Machine Learning in Produktion

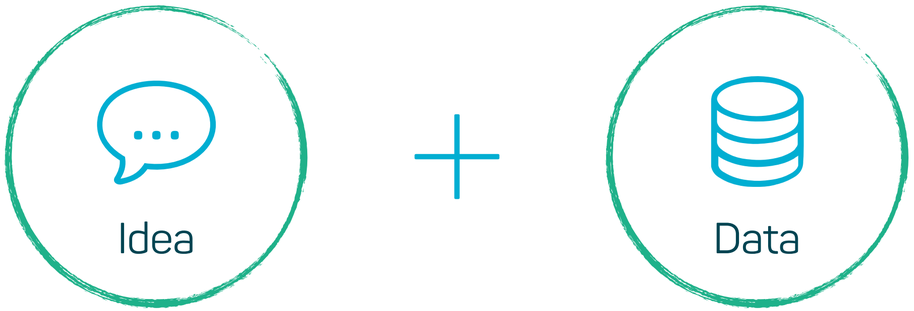
oder: Warum Software-Entwicklung auch hier wichtig ist

About Me

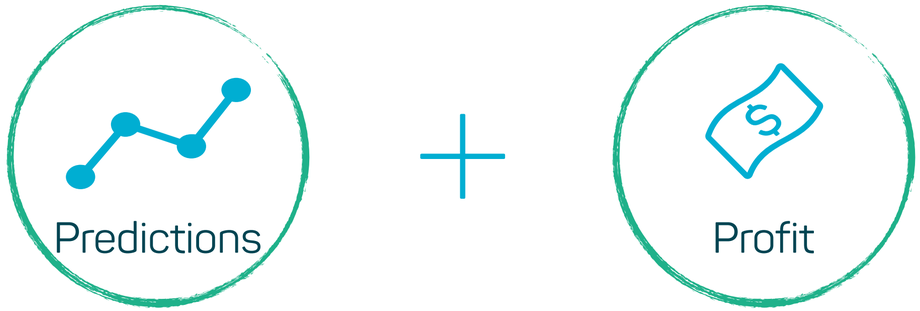
Matthias Niehoff
Head of Data & AI
codecentric AG

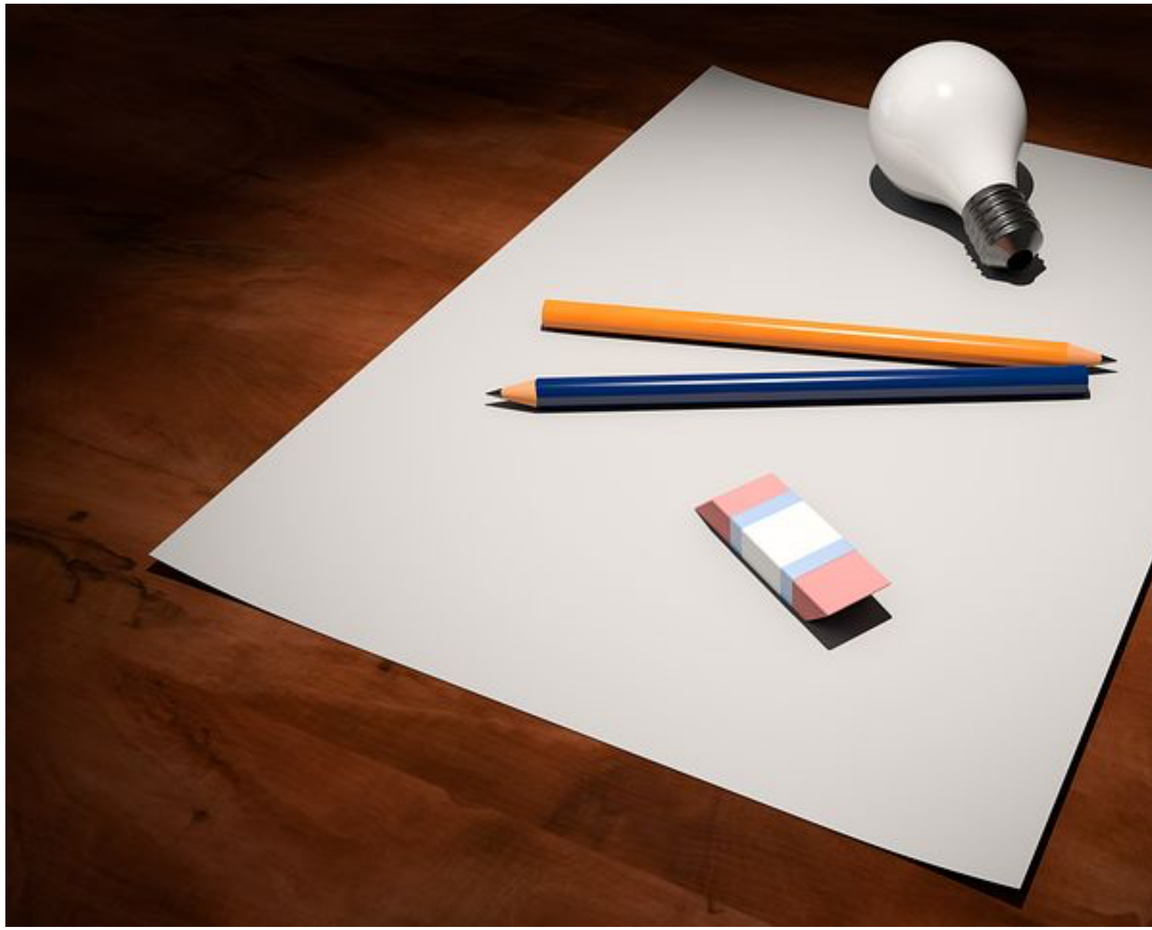
Data Science Projekte – Eine neue Idee

Have:



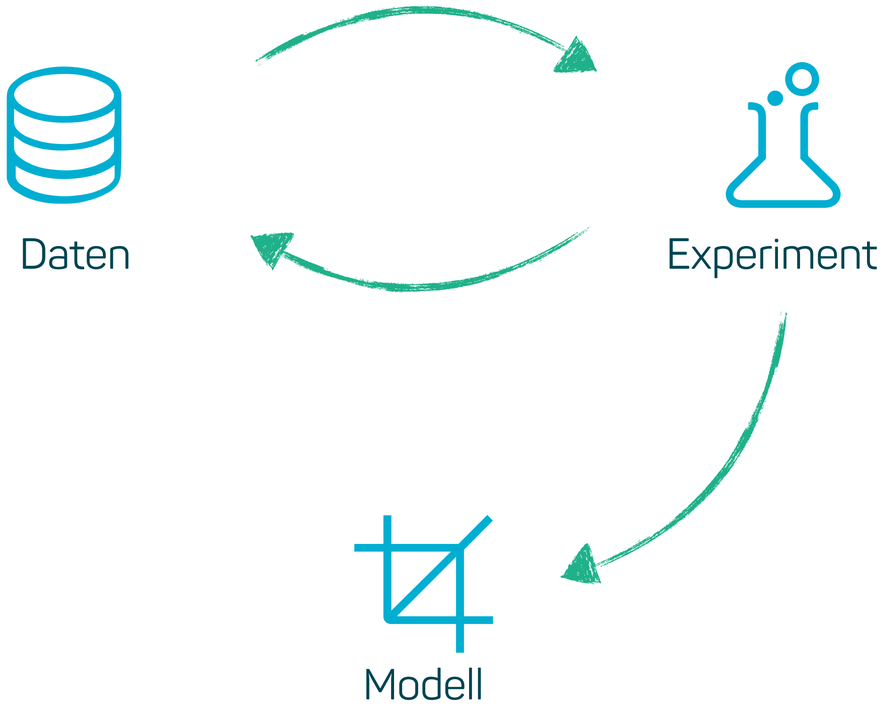
Want:





Data Projekte — Exploration

Ziel: Schnelle Exploration und schnelle Experimente

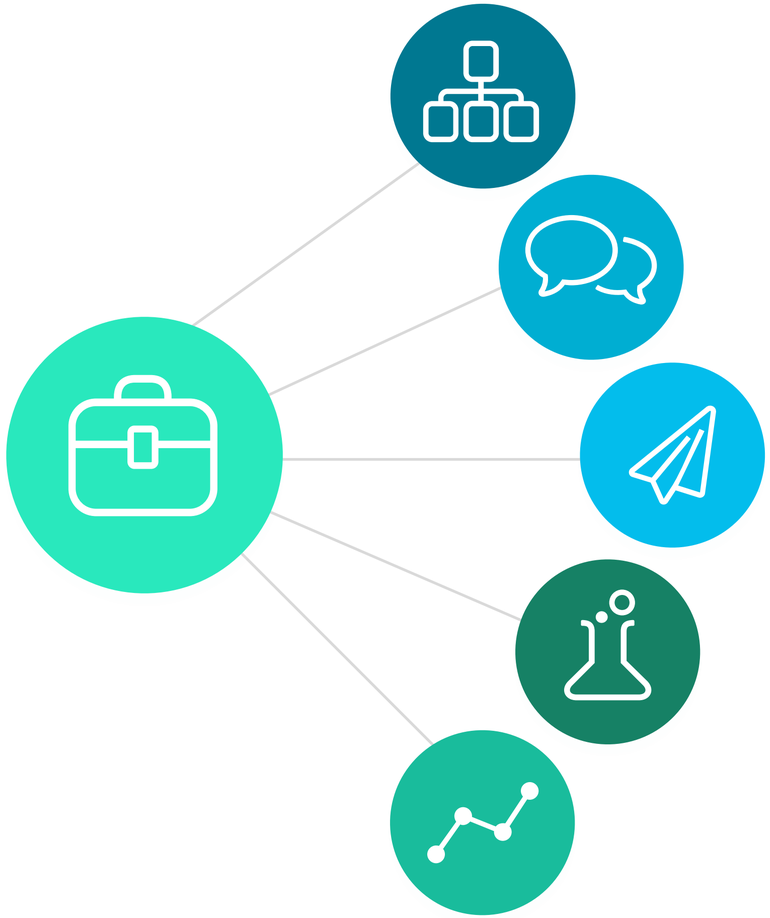


Jupyter notebook

```
data = load_data("input.csv")
data = preprocess(data)
model = train_model(data)
print(model.predictions)
```

Modell Entwicklung

- Datenbeschaffung & Speichern
- Cleaning
- Vorverarbeitung
- Modell Training
- Evaluation

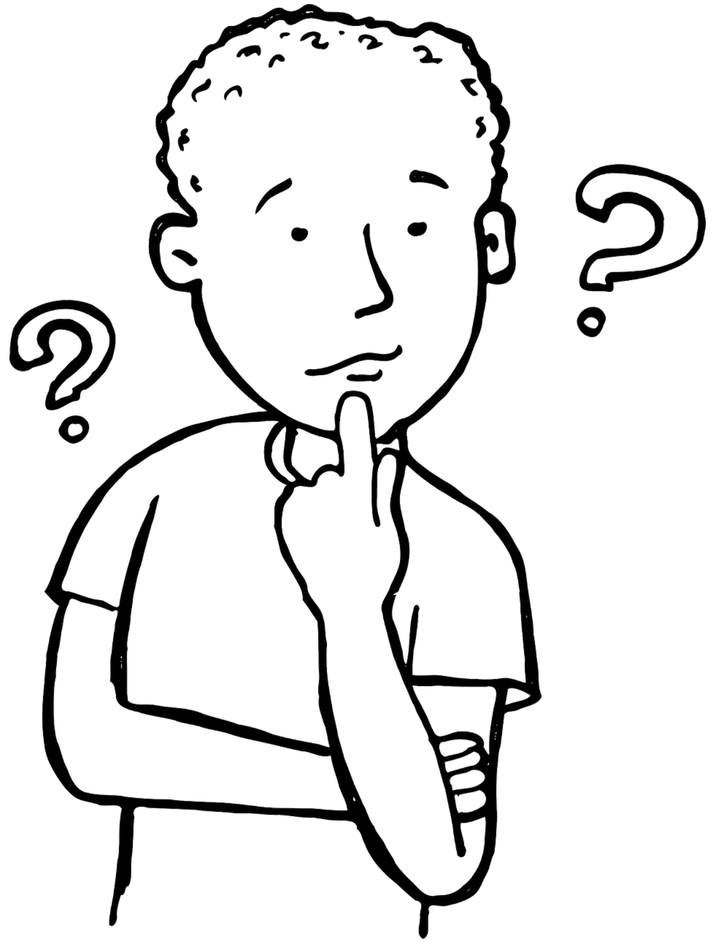


Experiment funktioniert!

Und nun?

Wie geht es weiter?

- Wie kommen die Predictions zum User?
- Wie soll das Modell deployed werden?
- Welche Bereiche des Unternehmens sind involviert?
- Woher kommen “live” Daten?
- Wie könnten User frühzeitig einbezogen werden?
- Was muss für einen wirtschaftlichen Nutzen passieren?



