LLMs for Metadata Enrichment and Question Answering in Open Data
Some Results and Lessons Learned

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HOCHSCHULE MERSEBURG

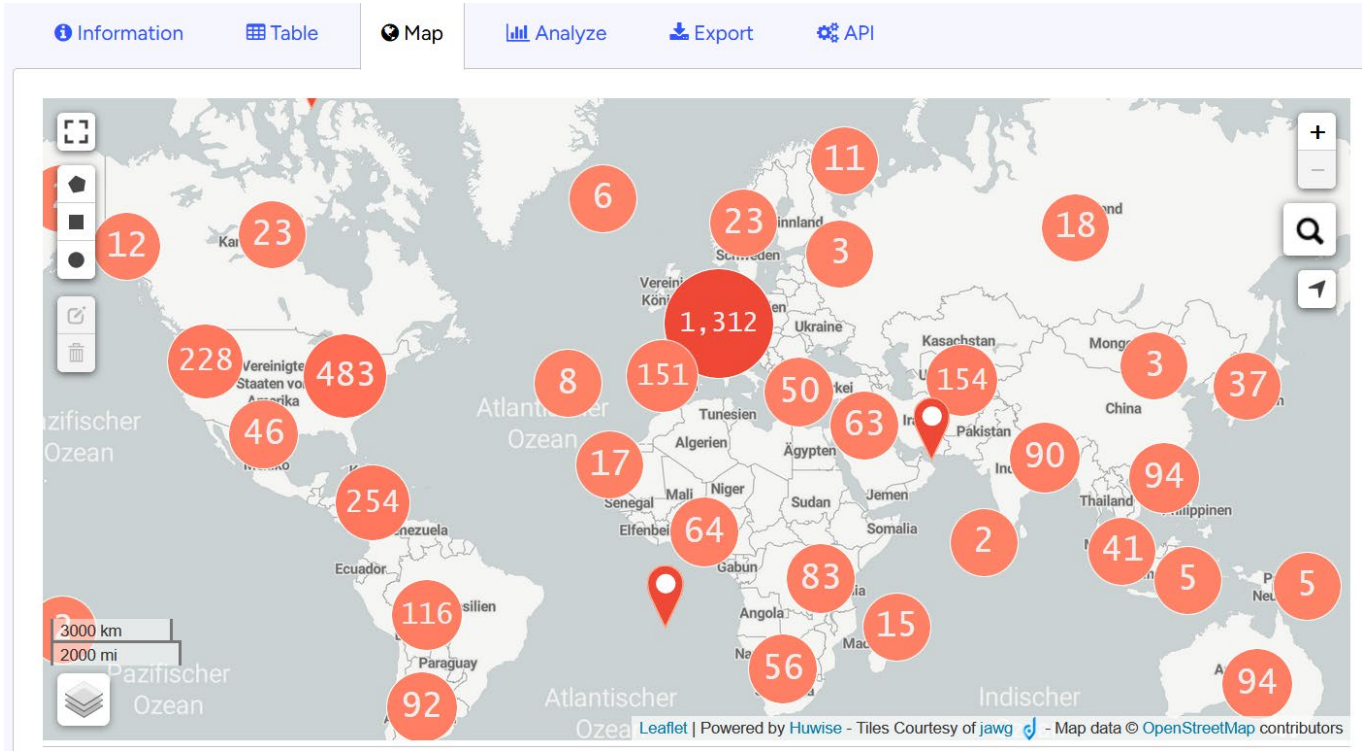
Open Data Question Answering - Motivation

Growing Significance of Open Government Data in recent years

- **Growing number of open data portals and datasets**

⇒ More than 3,700 data portals listed in Open Data Inception by Open Data Hub (compared to approx. 2,600 portals 10 years ago)

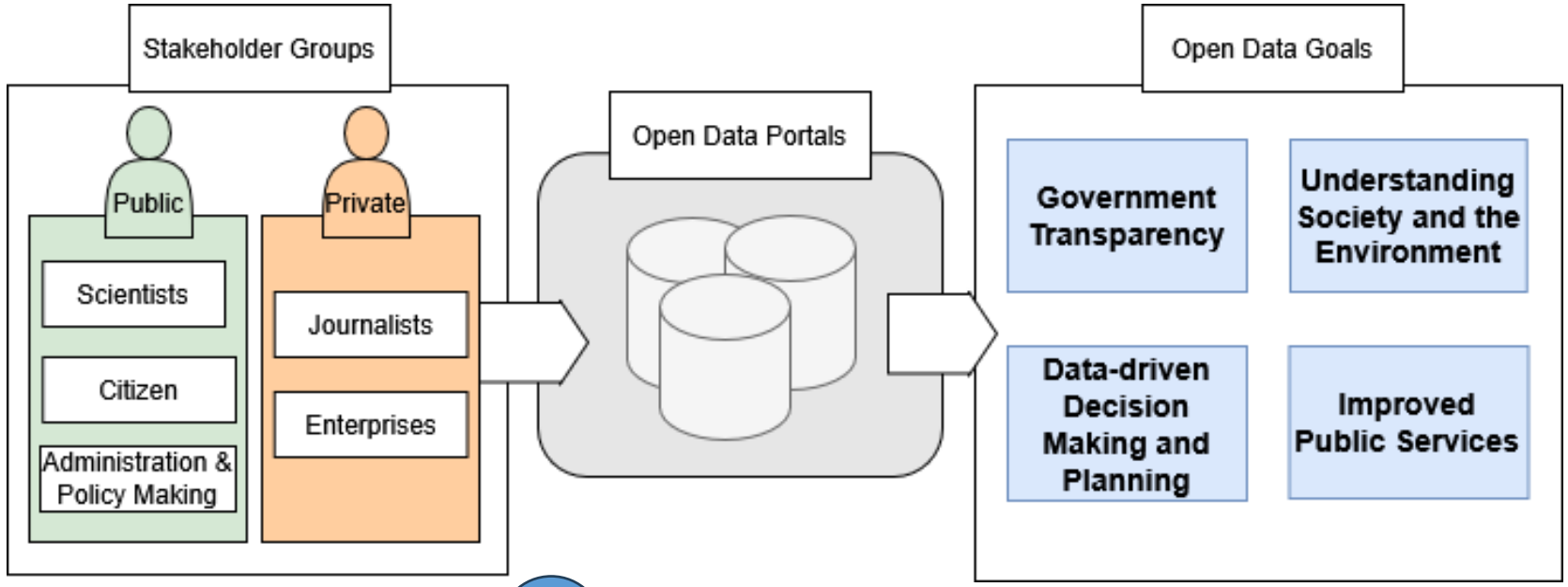
- **High Value Data (HVD) directive by the European Union** in 2023



Map of Open Data portals worldwide (https://opendatainception.io/)

