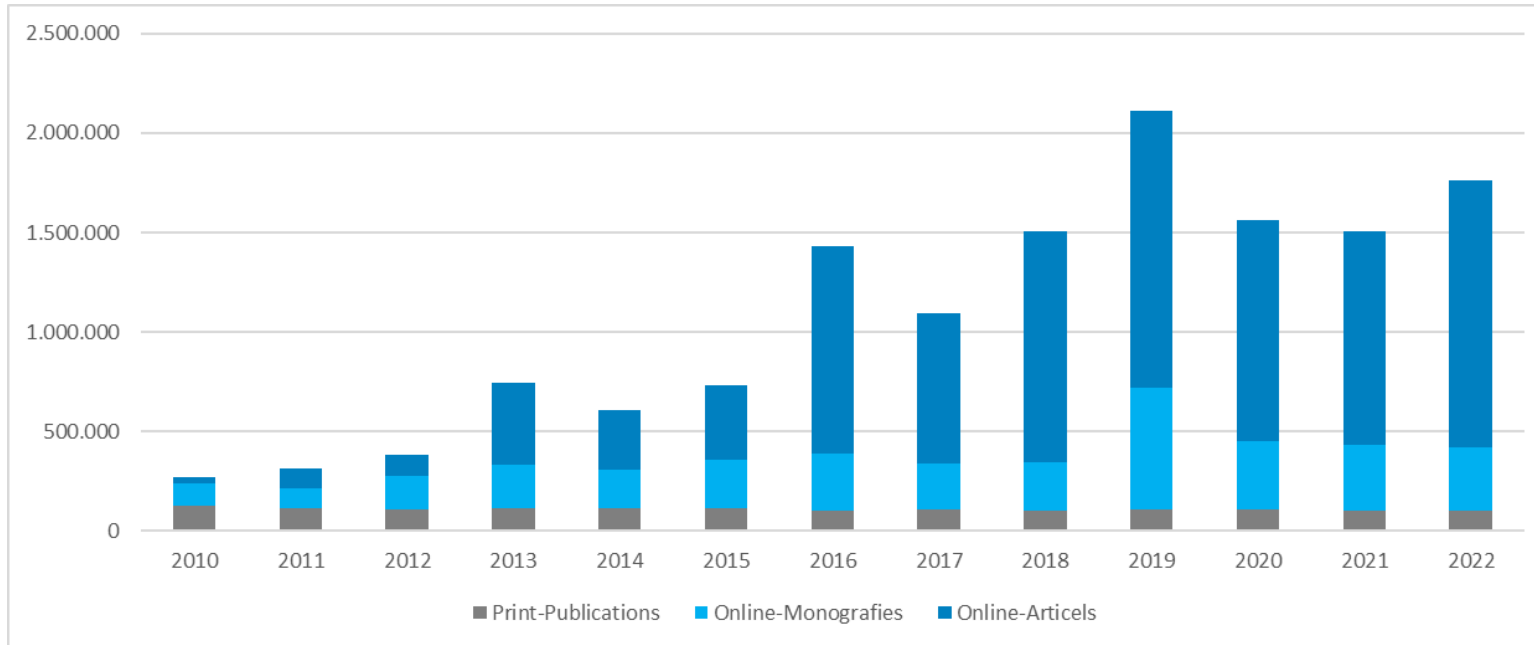


Maximilian Kähler, German National Library (DNB)

Machine-based Subject Indexing

Annual numbers of print- and online-publications collected by the DNB since 2010



Machine-based subject indexing@DNB

- In production since 2014
- Complete refactorization of software architecture in 04/2022^{1,2}
- Core component is now the open source library **annif**³
- Annual throughput of 170.000 publications per year
- Our target vocabulary is the **Integrated Authority File**⁴ (GND) containing ~1.3M potential concepts

¹<https://blog.dnb.de/erschliessungsmaschine-gestartet/>

²<https://blog.dnb.de/in-der-dnb-lesen-jede-nacht-die-maschinen/>

³Suominen, Osma; Inkinen, Juho; Lehtinen, Mona: Annif and Finto AI: Developing and Implementing Automated Subject Indexing. JLIS.It, 13(1), 265–282. <https://doi.org/10.4403/jlis.it-12740>

