Extraction of tabular data from annual reports with LLMs

Using in context learning with open source models and RAG

submitted by

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Studiere Zukunft

Abstract

Content of this thesis is a benchmark on information extraction from PDFs. The focus are annual reports of German companies. Special characteristic of the task is handling hierarchies in tables with financial data to prepare the data for import into a relational database.

The benchmark is composed of two sub tasks and the performance of different open source large language models is tested with different prompting approaches and compared to alternative methods.

This can be seen as a reimplementation study of "Extracting Financial Data from Unstructured Sources: Leveraging Large Language Models" - a paper published by H. Li, Gao, et al. (2023). The key differences are the application on German documents using open source large language models.

We show, that also smaller open source LLM (large language model)s can be used to identify the pages that contain the information of interest and to extract it. Based on these findings we sketch a process, how humans can use LLMs to extract information from financial reports.

Zusammenfassung

Gegenstand dieser Arbeit ist ein Benchmark zur Informationsextraktion aus PDF-Dateien. Dabei wird sich auf das Auslesen der Bilanzen und Gewinn- und Verlustrechnungen aus Jahresabschlüssen deutscher Unternehmen beschränkt. Ein besonderer Aspekt der Aufgabe ist die Berücksichtigung der Hierarchie innerhalb der Tabellen, um die Werte einem festen Schema zuzuordnen und so den Import in eine relationale Datenbank vorzubereiten.

Reading advices

The author recommends to read the thesis in its digital gitbook version instead of the PDF version. Furthermore, the author recommends to read the thesis (any version) on a screen that is larger than 21" and has at least full HD resolution[1]. The more, the merrier.

😊

Declaration of the Use of Artificial Intelligence

We use Github Copilot in VSCode for coding assistance. Mostly the GPT-4.1 is used. Sometimes Claude Sonnet 4.

We use perplexity.ai in our literature research process.

We use [] for

[1] Most of the time the thesis was inspected at a third of the authors 42" screen with 4k resolution. For inspecting the large overview graphics it is a very handy tool the author recommends every data scientist or software developer.

Goals and Learnings

Achieved:

- thesis with bookdown
- docker image creation
- cluster orchestration
- llm usage
- guided decoding

Missed:

- Administrating a k8s cluster
- Fine tuning a model
- using small language models
- training a lm
- using vllms

Dedication

Micha

Contents

Chapter 1

Introduction

Information is generated and processed by humans. And it is shared among humans. At first this information sharing was done synchronous using their voice. Later they developed the capabilities to store information at clay tablets, paper and most recently in digital files (Bentley, 2025). The amount of stored information, the human knowledge base grew paper by paper, file by file. The field of library and information science emerged, to organize these information, in order to allow efficient access. Since the information was shared only among humans, the format of stored data was optimized for human perception as well.

But things have changed in multiple ways. First, the amount of information generation is growing rapidly and the amount of relevant knowledge is increasing faster, than humans can absorb (Chamberlain, 2020). Alone in the field of science each year volumes of new information is beyond any human's ability to read are created (Hong et al., 2021). Luckily, the advent of recent LLMs gives us a tool to compress this information before reception by summarizing texts.

But on the same time generative AI (artificial intelligence) drives the increasing rate of information generation. A human can initiate the generation of a whole website or book with a single sentence of natural language. Most recently AI agents can, once created, react to triggers in the digital or real world and automatically generate content. Together with the information generated by devices in the Internet of Things the extrapolation of a information duplication every eleven hours (IBM Global Technology Services, 2006) might have become reality. This is the second thing that changed: algorithms generate, process and share information too.

What often remains unchanged until today: a lot of the published information is optimized for human processing, e.g. in PDF (Portable Document Format) documents. Algorithms can be very efficient in information processing, iff the information is machine readable. Since it is inefficient and error-prone to let humans encode the information, the field of information retrieval emerged as a new field of research. LLMs can help to retrieve information, even in a structured format, that can be used from other algorithms in downstream tasks.

For older sources of information this is the only way possible. For information shared in future there is another, more direct solution: additionally providing the information in a machine readable format in the first place. Otherwise we keep facing the "Last Mile Problem" (H. Li, Wei, et al., 2023). Since the format, data is provided in, can only be changed for the data owned by one self, one has to cope with the data received, until the needs for machine-readable formats is successfully communicated to and served by the data owners.

Section 1.1 describes, that the amount and format of information provided to the RHvB (Rechnungshof von Berlin) are raising challenges for the audition process. Section 1.2 specifies these challenges to specific real world problem. We derive our research questions from this use case. Section 1.3 gives an overview of our methodology and the thesis outline can be found in section 1.4.

1.1 Motivation

In the last decades the digital transformation accelerated and "electronic documents have increasingly supplanted paper documents as the primary medium for information exchange across various industries" (Q.

Zhang et al., 2024, p. 1). And also within the finance industry a lot of information is stored in (unstructured) digital formats, i.e. in PDF files (H. Li, Gao, et al., 2023). This is not only impeding investment decisions (El-Haj et al., 2020) and academic research (Jr et al., 2015) but also regulatory processes (H. Li, Wei, et al., 2023).

Such regulatory processes may be grounded on the audition reports by the RHvB. The RHvB is contributing to the transparent usage of tax money in Berlin by auditing public administrations and companies, where the state of Berlin is a shareholder or that get funded with public money. This prevents corruption and ensures efficient spending procedures.

In the audition process the employees at RHvB are faced with a lot of information embedded in PDF documents. Some are native digital documents, while other are just scanned paper pages.For the audition of the UEFA football championship they receive gigabytes of data. To extract the information necessary to perform the audition is a big challenge and would require a huge amount of human work force. Algorithmic assistance is highly welcome.

Since the targets of the audition change frequently, classical rule based approaches seem to have a rather limited payoff, comparing time used programming the system and the times it gets used. Thus, leveraging the flexible automation capabilities through programming by examples with LLMs (W.-D. Li & Ellis, 2024) seems promising. The need for automation is also driven by the impending shortage of experienced employees due to large number of retirements.

1.2 Objectives

The sixth division at RHvB is auditing the companies where Berlin is a shareholder (see Figure 1.1. They have to process the balance sheets and profit and loss accounting as a fundamental information. Those information is provided via the companies annual reports in form of PDF files. Automate the extraction of those information would be a good starting point for AI assisted information retrieval from PDFs for the RHvB overall. It especially is worth the effort invested in a thesis, because exporting financial data from the 59 companies is a recurring task.

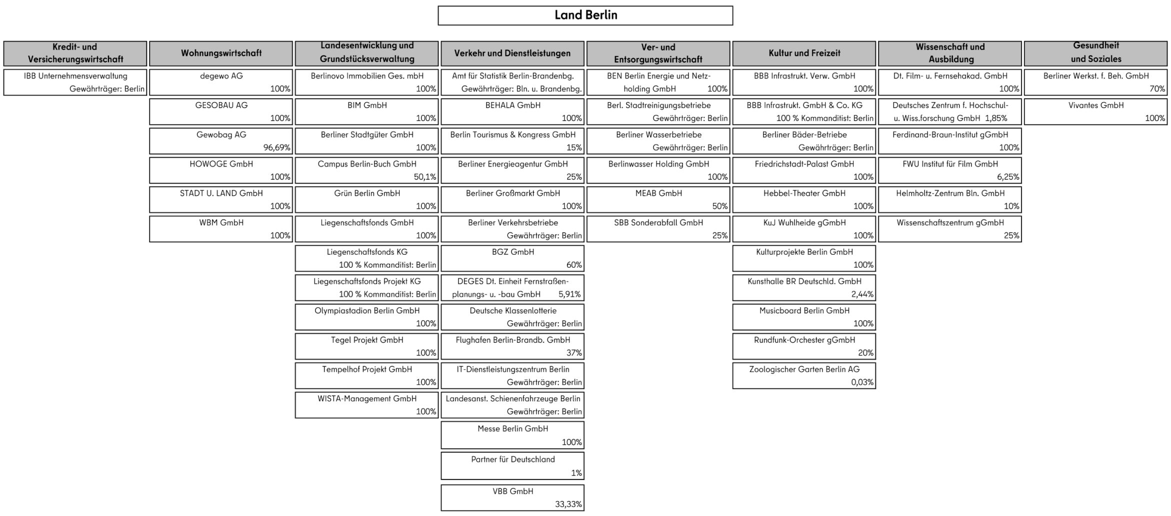

Figure 1.1: Overview of the 59 companies Berlin holds share at.

The provided annual reports often differ from the publicly available ones in matter of information granularity and design and are treated as non public information. For this thesis we use the publicly available versions to allow a comparison of open-source models with OpenAIs GPT (generative pre-trained transformers) models. We focus on open-source models, because the information in the non public reports might be confidential. The Berliner IKT-Richtlinie prohibits the processing of such information at public clouds and empowers the usage of open-source solutions.