Open Data Question Answering - Motivation

Current Dataset Access Limitations



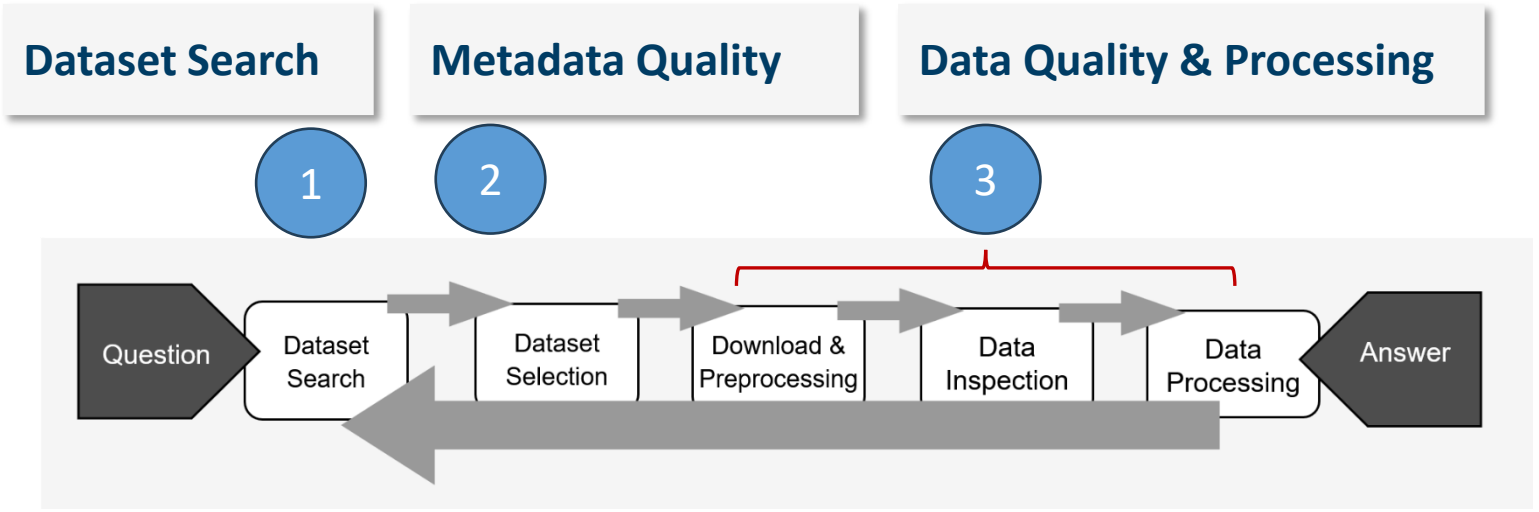
Limited FAIRness

1. **Dataset Search**
2. **Metadata Quality**
3. **Data Quality & Processing**

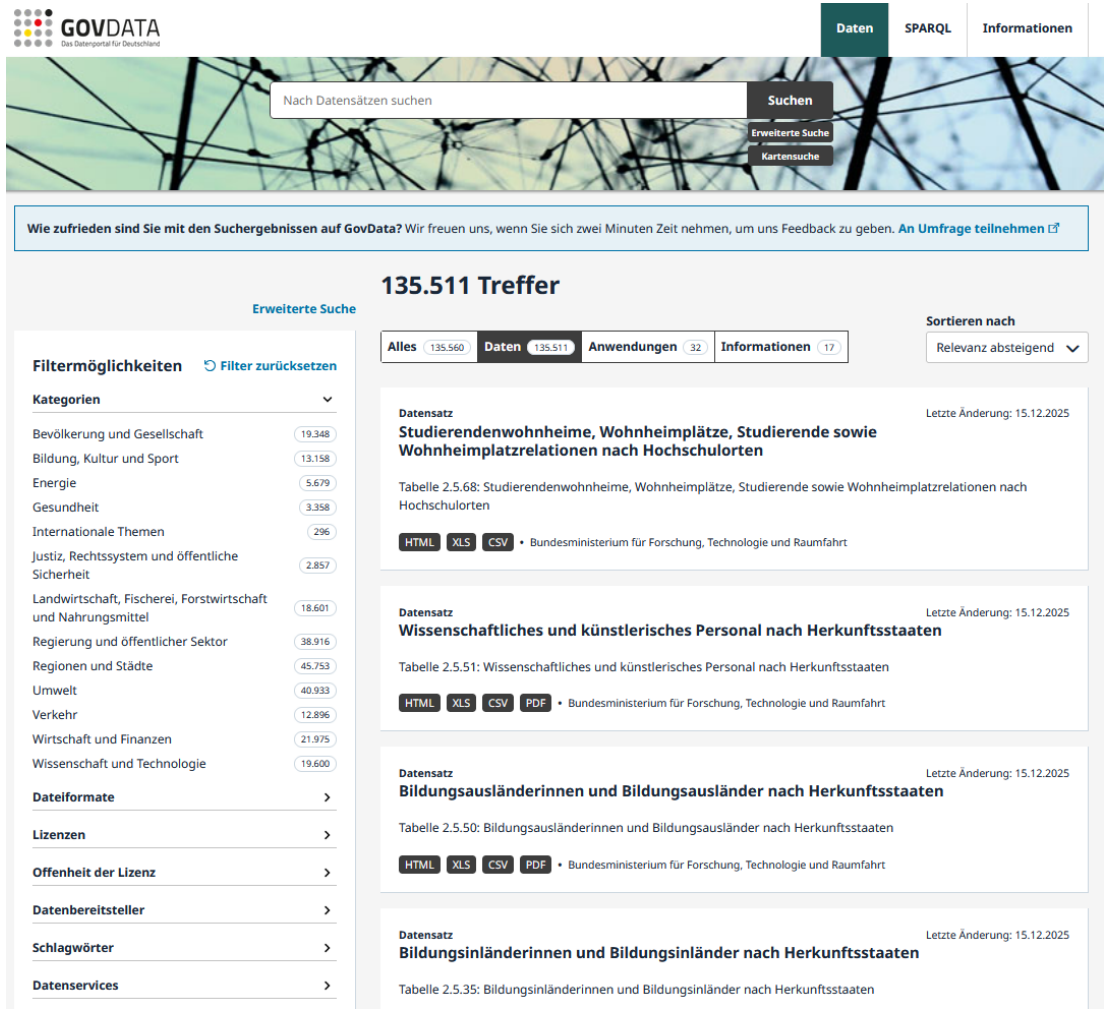
Open Data Question Answering (ODQA)

- The typical ODQA workflow is labor-intensive and mostly executed manually
- Dataset access limitations potentially hinder correct question answering at each workflow step

ODQA-Workflow



Open Data Question Answering – Challenges



https://www.govdata.de

1

Dataset Search

- Search interfaces are designed for expert users
- Sparse retrieval

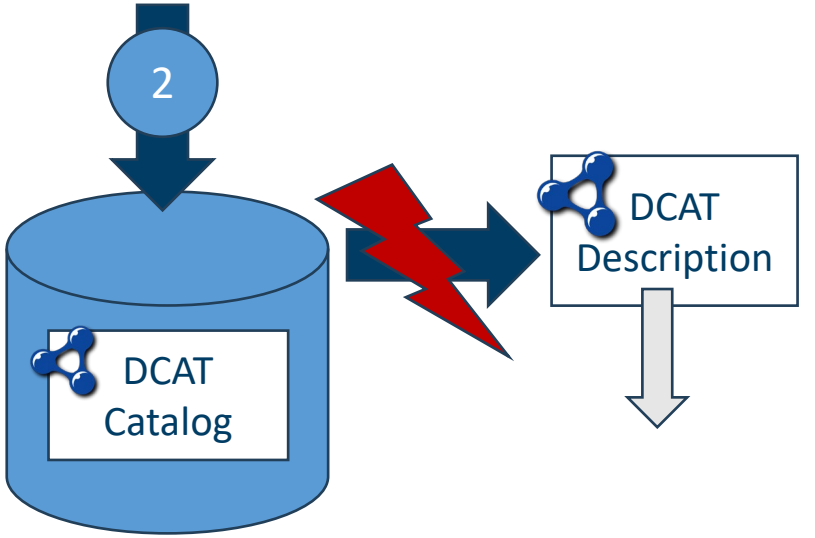
Open Data Question Answering – Challenges

How many places are there at the „Maja Bee" nursery in the city of Rostock?

