IFC-Bank of Italy Workshop on "Data science in central banking: enhancing the access to and sharing of data"

17-19 October 2023

From the ML model to practice: case study on NLP-based decision-making on the eligibility of security prospectuses[1]

Janek Blankenburg, Maximilian König, Philipp Rothhaar and Bernd Rusitschka,
Deutsche Bundesbank

[1] This contribution was prepared for the workshop. The views expressed are those of the authors and do not necessarily reflect the views of the Bank of Italy, the BIS, the IFC or the other central banks and institutions represented at the event.

DEUTSCHE BUNDESBANK EUROSYSTEM

SCAI Service & Community Center for Artificial Intelligence

From the ML Model to Practice

Case Study on NLP-based Decision-Making on the Eligibility of Security Prospectuses

SCAI
Service & Community Center
for Artificial Intelligence

Maximilian König
AI Solution Architect

Bernd Rusitschka
AI Expert in DG Markets

Janek Blankenburg
AI Application Engineer

Philipp Rothhaar
Expert in DG Markets

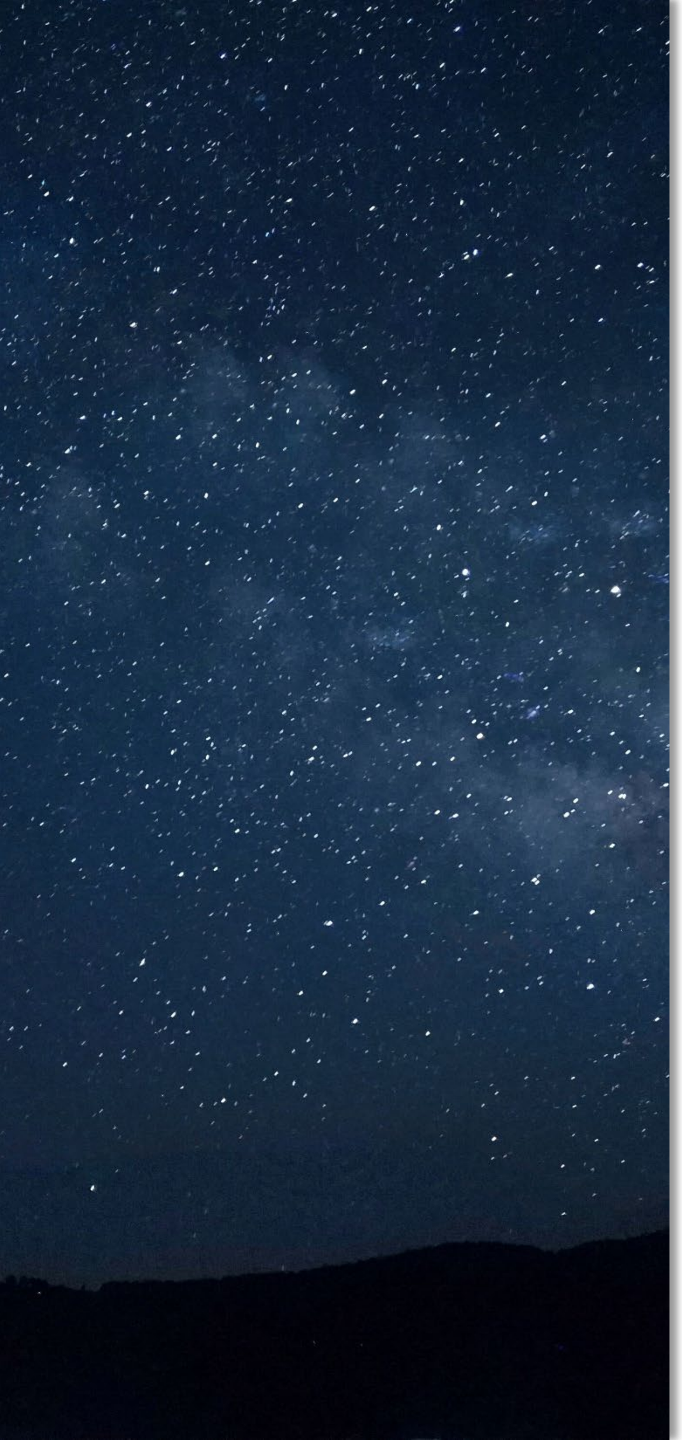
In collaboration with further colleagues from DG Markets and Prof. Christian Hänig and Serhii Hamotskyi from Anhalt University of Applied Sciences

Agenda

Status quo ante	Deciding the Eligibility of Securities' Prospectuses
Training a model	Proof of Concept with a fine-tuned model
Integration	... of the model into the business process
Learnings	... from the process

Status Quo Ante

Deciding the Eligibility of Securities‘ Prospectuses



Status Quo Ante

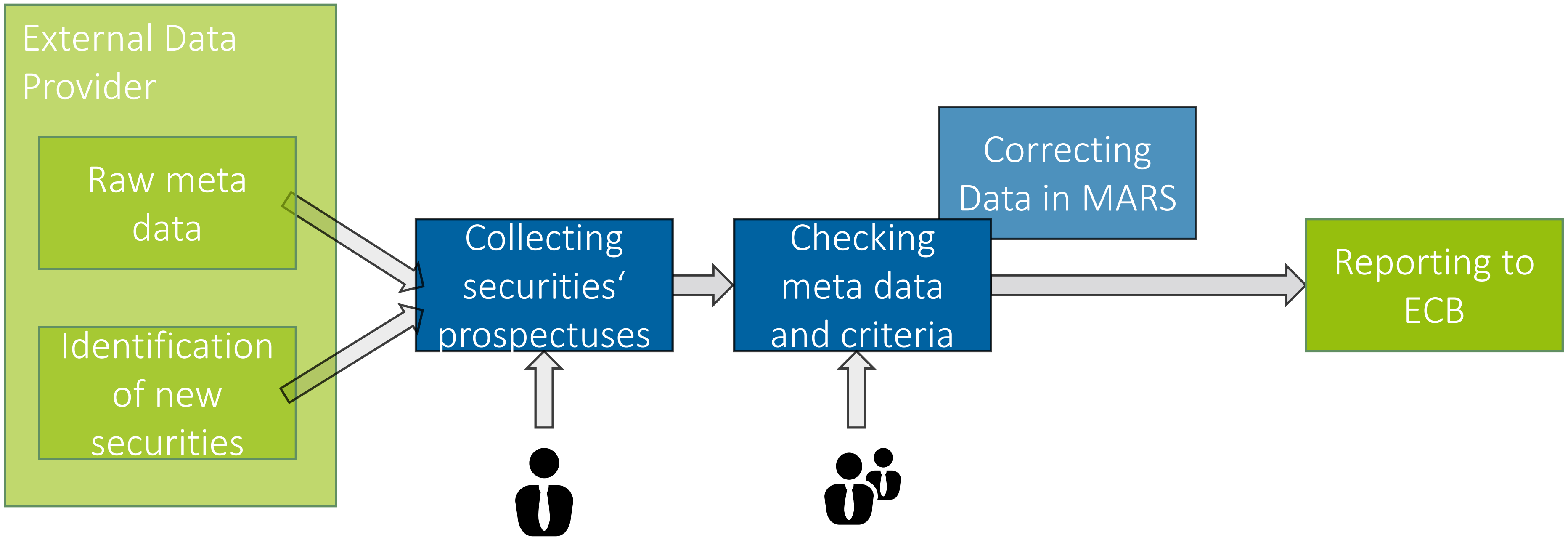
Deciding the Eligibility of Securities Prospectuses