We limit the broad field of information retrieval for this thesis on the extraction of the assets table, that is part of the balance sheet. To reach a high degree of automation, we investigate the possibilities of detecting the table, without having the user to provide the page number or area, as a second task. We formulate our two main research questions:

Q1 How can we use LLMs effectively to locate specific information in a financial report?

Q2 How can we use LLMs effectively to extract these information from the document?

Since the results of this thesis will be used to create an application with HITL (human-in-the-loop) approach, we want to investigate an additional side research question. Section E.1 presents the idea for the application. The user should check the information extraction results and resolve issues, the system alone could not handle. But redundant double work should be minimized. Therefore we formulate our third research question:

Q4 Can we use additional information from the extraction process, to guide the user which values need to be checked and which can be trusted as they are?

The following section will briefly describe our methodology to investigate our research questions. The corresponding hypotheses are formulated in section 3.2.1.

1.3 Methodology

This thesis is aiming to give a recommendation, how to solve the described extraction task best. Thus, it is placed in the field of applied research. We benchmark a broad variety of approaches and conduct experiments, to identify general predictors for the task performance. We start our investigation, implementing the framework described by H. Li, Gao, et al. (2023). Figure E.4 shows that they describe two stages, that match with our main research questions.

First, they show different approaches to identify the page, that contains the searched information, and how to combine those approaches efficiently. Additionally to a regex (regular expression) based and a LLM driven TOC (table of contents) based approach, we test a LLM driven classification approach, as well as a term-frequency based ranking approach.

Second, they show that LLMs can effectively extract the target information with the correct prompting strategy. We extend their task by testing, how well LLM can extract multiple values in a single prompt and designed experiments measure the effect of different influence factors. Besides model and prompting specific predictors, we systematically evaluate characteristics of the tabular structure as well.

Furthermore, we test the upper limits for the extraction performance with a synthetic dataset, that is free of unknown target row identifiers. This allows us, to test, if a simple text extract can be sufficient as input or if additional effort - e.g. performing a document layout analysis or using specialiced table extraction techniques - should be invested, to extract the assets tables structure as well.

Our work is also contributing to the question, if the presented framework is promising on more heterogeneous documents, how open-source models perform and if the German language of the annual reports may hold unique challenges.

1.4 Thesis Outline

Chapter 2 briefly introduces into the theoretical background of the used concepts and references literature, that is describing them in depth.

Chapter 3 is describing our research design, research questions and hypotheses. Separate for our three research questions, it presents our evaluation and data strategy. It gives an overview about the experimental setting, including the used evaluation methods and expected error types .

Chapter 4 describes the hardware the experiments run on and the software used to implement them. It presents a flow chart and description of the data processing workflow.

Chapter 5 briefly presents the results for the three investigated research questions. Detailed descriptions, how the results are obtained can be found in the appendix.

Chapter 6 discusses the results. It interprets the results in regard to the research questions and hypotheses. It contains the error analysis. It shows the limitations of this study and names what is not covered yet. It gives an outlook, on how we will proceed with the results of this thesis, to solve the real life problem.

Chapter 7 summarizes the answers on our research questions.

1.5 Summary

This chapter, showed the challenges that result from the ever growing amount of information to process and the hurdles that non-machine-readable data is placing on the way to use algorithms, to handle the information overflow. It described the specific problem we tackle with this thesis of extracting financial information from annual reports, to prepare the audition processes at RHvB. We formulated our research questions, sketched our methodology to investigate them and gave an outlook on the subsequent chapters.

1.6 To place in chapters above

XBRL reports instead of PDFs? employees need to know, that they exist and how to work with those

It is important to get numeric values totally accurate; numeric values are difficult to handle for langauge models

Research questions and hypothesss

Q1: Can a LLM be used to efficiently extract financial information from German annual reports? Q2. Can LLMs be used to identify the page of interest automatically?

Q3: Can confidence scores be used to head up the human in the loop on which results to double check? (How can sources of the automatic extraction being communicated down stream in order to make double checking easy before making decisions?) Q4: Can contextual information from similar documents reduce errors made during table extraction? Q5: What are characteristics of financial tables that make it hard for LLMs to identify / extract them? (How does the length and complexity of financial documents (e.g., multi-column layouts, nested tables) affect table extraction performance?)

missing law to access digital data and no law to choose the format of the data extensible Business Reporting Language as a standard changing from HGB to IFSR

1.7 Unstrukturierte Daten

- Beispielbilder

1.7.1 Portable Document Format

- print optimized
- Table structure information gets lost
- Bild und Textextract
- see Erics thesis ;)

Chapter 2

Literature review

(less than 10 p)

The introduction described, that the problem, we want to solve with thesis, is part of the field of information retrieval. Thus, section 2.1 describes methods, used to retrieve information from documents. It gives a brief overview on regex (regular expression), before subsection 2.1.5 describes the mechanisms and architecture of recent LLM (large language model)s, including MoE (mixture of experts) architecture.

Afterwards, subsection 2.1.6 describes the method of few-shot prompting, that leverages the programming by example paradigm, and how RAG (retrieval augmanted generation) fits in this picture. We show how guided decoding can be used to generated structured responses for usage in down stream tasks.

Section 2.2 presents the SHAP (SHapley Additive exPlanations) framework. It is a unified explanation model for machine learning models and can be applied to complex models like deep neutral networks or random forests. The latter are briefly introduced as well. We use random forests and SHAP to check our hypotheses on possible predictors for the information extraction task (see 3.2.1).

2.1 Natural language processing

closed-domain vs open-domain

2.1.1 Document Layout Analysis (edit this)

An important step in the process of extracting information from documents is to recognize the layout of a document (Zhong et al., 2019).

Getting the order of texts correct align captions to tables and figure identify headings, tables and figures

One of the most popular datasets used for training and benchmarking is PubLayNet (see PubLayNet on paperswithcode.com). It contains over 360_000 document automatically annotated images from scientific articles publicly available on PubMed Central (Zhong et al., 2019, p. 1). This was possible, because the articles have been provided in PDF and XML format. For the annotations most text categories (e.g. text, caption, footnote) have been aggregated into one category. <– is this a problem for later approaches where a visual and textual model work hand in hand to identify e.g. table captions?

Manual annotated datasets often were limited to several hundred pages. Deep learning methods need a much larger training dataset. Previously optical character recognition (OCR) methods were used.

Identify potentially interesting pages with text / regex search. Check if there is a table present on this page.

Object detection

2

2.1.2 Term frequency

Term frequency $\mathrm{tf}_{t,d}$ is a very simple measure. It just counts the number of occurrences of a term in a document. Document is an abstraction in this case. It can be a sentence, a page or a file. Since longer documents might have higher term frequency for each term, it is useful to normalize the value by the document length $|d|$. This measure could be called term rate:

$$\mathrm{tr}_t = \frac{\mathrm{tf}_{t,d}}{|d|} \tag{2.1}$$

It is part of well established measures as TF-IDF (Frequency-Inverse Document Frequency) and Okapi BM25 (best matching 25). Both are used for ranking, how relevant a document is for a given search query and are widely used in information retrieval systems (Robertson, 2004; Robertson & Zaragoza, 2009) and thus can be part of a RAG architecture too. BM25 is one of the "most successful Web-search and corporate-search algorithms" (Robertson & Zaragoza, 2009, p. 1).

The IDF (Inverse Document Frequency) is often used as a weighting function. If the ranking of possible results of a search query is simply calculated as sum of all term frequencies in a document, that are present in the query as well less informative terms get equal weight.

Looking at the search query: "Is the positron blue?", helps to illustrate the problem. The terms *is*, *the* and *blue* might be present often in a document for children that is talking about the sky or sea. Such a document could get high score, even though *positron* is never mentioned. It would be good, if it is most important if the term *positron* is in the document. We can achieve this by multiplying all term frequencies with the IDF score (Manning et al., 2008, p. 118):

$$\mathrm{idf}_t = \log \frac{N}{\mathrm{df}_t} \tag{2.2}$$

N is the number of documents in the collection of documents and df_t the number of documents, that contain term t. While the term frequencies $\mathrm{tf}_{t,d}$ are calculated separate for each document, the IDF score is computed once for the whole collection. The TF-IDF score is then defined by:

$$\text{tf-idf}_t = \mathrm{idf}_t \cdot \mathrm{tf}_{t,d} \tag{2.3}$$

The more advanced measure BM25 is derived in Manning et al. (2008).

Measures as TF-IDF are also used for classification tasks, i.e. in the context of sentiment analysis (Carvalho & Guedes, 2020) and semantic understanding (Rathi & Mustafi, 2023).

2.1.3 Text processing

document layout analysis?

2.1.4 Regular expressions

2.1.5 Large Language Models

Wichtig

2.1.5.1 Transformers

Wichtig

hauptsächlich decoder (generieren)

seit 2017

2.1.5.2 Attention

The most obvious challenge is computational cost. The amount of processing power required scales quadratically with the length of the input (Tahir, 2025).