⁴<https://gnd.network/#>

Our Project: AI for automated indexing

<https://www.dnb.de/ki-projekt>

- Funded by German national AI-Strategy through BKM¹
- Duration: 3 1/2 Jahre (October 2021 – March 2025)

Project Goals:

- Accelerate knowledge transfer of NLP, Data Science and Machine Learning-Methods into the Organization
- Provide new methodological directions to machine-based subject indexing

¹BKM: Federal Government Commissioner for Culture and the Media <https://www.kulturstaatsministerin.de/>

Subject Indexing as XMLC-Problem

- Subject Indexing with a large target vocabulary constitutes an **Extreme Multi-Label Classification Problem**
 - Text documents are assigned with labels from an **a-priori known vocabulary**
 - Multi-Label problem: The number of labels per document may vary and is not a-priori bounded
- Why **extreme**?
 - Large Label-Set: $10^5 - 10^6$ labels
 - Long-Tail Characteristic: The majority of labels has few/zero training material

Interpreting subject indexing as XMLC-Problem opens up a new world of methods!



List of methods registered in the benchmark-initiative: [The Extreme Classification Repository](https://www.extremeclassification.com/) ([manikvarma.org](https://www.extremeclassification.com/)), weighted by Google-Scholar-Citations per Year, 02/2023

Core work of our project:

Systematically benchmark XMLC-methods for German scientific texts

- Identify a suitable subset of methods to test
- Adjust methods to work with our data and hardware
- Evaluate and compare

Our Evaluation setup:

- Methods are benchmarked in **two evaluation tasks**
 - Book Titles¹
 - Full Text²
- Machine-based predictions are compared with **intellectually assigned gold-standard** on an a Test-Set and we look at:
 - Overall performance
 - Performance in various evaluation dimensions
- Promising methods will undergo **qualitative rating** by professional subject indexers to rate idexates of previously unseen material

¹~950K training titles with intellectually assigned keywords

²~167K digital training documents with intellectually assigned keywords

Results

Methods analysed until now...

- 1vsAll-Classifier: Dismec++¹
- Partitioned Label Tree: Omikuji Rust-Library^{2,3,4}
- Lexical Indexing: MLLM^{5,6}
- LLM with few-shot instructions: Luminous by Aleph Alpha⁷

¹Schultheis, E., & Babbar, R. (2021).

Speeding-up One-vs-All Training for Extreme Classification via Smart Initialization. <https://doi.org/10.48550/arxiv.2109.13122>

²Khandagale, S., Xiao, H., & Babbar, R. (2020).

Bonsai: diverse and shallow trees for extreme multi-label classification. <https://doi.org/10.1007/s10994-020-05888-2>

³Prabhu, Y., Kag, A., Harsola, S., Agrawal, R., & Varma, M. (2018).

Parabel: Partitioned label trees for extreme classification with application to dynamic search advertising. <https://doi.org/10.1145/3178876.3185998>