Die zwei Seiten eines Daten-Projekts

codecentric

Daten-Projekt – Zwei Perspektiven

Data Scientist

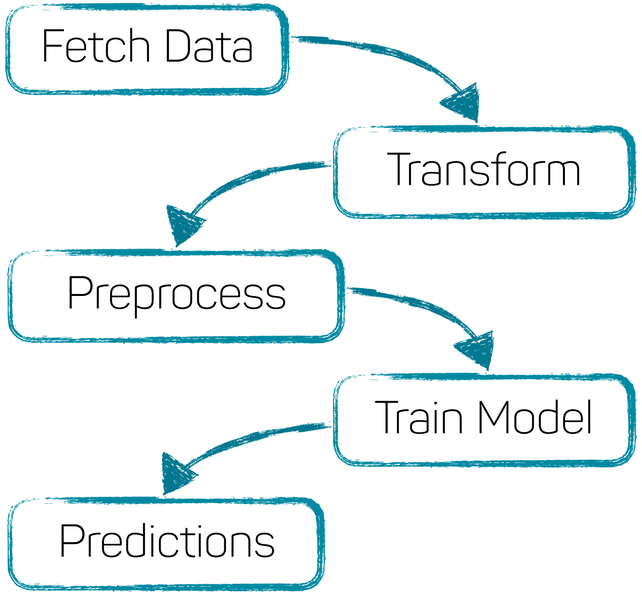
- Neue Features
- Neue Algorithmen
- Optimierung des Modells
- Visualisierung der Ergebnisse
- Verbesserung der Predictions

Jupyter notebook

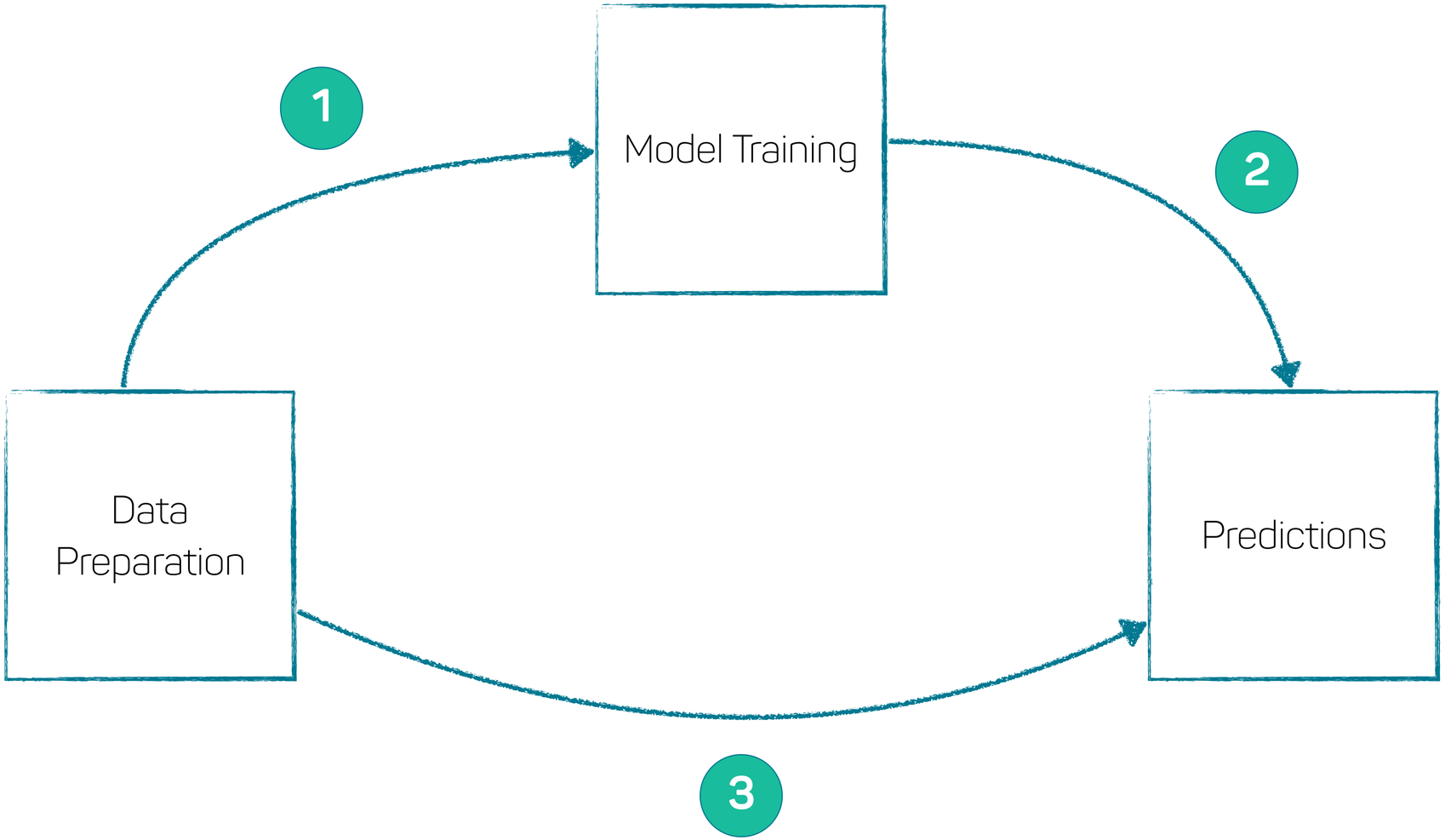
```
data = load_data("input.csv")
data = preprocess(data)
model = train_model(data)
print(model.predictions)
```

Software/Data Engineer

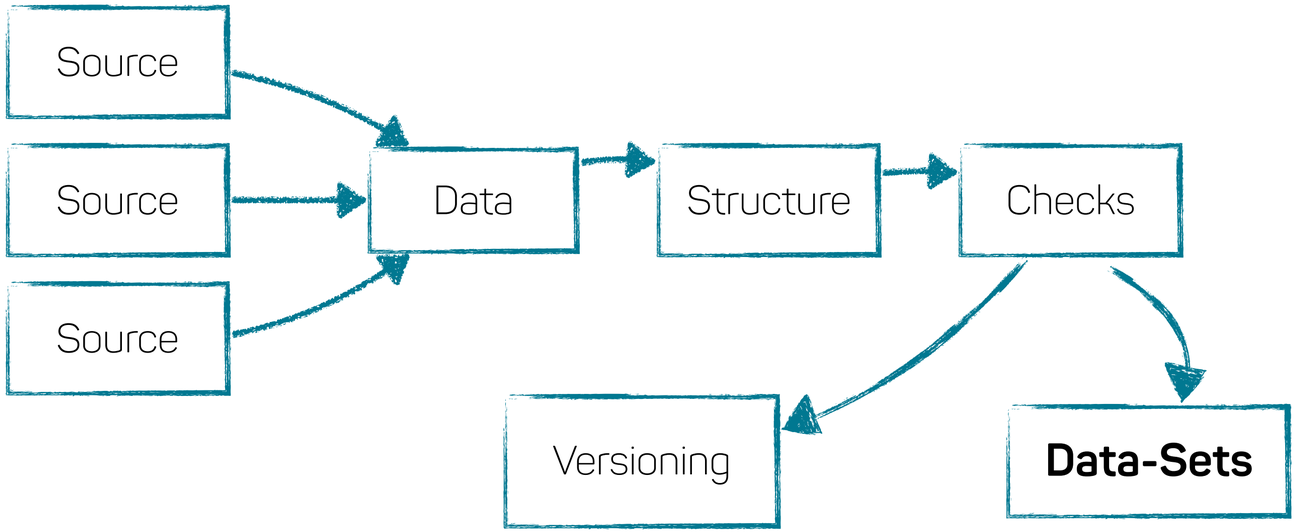
- Schneide Module
- Artefakte und Interface
- Deployment
- Maintainable Code
- Unittests, Integrationtests
- Build Pipelines
- Automatisierung