2.1.5.3 Encoder

Wichtig

positional encoding important (and distinguishes from tf-idf): dog eats cat

sinusoidal positional encoding, which uses sine and cosine functions of varying frequencies to create unique positional vectors, and Rotary Position Embedding (RoPE), which applies a rotation to the token embeddings based on their position (Khowaja, 2025)

2.1.5.4 Decoder

For each generated token, the attention mechanism needs to access the key and value vectors of all preceding tokens in the context window. To avoid recomputing these key and value vectors at each step, they are stored in the KV-cache. (Khowaja, 2025) However, the memory required to store the KV-cache scales linearly with the size of the context window.

Wichtig

Token sampling, temperature 0

2.1.5.5 GPT (Generative Pretrained Transformers)

Wichtig

2.1.5.6 Mixture of Experts

Recent LLM (large language model)s often use a MoE architecture. The models of Llama 4, Qwen3 and GPT-4.1 are prominent examples for this kind of LLMs. D. Zhang et al. (2025) and Cai et al. (2025) give an exhaustive overview of different types of MoE architectures. While D. Zhang et al. (2025) lists also models released this year and shows some applications of MoE, is Cai et al. (2025) discussing different architecture types in more detail. Grootendorst (2024) gives a guid to MoE with many helpful illustrations.

The basic idea of MoE models is to combine multiple smaller, specialized FFN (feed forward network)s to achieve better predictions overall. The MoE "paradigm offers a compelling method to significantly expand model capacity while avoiding a corresponding surge in computational demands during training and inference phases" (Cai et al., 2025, p. 21).

Figure 2.1 shows two main differences in the architecture. One one hand there is the dense (a) architecture. Here, each token is fed into every FFN and all results are pooled. On the other hand, there is the sparse architecture. Here, each token is just fed into a subset of FFNs. Dense MoE models often yield higher prediction accuracy, but also significantly increase the computational overhead (Cai et al., 2025).

The gate (also router) takes care of the distribution of tokens to the FFNs. There is a high diversity of the routing algorithms and its goals are to "ensure expert diversity while minimizing redundant computation" (D. Zhang et al., 2025). There are algorithms that focus on load-balancing, domain specific routing and many more. Traditional MoE assumes homogeneous experts, where load balancing might be the paramount goal. Recent advances explore more heterogeneous sets of experts and flexible routing strategies, that promise more efficiency (D. Zhang et al., 2025).

Most of the Qwen3 models have a dense MoE architecture. Only the two models released in July 2025 have a sparse architecture. These models have two parameter specifications. For example Qwen3-235B-A22B is specifying that the model has 235B token in total. But per token processed it uses (activates) just 22B parameters. In their mixture of experts architecture this means that 8 of 128 experts are participating in processing each token.

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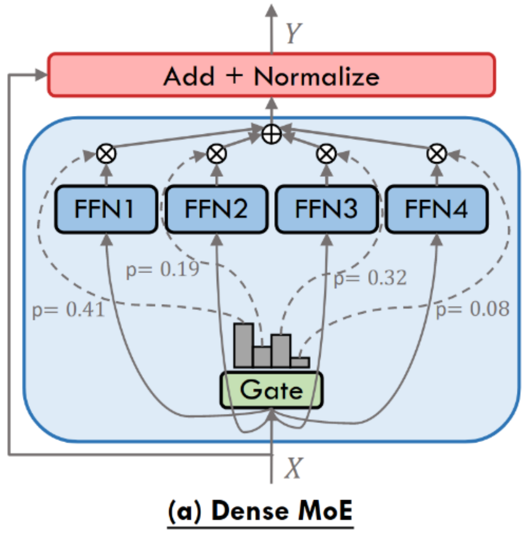

Figure 2.1: Showing schemas of the dense and sparse mixture of experts architecture.

The Llama 4 models have a shared expert MoE architecture. It combines a shared, fixed expert that processes every token and combines those results with results from a sparse MoE layer.

Googles gemma-3n-E4B uses a selective parameter activation as well. They use the prefix E for effective instead of A for active (Google, n.d.). In gemma-3n there are parameters to handle input of different types - text, vision and audio - and they get loaded and activated as necessary. This allows a multi modal functionality. It additionally caches the PLE (Per-Layer Embedding) in fast storage (RAM) instead of keeping it in the model memory space (VRAM), allowing to run models in low resource environments.

Raus oder woanders hin: The Qwen3 models support two operating modes: A thining mode and a non-thinking mode. The thinking mode should yield better answers in complex tasks and the additional amount of processing can be controlled by setting a thinking budget (Qwen Team, 2025). This thinking budget can be seen as the amount of tokens used for a step wise solution.

2.1.5.7 Mixed modal

(Team, 2024)

2.1.6 Methods for LLM application

2.1.6.1 Few-shot Learning

Wichtig

2.1.6.2 RAG

Wichtig

2.1.6.3 Guided and restricted decoding

generation template strict (closed) vs open

always selecting the most probable response (temp = 0), so numeric values are correct and classification as well

2.2 General machine learning and statistics

2.2.1 Sample distribution visualization methods

Boxplots Wickham & Stryjewski (2011) describe boxplots as "a compact distributional summary, displaying less detail than a histogram or kernel density, but also taking up less space. Boxplots use robust summary statistics that are always located at actual data points, are quickly computable (originally by hand), and have no tuning parameters. They are particularly useful for comparing distributions across groups."

Figure 2.2 shows a box and whiskers plot and its components and compares it to a gaussian probability distribution. Half of all observations fall within the box and the median is marked by a thick line. Outliers are defined as observations that are outside the area marked with the (horizontal) lines -called whiskers - that potentially have small bars at their ends. Outliers can be shown by circles or dots.

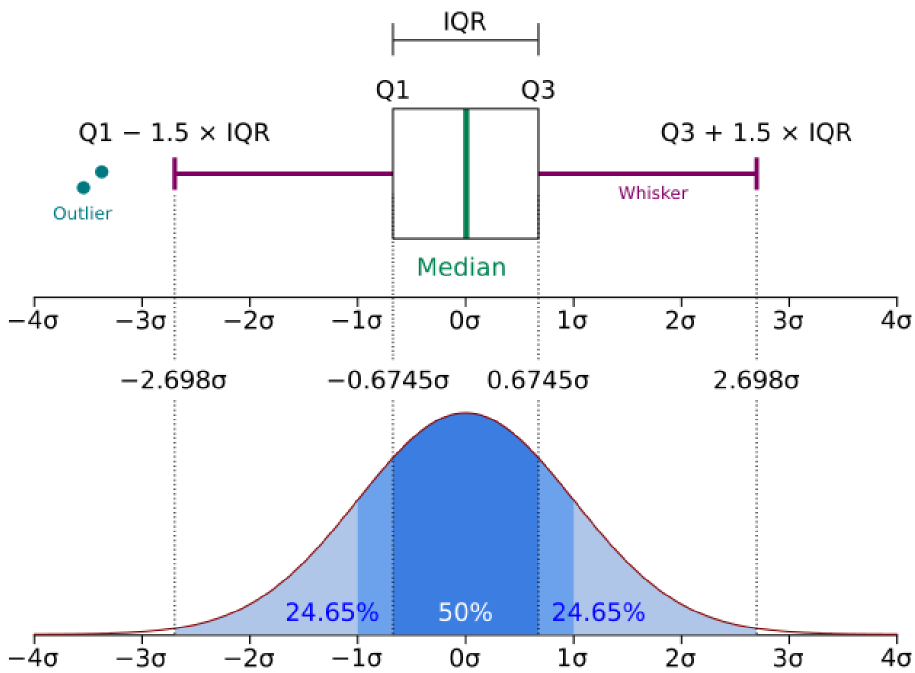

Figure 2.2: Showing a box and whiskers plot with its components - median, quartiles, whiskers and outliers - and compare it with a gaussian probability distribution. Graphic adjusted from Jhguch (2025).

The median and quartiles are less sensitive to outliers, than the mean and standard deviation of a sample. Thus, they are more suitable for distributions that are asymmetric or irregularly shaped and for samples with extreme outliers (Krzywinski & Altman, 2014). They can be used with five observations and more. But even for large samples ($n \geq 50$), whisker positions can vary greatly.

Violin plots There are variations, that try to communicate the sample size of a box plot, either by adjusting the width of the whole box or by introducing notches, that indicate the confidence interval for the median (Wickham & Stryjewski, 2011). Violin plots (Hintze & Nelson, 1998) additionally indicate an density estimate, dropping the strict rectangular shape of the box. Figure 2.3 shows, that the shapes can be necessary to identify multi-modal distributions, that are invisible with regular boxplots (Wickham & Stryjewski, 2011). One can tackle this problem by adding a jitter plot layer to the boxplots. Violin plots can also be used for large datasets, preventing to plot a lot of outliers.