Maja and Paul, Parents (Citizen)

Nursery „Maja Bee" Rostock

2

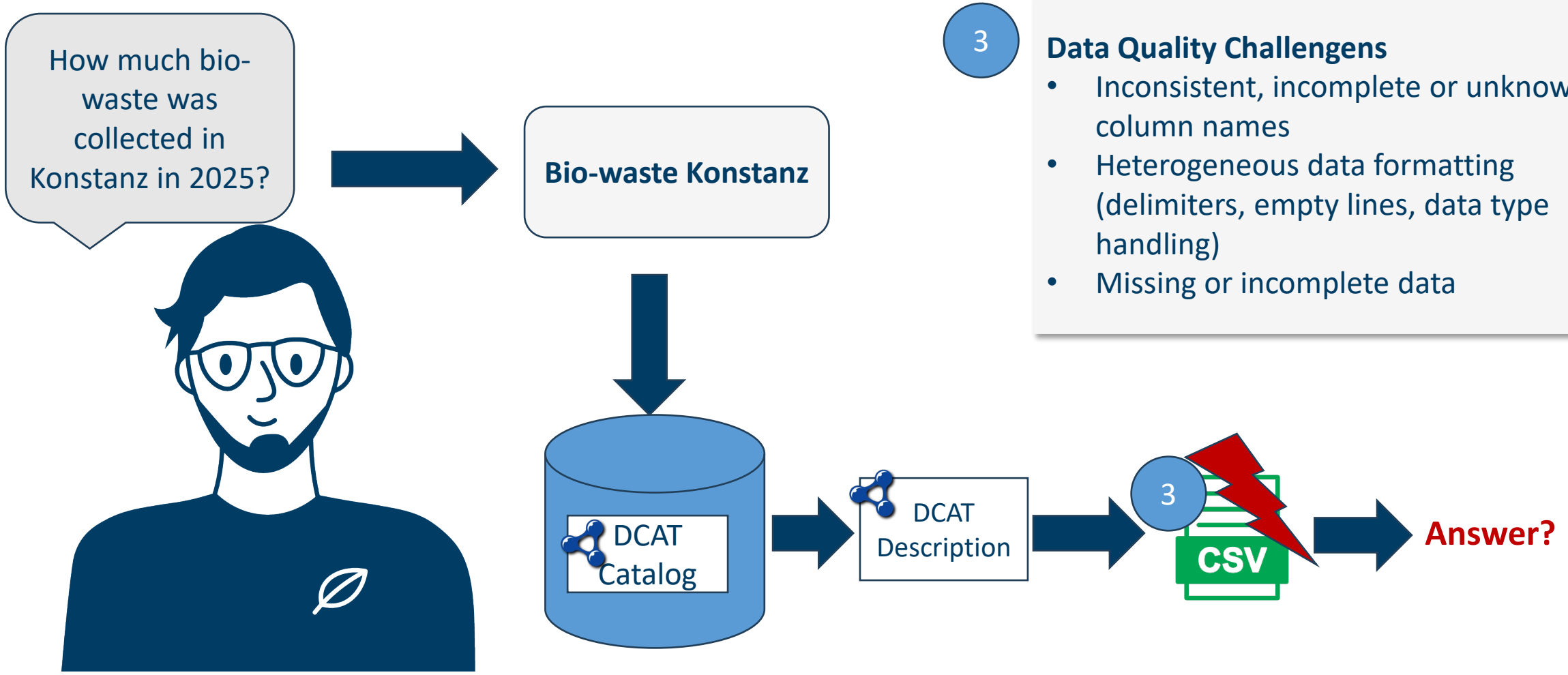


2

Metadata Challenges

- Incomplete metadata
- Limited semantic expressiveness
- Limited (semantic) web integration

Open Data Question Answering – Challenges

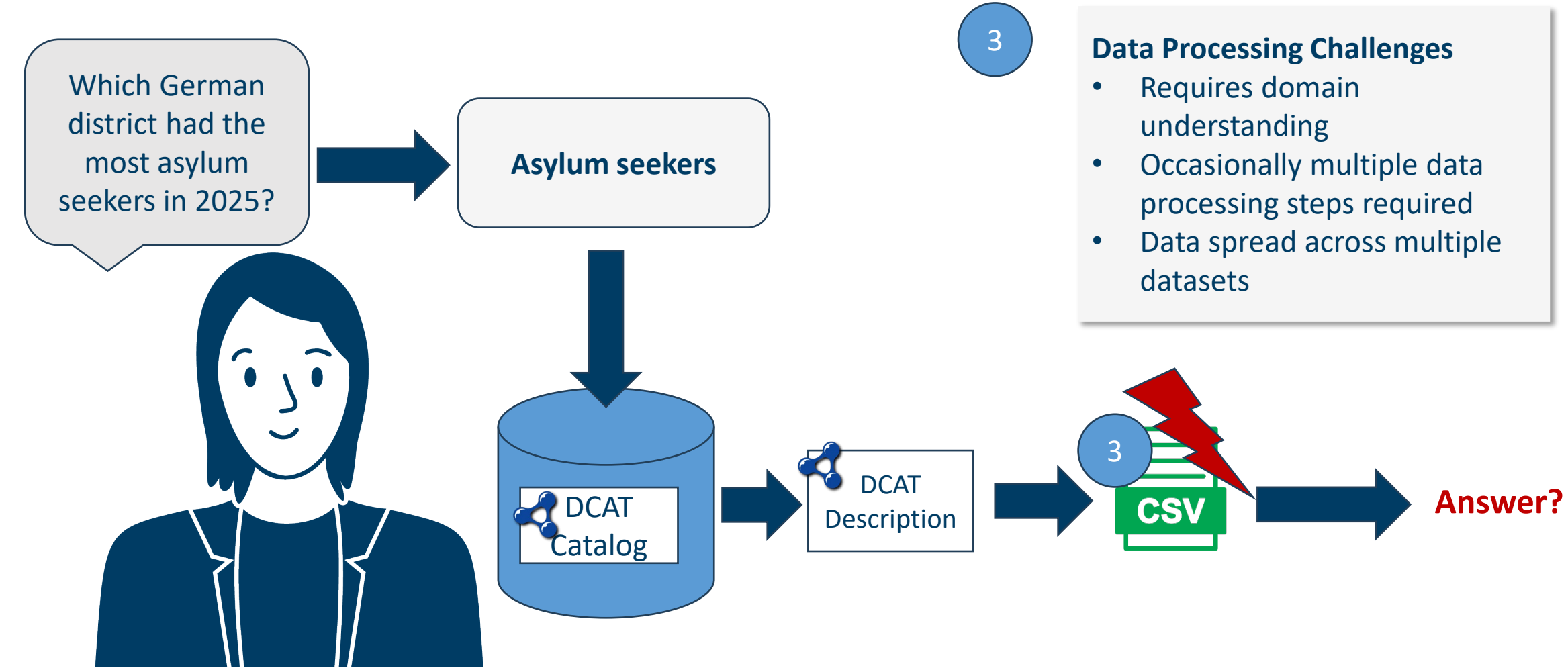


3

Data Quality Challengens

- Inconsistent, incomplete or unknown column names
- Heterogeneous data formatting (delimiters, empty lines, data type handling)
- Missing or incomplete data

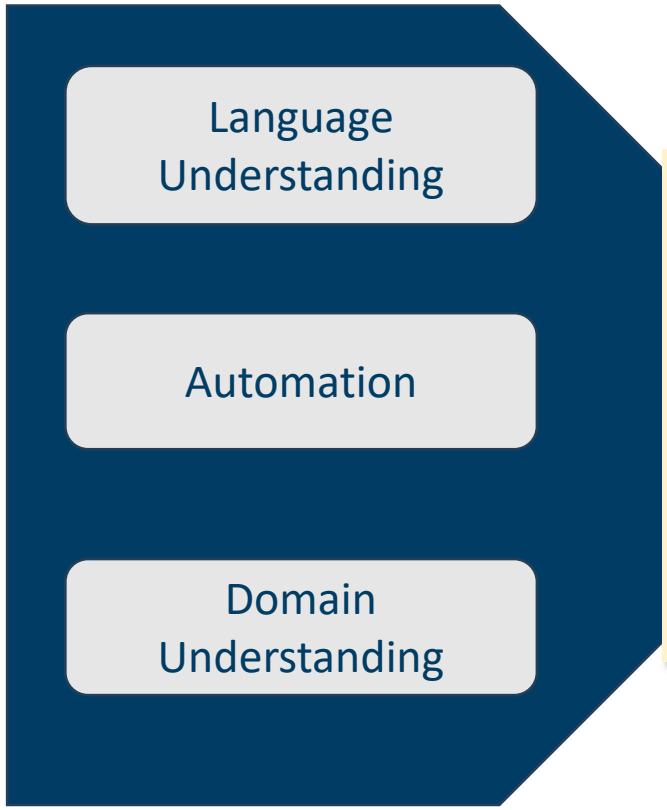
Open Data Question Answering – Challenges



Sandra, Refugee Policy and Finance Advisor, Federal Ministry of the Interior

Open Data Question Answering

Project 1:
Agentic Open Data Question Answering



Research Question
Can **LLM and agentic approaches** be feasibly **applied to open data question answering** (ODQA)?