- NCBs report daily new **eligible marketable assets** to ECB, which collects them into **EADB (Eligible Assets Database)**
- Checking a security / asset for eligibility is based on harmonized criteria (Guideline (EU) 2015/510)
- The reporting contains the **eligible assets** as well as related **meta data**

- Several eligibility criteria are established based on a security’s prospectus
  - So far this is achieved by manually checking / reading the prospectuses in a four-eyes principle
- At Deutsche Bundesbank (BBk) the (BBk-made) application MARS is used for collecting the securities’ data and reporting them to ECB

Status Quo Ante

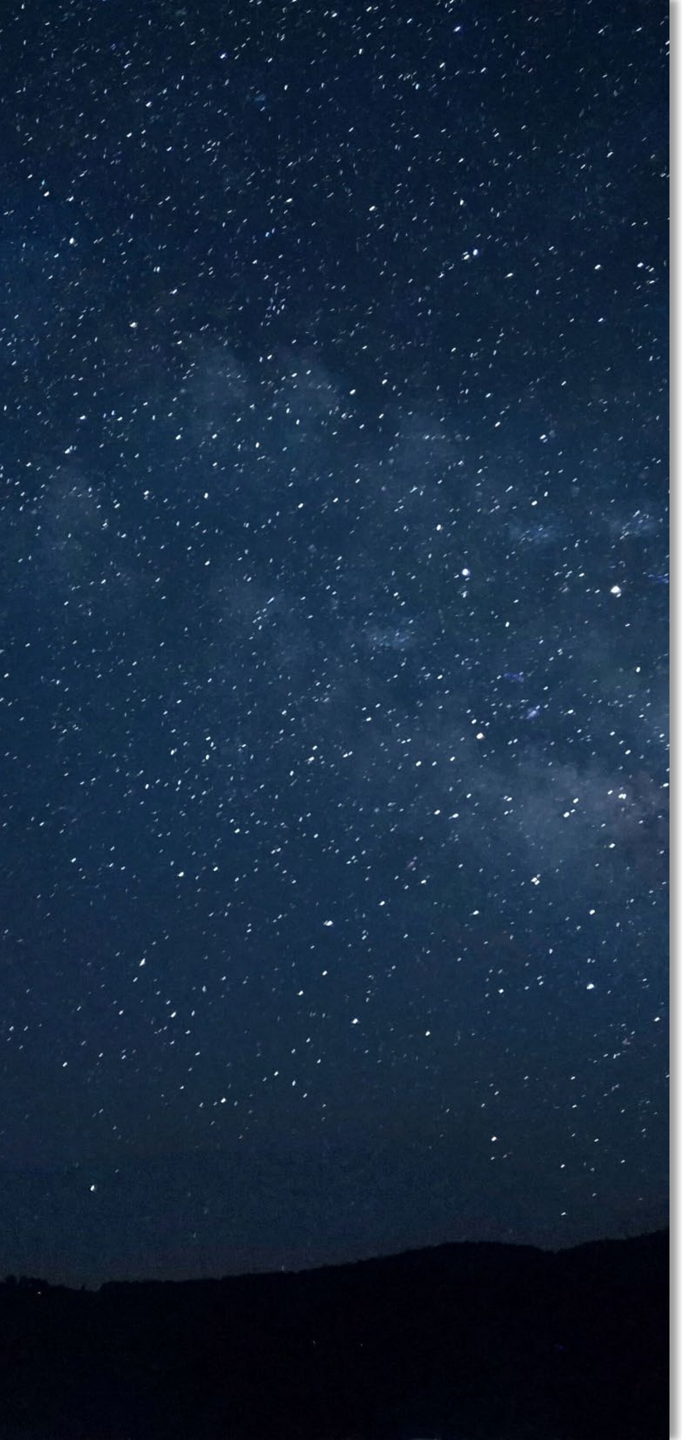
Process Flow



Manual assessment is time-consuming and repetitive

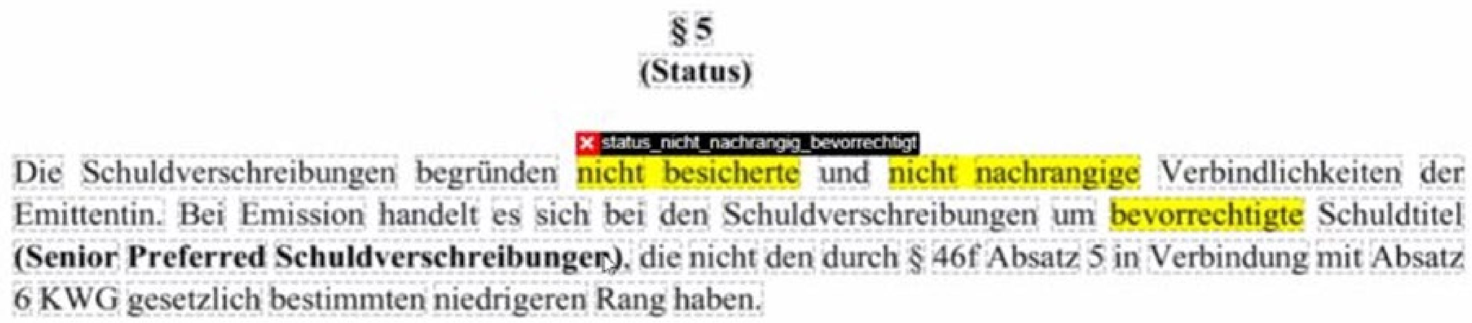
Training a model

Proof of concept with a fine-tuned model



Research Project Automatic Annotation

Proof of Concept using NLP

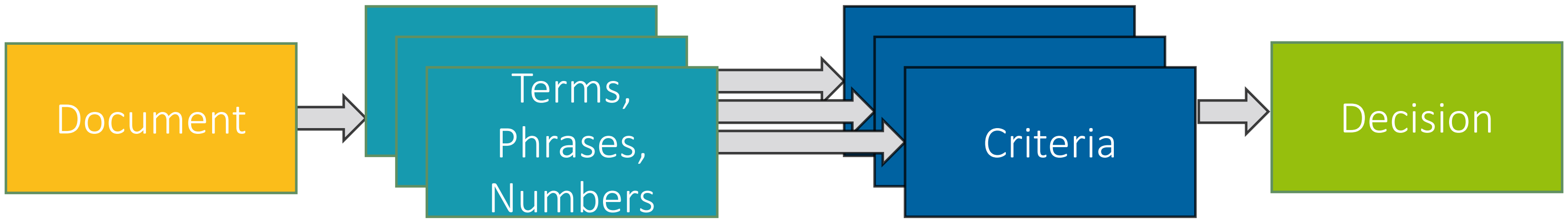


§ 5
(Status)