2.2.2 Tree based machine learning algorithms

Random forests are a ensemble supervised machine learning technique, composed of multiple decision trees (V. Kulkarni & Sinha, 2013). Mienye & Jere (2024) give a detailed insight into decision trees and their

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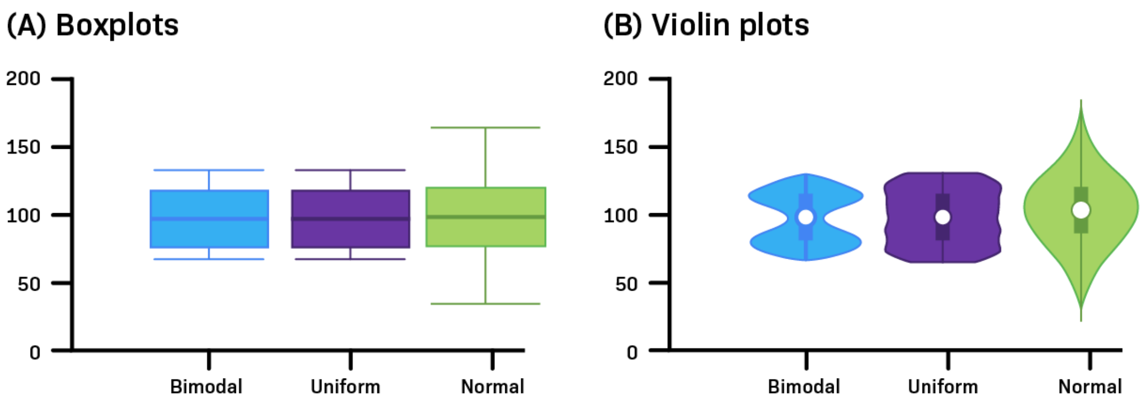


Figure 2.3: Comparing boxplots and violinplots, showing that boxplots can not identify multi-modal distributions on their own. Graphic adjusted from Amgen Scholars Program (n.d.).

high-performing ensemble algorithms. Tree based machine learning algorithms have gained significant popularity, due to their simplicity and good interpretability (Mienye & Jere, 2024).

Decision tree "The basic idea behind decision tree-based algorithms is that they recursively partition the data into subsets based on the values of different attributes until a stopping criterion is met" (Mienye & Jere, 2024). Figure 2.4 shows this for artificial data of two continuous features. Popular measures to determine how to split a set of observations are the Gini index, information gain or information gain criteria (Mienye & Jere, 2024).

The tree shown is used for a regression task and will predict the average of all values of the corresponding terminal node (leaf). To find out, which leaf will be the target terminal node for a given set of features one just follows the path from the top node (root) downwards, checking the splitting criteria. Thus, the interpretation of decisions made by a decision tree is very easy.

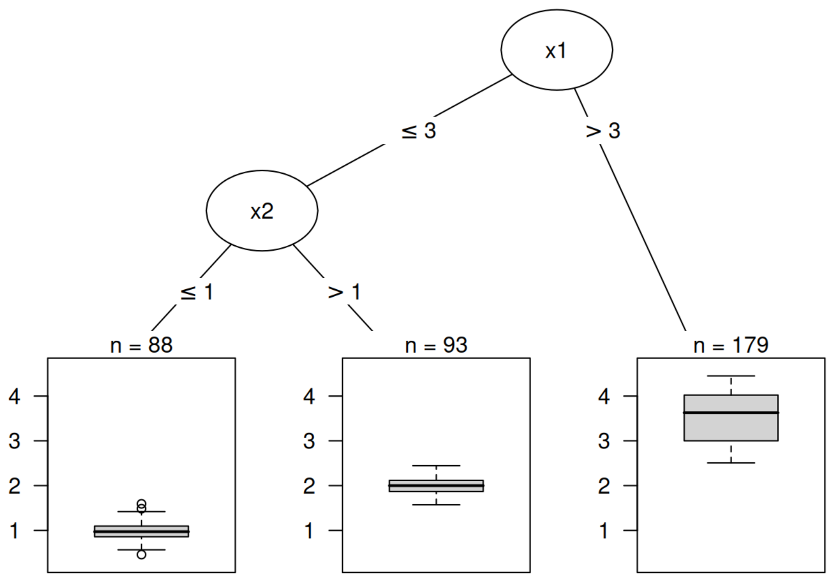
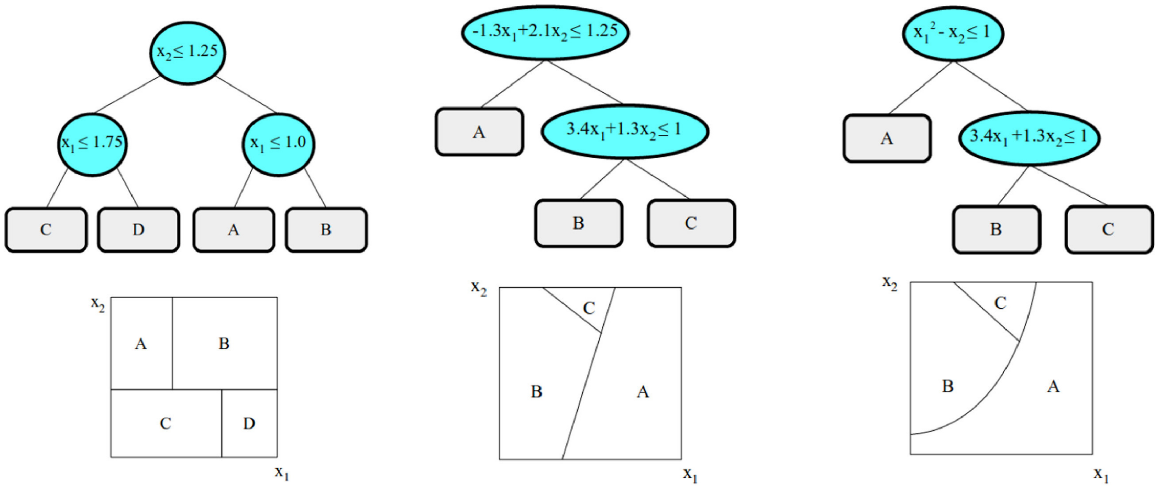


Figure 2.4: Visualizing the of partitioning of a two-dimensional continuous feature space based on multiple splitting criteria for decision tree inducing. Graphic adjusted from Molnar (2025).

Further benefits of decision trees - besides the good interpretability and computational efficiency - are the native capturing of interactions between features (Molnar, 2025), without modeling this explicitly, as it would for example be necessary in a linear regression. Decision trees can be used for classification and regression. They even can incorporate linear functions as leafs, enabling them to better capture linear relationships (Raymaekers et al., 2024).

Problems of decision trees are, that they lack resilience against data changes and a tendency to overfitting. A method against overfitting is pruning (Mienye & Jere, 2024). Building an ensemble of decision trees is another possibility, that results in the random forest algorithm, described in the next paragraph .

Rivera-Lopez et al. (2022) are focusing on decision trees, describing multiple decision tree types, e.g. based on the splitting procedure (see Figure 2.5). In addition to axis-parallel splitting, they show oblique and non-linear splitting criteria. They present a state-of-the-art review and a summary analysis of metaheuristics based approaches for decision tree induction.



(a) Axis-parallel-DT (b) Oblique-DT (c) Non-linear-DT

Figure 2.5: Visualizing the of partitioning of a two-dimensional continuous feature space based on multiple splitting criteria for decision tree inducing. Graphic adjusted from Rivera-Lopez et al. (2022).

Random forest A random forest is using the principle of bagging and applies it on the level of features and observations. This means, it starts, creating basic decision trees with differing subsets of features and uses bootstrapping to select a randomized set of observations to train the tree with. The final prediction is then determined by voting (for classification) or averaging (for regression) the predictions of all trees in the ensemble.

The induction of the trees can be be parallelized, making it efficient on modern hardware. Random forests can cope with thousands of features and can be applied to large datasets (Breiman, 2001). There are methods that address the problems of imbalanced datasets too. As there are methods to prune a decision tree to fight overfitting, there are methods to prune a random forest by removing whole trees, to improve the learning and classification performance, too (V. Y. Kulkarni & Sinha, 2012).

Random forests are "powerful learning ensemble[s] given its predictive performance, flexibility, and ease of use (Haddouchi & Berrado, 2024). While it is based on decision trees, that are considered to be *white boxes*, because of their easy interpretability, random forests are seen as *black boxes*. The decision could be tracked without complicated math, but is tedious, because it would require propagating through many decision trees, noting their predictions and then averaging those.

The fact that the RF model is categorized as a black-box model restricts its deployment in many fields of application (Haddouchi & Berrado, 2024). One feature oriented tool for explainability is the SHAP framework, presented in section 2.2.3. It allows local explanation, a global overview and pattern discovery for random forests (Haddouchi & Berrado, 2024).

Gradient boosted decision trees Another highly effective and widely used advancement to decision trees are gradient boosted decision trees (Chen & Guestrin, 2016). Instead of the principle of bagging it applies the principle of boosting. it is sequentially building decision trees, where the later ones correct the errors in predictions made by the former trees. It uses gradient descent to minimize those errors (Mienye & Jere, 2024).

The XGBoost (Extreme Gradient Boosting) algorithm is a famous member of this family, with "an outstanding performance record" (Burnwal & Jaiswal, 2023). "Among the 29 challenge winning solutions published at Kaggle's blog during 2015, 17 solutions used XGBoost" (Chen & Guestrin, 2016).