⁴<https://github.com/tomtung/omikuji>

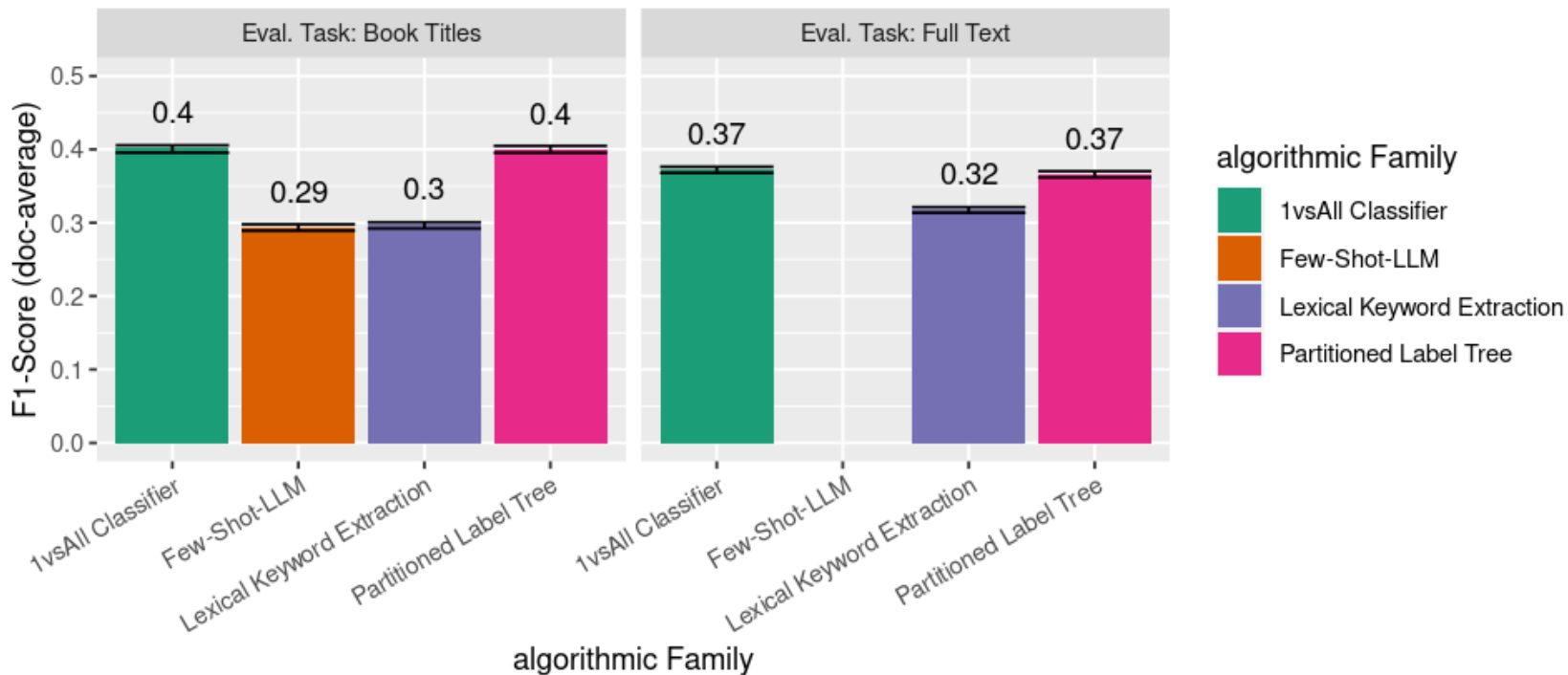
⁵Medelyan, O., Frank, E., & Witten, I. H. (2009).

Human-competitive tagging using automatic keyphrase extraction. <https://doi.org/10.5555/3454287.3454810>