Open Data Question Answering – Related Work

Project 1: Agentic Open Data Question Answering

Agentic Data Science

Previous studies have shown that data science tasks can be tackled with the help of agentic approaches (Sun et al.; Hong et al. 2024). **So far, agentic data science approaches have not been applied for the open data domain.**

Natural Language Interfaces for Open Data

Studies have predominantly focused on Natural Language interfaces for text data, where a RAG approach was chosen (Schelhorn, 2024; Kalyuzhnaya, 2025). **Natural language interfaces for question answering on tabular data from open data portals are missing.**

Open Data Question Answering – ODQA Benchmark

Project 1: Agentic Open Data Question Answering

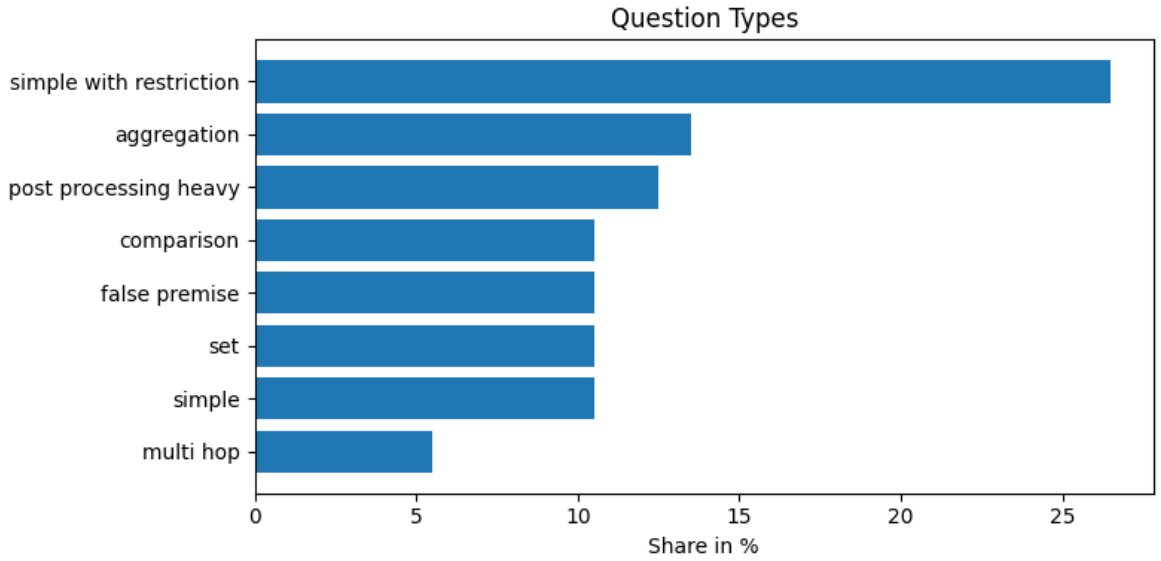
- **{en,de}-questions.csv**: Files containing the question–answer pairs in German and English.
- **sources.csv**: File including a unique mapping of each question id to corresponding source file(s)
- **data**: Directory containing the source files.
- **metadata**: Directory containing the DCAT metadata descriptions
- **govdata-catalog**: snippet of the GovData DCAT catalog (serialized in rdf/xml or turtle) as of August 2025

Statistic	Value
Total questions	200
DCAT themes	13
Task types	2
Question types	8
File types	2
Source files	220

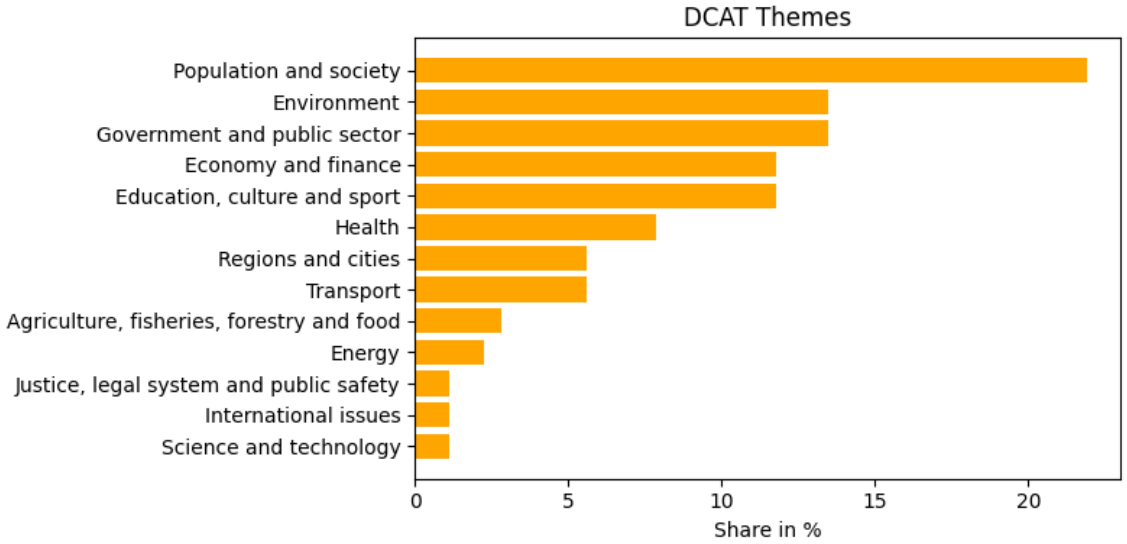
ODQA-Benchmark-Repository: https://github.com/OpenData-IQ/ODQA/tree/master/open-data-benchmark

Open Data Question Answering – ODQA Benchmark

Project 1:
Agentic Open Data Question Answering



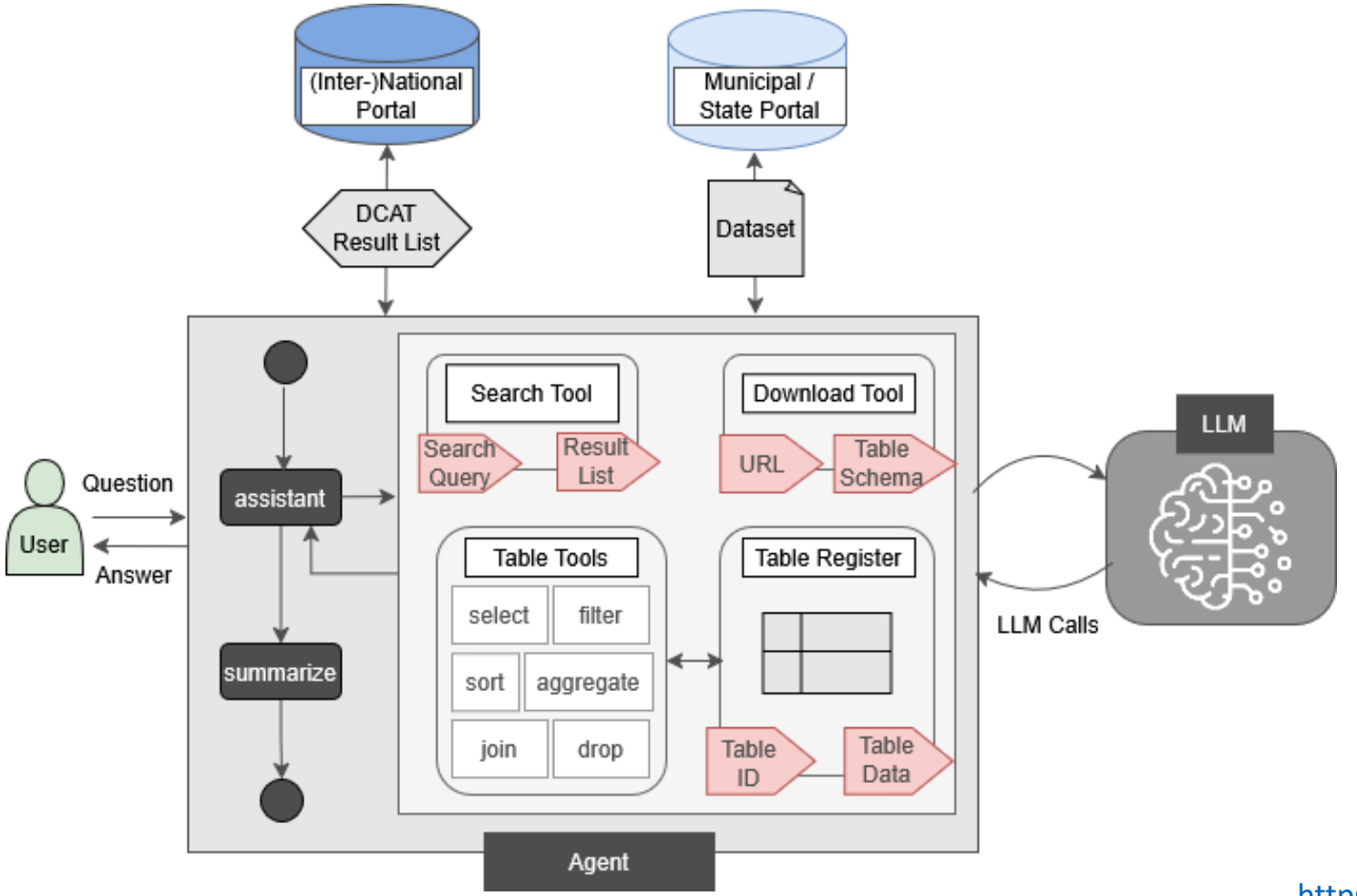
Question types come from the CRAG benchmark (Yang, 2024)