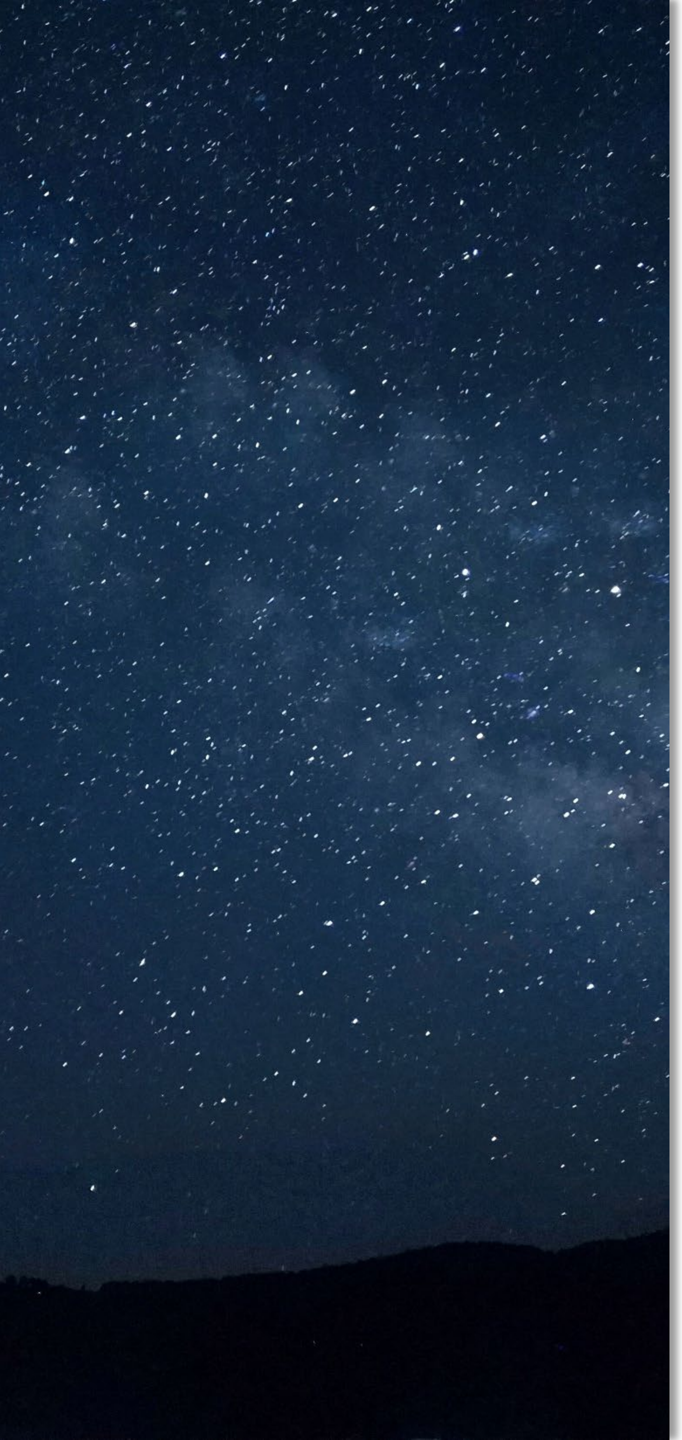
status_nicht_nachrangig_bevorrechtigt

Die Schuldverschreibungen begründen nicht besicherte und nicht nachrangige Verbindlichkeiten der Emittentin. Bei Emission handelt es sich bei den Schuldverschreibungen um bevorrechtigte Schuldtitel **(Senior Preferred Schuldverschreibungen)**, die nicht den durch § 46f Absatz 5 in Verbindung mit Absatz 6 KWG gesetzlich bestimmten niedrigeren Rang haben.

- Task at hand: **Identifying in PDF-Documents a given number of terms, phrases, numbers etc. that form the basis for the decision**



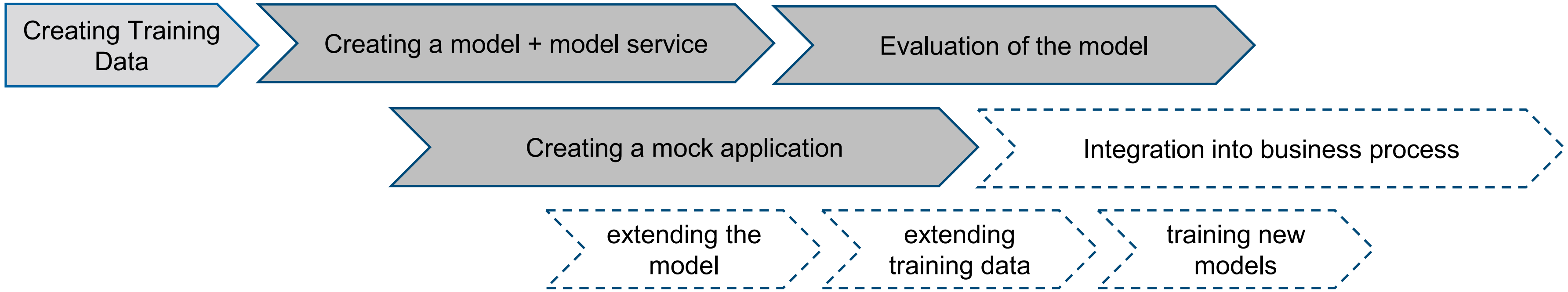
- In ML terms: **Multiclass/multilabel Classification Task (≈ 20 categories)**



Research Project Automatic Annotation

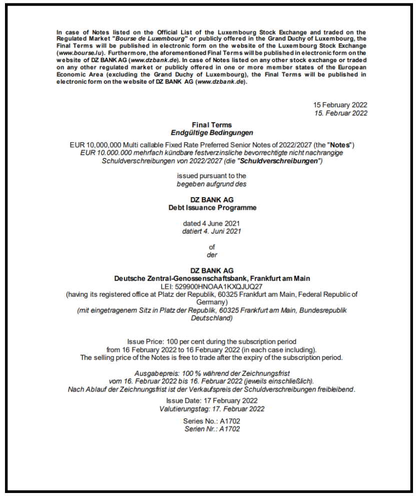
Starting Point

- At the start of the project (early 2022, pre „GPT breakthrough“):
  - No German-language domain specific (i.e. financial) language model available
  - Hence 2-Step modelling process:
    - (1) Fine-tuning a language model for German financial documents
    - (2) Training a multilabel classifier on top of the language model
  - No public dataset available -> creating training data is the first step



Creating Training Data

Data collection



Number of prospectus: 413
Issuing period: 2021 - 2022
Eligible documents: 369
Ineligible documents: 44
Training set: 272
Test set: 141 + 141

Data annotation

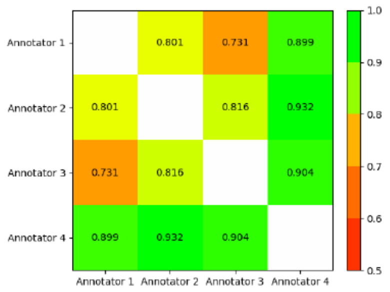
Annotation tool: Konfuzio
Annotation types: ~40

Disregarding of pages without annotations for training and validation purposes.

Annotation statistics

Target type	Train	Test
coupon fixed	431	375
coupon variable index	56	84
coupon variable margin	38	42
coupon variable operator	37	43
coupon variable tenor	45	75
currency	514	577
early redemption amount	64	52
early redemption	177	108
isin	421	417
principal amount	784	800
redemption at maturity amount	26	42
redemption at maturity	370	347
special termination	96	109
special termination amount	61	63
status non preferred	56	47
status senior non preferred	488	333
type of instrument	431	422