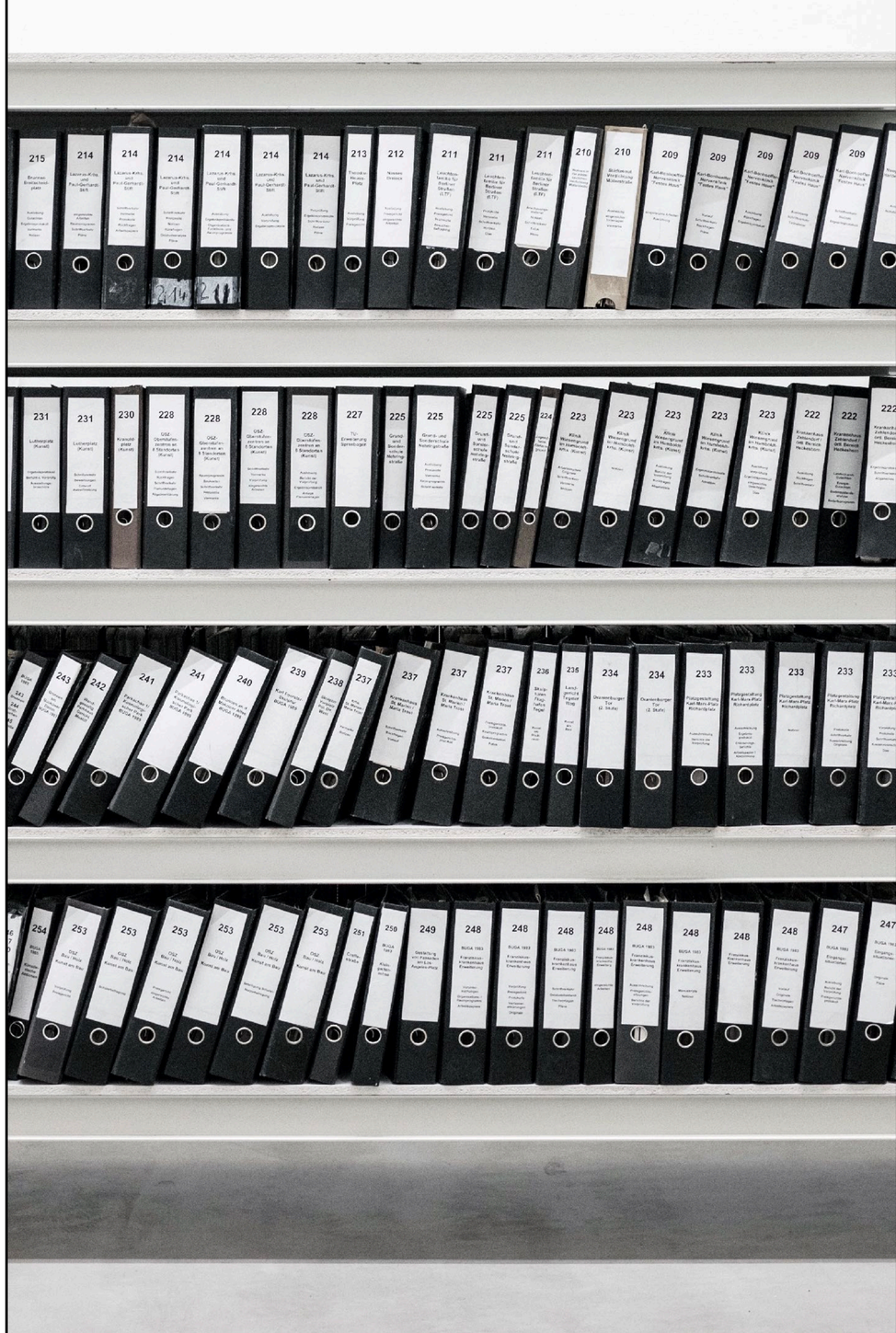


Data Science - Zyklus

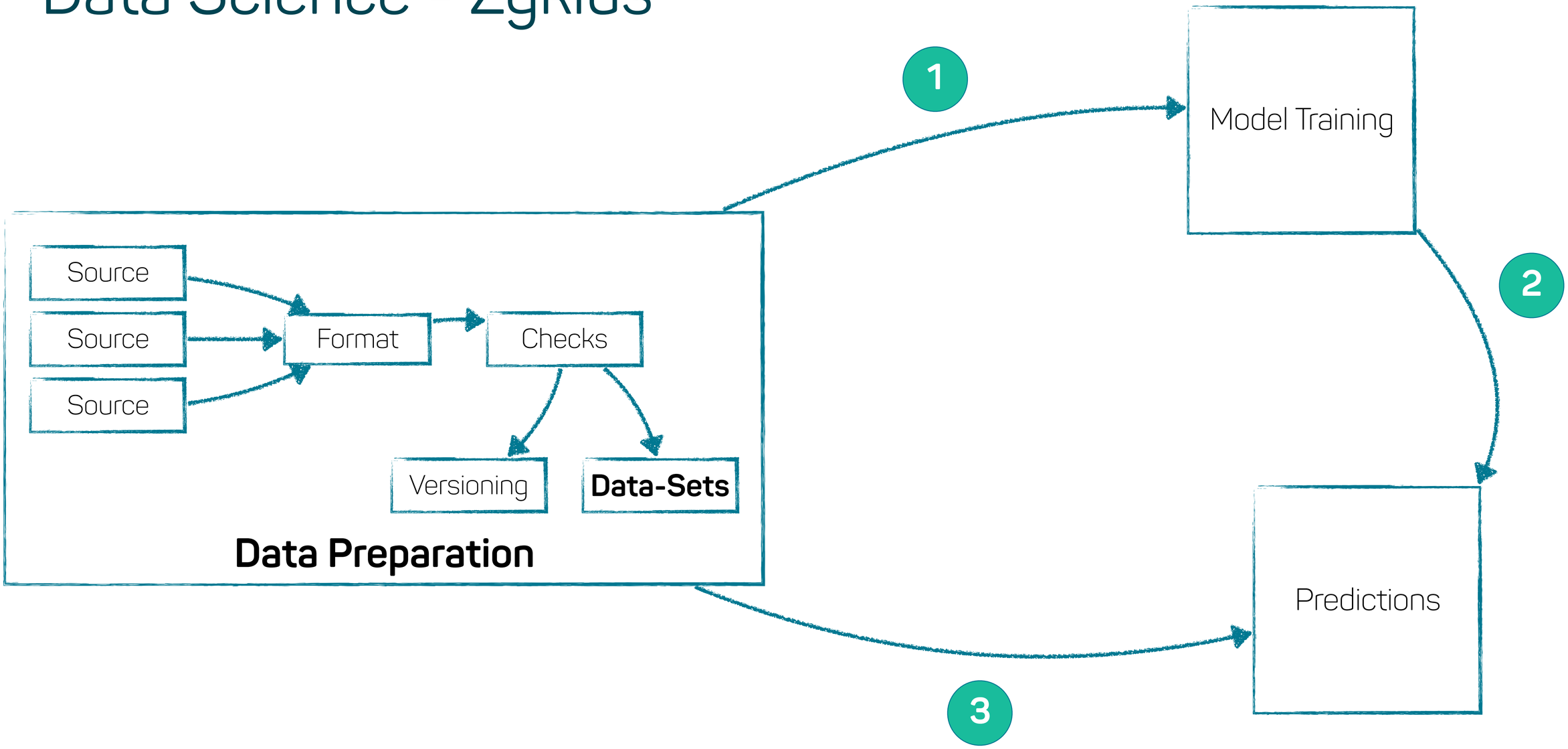


Vorbereiten der Daten

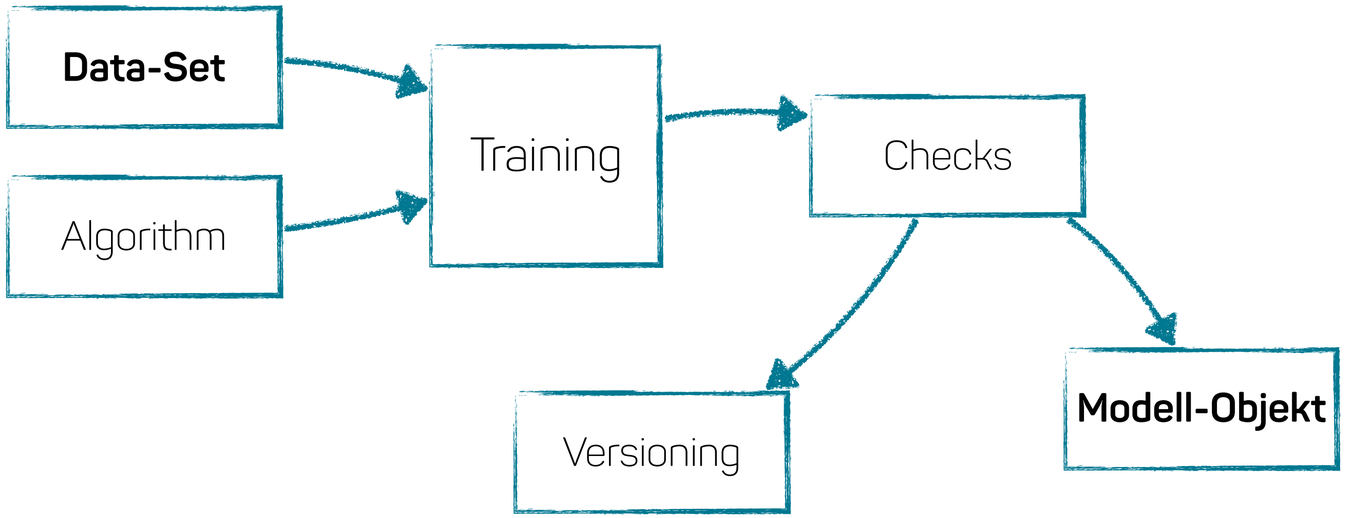


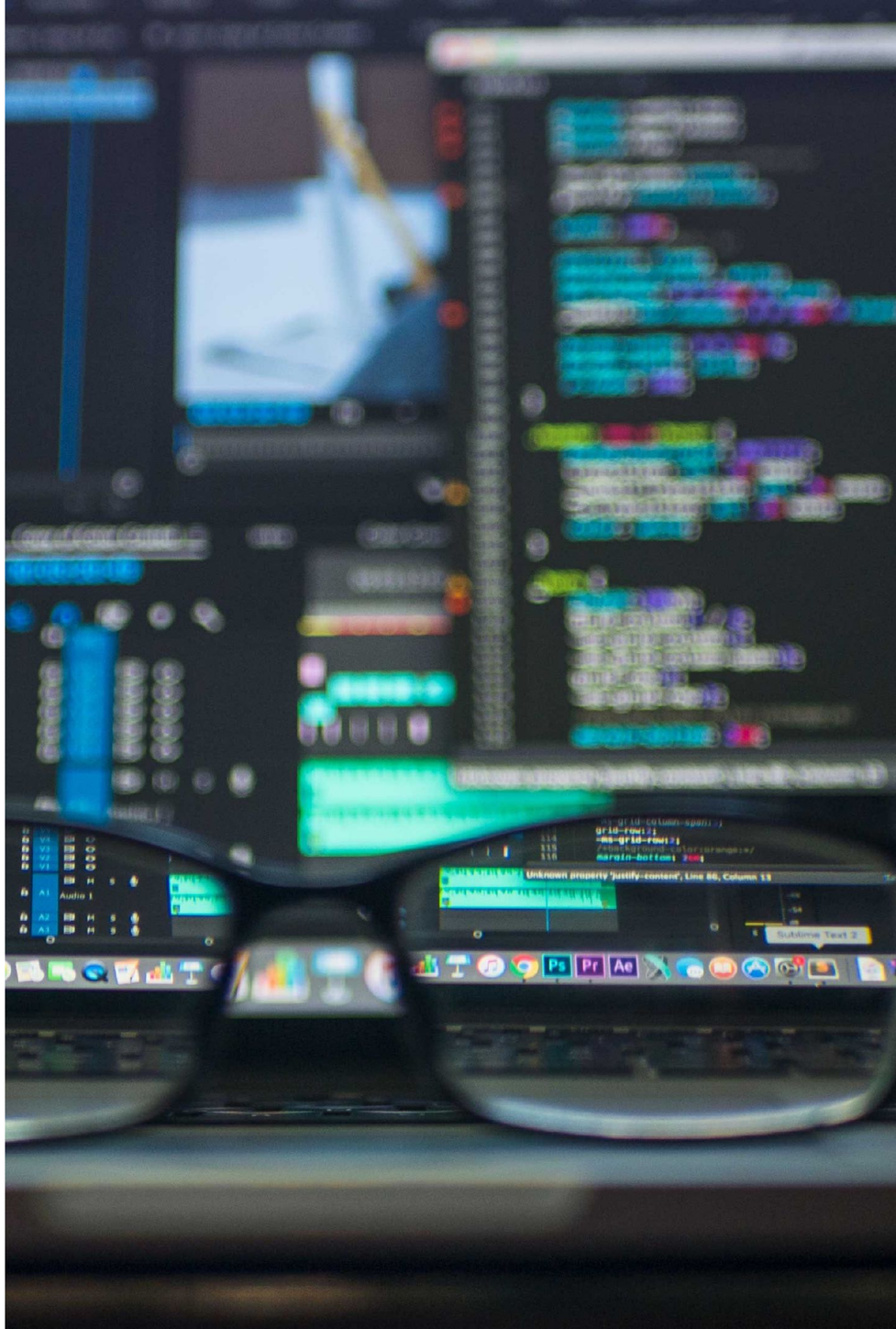


Data Science - Zyklus

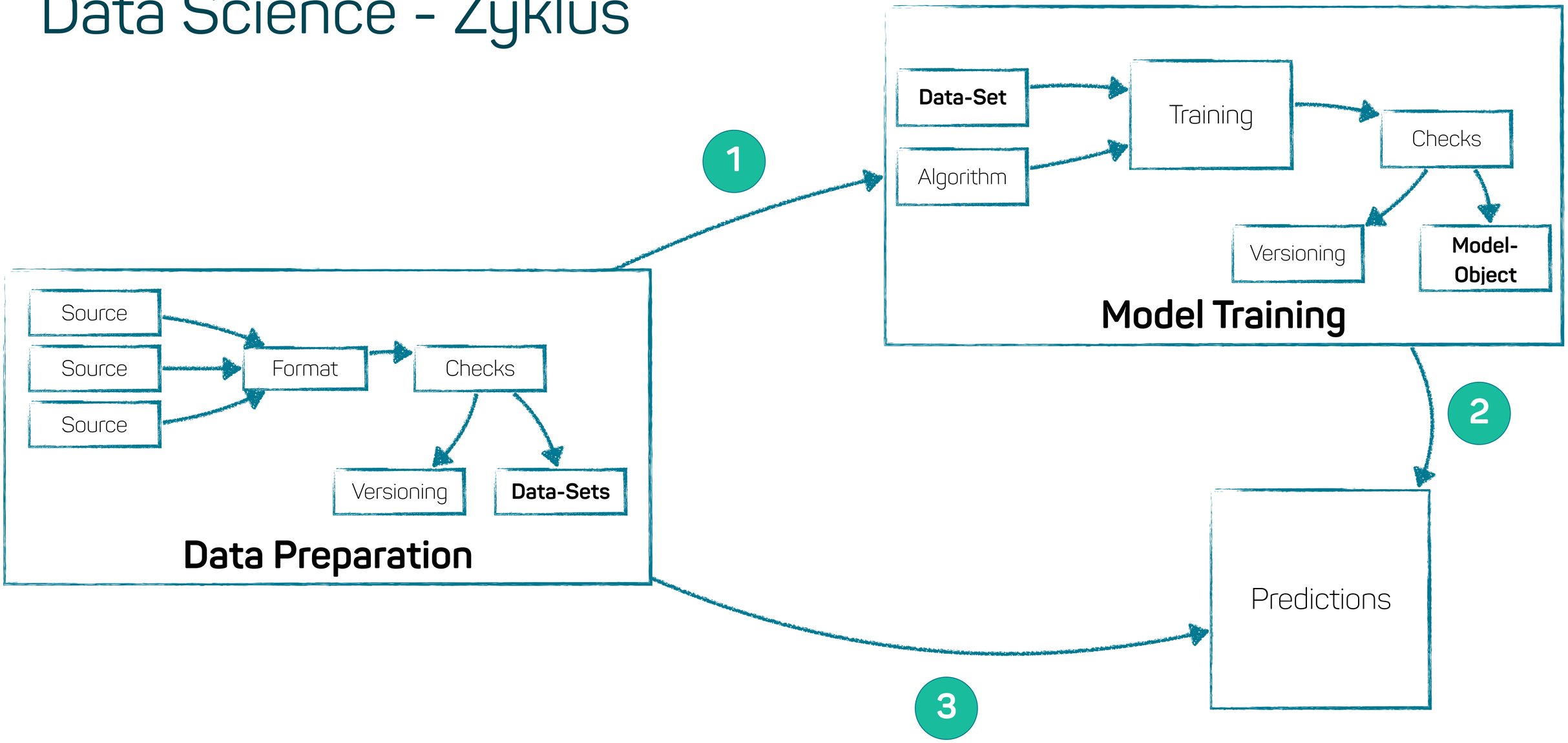


Trainieren des Modells

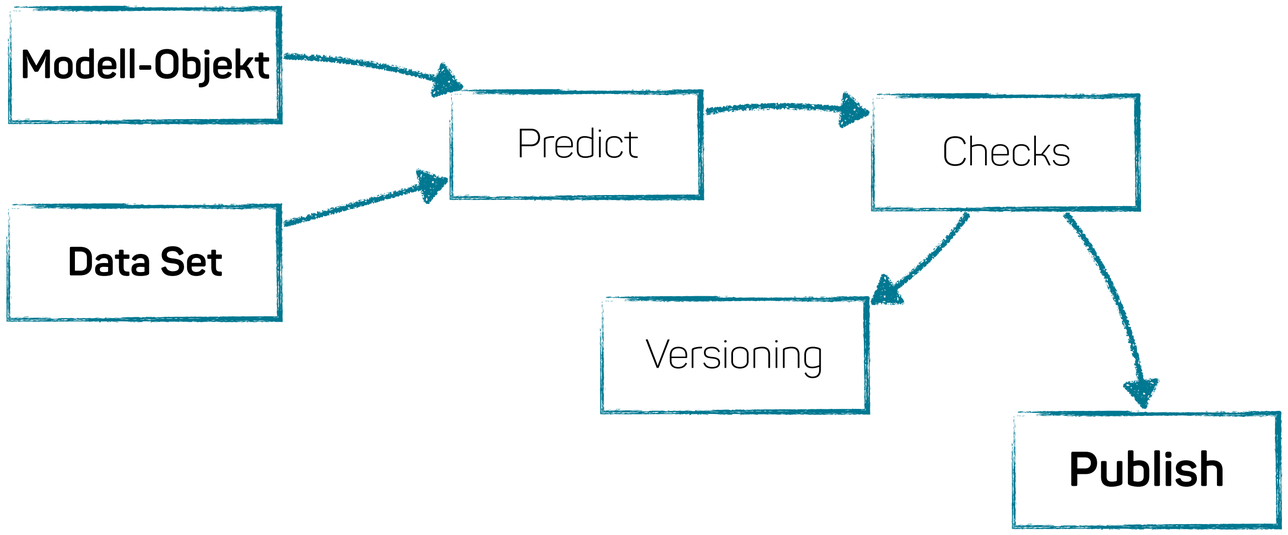




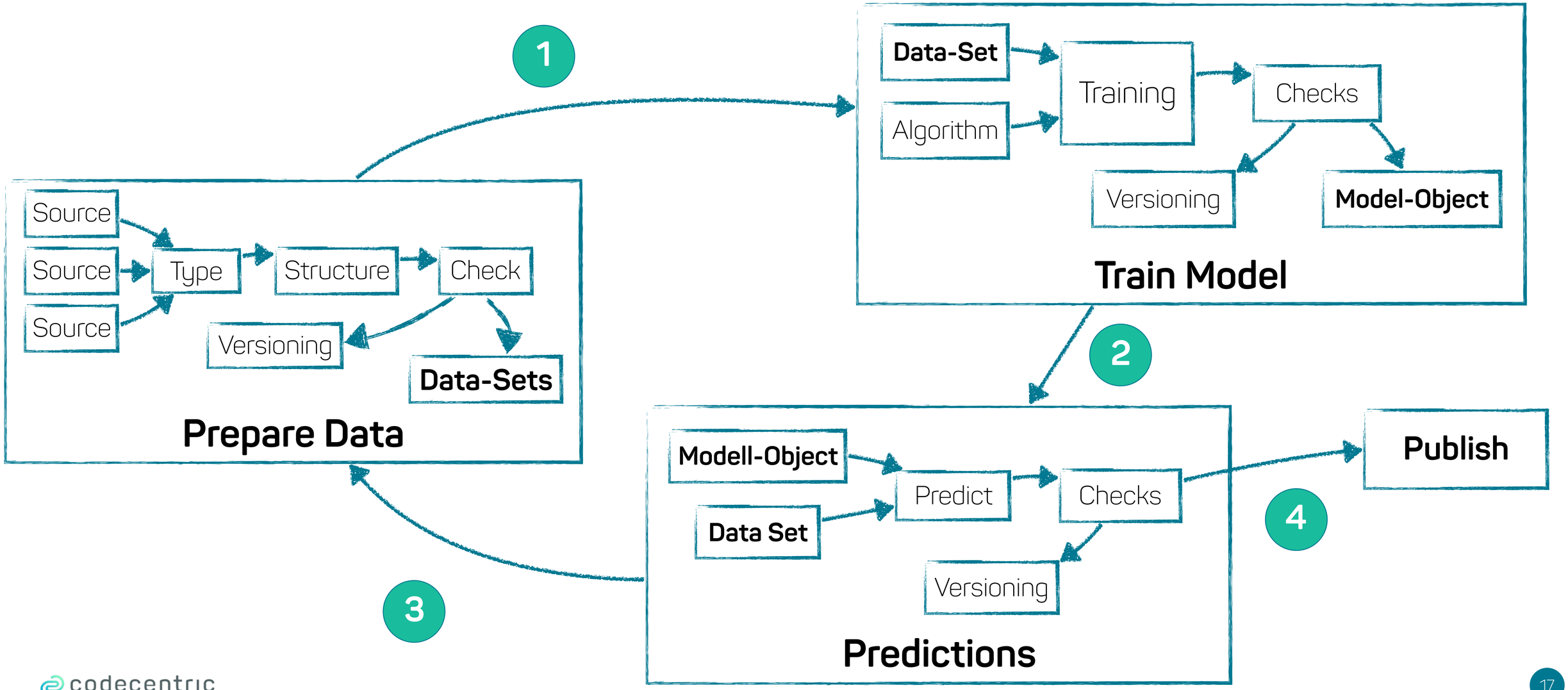
Data Science - Zyklus



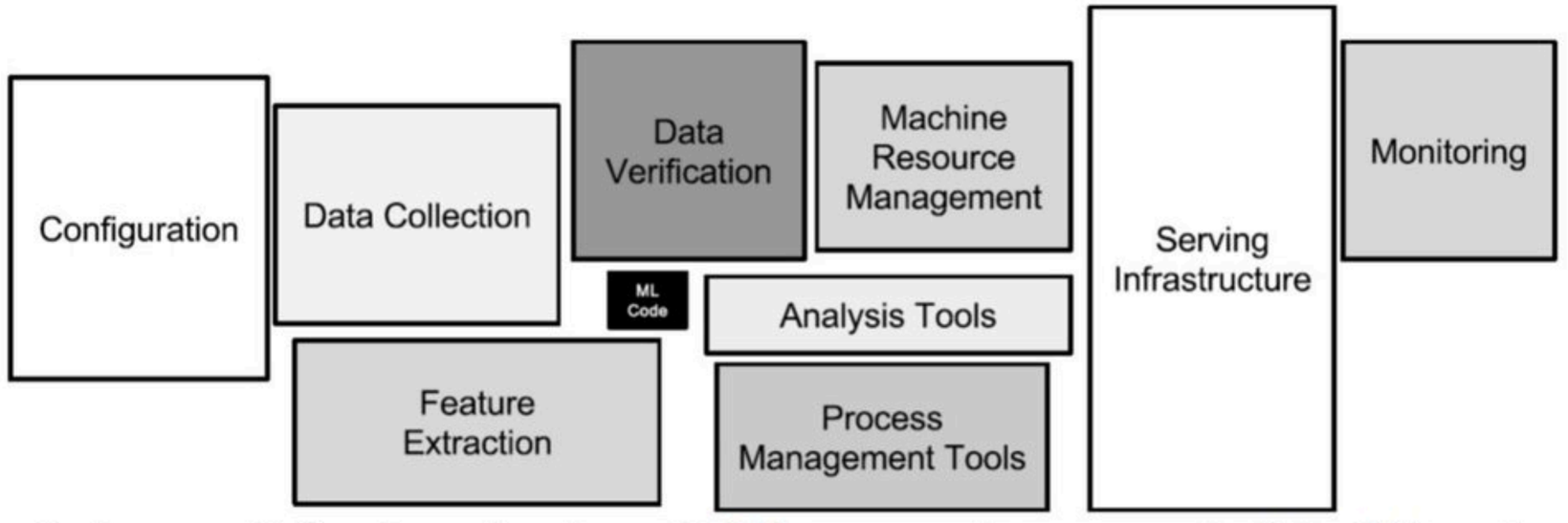
Forecasting



ML-Systeme


1
Data-Set
Algorithm
Training
Checks
Versioning
Model-Object
Train Model
2
Source
Source
Source
Type
Structure
Check
Versioning
Data-Sets
Prepare Data
3
Modell-Object
Data Set
Predict
Checks
Versioning
Predictions
4
Publish

ML-Systeme sind komplex

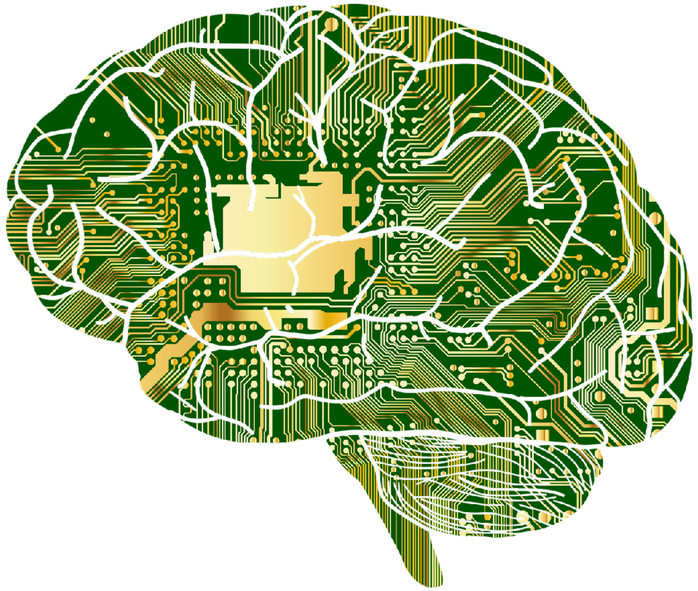


Sculley, David (Google), et al. "Hidden technical debt in machine learning systems." *Advances in neural information processing systems*. 2015.

ML-Systeme

Ziel: Automatisiertes System, um aus Daten Business Value zu generieren