In the following we will emphasize some of its benefits as described by Burnwal & Jaiswal (2023):

- XGBoost employs both L1 (Lasso) and L2 (Ridge) regularization in its objective function to penalize model complexity, mitigating overfitting. However, overfitting can occur, especially if hyperparameters are not adjusted properly.
- XGBoost provides feature importance metrics to facilitate model interpretation, facilitating feature selection and improving the understanding of the model's decision-making process.
- XGBoost "runs more than ten times faster than existing popular solutions on a single machine and scales to billions of examples in distributed or memory-limited settings" (Chen & Guestrin, 2016) using parallelization techniques.

But there are some challenges, that are to investigate in future research. E.g. finding methods to handle imbalanced data and automate the hyperparameter tuning process.

2.2.3 Model agnostic explanation models

Shapley values Shapley values are introduced by Shapley (2016) originally in 1952 in the field of game theory. He defined three axioms that a fair allocation of value must fulfill:

1. Symmetry: If two players contribute the same amount, they are interchangeable and should gain equal reward.
2. Efficiency: The whole value of the game is distributed among the players.
3. Law of aggregation: If a player contributes to multiple independent games, his contribution in total should be the sum of contributions in each game.

From the third axiom a fourth property derives, that is sometimes named independently. If a player is not contributing to a game, he gets no share. O'Sullivan (2023) calls this the *null player* property.

The formula for a single shapley values is given by (S. Lundberg & Lee, 2017)[1]:

$$\phi_i = \sum_{S \subseteq P \setminus \{i\}} \frac{|S|!\,(|P| - |S| - 1)!}{|P|!} \left[val(S \cup \{i\}) - val(S)\right] \tag{2.4}$$

Molnar (2025) bridges the game theory terms to the field of machine learning as follows: "The *game* is the prediction task for a single instance of the dataset. The *gain* is the actual prediction for this instance minus the average prediction for all instances. The *players* are the feature values of the instance that collaborate to receive the gain (= predict a certain value)."

SHAP framework S. Lundberg & Lee (2017) are presenting "A Unified Approach to Interpreting Model Predictions" based on shapley values, called SHAP (SHapley Additive exPlanations). It assigns each feature an importance value for every observation. This allows to inspect, why a specific prediction is made and might explain, why a model makes a mistake for specific observations. Inspecting the predictions for all observations can show generalized effects of features.

S. Lundberg & Lee (2017) show that their approach is the only possible explanation model for the class of additive feature attribution methods, that has three desirable characteristics: local accuracy, missingness

[1] We replaced F by P to speak in the terms of players instead of features. We also replcaed f by val, because it better fits the story, that this is the value gain in a game, as explained by O'Sullivan (2023).

and consistency. Shapely values can be computed for any machine learning model, but its exact calculation is computationally extremely expensive (Hu & Wang, 2023), since it is of exponential complexity $\mathcal{O}(2^p)$ regarding the number of features (or predictors) $p = |P|$.

Even with the approximation of the shapley values, introduced in S. Lundberg & Lee (2017) as Kernel SHAP, the complexity for tree based algorithms is $\mathcal{O}(MTL2^p)$, with the number of samples M, number of trees T and the number of leaves L. The tree based optimization of the algorithm, TreeSHAP, allows an approximation in $\mathcal{O}(MTLD^2)$ (S. M. Lundberg et al., 2019), with the maximum tree depth D. Depending on the number of observations to calculate shapley values for (M), the Fast TreeSHAP algorithm has a even lower time complexity of $\mathcal{O}(TLD2^D + MTLD)$ (Yang, 2022).

Calculating the effect a feature has for the whole model, we calculate the mean of the absolute for single shapley values. Adjusting Molnar (2025) so it follows the notation of Equation (2.4) yields:

$$mean(|SHAP|) = \frac{1}{n} \sum_{k=1}^{n} |\phi_i^{(k)}| \tag{2.5}$$

This value is called SHAP feature importance. It can be interpreted similar to standardized beta values for a linear regression. In some cases it would be possible to calculate an effect direction for the feature importance. But it is not common practice. Instead visual representations presented in section @ref() are used for such interpretations.

S. Lundberg & Lee (2017) also showed that SHAP values are more consistent with human intuition than preceding local explainable models. Z. Li et al. (2024) mention, that explainability of machine learning models is not only important for researches but also for practitioners, to demonstrate their reliability to potential users and build trust. Regardless of the popularity of SHAP scores, there are claims that they can be inadequate as a measure of feature importance (Huang & Marques-Silva, 2024). The approximated as well as exact SHAP scores can assign higher value to unimportant features than to important ones.

However, the need for a high explainability of machine learning algorithms is more urgent than ever, since the EU's regulatory ecosystem is emphasizing the importance of XAI (explainable artificial intelligence) (Nannini et al., 2024).

2.3 Summary (0.5 p)

- lessons learned
- link to goal thesis
- link to next chapter

Chapter 3

Methodology

This chapter describes the research design of this thesis. In the subsequent sections it elaborates

3.1 Problem Definition

This thesis aims to evaluate a framework for information extraction from financial reports using advanced computing algorithms as LLMs, presented by H. Li, Gao, et al. (2023). We apply this framework on German annual reports of multiple companies and focus on using open source LLMs. This task requires two problems to be solved:

1. The information to extract has to be located in the document.
2. The information has to be extracted correct and in form that allows further processing in down stream tasks.

We limit the information of interest on the data found in the balance sheet and profit and loss statement. Both are found on separate pages and have a table-like structure. The information of interest is ordered by a hierarchy defined in HGB (2025). The information to extract are numeric values.

Since the information of interest is placed on separated pages, the first problem is to find the pages that contain the balance sheet and profit and loss statement. We do not attempt to select a specific part of the page, where the data can be found. Thus, this becomes a classification task, if a page contains the information of interest. Spatial information is not processed.

The second problem is an information extraction task. Potential information has to be identified, its entity has to recognized and finally its numeric value has to be extracted. In this thesis no special techniques for the table extraction sub field are used.

3.2 Research Design & Philosophy

The research design for this thesis is set up, following the guideline found in Wohlin et al. (2024) and Figure 3.1 shows the decisions made. According to Collis & Hussey (2014) research classification the outcome of this thesis is applied research, focusing on solving a practical problem. Its purpose is evaluation research, comparing different approaches with each other. The data collected in our experiments is of quantitative nature and its evaluation uses (semi-)quantitative methods.

Research logic? Methods fit deductive. But I start with a very specific problem. Literature describing basic approaches?

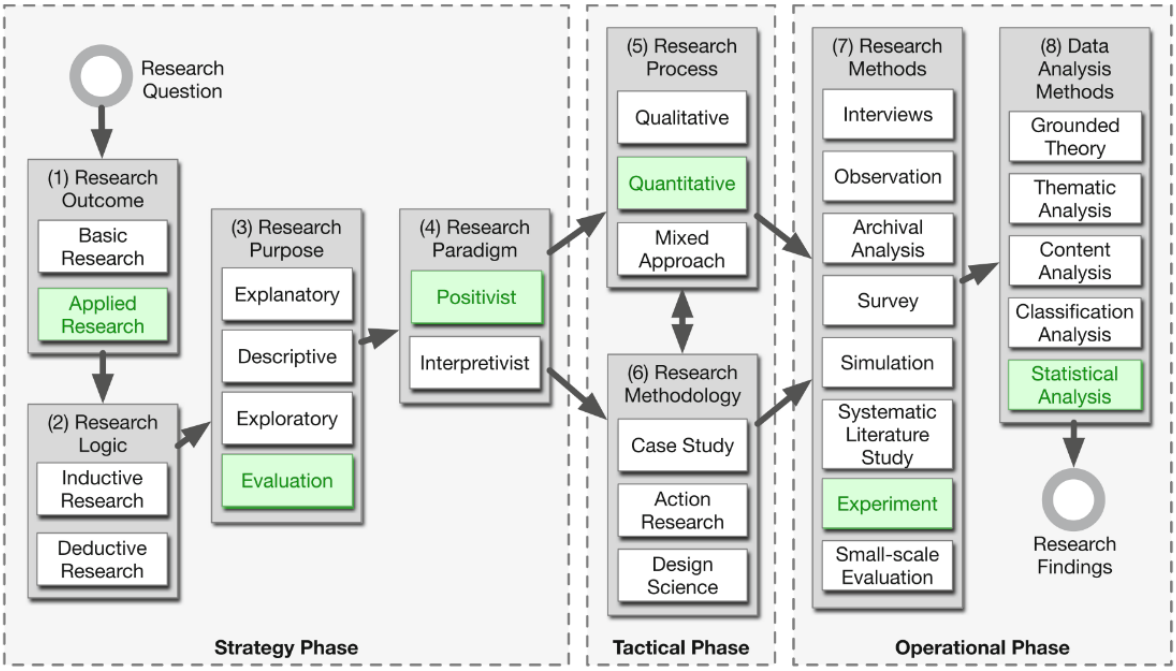


Figure 3.1: Showing the decisions made regarding the research design. (The figure is adapted from Wohlin & Aurum (2015). The copyright for the original figure is held by Springer Science+Business Media New York 2014.)