DCAT themes come from the EU vocabularies authority files

Open Data Question Answering – Agentic Setup

Project 1:
Agentic Open Data Question Answering



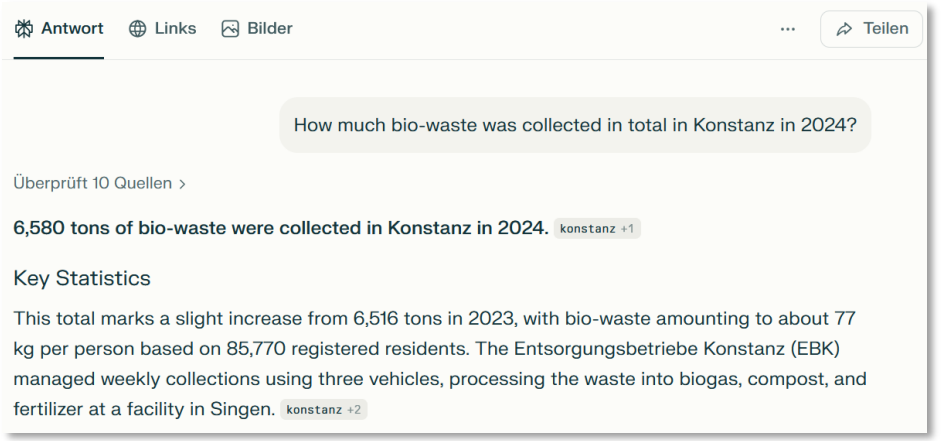
https://github.com/OpenData-IQ/ODQA

Open Data Question Answering – Experiments

Project 1: Agentic Open Data Question Answering

- **Testing the performance of the tool-calling LLM agent on the ODQA benchmark with different LLM models**
  - Higher-priced / proprietary: Claude Sonnet 3.7, GPT-5
  - Lower-priced / proprietary: Gemini 2.5 Flash, GPT-5 Mini
  - Open- Source models: Deepseek R1, Mistral Medium 3.1
- **Comparing agent performance with state-of-the-art retrieval-augmented generation systems (SOTA RAG),** such as GPT-4o-Search and Perplexity.AI (Perplexity Sonar)

SOTA-RAG-System Perplexity.AI



Open Data Question Answering – Experiments

Project 1: Agentic Open Data Question Answering

Model	Search Setup	Completion Rate	Success Rate	Conditional Accuracy	Tool Calls
Claude 3.7 Sonnet	LLM Agent	55.5	44.5	80.2	8.3 ± 3.5
Deepseek R1	LLM Agent	75.1	26.4	35.1	5.9 ± 2.9
Gemini 2.5 Flash	LLM Agent	**82.4**	40.7	49.4	3.7 ± 2.5
GPT-5	LLM Agent	58.5	57.0	**97.4**	8.4 ± 4.0
GPT-5 Mini	LLM Agent	64.0	55.0	85.9	7.5 ± 3.5
GPT-5 Mini (40)	LLM Agent	78.0	**66.5**	85.3	8.5 ± 6.0
Mistral Medium	LLM Agent	67.5	37.5	55.5	5.8 ± 3.6
GPT-4o Search	*SOTA RAG*	92.5	21.5	**23.2**	-
Perplexity Sonar	*SOTA RAG*	96.5	23.0	**23.8**	-

Open Data Question Answering – Results Summary

Project 1: Agentic Open Data Question Answering

Non-trivial accuracy results, but still not production ready

Public search / RAG systems should not be used for OQDA

Agentic approaches for ODQA need AI ready DCAT metadata

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Related Work

Authors	Models	Keywords `dcat:keyword`	Themes dcat:theme	Description dct:description	Additional fields	LLM Parameter	Few-Shot-Prompting	Prompting with example data	Evaluation with historic data and F1-Scoring (unless indicated otherwise)	Evaluation	User Interface
Kliimask & Nikiforova (2024) **Open Data Portal Estonia**	GPT-3.5-turbo, GPT-4	✅	❌	❌		❌	❌	✅	❌	✅ N=22 (Users) Ø 4.4 of 5	✅
Ahmed & Polini (2025) **European Open Data Portal**	(Fine-tuned) T5-small, T5-Large	✅	✅	❌	❌	❌	❌	❌	✅ Keywords: 0.45 (T5-small) 0.61 (T5-large) Themes: 0.63 (T5-small) 0.83 (T5-large)	❌	✅
Eger et al. (2025) **Open Data Portal Saxony**	Mistral-7B	✅	✅	✅	✅ Temporal and spatial data based on file names	❌	❌	✅	❌	✅ N=4 (Users), n=90 (Test runs) Approx. 87% correctly generated descriptions	✅