- Besteht aus Data-Science und Data-Engineering Anteilen
- Beinhaltet eine Machine Learning Komponente
- Ist ein Software System mit “Intelligenz”
- Verfügen über einen Continuous Improvement Cycle
- Sind Software Systeme



Mit welchem Team?

Data Scientist

Data/Software Engineer

Data/Software Engineer

Data/Software Engineer

Bonus: „Machine Learning Engineer“

Machine Learning Deployment

ML Deployment - Das Modell

Iterativer Prozess

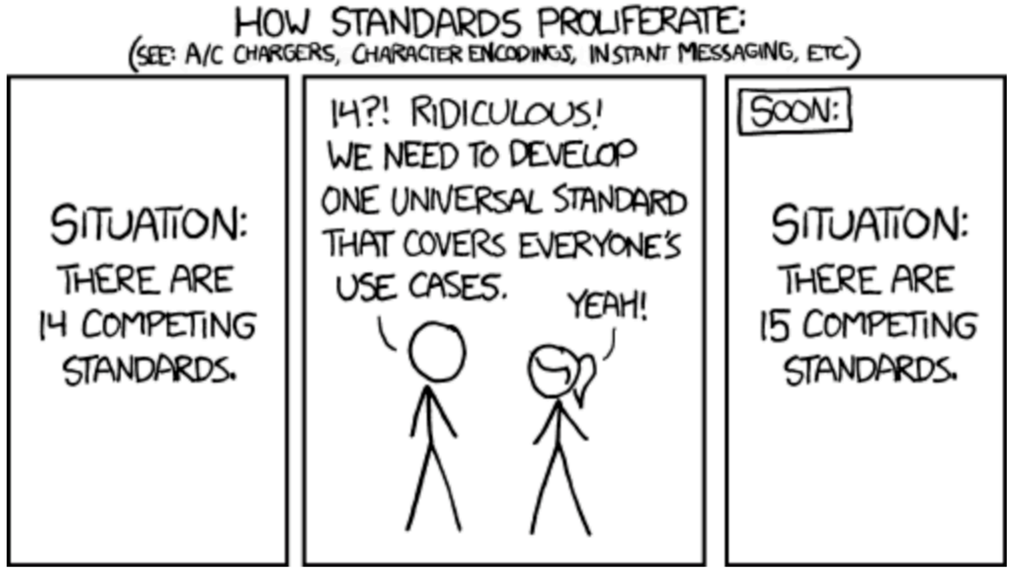
Das Modell

mxnet

ONNX - Open Neural Network Exchange

Ziel: Alle Modelle in einheitlicher Laufzeitumgebung

- Open Source Standard für ML Modelle
- Bietet eine einheitliche Representation für Modelle
- Wird von großen Firmen unterstützt



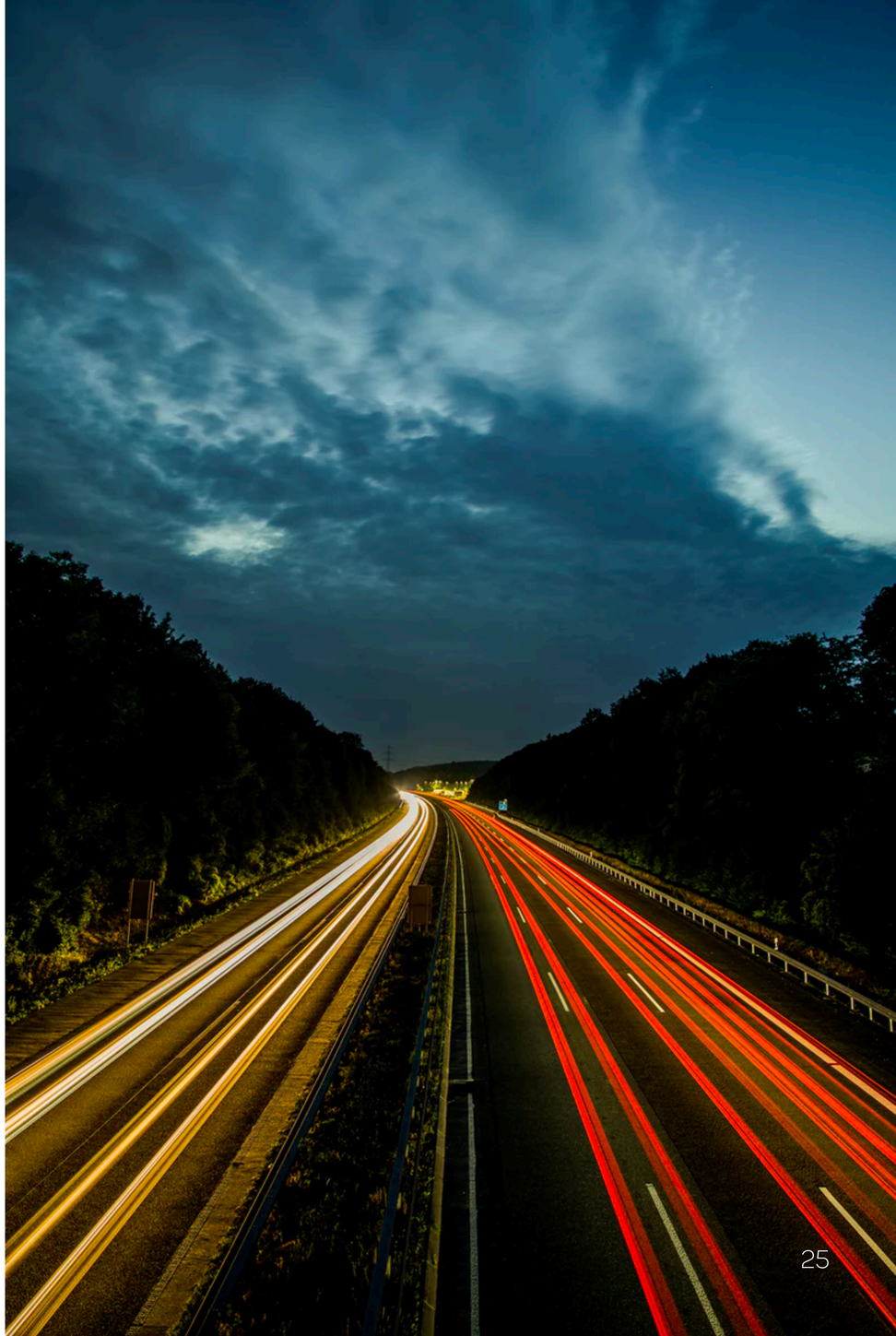
Deployment - Runtime

- Deployment von Code -> Docker
    - Deployment von Containern (K8s)
- TensorFlow Serving
- AWS SageMaker
- Google Cloud ML Engine
- Azure ML Service
- FaaS