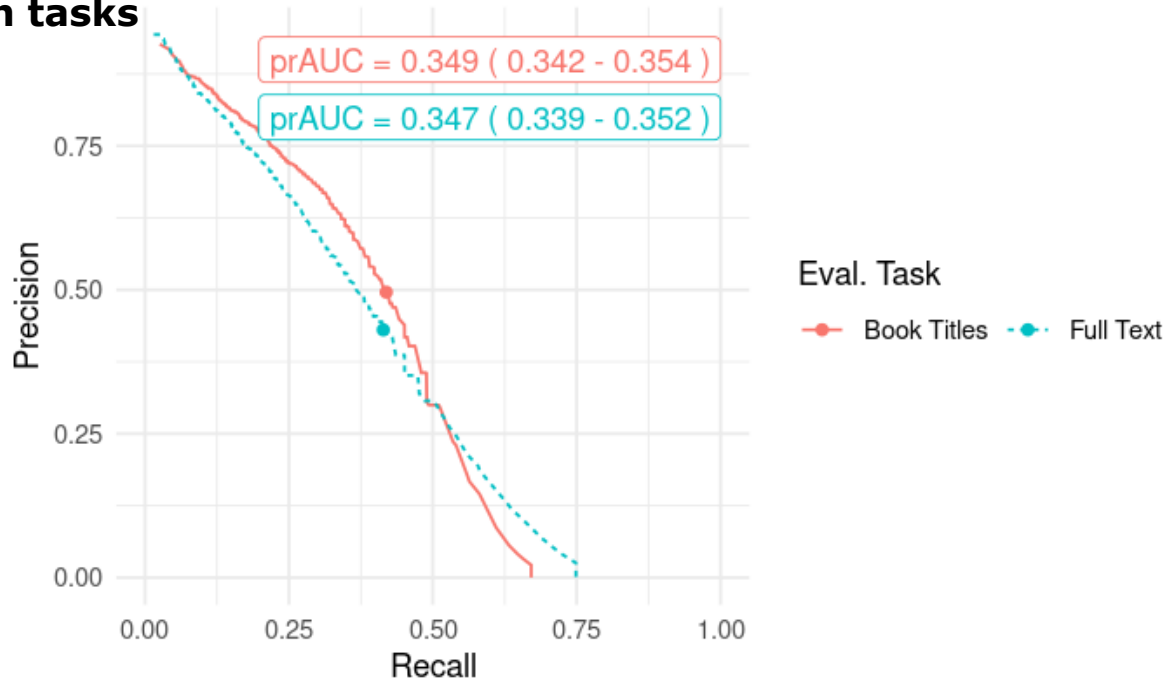
⁶<https://annif.org/>

⁷<https://docs.aleph-alpha.com/docs/introduction/luminous/>

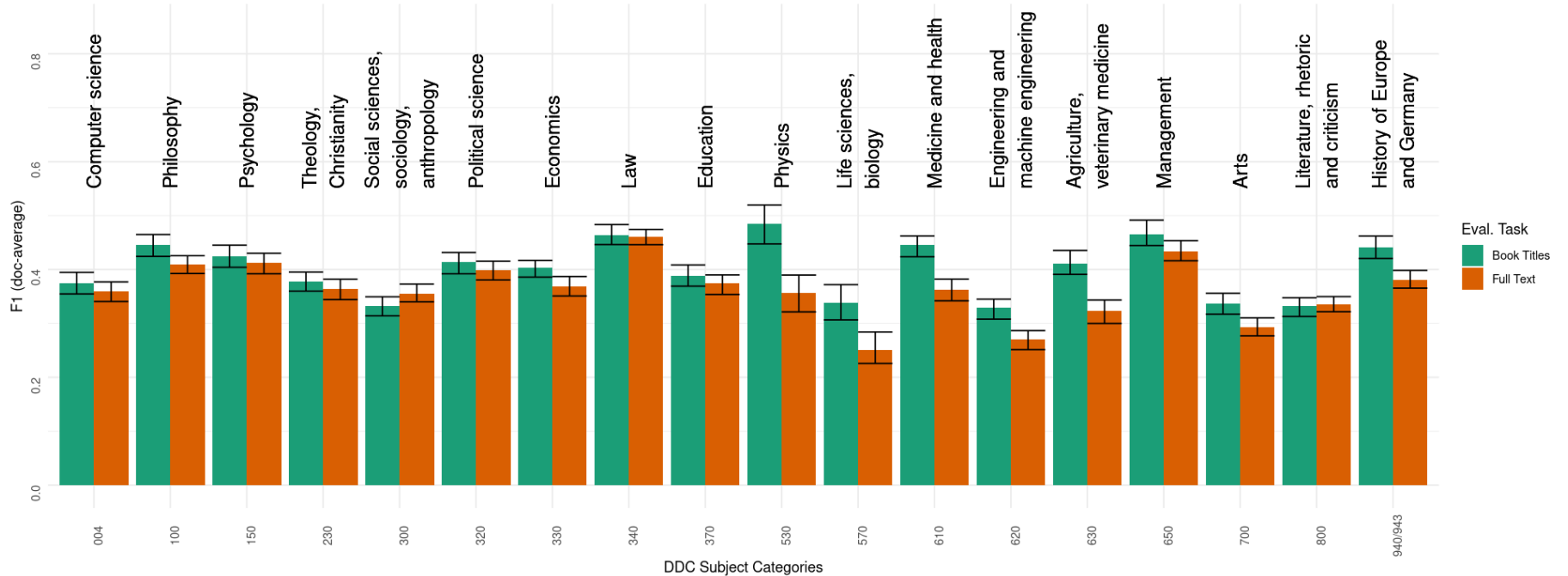
F1-Score on Test-Set (Preliminary)