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Verwandte Arbeiten

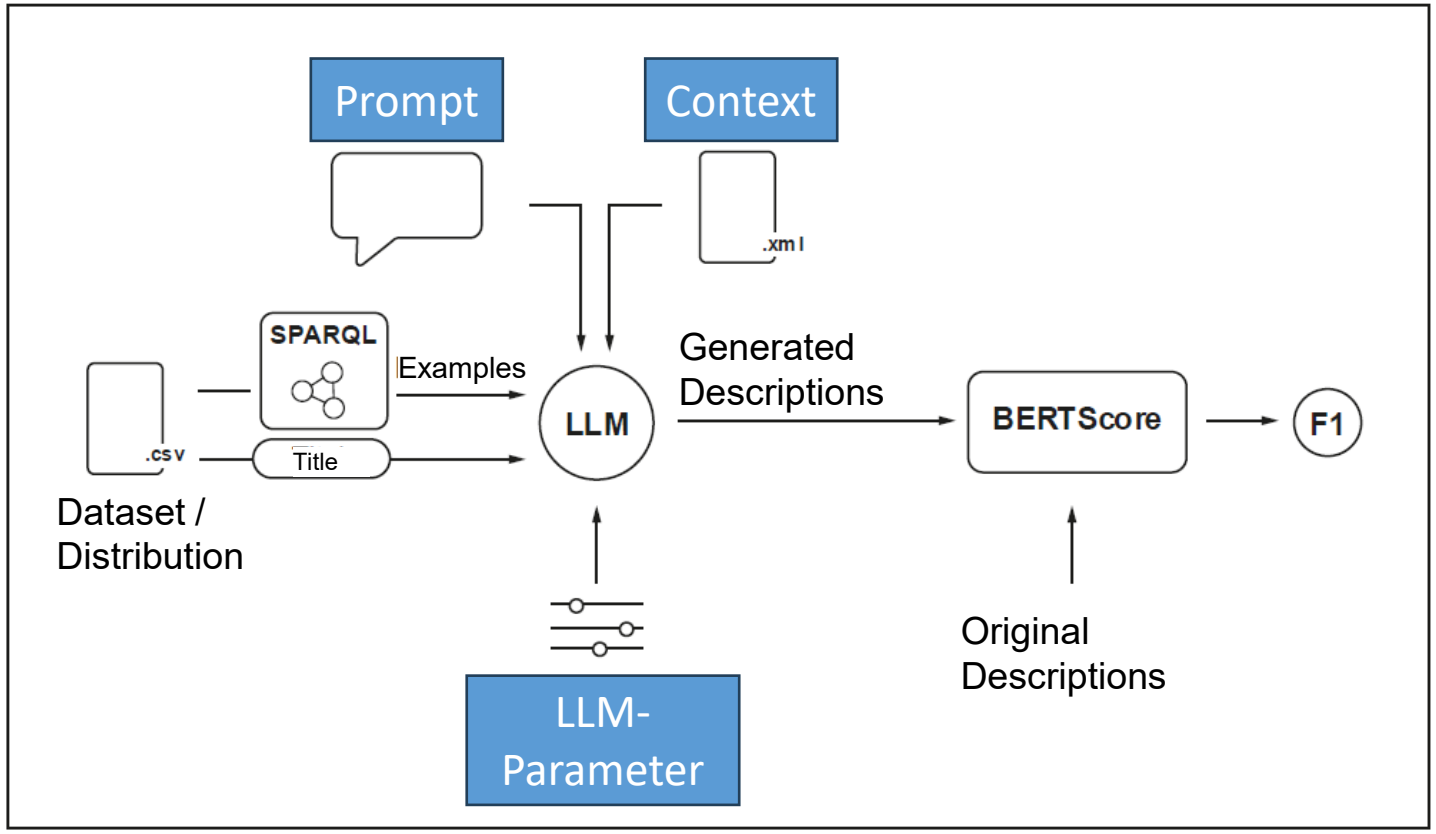
Authors	Models	Keywords `dcat:keyword`	Themes dcat:theme	Description dct:description	Additional fields	LLM Parameter	Prompting-Techniques (CoT, Few Shots)	Prompting with example data	Evaluation with historic data and F1-Scoring (unless indicated otherwise)	Evaluation	User Interface
Busch et al. 2025 **EUR-LEX, GIZ sector dataset**	T5, LLM (3B, 8B, 70B), Gemini (Flash, Pro, GPT (2, 4o, 4o-mini)	✅	✅	✅	✅ Temporal and spatial fields, creator, language	❌	✅ One-Shot vs. Few-Shot-Prompting	❌	✅ Beschreibung: 0.89 cosine similarity (Bertscore) with reference texts Themes: 0.55-0.79	❌	❌
Zhang et al., 2025, **Open Data Portal USA**	Llama 8B, GPT (4o-mini)	❌	❌	✅	❌	❌	✅	✅ Automatic generation of semantic profilea as preprocessing steps	✅ 0.71-0.89 NDCG@20 (best configuration)	✅ N=3 (Users) N= 148 (descriptions) 8.85 out of 10 for text quality (accuracy, readability)	❌
Markgraf, Mark, 2025 **Open Data Saxony-Anhalt**	GPT-4	(✅) Not quantitatively evaluated	❌	✅	❌	✅	✅	✅	✅ ca. 0.82 cosine similarity (Bertscore)	✅ N=7 (Users) SUS-Score=80.7	✅

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Test setup for LLM-based descriptions

`dct:description`



78 Test Cases
Open Data
Saxony Anhalt

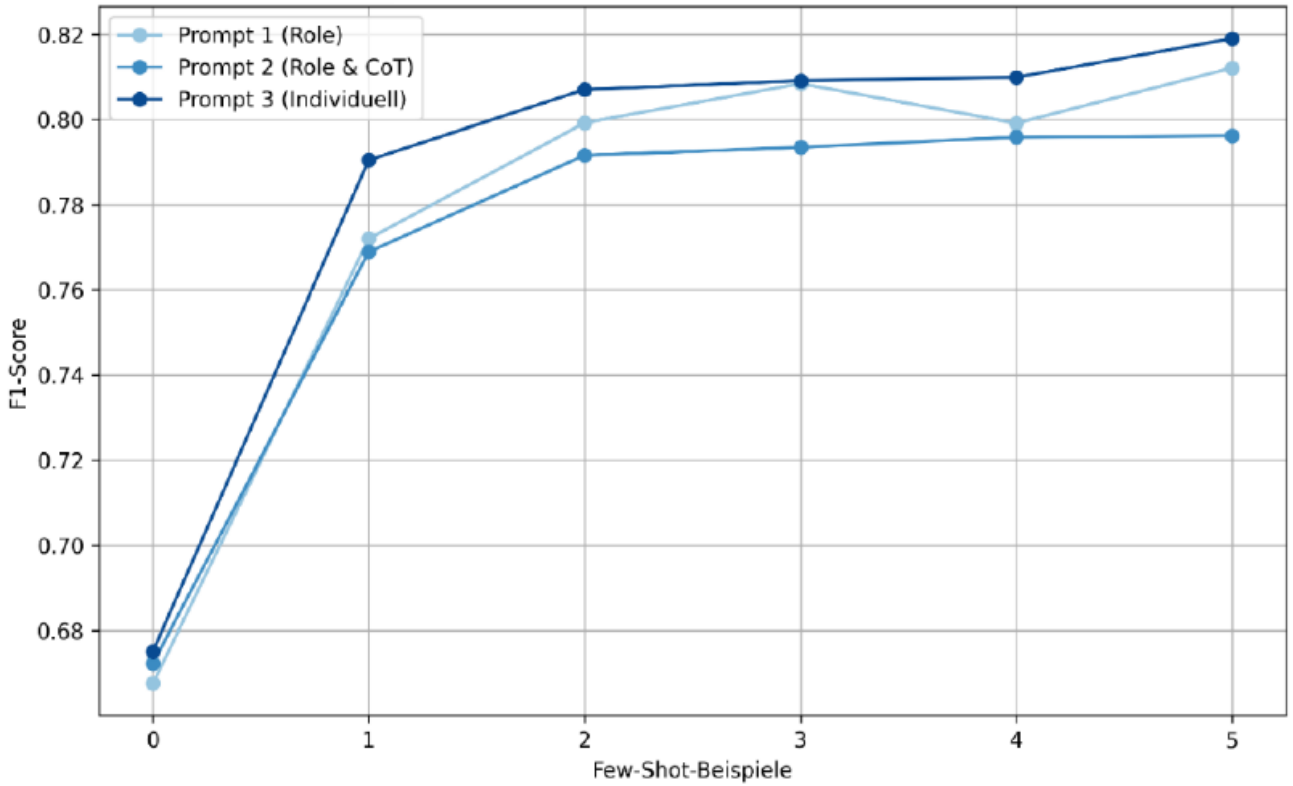
Source: Bachelor thesis, Markgraf, 2025

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Results of LLM-based descriptions