- Inference != Training

Deployment - Batch vs Online

- Batch: Speichern & Exportieren der Resultate zur weiteren Verarbeitung
  - Langsameres Feedback
  - Einfacher zu implementieren
- Online: API, PubSub, Datenbank
  - Schnelle Reaktionszeiten
  - Häufig einhergehend: kürzere Feedbackzyklen
  - Aber auch: komplexere Evaluierung
- Außerdem zu beachten:
  - Skalierung
  - Infrastruktur / Monitoring
  - Kosten
  - Komplexität des Modells



Deployment - Scheduling & Orchestrierung

- Scheduling -> Airflow/Luigi
  - Tool zum kontinuierlichen Ausführen des Cycles
  - Löst Dependencies zwischen Tasks

- Orchestrierung bei
  - Feature Engineering
  - Hyperparametertuning

Deployment - Feedback

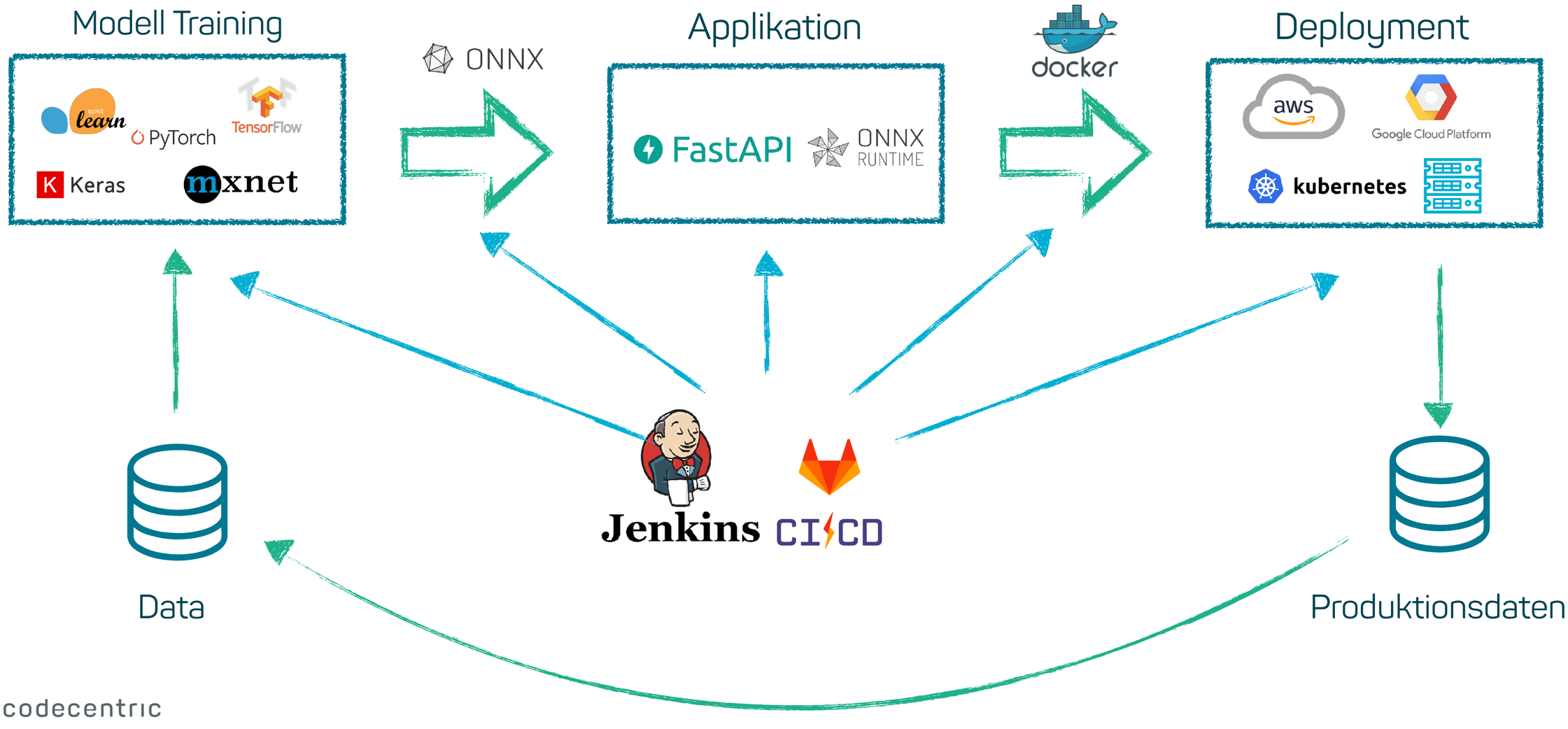
- Einfach: Scoring Evaluierung
  - Samples mitloggen / extrahieren
  - Metriken bereitstellen

- Challenge: Business Feedback für Backfeeding bekommen
  - Feedback häufig erst lange nach der Prediction möglich
  - Feedbackkanal häufig nicht vorgesehen

Monitoring

- Technisches Monitoring:
  - Laufen Predictions durch? Wie ist die Cycle-Time?
  - Wie ist die Auslastung der Ressourcen: CPU/RAM/IO
- Fachliches Monitoring:
  - Verteilung der Klassen innerhalb der Predictions
  - Grundverteilung der Input Daten
- Nachträgliche Evaluierung:
  - A/B Testing: Aufteilung in unterschiedliche Gruppen
  - Post-Eval: Zurückschauen in die Vergangenheit auf alte Prognose und mittlerweile bekannte Ground-Truth

ML Deployment - Applikationssicht



Weitere hilfreiche Tools

Data Version Control / Version Control

ML Deployments

Beispiel aus der Praxis - Ausgangslage

Churn Prediction, Recommender

Erste Modelle mittels R implementiert

Komplett manueller Prozess

Langwierig und deshalb wenig genutzt

Skalierung nicht möglich

- Technisch (lokaler Rechner, on-premises)
- Business (Ausrollen in mehrere, unabhängige Regionen)