3.2.1 Research questions

For this thesis we formulate two main research questions:

Q1 How can we use LLMs effectively to locate specific information in a financial report?

Q2 How can we use LLMs effectively to extract these information from the document?

Each of this questions is investigated with its own methods and experiments. In the following we will use the term *page identification* to refer to the first research question and *information extraction* to refer to the second.

Additionally, we formulate a UX (user experience) motivated side research question:

Q4 Can we use additional information from the extraction process, to guide the user which values need to be checked and which can be trusted as they are?

The third question is refered to, using the term *error rate guidiance*.

3.2.2 Evaluation framework

Page identification The page identification task is successful, if a page is correctly classified to contain the information of interest. The balance sheet is composed of the assets (*Aktiva*) and liabilities (*Passiva*) table. Together with the profit an loss statement (*Gewinn- und Verlustrechnung, GuV*) they form the three target classes. The fourth class is called *other*. Subsequently will will use the German terms for the target classes (or table types): **Aktiva**, **Passiva** and **GuV**.

Information extraction The information extraction task if successful, if the correct numeric value is extracted with the correct entity identifier in the correct json (JavaScript Object Notation) format. If a value, defined by the legal text, is not present *null* should be returned with the corresponding entity identifier. The entity identifier can be composed of up to three labels, representing the hierarchy defined in the legal text.

Error rate guidance A error rate guided result checking process can be implemented, if we can use extraction task related information, to identify thrust worthy. This means, we could white list these values and red flag the remaining ones. Thus, we could guide the users attention in the error checking process on those values, that empirically tend to have a high chance to be faulty.

3.2.3 Evaluation research

We compare different approaches to solve the two tasks, searching for the most effective setup, to solve the problems. A task is considered effective if it achieves good results while being as computationally efficient as possible. As a baseline for each task a regex (regular expression) based approach is set up. Regular expressions are chosen as baseline because they are computationally efficient. The results are compared with the authors performance as well.

The results should be used to implement an application that is used by the employees of RHvB in future.

3.3 Evaluation Strategy

3.3.1 Metrics

Page identification The distribution of target classes and pages of type *other* is highly imbalanced. At most two pages per target class are found in documents with up to 152 pages. Thus, following Saito & Rehmsmeier (2015) suggestion, we report measures as precision, recall and F1 score instead of accuracy, to describe the approaches performances.

In a HITL application the recall value might be of higher interest than the F1 score. More precisely, in those cases the number of pages to check until the correct page is found is of interest. Thus, the top k recall is reported additionally, if the approach permits to rank the classified pages according to a score.

Precision-recall curve

Information extraction We use two measures to describe the approaches performances for the information extraction task. First, we check how many of the predicted numeric value are matching the numeric values in the ground truth. The only permitted differences are based on the number of trailing zeros. We do not check for partial correctness, since the real life application requires totally correct extracted numbers.

Second, we report the F1 score for correctly predicting values as missing and thus returning *null*. The distribution of missing values and given numeric values is not very imbalanced. Nevertheless, we report the F1 score to establish a comparability with the results od the page identification task.

Error rate guidiance In this thesis we focus our attention on a criteria, which we name *confidence*. We calculate the *confidence* score for answers received from LLM based on the non-normalized sum of token log probabilities (Boseak, 2025):

$$confidence = \exp\left(\sum logprob(token_i)\right) \tag{3.1}$$

For the classification tasks this is equal to the normalized sum, since the answer is either containing just one token or the subsequent tokens have a log probability of 0, because the fully answer is determined by the first token.

We are using the non-normalized sum of token log probabilities as well, because we want a single uncertain digit to flag the whole numeric value as as unreliable. This means, that shorter answers tend to have higher *confidence* scores. This is especially true for predicting *null*. Thus, we investigate the prediction of numeric values and *null* separated.

3.3.2 Benchmarking

Comparing the performance of different approaches benchmarked in this thesis is possible, because the approaches within a task are performed on a common document base. The task to solve is the same for each approach. The prompts for the different prompting strategies are build systematically and derive from the base prompt formulated for the *zero shot* strategy. Comparing the runtime or energy consumption gets possible with the GPU (graphics processing unit) benchmark data (see section 3.5.3)

3.4 Data Strategy

The population of annual reports of interest for the work at the RHvB is composed of all annual reports of companies, where the state of Berlin holds a share. There are often multiple versions of those annual reports: one that is publicly available and targeting share- and stakeholders. The structure and layout of there reports is quite heterogeneous. Often there is a second version that is used internally or for communications with public administrations. They often consist of plain text and tables and shows neither diagrams nor photos.

Since the evaluations are run on the BHT (Berliner Hochschule für Technik) cluster and partially in the Azure cloud, we work with the publicly available reports, while at RHvB the internal documents are more common. The annual reports mostly are downloaded from the companies websites. Some documents are accessed via Bundesanzeiger or the digitale Landesbibliothek Berlin.

For the page identification task all kinds of pages from the annual reports are used. For the information extraction only pages with **Aktiva** tables are used. In addition, a set of self-generated synthetic **Aktiva** tables is used for the information extraction task. It is created to systematically investigate potential effects of characteristics financial tables could have.

3.4.1 Sampling methodology

Page identification Figure 3.2 shows how the document base for the tasks in this section is composed[1]. Overall 74 annual reports from 7 companies are used. For this thesis the tables of interest are those that show **Aktiva**, **Passiva** and **GuV**. Among the 4981 pages 265 tables have to be identified on 251 pages. Figure 3.2 also gives an impression on how many pages the documents have. The documents of *IBB* tend to be longer. The documents of *Amt für Statistik Berlin-Brandenburg* tend to be shorter.

Table 3.1 shows how many documents have multiple target tables per type and how many target tables span two pages. In total 21 tables are distributed on two pages. In 8 documents there are multiple tables per type of interest. There are 14 pages with two target tables (**Aktiva** and **Passiva**) on it.

Information extraction For the manual information extraction we need up to 12 minutes per table. The maximum amount of values to copy and format (or type manually) among the tables used is 40. In addition to this manual process conceptional process can be necessary, because the values have to matched to the

[1] I downloaded all publicly available annual reports for some of the companies shown in the first row of Figure 1.1. I assumed that this will give a representative sample of document structures for the other companies of the same type. Realizing that the degewo AG reports would require ocr preprocessing I additionally downloaded reports for GESOBAU AG. This approach could have been more systematic. For the second task I downloaded reports for all companies available and tried to use a balanced amount of reports per company.

Table 3.1: Showing the number of documents with multiple target tables per type and the number of target tables that span two pages.

type	multiple targets in document	target two pages long
Aktiva	7	1
GuV	8	20
Passiva	7	0