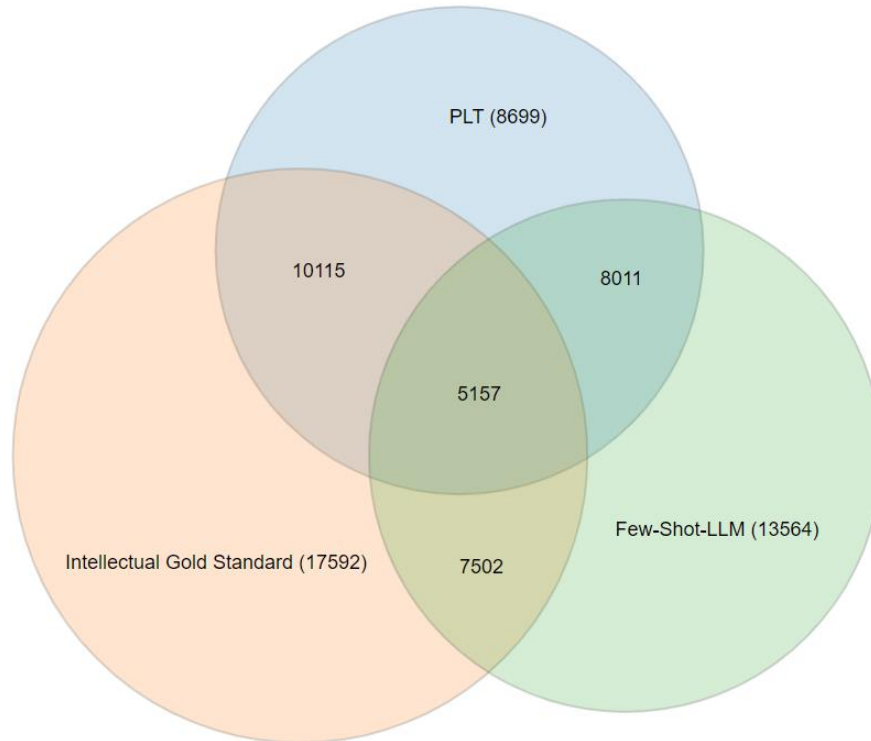
Example 1: Precision-Recall-Curve on Test-Set for Partitioned Label Trees in both evaluation tasks



Example 2: Results for Partitioned Label Trees in selected subject categories



Example 3: Comparing methods by their mutual overlap



Agreement in number of document-label-pairs for predictions on book titles with two methods:

	Total number of doc-label pairs ¹
Partitionel-Label-Tree (PLT)	21.668
Few-Shot-LLM	23.920
Intellectually assigned gold standard	30.052

¹Based on Test-Set with 8.415 documents

Project Challenges

- End-to-end pipeline of experiments has enormous complexity
 - data selection -> pre-processing -> training -> evaluation
- Setting up a fair benchmarking process for evaluation
 - Optimizing individual methods vs. producing valid comparison
- Adaption of NLP methods from English text to German text
- Hardware
- Legal challenges

Future Directions:

- Bring in more algorithmic families into benchmark:
 - Fine-Tuned Transformer-Architectures (e.g. XR-Transformer¹)
 - Embedding-Approaches (e.g. SLEEC²)
- Ensemble methods
- Qualitative evaluation by professional subject indexers

¹Zhang, J., Chang, W., Yu, H., & Dhillon, I. S. (2021).

Fast Multi-Resolution Transformer Fine-tuning for Extreme Multi-label Text Classification. <https://arxiv.org/abs/2110.00685v2>

²Bhatia, K., Jain, H., Kar, P., & Varma, M. (2015).

Sparse local embeddings for extreme multi-label classification. <https://doi.org/https://dl.acm.org/doi/10.5555/2969239.2969321>

Thank you!

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Please get in touch for further questions and discussion:

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Our Project@DNB:

<https://www.dnb.de/ki-projekt>

<https://blog.dnb.de/texte-erschliessen-mit-ki/>