Inter-annotator agreement

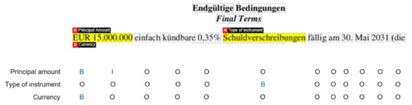


Average inter-annotator agreement scores

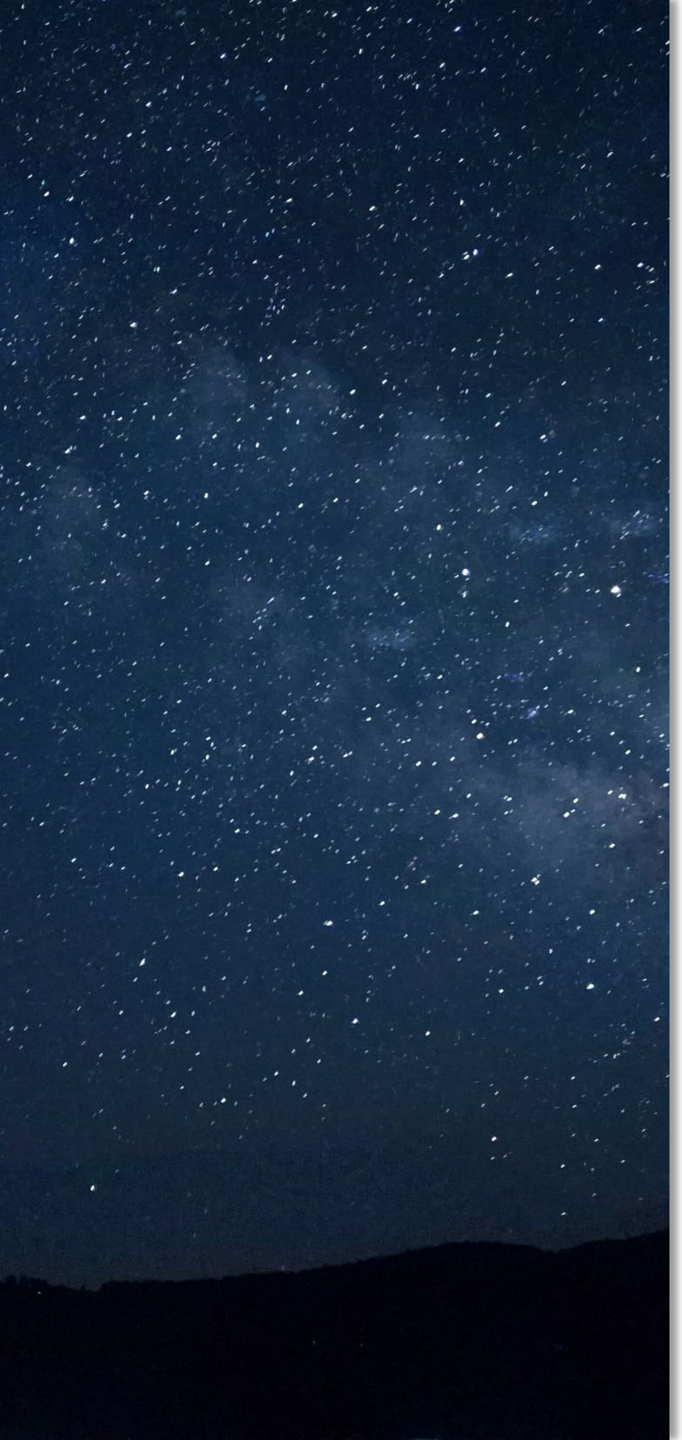
Test set was used to measure IAA. Therefore, every prospectus in the test set was annotated by a second analyst. 4 analysts seved as annotators in total.

Data preprocessing

1st step: Extraction of JSON-formatted raw data containing the annotations from the annotation tool
2nd step: Conversion and transformation of extracted data into dataset for token classification (BIO encoding)



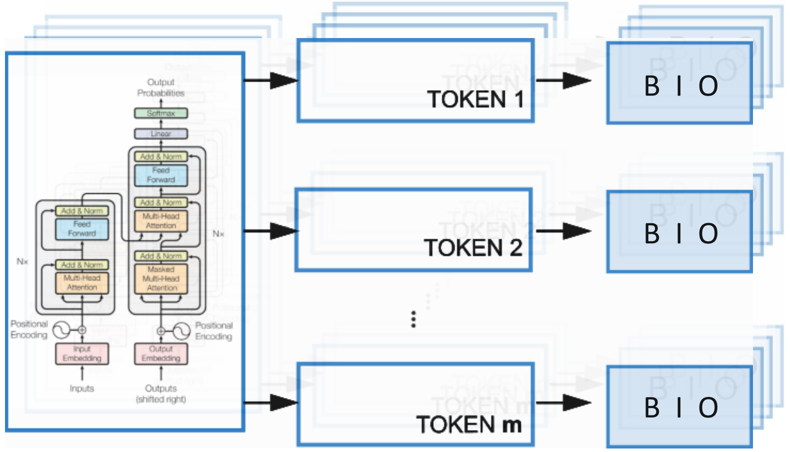
- Implementation of dataset classes using Hugging Face Datasets framework
- Challenge: overlapping text sequences belonging to different annotation types



Model Architecture / Document Processing

1. Conversion PDF -> Text (including OCR)
2. Text processing and clean-up (e.g. extraction of German parts of bilingual docs, analysis of textboxes, …)
3. *Embedding (Text to vectors) using fine tuned language model*
4. *Labelling with multilabel classifier*
5. Decision based on deterministic rules (derived from EU Guideline)

3 + 4



DEUTSCHE BUNDESBANK
EUROSYSTEM

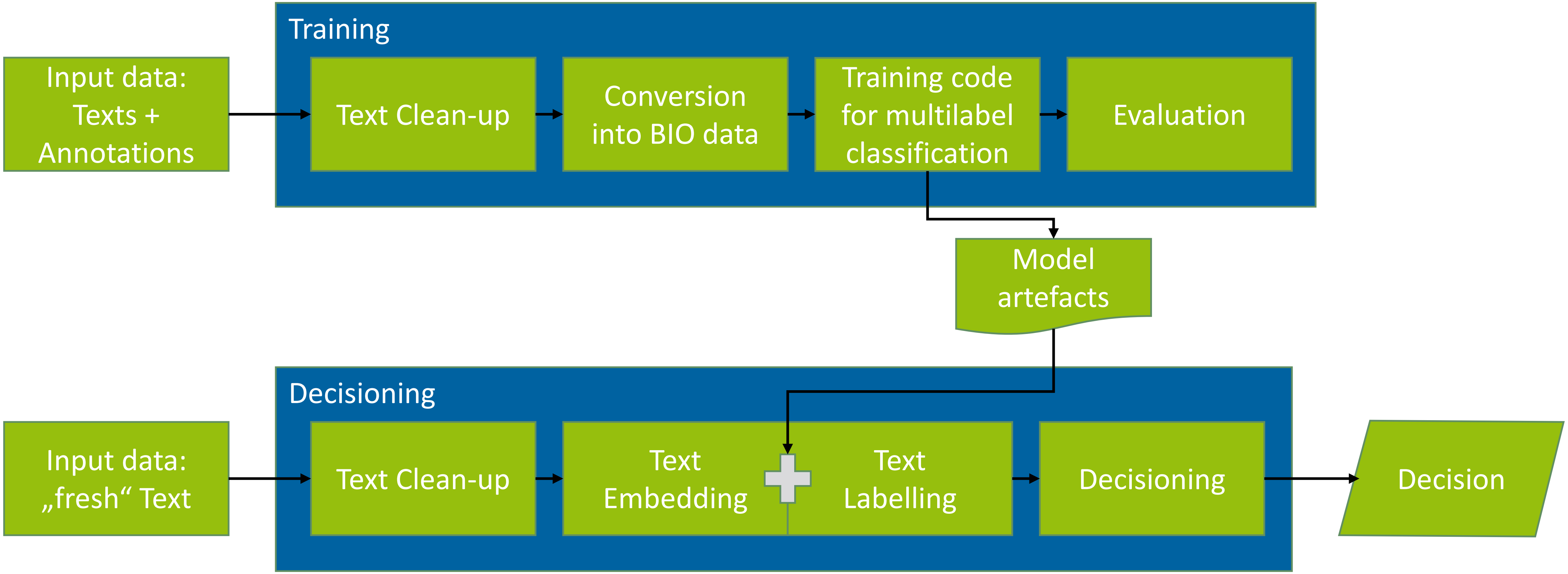
SCAI
Service & Community Center for Artificial Intelligence