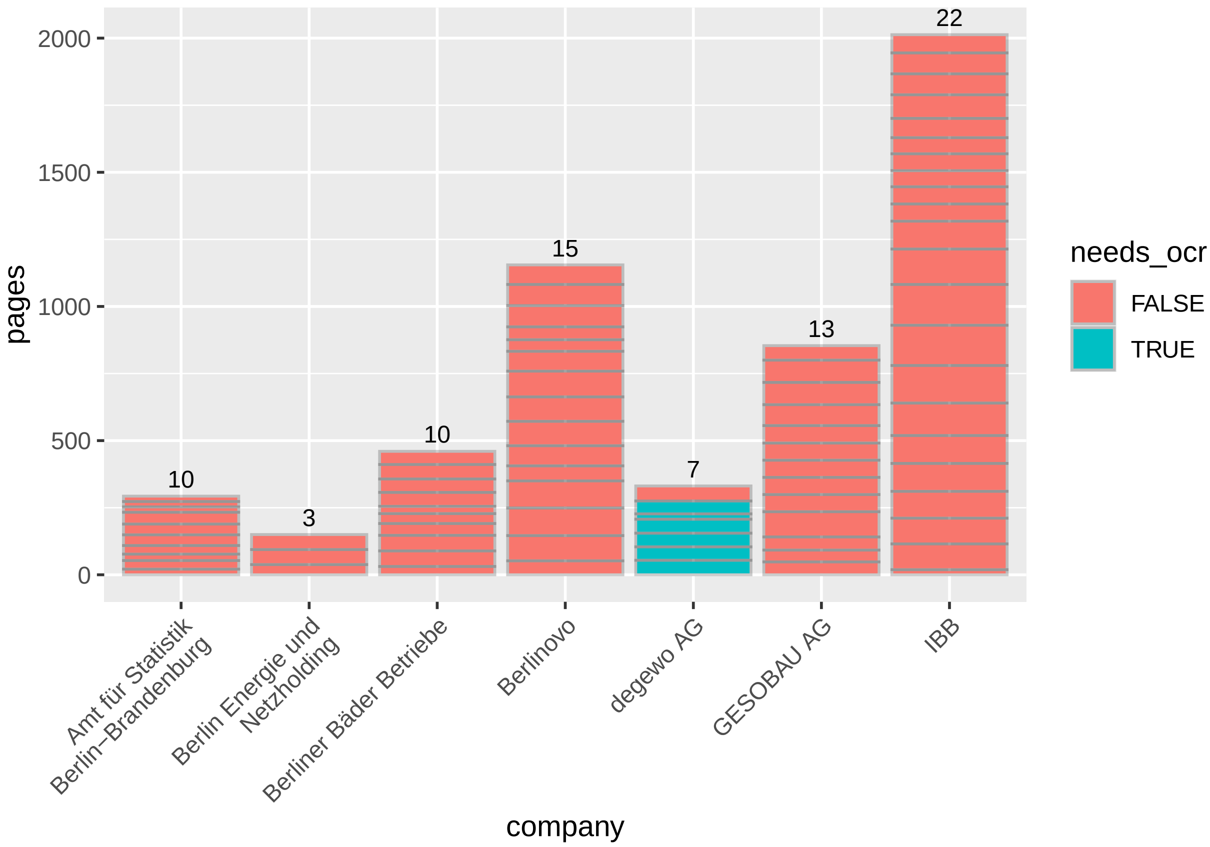


Figure 3.2: Showing the number of pages (bar height) and number of documents (number above the bar) per company for the data used for the page identification task. Some documents would require ocr before being processed and were not used.

strict grammar. Sometimes we have to decide that there is no row a value fits in or there are multiple values that have to get summed up in order to calculate the value that fits in the predefined schema.

This manual work was done for 36 documents. For every company that published the detailed form of balance sheets a single document was included. Additionally documents were included for *Amt für Statistik und Brandenburg* to check, if a context learning approach is benefiting from documents from the same company.

Later, the predictions of the LLMs were used, to create additional 106 ground truth tables. The old ground truth tables were checked in this this iteration and an error rate of 2.4 % was detected. Thus, the human reference score for percentage of correct predictions is 0.976. Figure 3.3 shows how many **Aktiva** tables are used for all tasks in this subsection, that use real data instead of synthetic data.

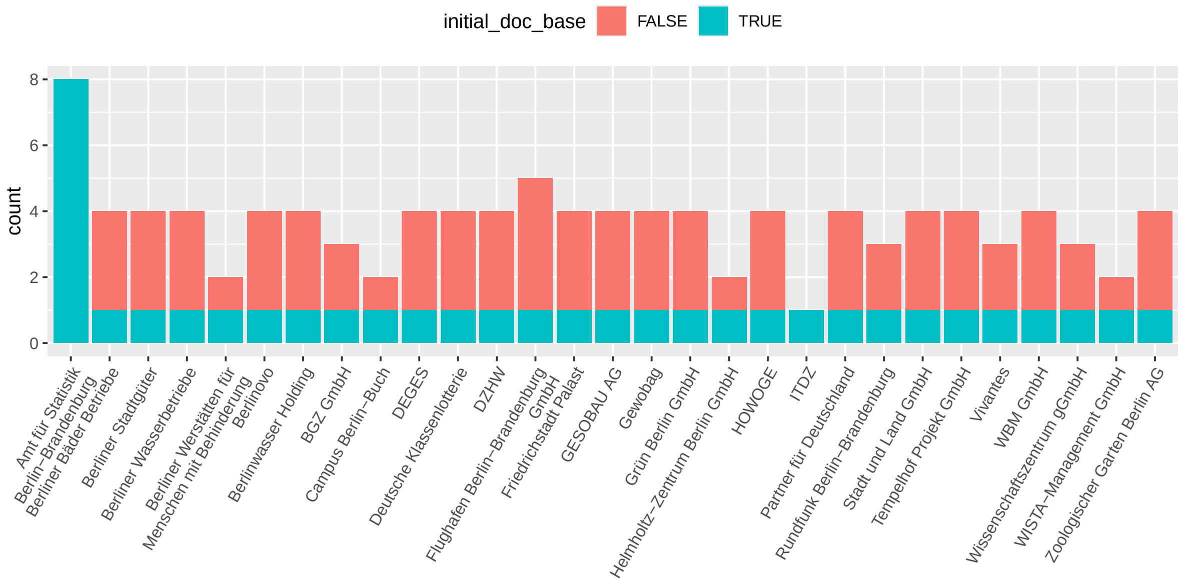


Figure 3.3: Showing the number of documents used for the table extraction task. The number of Aktiva tables is equal to the number documents.

To overcome the limited amount of real data and to allow the systematic investigation of potential predictors for the extraction performance, even if their occurrence is very unbalanced within the real data, synthetic **Aktiva** tables were created. Subsection B.2.2 gives a detailed description, which table features are varied systematically, resulting in 16_504 tables in three formats each.

Error rate guidiance We investigate the third research question on the two datasets described above, instead of creating a separate dataset.

3.4.2 Ground truth creation process

The ground truth for both tasks is created by by manual labor of the authors. The results of early experiments are used to check the ground truth for mistakes or missed items.

Page identification For the page identification task the chosen documents are searched for the target pages either by using the search functionality, TOC or scrolling through all pages. For each target page the filepath, page and type is listed in a csv file. For some reports there are multiple pages present for a single target type. In this case, both pages are added to the ground truth. Sometimes the **Aktiva** and **Passiva** page are on a single page. In this case a single entry is made and its type is *Aktiva&Passiva.* If a table spans two pages, both pages are recorded. Excluding pages that need OCR (optical character recognition) processing we created 252 entries.

For double checking all identified pages are extracted from their original PDF files and combined in a single file. Thus, problems with the numbers shown in the PDF viewer and the actual page number in the file are identified and resolved. After the first experiments pages, that have been classified as a target by multiple models, are checked. Thus, some additional target tables, that span two pages, are identified.

Information extraction For the information extraction task we copy the numeric values from the annual reports into csv files, replace the thousands separators and floating point delimiters and multiply those values by 1_000, if a currency unit is given for the column the value comes from. The csv files are already prefilled with all entities defined in the legal text, identified by their full hierarchy. Thus, we choose which line to put the value in, if the description in the annual report is different.

There are cases, where a single line defined in the legal text is split up into multiple lines in the annual reports. In those cases we enter the sum into the according row in the csv file. If entities are found, that do not fit any entity given in the legal text, this entry is dropped. For the first iteration the csv files just contained the entities and column names but no values.

In the second iteration we use the predictions of Qwen3-235B, check the values and mark mistakes, correct the values and log all mistakes found. In this iteration we check the ground truth created in the first iteration as well and correct mistakes made earlier.

Error rate guidiance There is not ground truth for the calculated *confidence* scores. We will simply check, if the true and false predictions can be separated based on the returned *confidence scores*.

3.4.3 Preprocessing

We use plain text extracted from the annual reports for all tasks. We do not extract geometric coordinates for the text. Auer et al. (2024) describes, that available open-source PDF parsing libraries may show issues as poor extraction speed or randomly merged text cells. We tested five PDF extraction libraries, because the results of all subsequent experiments will depend on the text extracts. Section E.3.1 shows the results.

We perform no manual data cleaning, because this will not be done from the employees of RHvB either.

3.4.4 Data splitting

When we train a machine learning model, we split the data into train and a test set. We do not use a validation set, because we do not compare models using an extended hyper-parameter variation strategy. Instead we just report the performance found for the models build with default settings. We build two random forests for the term frequency approach in the page identification task and more random forests for evaluating the hypotheses for the information extraction task.

Building the term frequency random forest, we face a highly imbalanced dataset. We apply undersampling for the training and evaluate the model on the imbalanced test set.

3.5 Experimental Framework

3.5.1 LLM overview

Table 3.2 gives an overview on all LLMs used for the tasks in this thesis. It shows the passive parameter count in billions for each LLM and shows in which specific approach it is used with a tick. Overall 37 models from 10 model families are used.