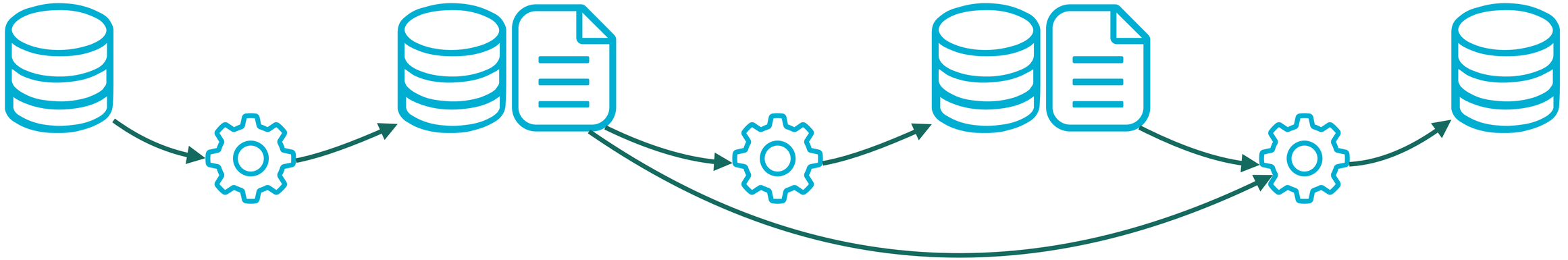
Beispiel aus der Praxis

Ausgangsdaten

Data Sets / Features

Modell Storage

Predictions



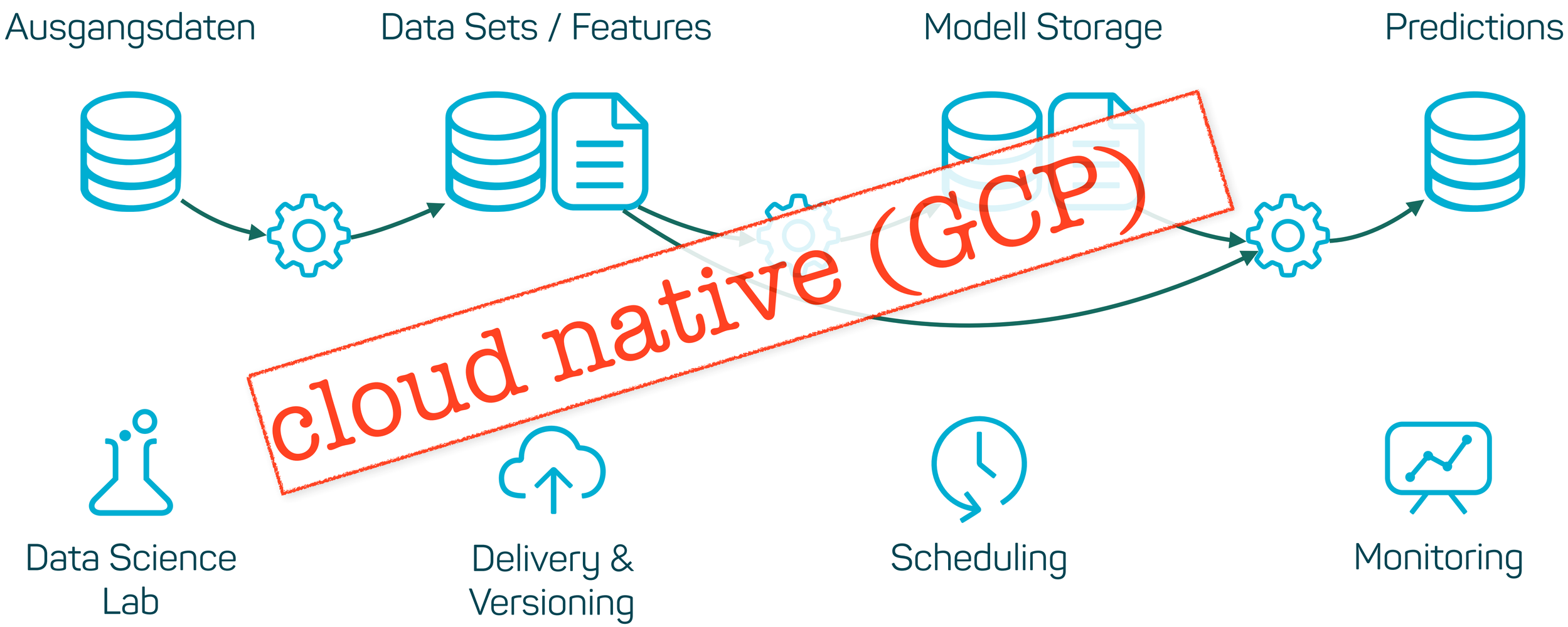
Data Science Lab

Delivery & Versioning

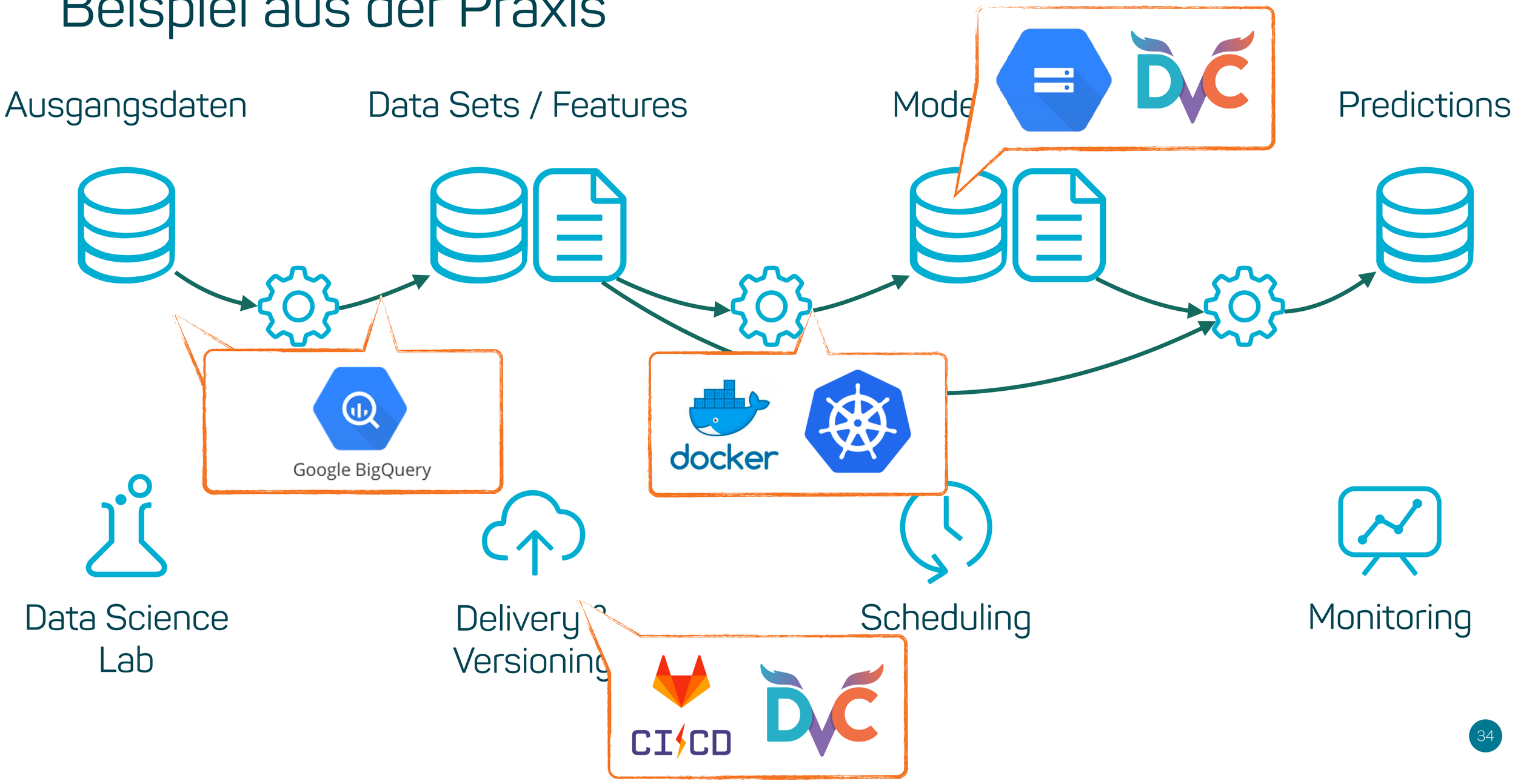
Scheduling

Monitoring

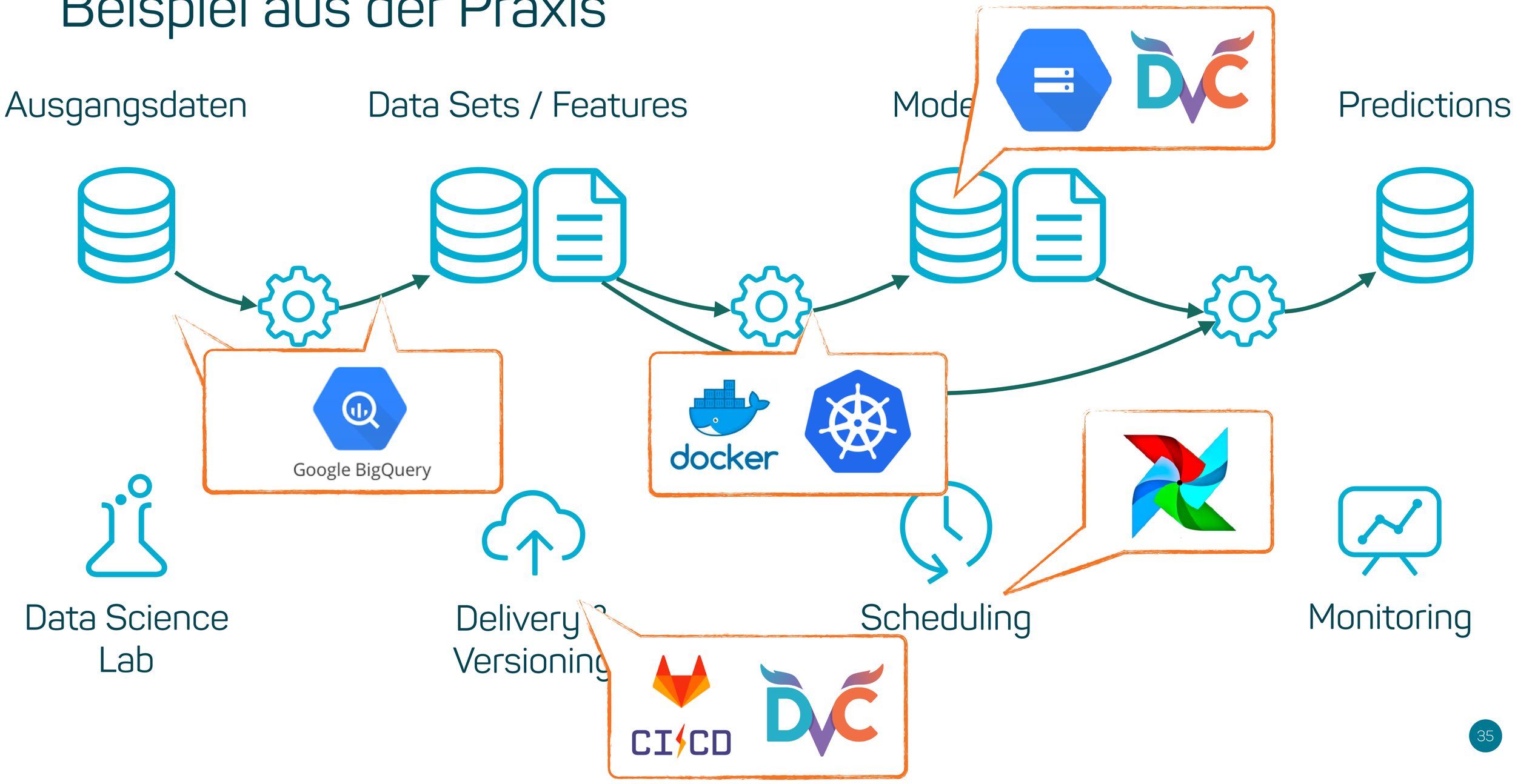
Beispiel aus der Praxis



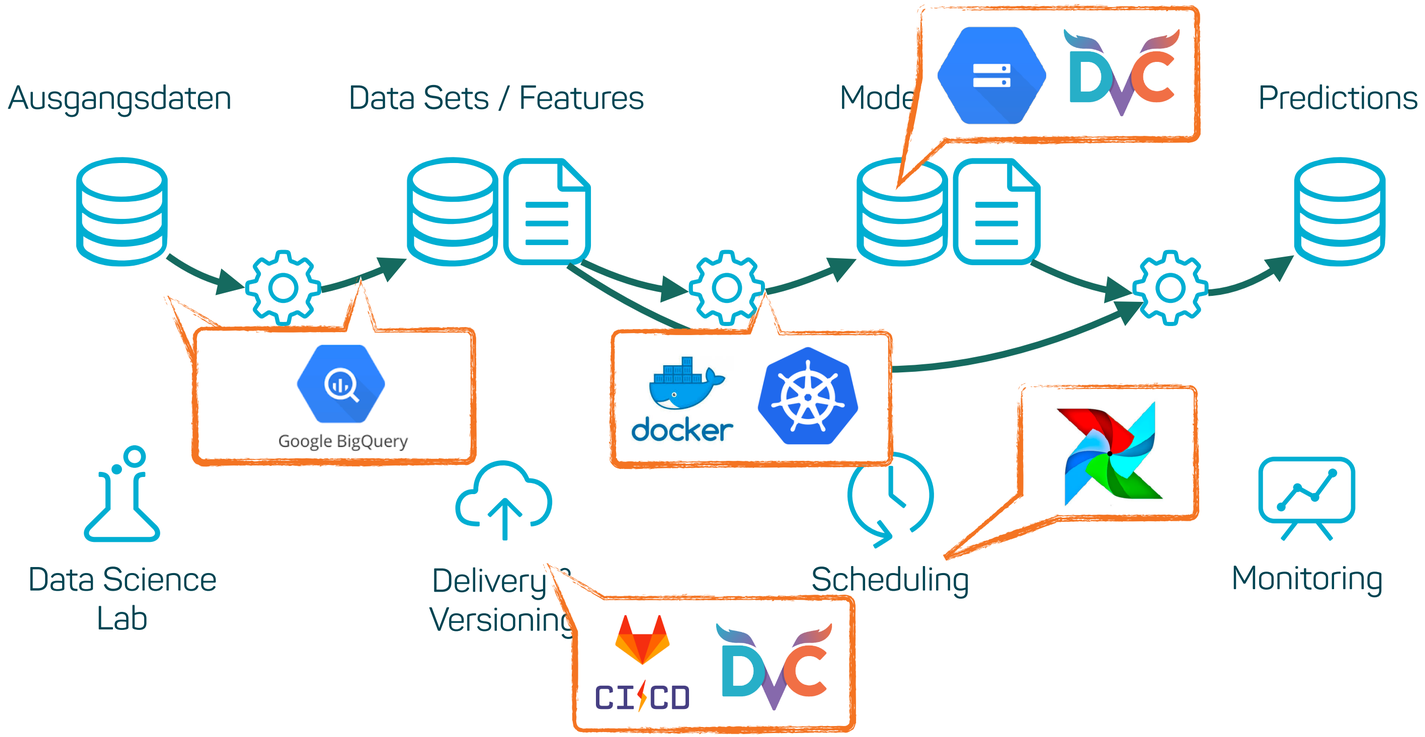
Beispiel aus der Praxis



Beispiel aus der Praxis



Beispiel aus der Praxis



Eine mögliche technische Lösung unter Berücksichtigung von

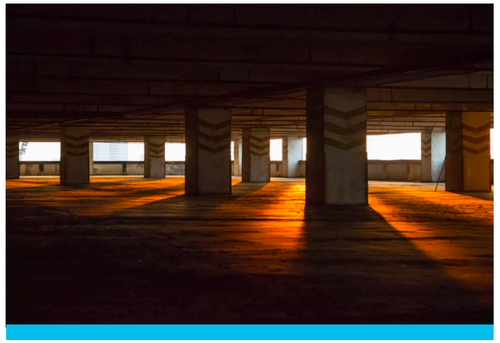
- Vorhandener Infrastruktur
- Vorgaben bzgl. Cloud Nutzung
- Skills
- Flexibilität

- Viele spezialisierte Lösungen am Markt
- Erste All-in Lösungen on-Prem
- ML-Plattformen der großen Cloud Anbieter

Beispiel aus der Praxis - Nutzen

Regelmäßige, automatisierte Vorhersage für alle Regionen

Berücksichtigung neuer und aktueller Daten



Nutzung der Plattform für weitere Use Cases (z.B. Recommender)

Technische Herausforderungen

- Experiment Tracking
- Reproduzierbarkeit
- Skalierung & (lokale) Infrastruktur
- Monitoring
- Hohe Anzahl verschiedener Komponenten
- (noch) wenige Standards
- Integration in bestehende Umgebung
- Datenschutz erhöht die Komplexität

Soviel zur Technik...

Aber wie gehe ich ein Projekt an?

Roadmap

- Klärung der Durchführbarkeit
- Klärung des Business Cases
- Schnelle Iterationen und Exploration des Problems
- Data Scientist + Data Engineer

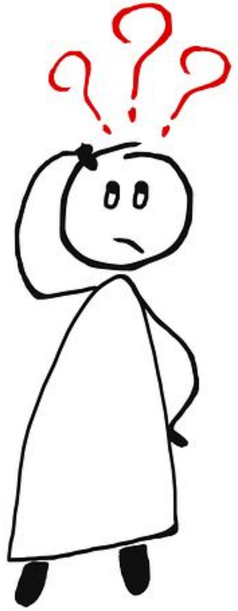
- Durchstich in Produktion
- Data Science Fokus auf Stabilität und Reproduzierbarkeit
- Data Engineering Fokus auf Automatisierung
- Mehr Data Engineers

- Continuous Improvement Cycle
- Kontinuierliche Weiterentwicklung
- Resilient Software Design
- technisches/fachliches Monitoring
- 2-3 Data/Software Engineers pro Data Scientist

PoC — Mindset

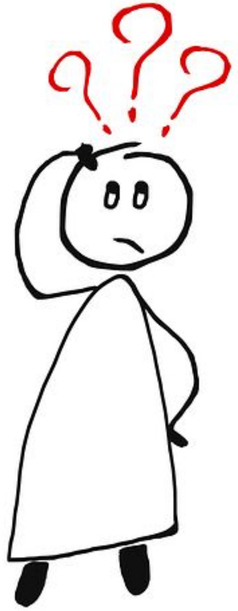
Aufgabe: Evaluierung der Durchführbarkeit

- Entwickle ein einfaches Basis Modell
- Treffe pragmatische Entscheidungen und Annahmen
- Schärfe den Use-Case / Business Case
- Helfe dem Management zu Verstehen (Business Metrics)
- Nur Experimente liefern belastbare Entscheidungsgrundlagen
- Arbeite data-driven nicht discussion-driven



PoC — Mindset

- Jupyter Notebooks sind am Anfang okay
- Reproduzierbarkeit und Vergleichbarkeit sind wichtig
- Beginne mit Automatisierung, Bash-Scripte sind okay
- Entwickle ein "ausreichend gutes" nicht "das beste" Modell
- Denke an das Big Picture
- Sobald ein Mehrwert geschaffen ist Integration