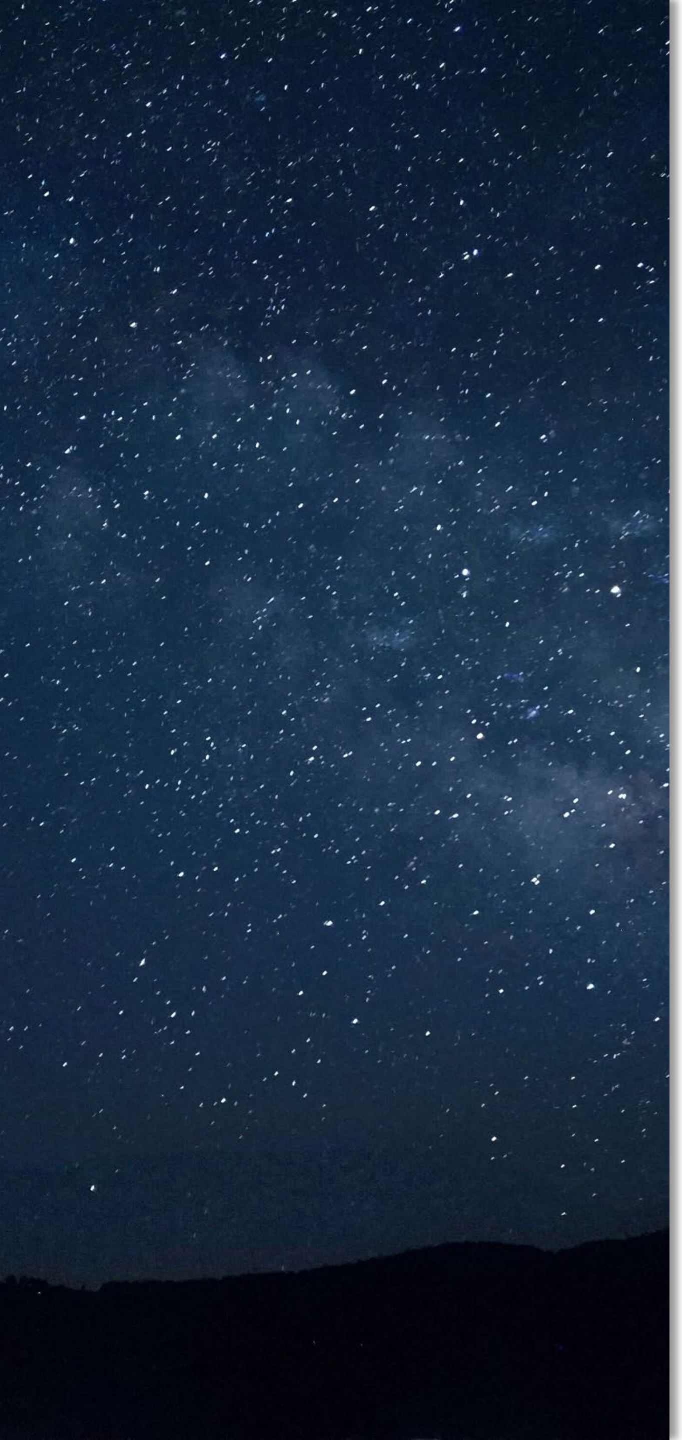
Integration

of the model into the business process

Operating the Model

Model Training and Decisioning





Integration into Business Process

Process Needs

- Given a document the experts needs:
  a. the decision of the model,
  b. the criteria causing that decision and
  c. (optimally) the relevant passages in the document (or relevant meta data) to
- check the validity of the ML decision.

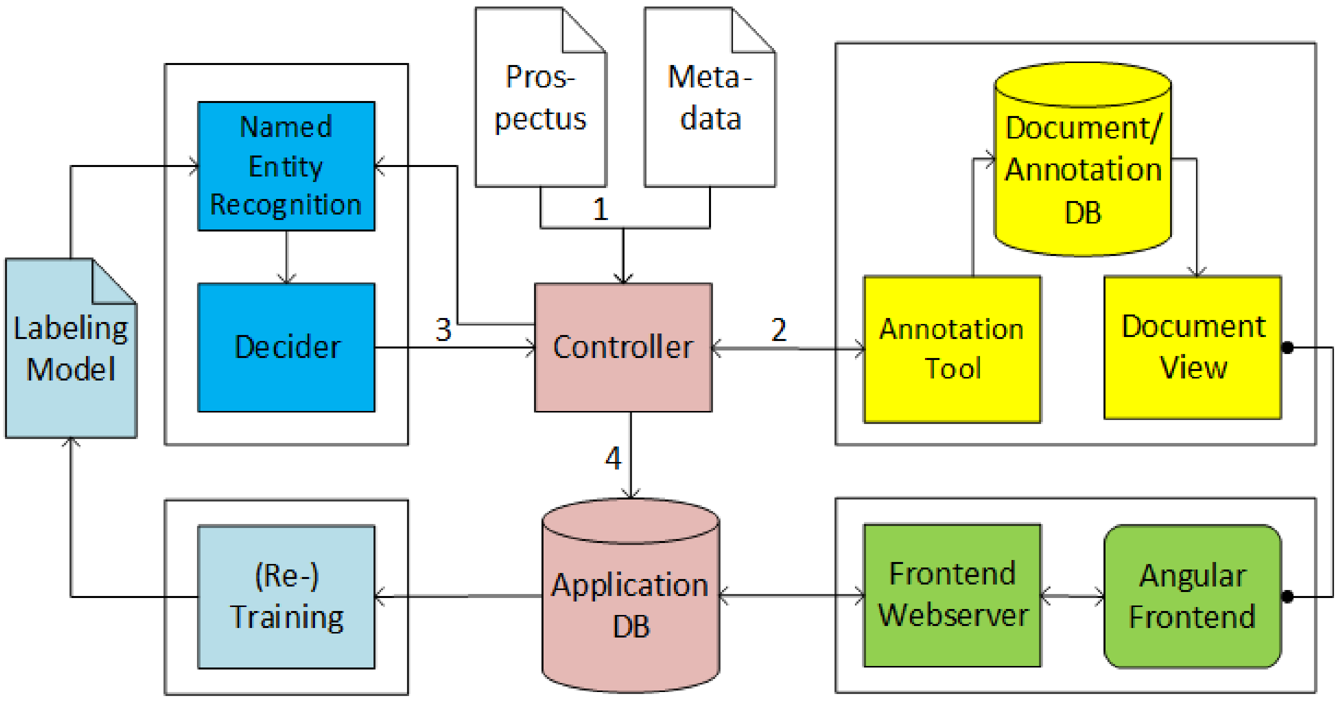
- If the model makes a mistake, the expert needs to **overwrite that decision** and
- (optimally) collect the data for future model improvements (retraining)