`dct:description`



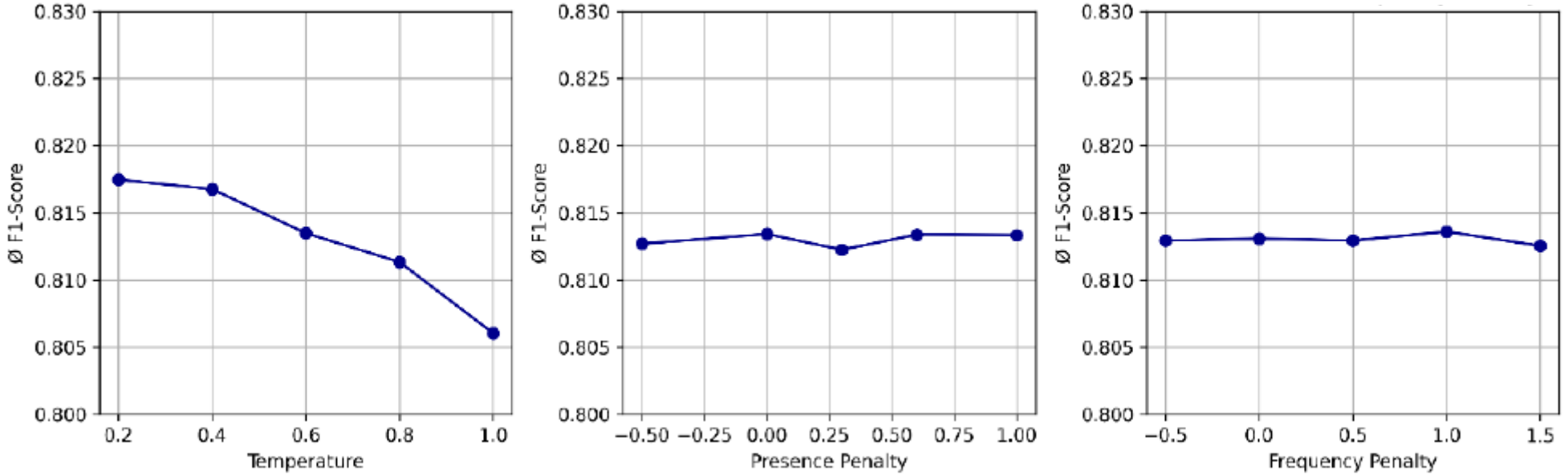
Source: Bachelor thesis, Markgraf, 2025

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Results of LLM-based descriptions

`dct:description`



Quelle: Markgraf, 2025

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Expert study with exploratory metadata editor
https://llm4opendata.streamlit.app

Research Question

What defines an effective open data metadata editor in the LLM era?

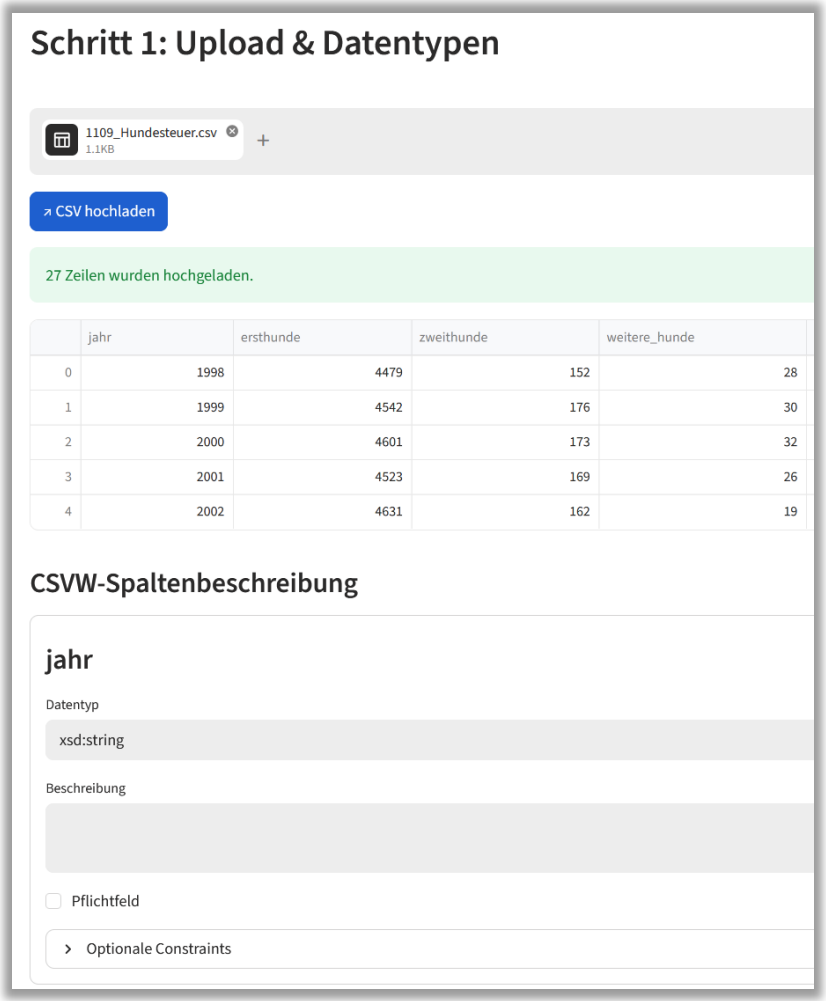
- Process
- Features
- Human vs. LLM

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Step 1:
Upload & Data Types

Expert study with exploratory metadata editor
https://llm4opendata.streamlit.app



Desired Features

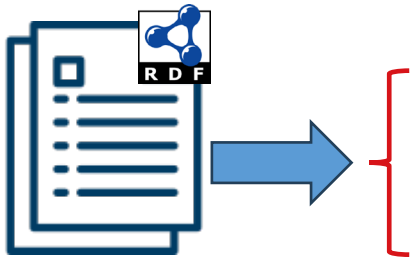
- Data Upload
- Schema Description
- Data Quality Assurance (planned)

Addressing Metadata Challenges

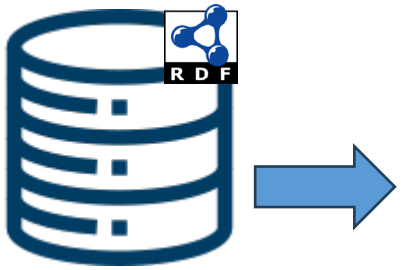
Project 2: Automatic Metadata Enrichment with (L)LMs

Step 2:
Metadata Fields &
LLM Configuration

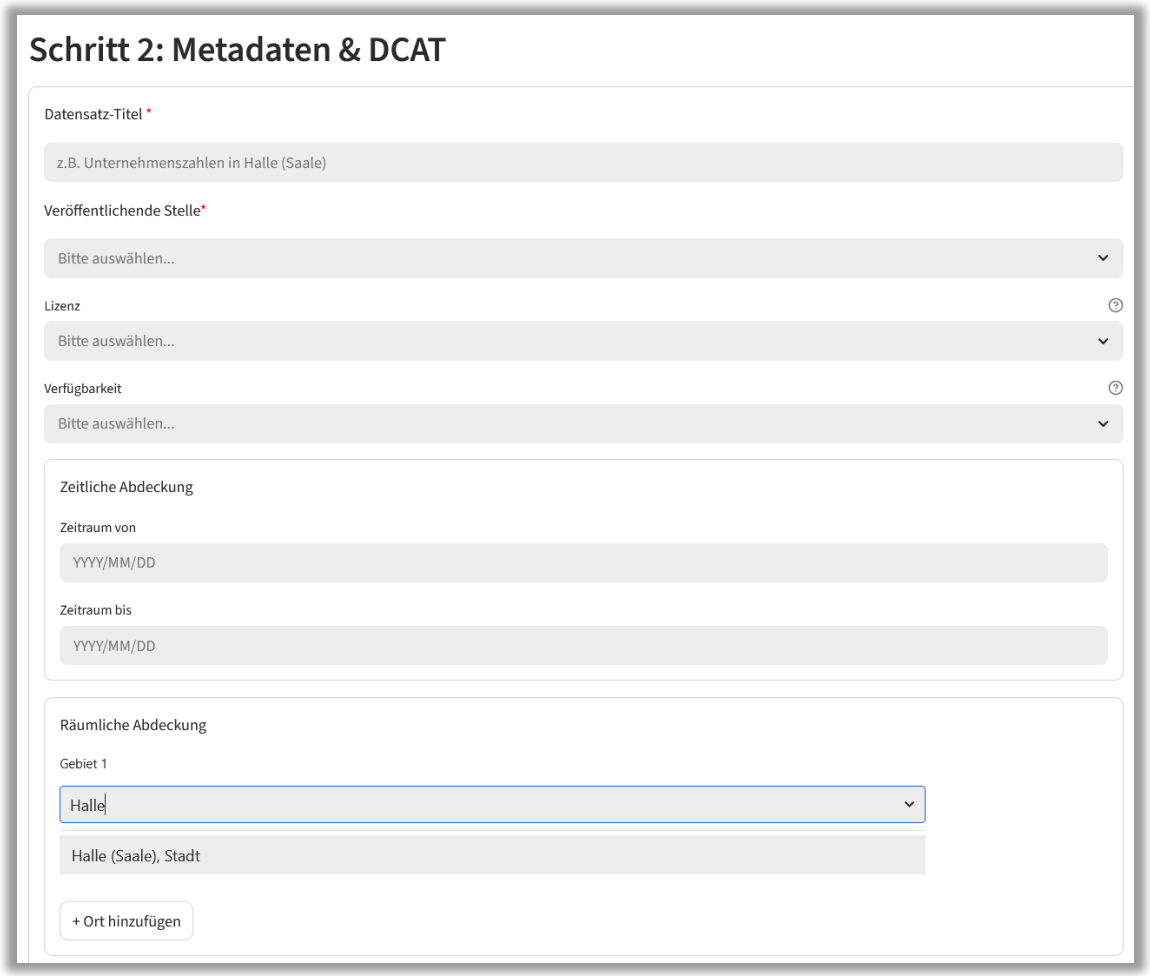
Expert study with exploratory metadata editor
https://llm4opendata.streamlit.app