Minimal Valuable Product — Pipelines

Herausforderung: Deployment der gesamten Pipeline

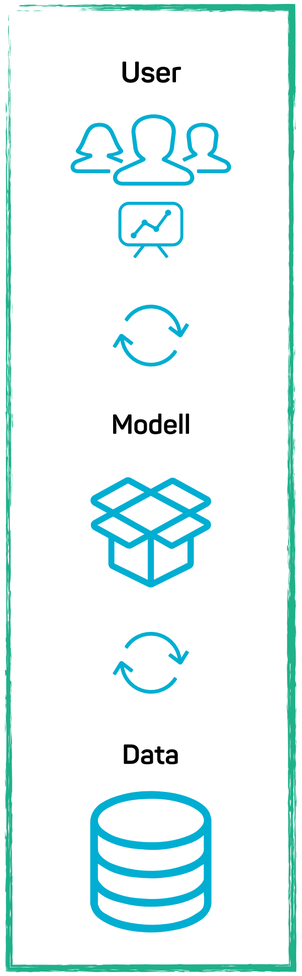
Trainings-Phase

Prediction-Phase

Minimal Valuable Product

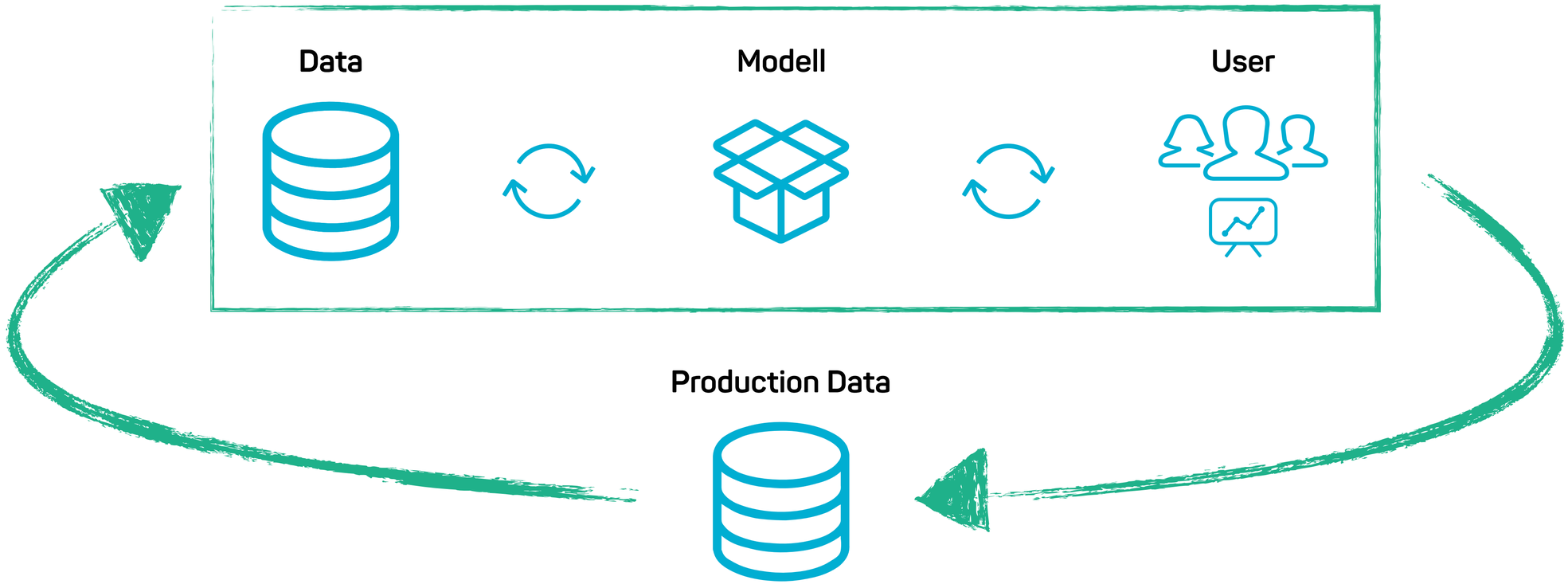
Aufgabe: Integration des Modells in die vorhandene Infrastruktur

- Baue “richtiges” Python aus den Jupyter Notebooks
- Schreibe Unittests und Integrationstests
- Entwickle eine initiale Deployment Infrastruktur
- Automatisiertes Training und Evaluation
- Es ist okay die Anwendung am User zu entwickeln



Professionalisierung des Systems

Ziel: Continuous Improvement Cycle und Monitoring



Take aways

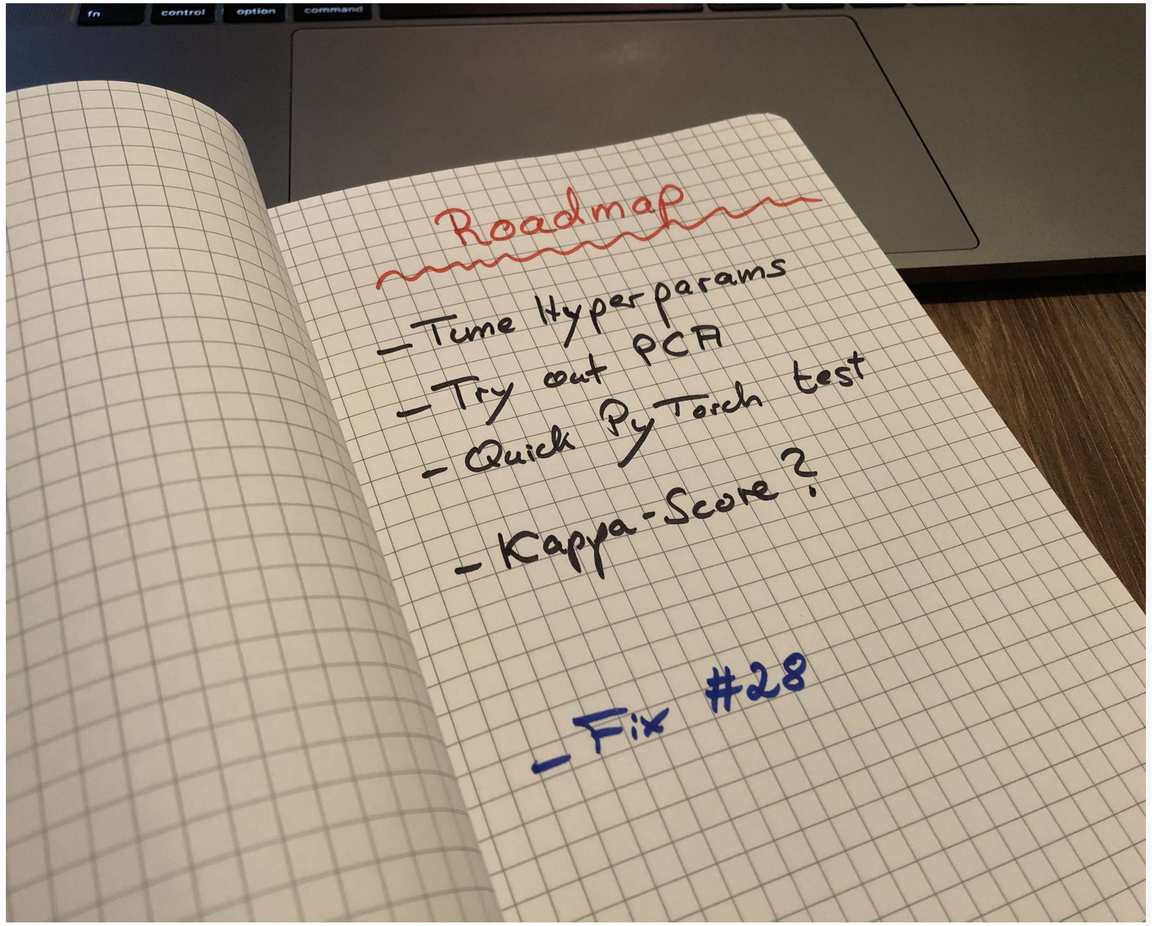
- ML in Production ist schwer
  - Engineering & Science Perspektive
  - Komplexe ML-Systeme
  - Mehr Software & Engineering als vermutet

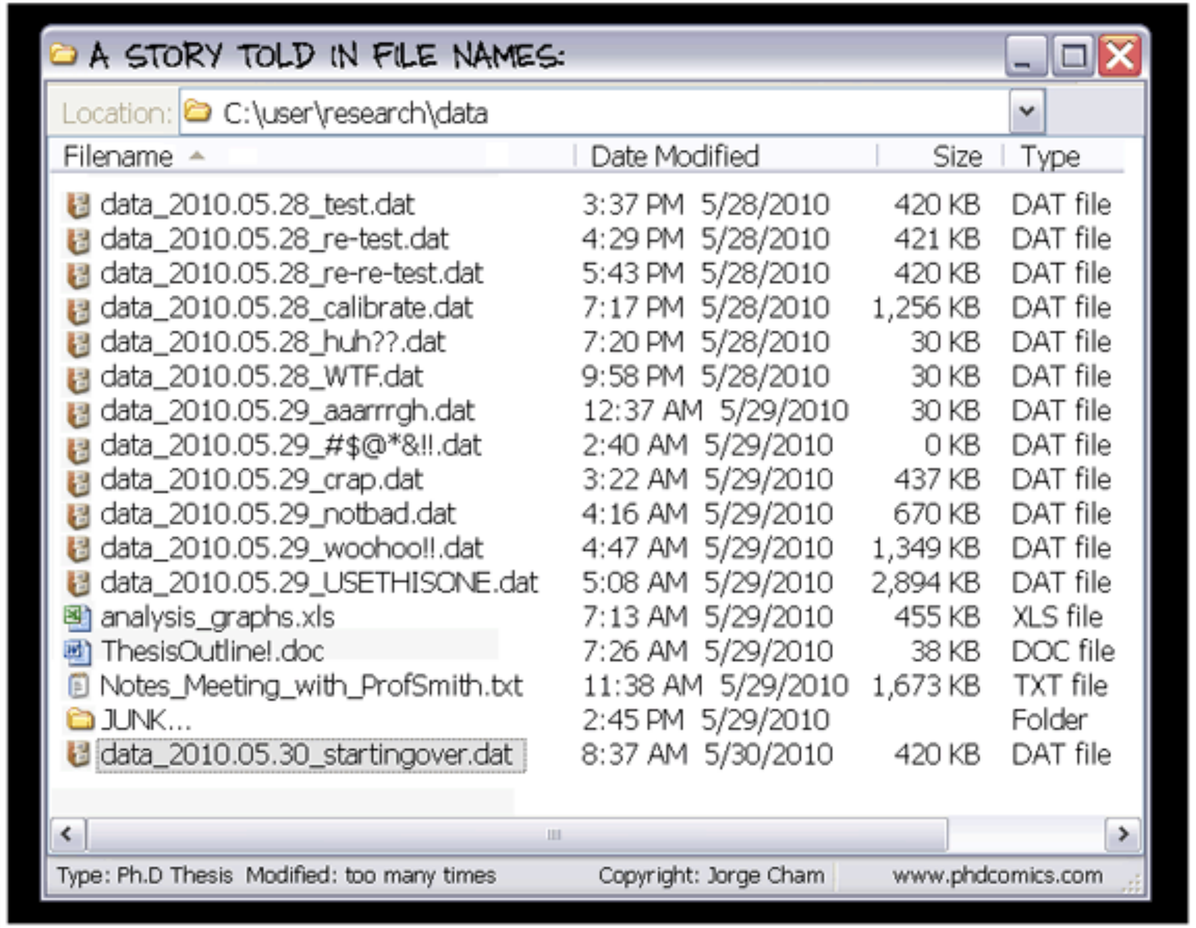
- „Klassische“ Lösungen aus der SE
- Vermehrt spezialisierte Lösungen bis hin zu Komplettansätzen
- Cloud kann die Fertigungstiefe verringern

- Vorgehen:
  - PoC schrittweise ausbauen
  - Nicht mit Plattform starten

Versioning and Reproducable Training

- Data Science is experiment-driven …





Reproducable Training

- ... and collaborative!

```
Tims-MacBook-Pro:code tsabsch$ git log --graph --decorate --oneline
*   fc88d36 (HEAD -> master) Merge branch 'tim_fix_zerodivisionerror'
|\
| * 2cc23f0 (tim_fix_zerodivisionerror) Fix ZeroDivisionError
* |   e486d76 Merge branch 'mark_batchnorm'
|\ \
| |/
|/|
| * b988f6e (mark_batchnorm) Decrease BN threshold
| * c83736d Add batch normalisation
* | f80b108 Add preprocessing
|/
* a87aa63 Add simple tensorflow model
* 7c0d21e Initial commit
Tims-MacBook-Pro:code tsabsch$
```

Modelmanagement - by hand - hyper parameters

A	B	C
Date	**Alpha**	**L1_ratio**
2019-04-03 1:00 PM	1	1
2019-04-03 4:00 PM	1	0.5
2019-04-04 9:00 AM	1	0.2
2019-04-04 11:00 AM	1	0

Modelmanagement - by hand - metrics

A	B	C	D	E	F
Date	**Alpha**	**L1_ratio**	**mea**	**r2**	**mse**
2019-04-03 1:00 PM	1	1	0.649	0.04	0.862
2019-04-03 4:00 PM	1	0.5	0.648	0.046	0.859
2019-04-04 9:00 AM	1	0.2	0.628	0.125	0.823
2019-04-04 11:00 AM	1	0	0.619	0.176	0.799

Modelmanagement - by hand - model

	A	B	C	D	E	F	G
1	**Date**	**Model**	**Alpha**	**L1_ratio**	**mea**	**r2**	**mse**
2	2019-04-03 1:00 PM	model_v7.p	1	1	0.649	0.04	0.862
3	2019-04-03 4:00 PM	model_v7_l1-05.p	1	0.5	0.648	0.046	0.859
4	2019-04-04 9:00 AM	model_v7_l1-02_d3.p	1	0.2	0.628	0.125	0.823
5	2019-04-04 11:00 AM	model_v7_l1-zero_d3.p	1	0	0.619	0.176	0.799