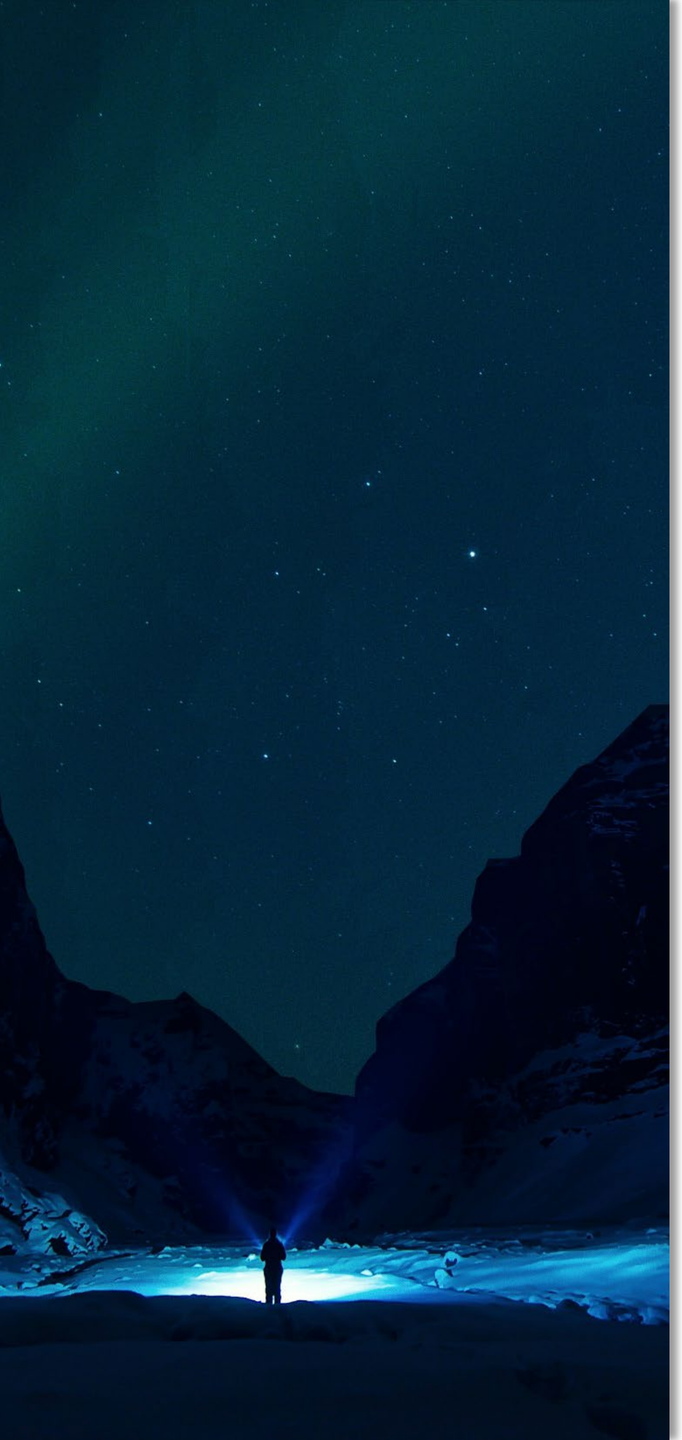
- If retraining is undertaken, we need both valid as well as invalid model decisions.

Integration into Business Process

Overview of Application Architecture

- Containerized application with communication via REST
- Integration into the actual business application (MARS) open as of yet





Implications of Using ML in the Process

- Using an ML model can reduce processing time by
  replacing manual reading with reviewing found passages

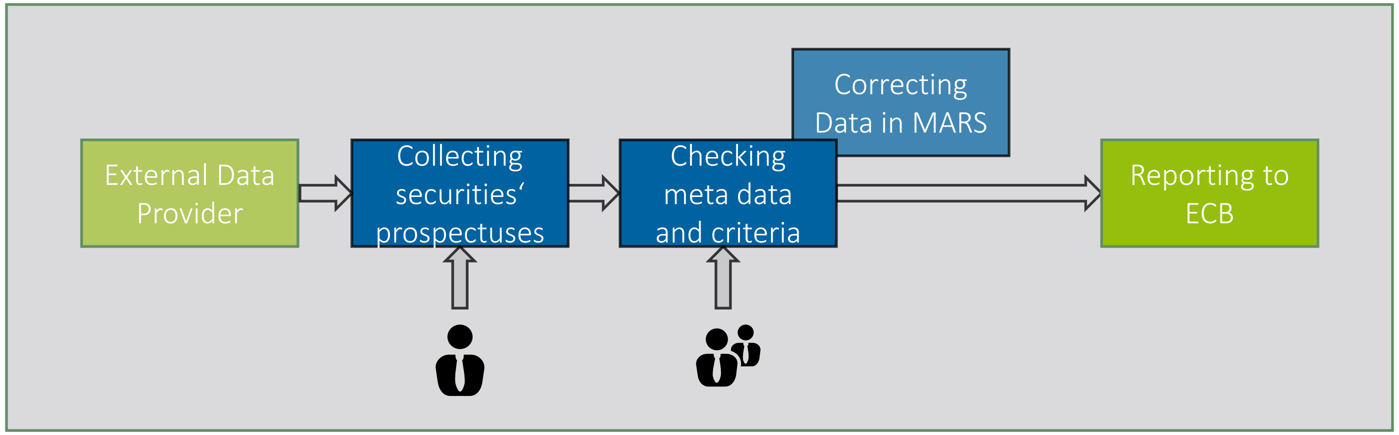
- An ML model will always have a chance for error, but
  the **accuracy can reach the Inter Annotator Agreement (IAA)** at the least

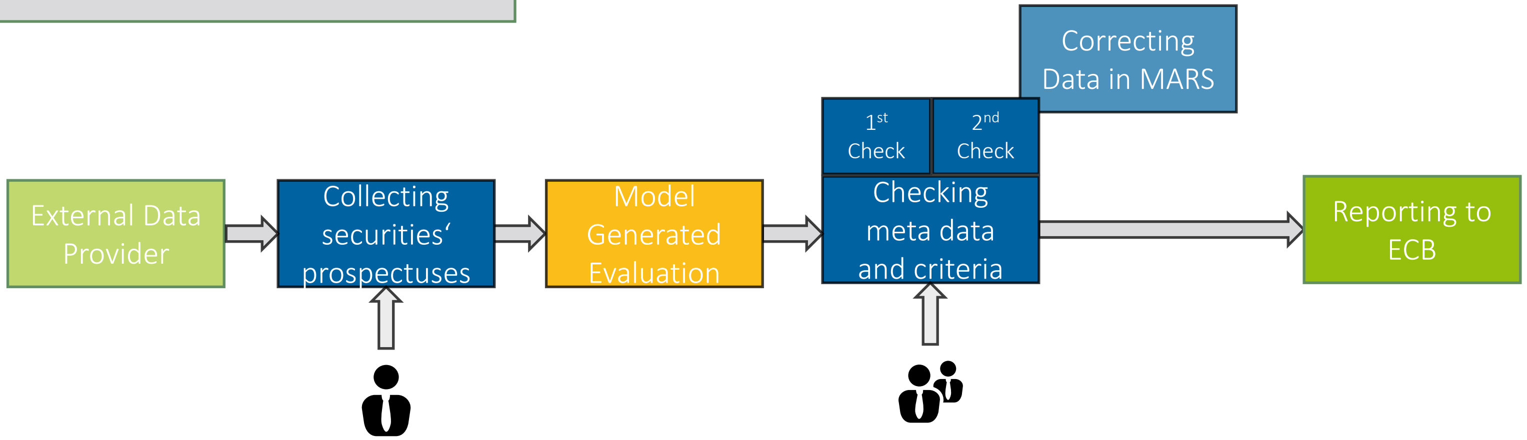
- Current legal environment requires a „**human in the loop**"
  - If model accuracy is (acceptably) high, the four eyes principle (as well as the review by two experts) could be replaced by a simple review
    (2 pairs of human eyes ⇒ „AI eyes" + 1 pair of human eyes)

- Using an ML model will require:
  - **continuous monitoring** of model performance
  - **continuous improvement** of model mistakes and training data