URI List



Search Index



Desired Features

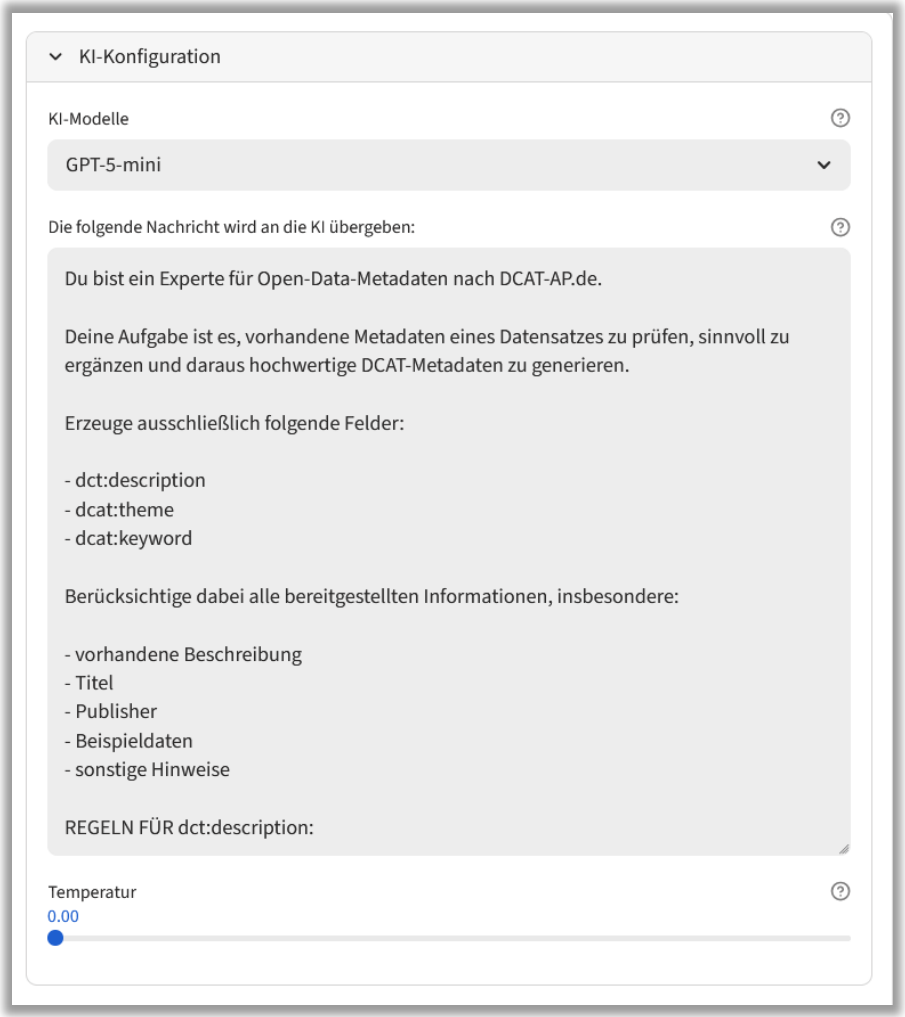
- Mandatory and recommended DCAT fields with online documentation
- URI-based term suggestions

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Step 2:
Metadata Fields

Expert study with exploratory metadata editor
https://llm4opendata.streamlit.app



Desired Features

LLM Configuration

- Model selection
- System prompt
- LLM parameter

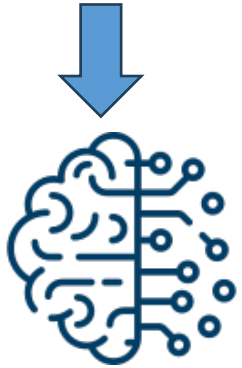
Addressing Metadata Challenges

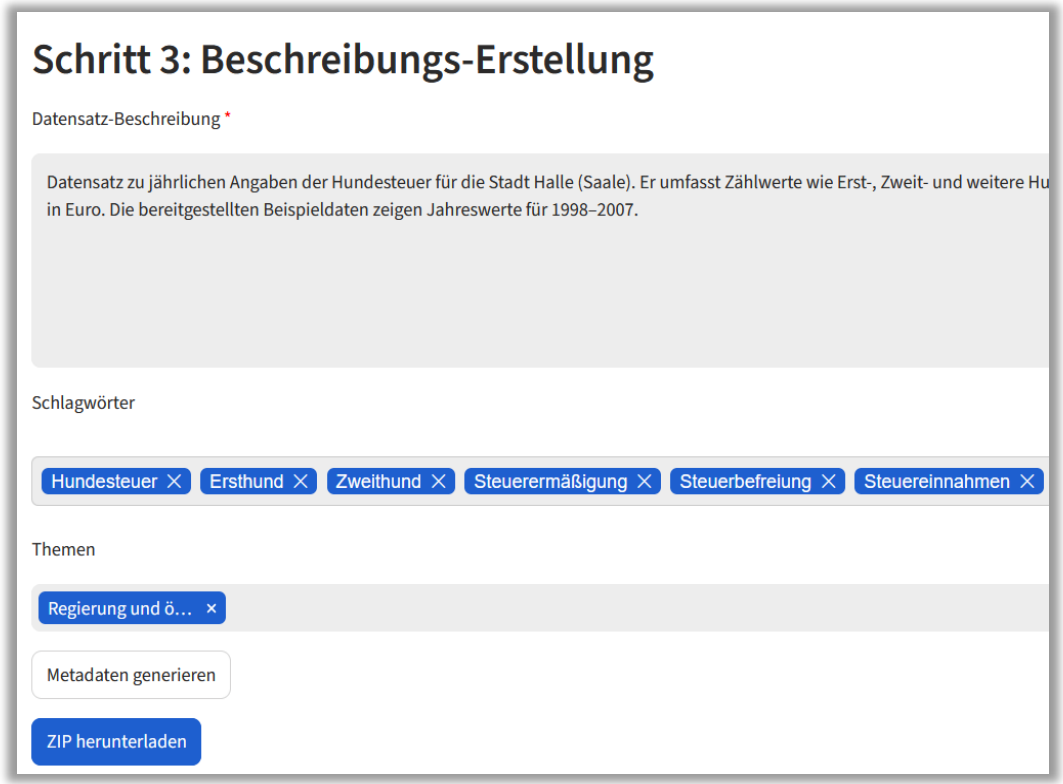
Project 2: Automatic Metadata Enrichment with (L)LMs

Step 3:
LLM-based metadata enhancement

Expert study with exploratory metadata editor
https://llm4opendata.streamlit.app

LLM Configuration
+ System Prompt
+ Example Data
+ initial metadata
+ similar datasets (planned)





Desired Features

- Metadata fields with LLM-based suggestion (editable)
- SHACL-based DCAT validation (planned)
- Download or publication of DCAT+ schema description + file(s)

Addressing Metadata Challenges

Project 2: Automatic Metadata Enrichment with (L)LMs

Summary (so far)

LLMs already produce good results when generating metadata

`dct:description` should be generated based on other metadata fields

Human-in-the loop approach needed

References

Work from HS Merseburg

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Literature

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Pictures

- Personas, Lena Tohoff
- Icons - Flaticon

Thank you for your attention!

Questions?

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