Modelmanagement - by hand - data

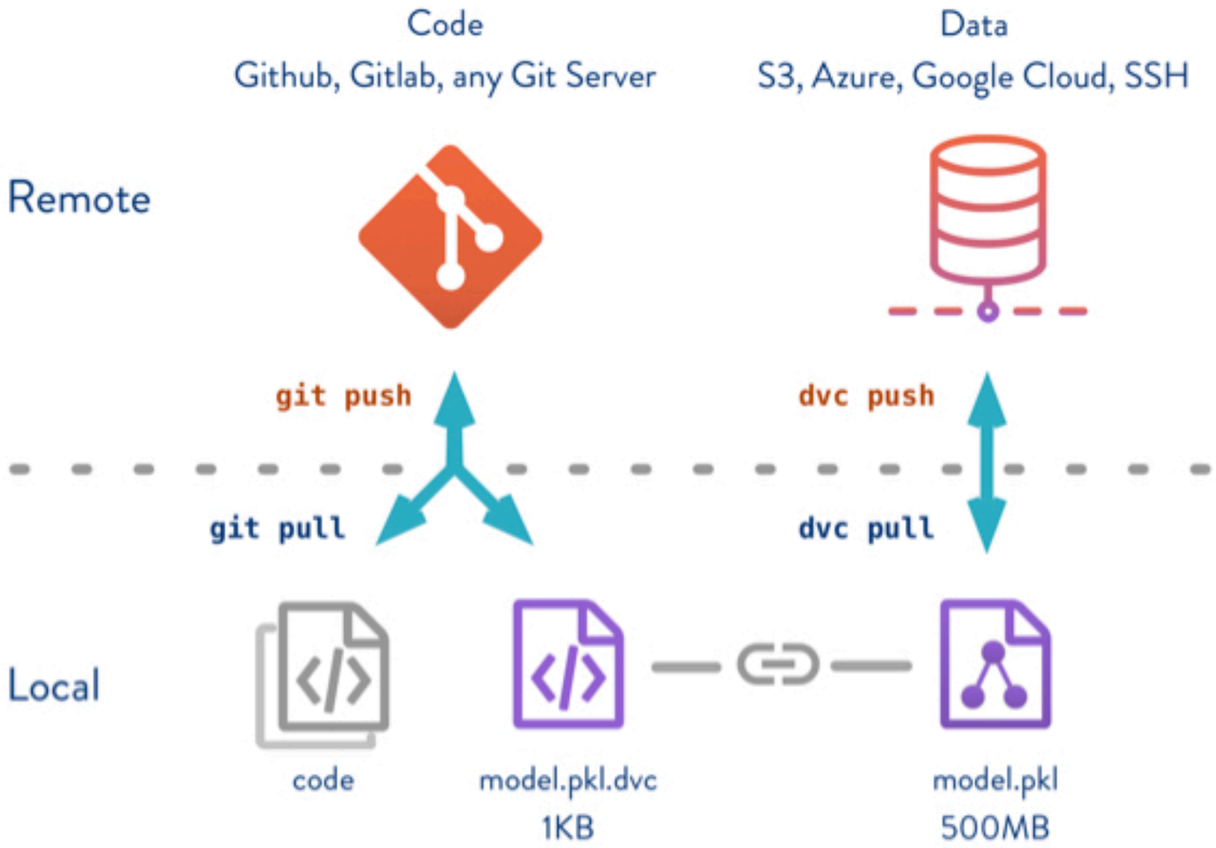
	A	B	C	D	E	F	G	H
1	**Date**	**Dataset**	**Model**	**Alpha**	**L1_ratio**	**mea**	**r2**	**mse**
2	2019-04-03 1:00 PM	data_v2	model_v7.p	1	1	0.649	0.04	0.862
3	2019-04-03 4:00 PM	data_v2	model_v7_l1-05.p	1	0.5	0.648	0.046	0.859
4	2019-04-04 9:00 AM	data_v2_upd_May	model_v7_l1-02_d3.p	1	0.2	0.628	0.125	0.823
5	2019-04-04 11:00 AM	data_v2_upd_May	model_v7_l1-zero_d3.p	1	0	0.619	0.176	0.799

Modelmanagement - by hand - code

A	B	C	D	E	F	G
Date	**Dataset**	**Model**	**Commit**	**Alpha**	**L1_ratio**	**mea**
2019-04-03 1:00 PM	data_v2	model_v7.p	9a5a01b	1	1	0.64
2019-04-03 4:00 PM	data_v2	model_v7_l1-05.p	9a5a01b	1	0.5	0.64
2019-04-04 9:00 AM	data_v2_upd_May	model_v7_l1-02_d3.p	9a5a01b	1	0.2	0.62
2019-04-04 11:00 AM	data_v2_upd_May	model_v7_l1-zero_d3.p	c8b2c10	1	0	0.61

DVC to the Rescue!

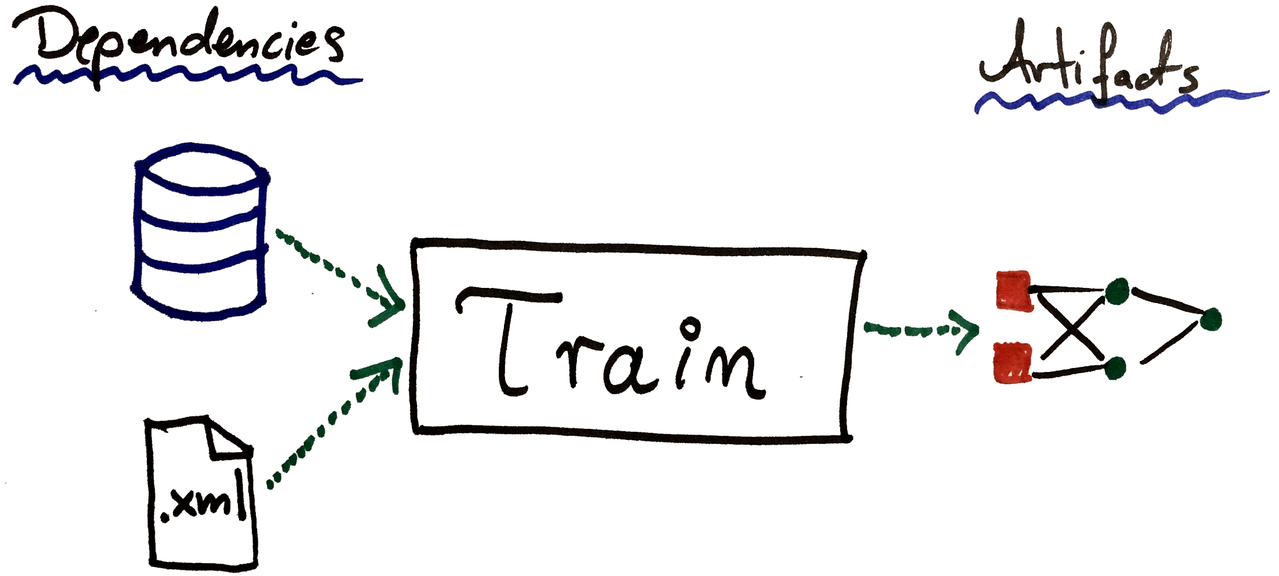
- **Large File Storage**, similar to git-lfs
- Metadata in git (name, hashsum etc.)
- Contents in cache + remote storage



https://dvc.org

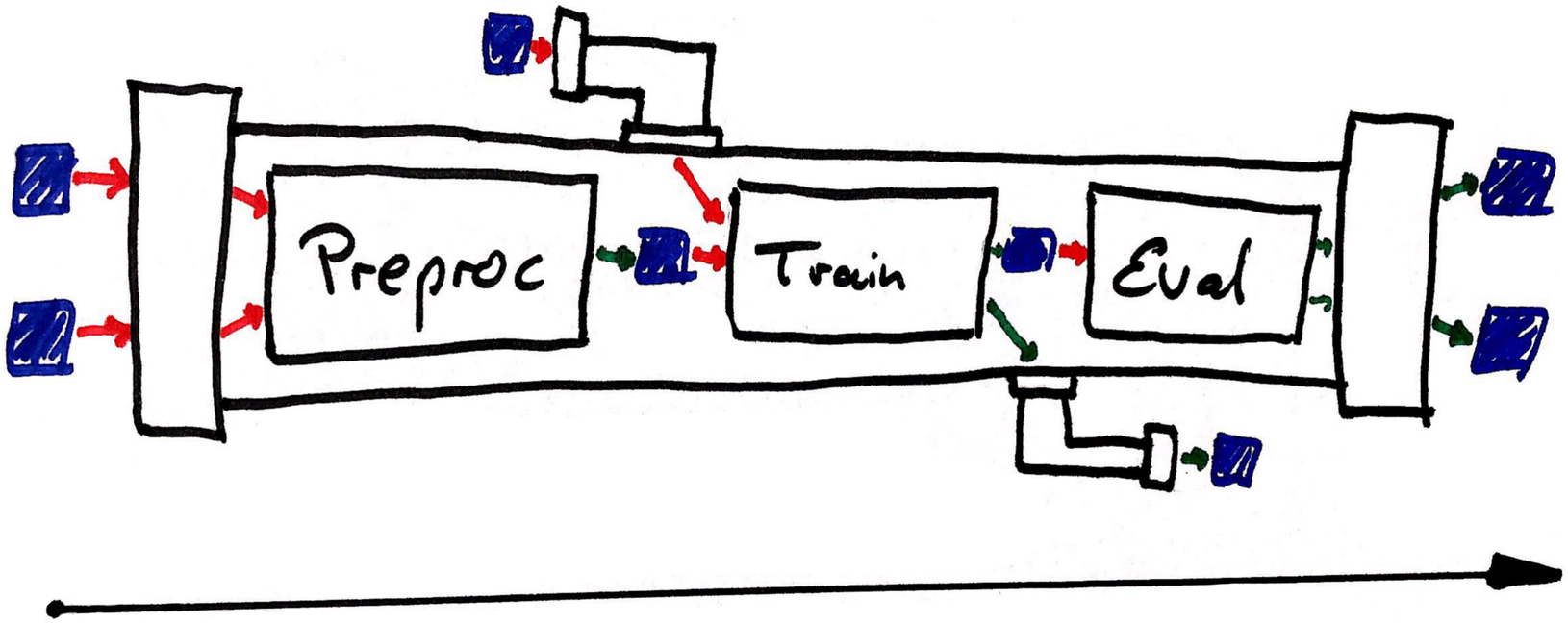
DVC to the Rescue!

- **Pipelines**
- Optimize reproduction by splitting your process into stages
- Stages store dependencies, processing and output artefacts

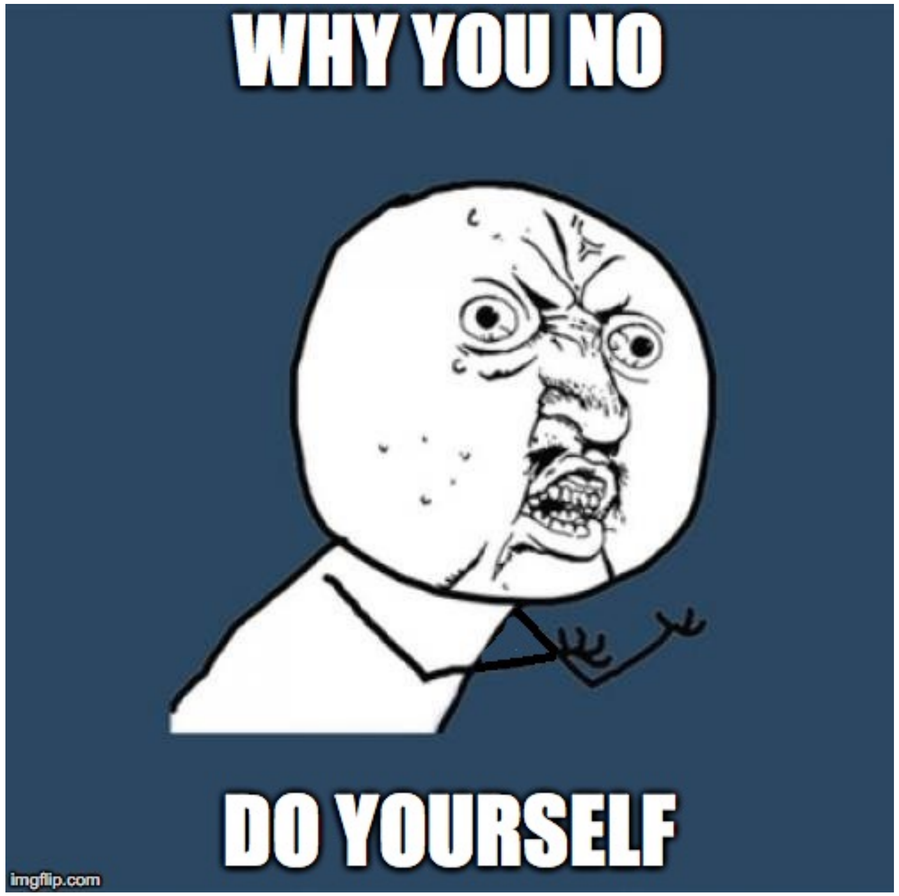


DVC to the Rescue!

- **Pipelines**
- Connect stages to a pipelines via dependencies



Let's get Practical: DVC



DVC cares about

Code ✓

Data ✓

Hyper Params ✗

ML Models ✓

Metrics ✓

ML Flow

- Python Library (pip install mlflow)
- Focus on Hyperparameter Tuning
- Captures Output (Metrics & ML Models)

```
from mlflow import log_metric, log_param, log_artifact
log_param("lr", 0.03)
log_metric("loss", curr_loss)
log_artifact(„model.p")
```

ML Flow

```
$ mlflow ui
```

				Parameters		Metrics		
Date	User	Source	Version	alpha	l1_ratio	mae	r2	rmse
2018-06-04 23:00:10	mlflow	train.py	05e956	1	1	0.649	0.04	0.862
2018-06-04 23:00:10	mlflow	train.py	05e956	1	0.5	0.648	0.046	0.859
2018-06-04 23:00:10	mlflow	train.py	05e956	1	0.2	0.628	0.125	0.823
2018-06-04 23:00:09	mlflow	train.py	05e956	1	0	0.619	0.176	0.799

What about ML Flow

Code ✗

Data ✗

Hyper Params ✓

ML Models ✓

Metrics ✓

Deployment - Scheduling & Orchestrierung

- Scheduling -> Airflow/Luigi
  - Tool for continuous execution of the cycle
  - Solves dependencies between tasks

- Orchestration with
  - Feature engineering
  - Hyperparameter tuning

Workflow Management

- DVC pipelines are useful for research & development
- What about more complex workflows?
- What about an automated & scheduled process?

Let's get Practical: Airflow

- Developed by AirBnB, now Apache Foundation

- **Write**, **schedule** and **monitor** workflows
- Write: Workflows are defined as Directed Acyclic Graphs, defined and written in Python
- Schedule: Provides own scheduler, allows for cron-style scheduling
- Monitor: Inspect and interact via webserver / UI