Evolving the „4 Eyes Principle“

New Process Flow – Proof of Concept





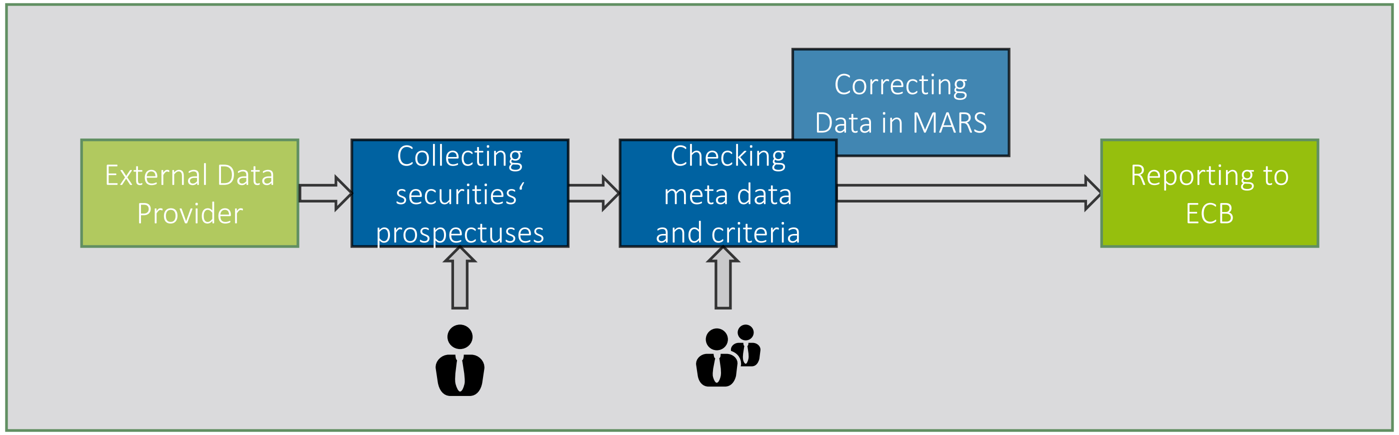
External Interface

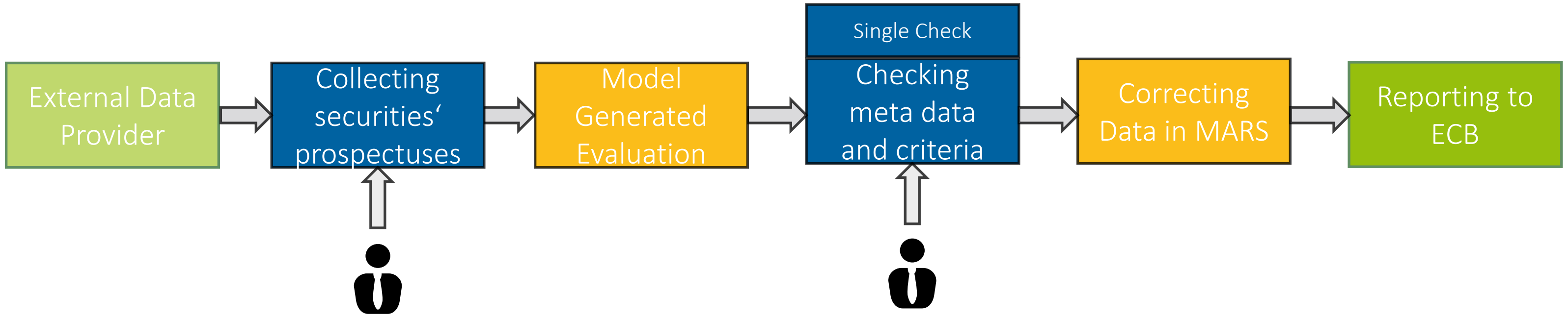
Human Interaction

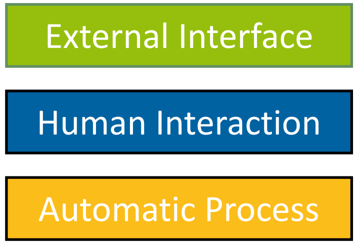
Automatic Process

Evolving the „4 Eyes Principle“

New Process Flow – 1st Evolution

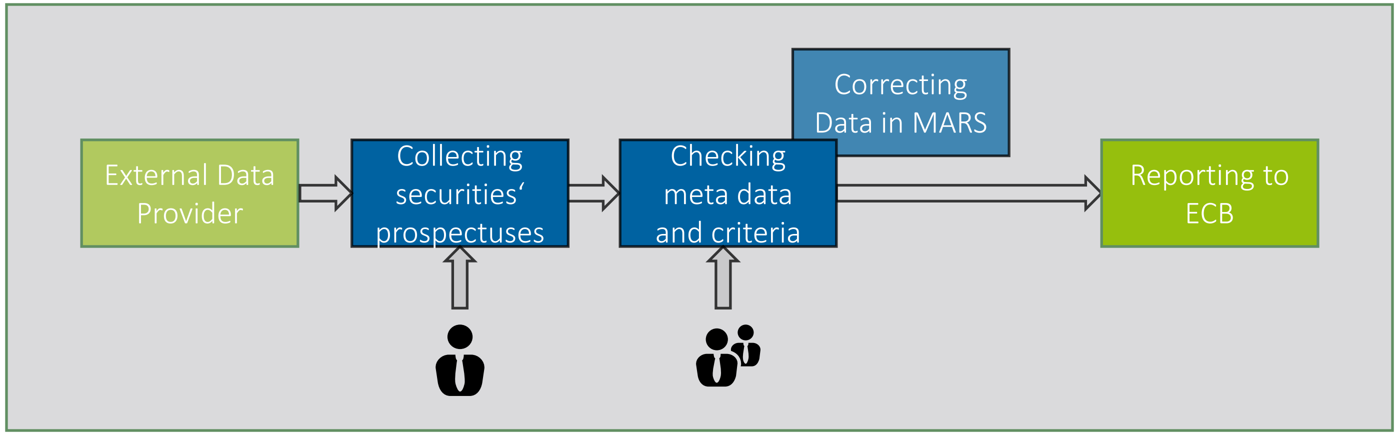


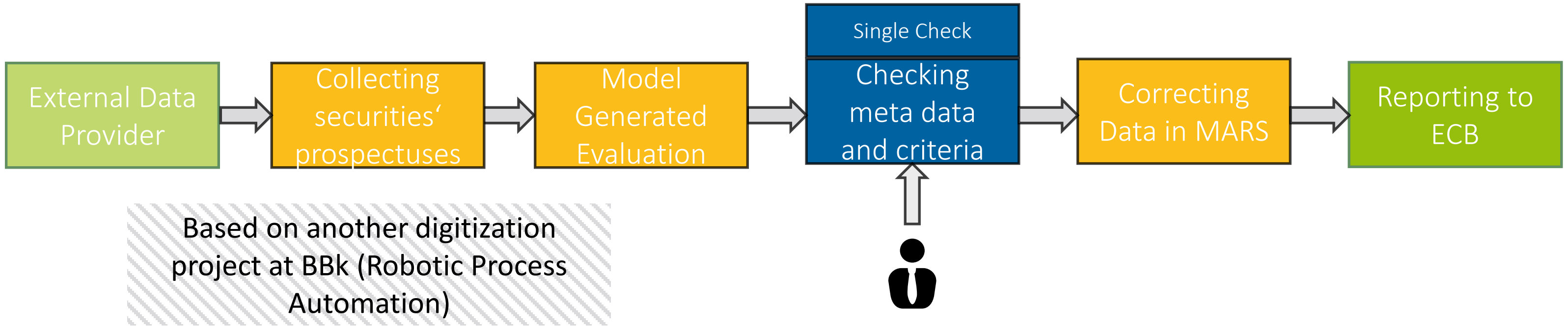




Evolving the „4 Eyes Principle“

New Process Flow – 2nd Evolution





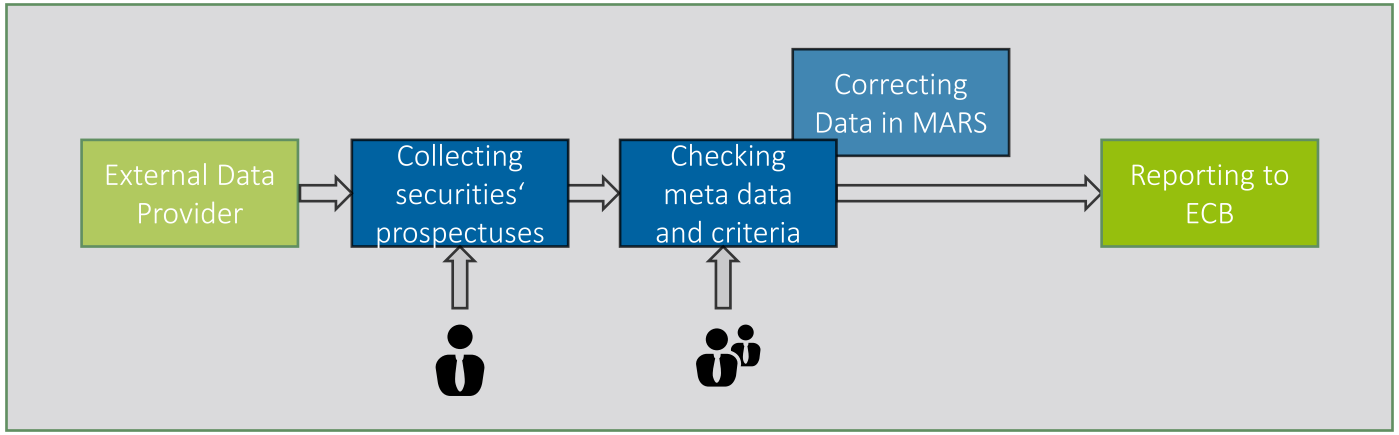
External Interface

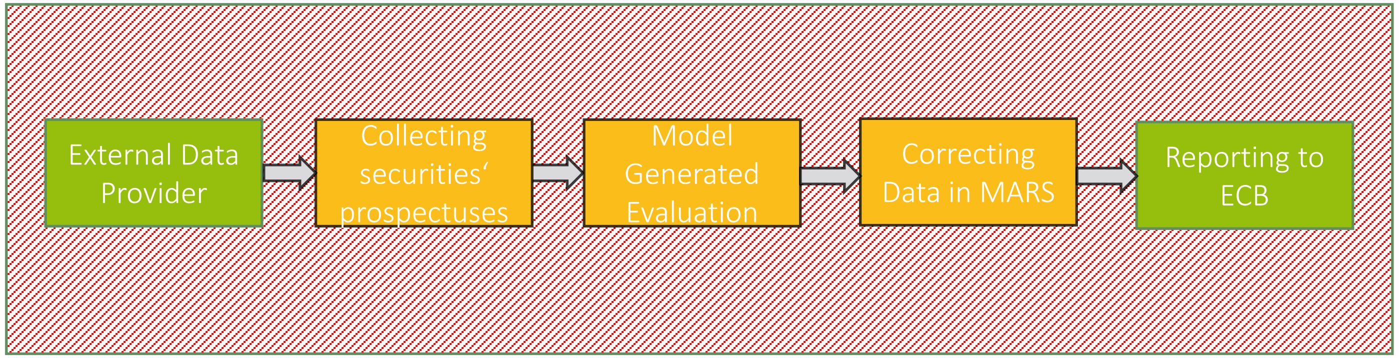
Human Interaction

Automatic Process

Evolving the „4 Eyes Principle“

Currently not Possible: Fully Automated Process – No Human in the Loop





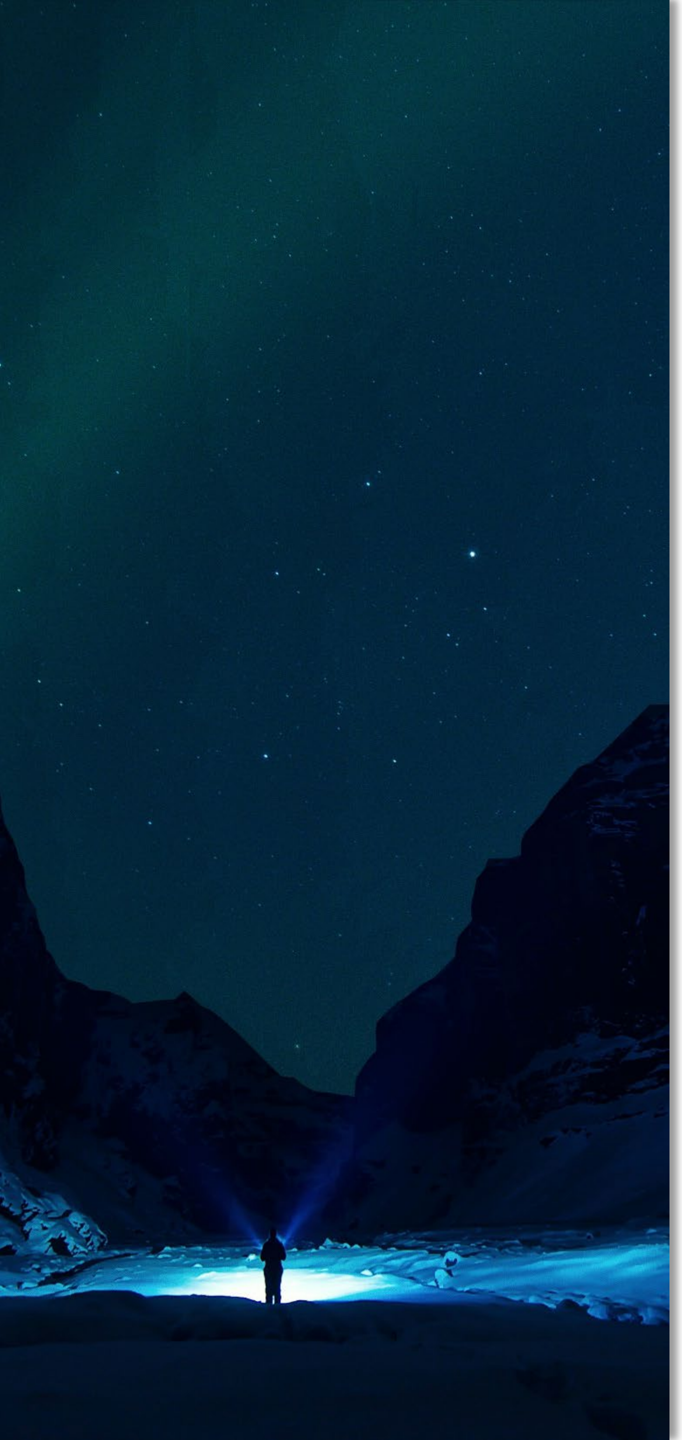
External Interface

Human Interaction

Automatic Process

Learnings

from the Process



Learnings from the Project

SCAI
Service & Community Center for Artificial Intelligence

- Creating training data is highly costly
- Understanding the business process is key
  - if only part of the process is automated, **the benefit may not outweigh the complexity**
- Building the necessary environment is highly complex
  - The codebase of the proof of concept easily reaches **10‘000 lines of code**
- **Integration into production is hard**, in particular if it necessitates new components, e.g.
  - Application for creating and storing text annotations
  - ML model monitoring and model archives (MLOps)
  - GPUs for model training

SCAI
Service & Community Center
for Artificial Intelligence

Questions?

SCAI

Service and Community Center for Artifical Inteligence

scai@bundesbank.de