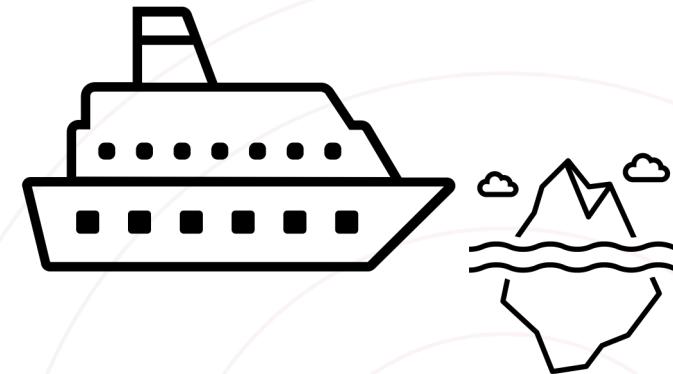
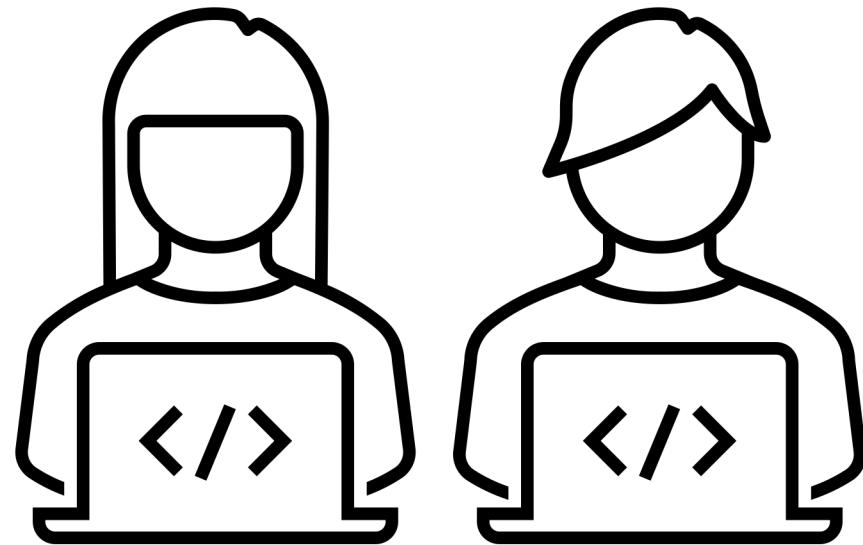
**nannyML**

# 6 Hands-on tutorial



# Jupyter Notebook

Happy coding!





# AI<sup>4</sup>Business



INVESTEERT IN  
JOUW TOEKOMST



Europese Unie