3.5.2 Approaches

3.5.2.1 Page identification

Regular expressions We develop multiple sets of regular expressions and filter out all pages that do not fulfill all regular expressions of a given set. There are different sets for each target type, **Aktiva**, **Passiva**

Table 3.2: Overview of benchmarked LLMs for all tasks. Parameter shows passive parametercount in billions.

		information extraction			page identification	
model	parameter	real tables	synth tables	hybrid	binary	multiclass
chat-gpt						
gpt-4.1	NA	✓				
gpt-4.1-mini	NA	✓				
gpt-4.1-nano	NA	✓				
gpt-5-mini	NA	✓				
gpt-5-nano	NA	✓				
google						
gemma-3-4b-it	4	✓			✓	✓
gemma-3n-E4B-it	4	✓			✓	✓
gemma-3-12b-it	12	✓	✓	✓	✓	✓
gemma-3-27b-it	27	✓	✓	✓	✓	✓
Llama-3						
Llama-3.1-8B-Instruct	8	✓	✓	✓	✓	✓
Llama-3.1-70B-Instruct	70	✓	✓		✓	✓
Llama-3.3-70B-Instruct	70	✓	✓		✓	✓
Llama-4						
Llama-4-Scout-17B-16E-Instruct	109	✓	✓	✓	✓	✓
Llama-4-Maverick-17B-128E-Instruct-FP8	402	✓	✓		✓	✓
microsoft						
phi-4	15	✓			✓	✓
mistralai						
Ministral-8B-Instruct-2410	8	✓	✓	✓	✓	✓
Mistral-Small-3.1-24B-Instruct-2503	24	✓	✓		✓	✓
Mistral-Large-Instruct-2411	124	✓	✓	✓	✓	✓
openai						
gpt-oss-20b	20	✓				
gpt-oss-120b	120	✓				
Qwen 2.5						
Qwen2.5-0.5B-Instruct	0.5	✓			✓	✓
Qwen2.5-1.5B-Instruct	1.5	✓			✓	✓
Qwen2.5-3B-Instruct	3	✓			✓	✓
Qwen2.5-7B-Instruct	7	✓	✓		✓	✓
Qwen2.5-14B-Instruct	14	✓			✓	✓
Qwen2.5-32B-Instruct	32	✓			✓	✓
Qwen2.5-72B-Instruct	72	✓	✓		✓	✓
Qwen 3						
Qwen3-0.6B	0.6	✓				
Qwen3-1.7B	1.7	✓				
Qwen3-4B	4	✓				
Qwen3-8B	8	✓	✓	✓	✓	✓
Qwen3-14B	14	✓				
Qwen3-30B-A3B-Instruct-2507	30	✓	✓		✓	✓
Qwen3-32B	32	✓	✓		✓	✓
Qwen3-235B-A22B-Instruct-2507-FP8	235	✓	✓	✓		
Qwen3-235B-A22B-Instruct-2507	235		✓		✓	✓
tiiuae						
Falcon3-10B-Instruct	10	✓			✓	✓

and **GuV**. The sets also differ in how versatile they can cope with additional white space introduced by a imperfect text extraction and how many different words for a given term are accepted. Figure 3.4 shows an example for two sets of regular expressions to identify a **Aktiva** page.

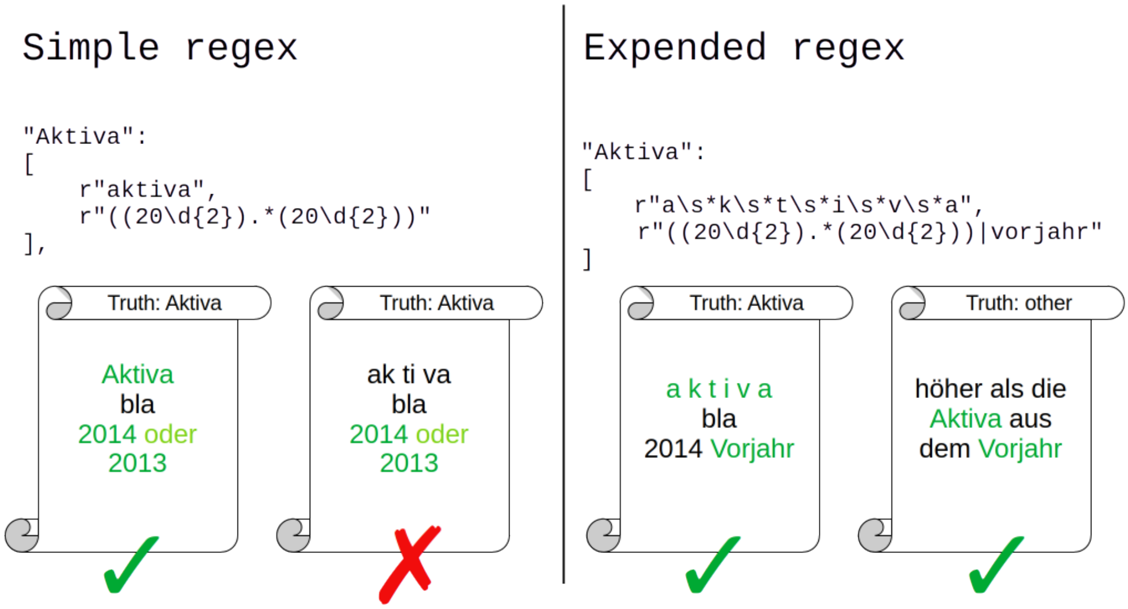


Figure 3.4: Comparing the prediction of two different sets of regular expressions on dummy pages. The simple one has a lower recall, while the expended one has a lower precision.

Table of Contents Understanding We use a LLM to extract the TOC from the first pages from a document or use the embedded TOC and prompt a LLM to identify the pages where the **Aktiva**, **Passiva** and **GuV** are located. Figure 3.5 shows a screenshot of a annual report with an embedded TOC and its TOC in text form.

Large Language Model Classification We use LLMs to classify if the text extract of a given page is containing a **Aktiva**, **Passiva** or **GuV** table or something else. We test binary classification and a multi-classification approach. The reported confidence scores can be used to form a ranking, which text extract might be most similar to the target type.

We test a wide range of open-weight models and compare different prompting techniques. Figure 3.6 shows, how the prompts are composed for the different strategies. Besides a zero shot approach we test few-shot in-context learning with examples that are either chosen randomly or retrieved based on their vector similarity. Finally, we test passing the legal text instead of examples from a annual report.

Term frequency Ranking We use normalized term frequencies and normalized float frequency to as features for a classification using a random forest. The predicted scores are used to build a ranking, which page most probably contains the target pages. Undersampling is used during training, to handle the unbalanced data. Figure 3.7 visualizes, how the prediction works in this approach.

3.5.2.2 Information extraction

Regular expressions We use regular expressions to extract the numeric values for matching row identifiers. The regular expressions handle line breaks between words in the row identifiers, but not within a word. They can handle multiple signs of white space. Besides that, they try to fully match the labels from the legal text with the text extract, ignoring upper case. They extract numbers with "." as thousands separator. Figure 3.8 is visualizing those capabilities.

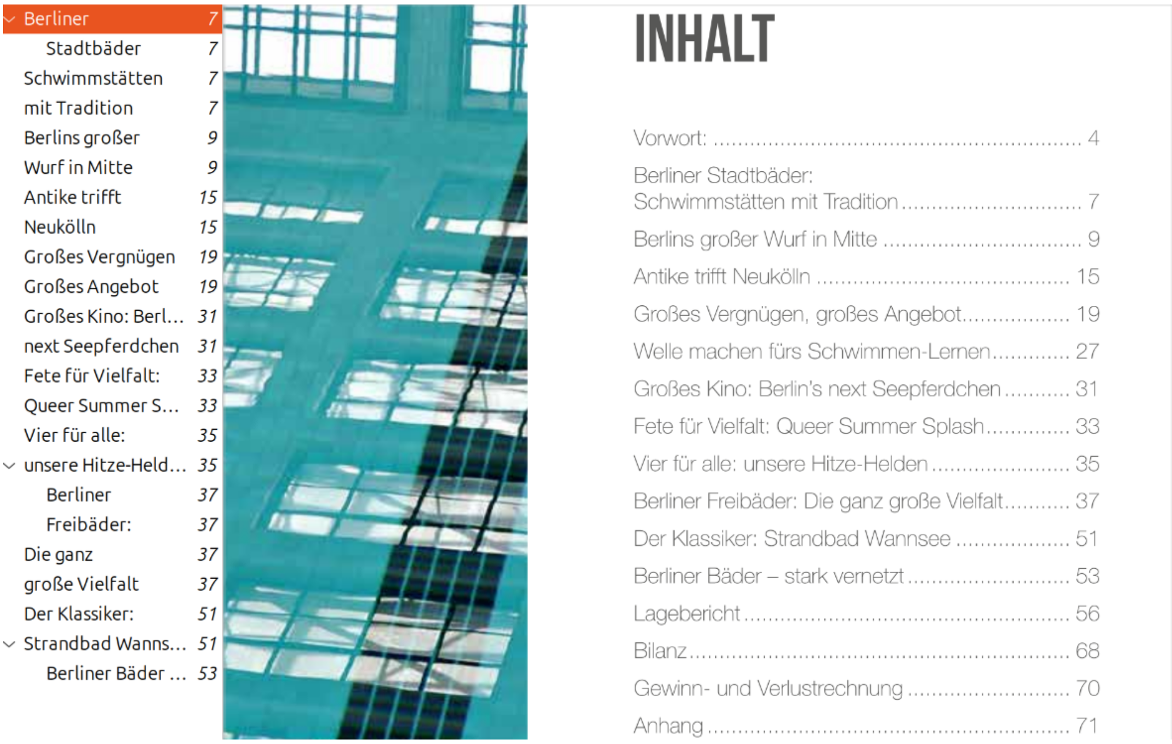


Figure 3.5: Showing a screenshot of a annual report with an embedded TOC (left) and its TOC in text form (right). The embeded TOC is not listing all entries from the TOC in text form.

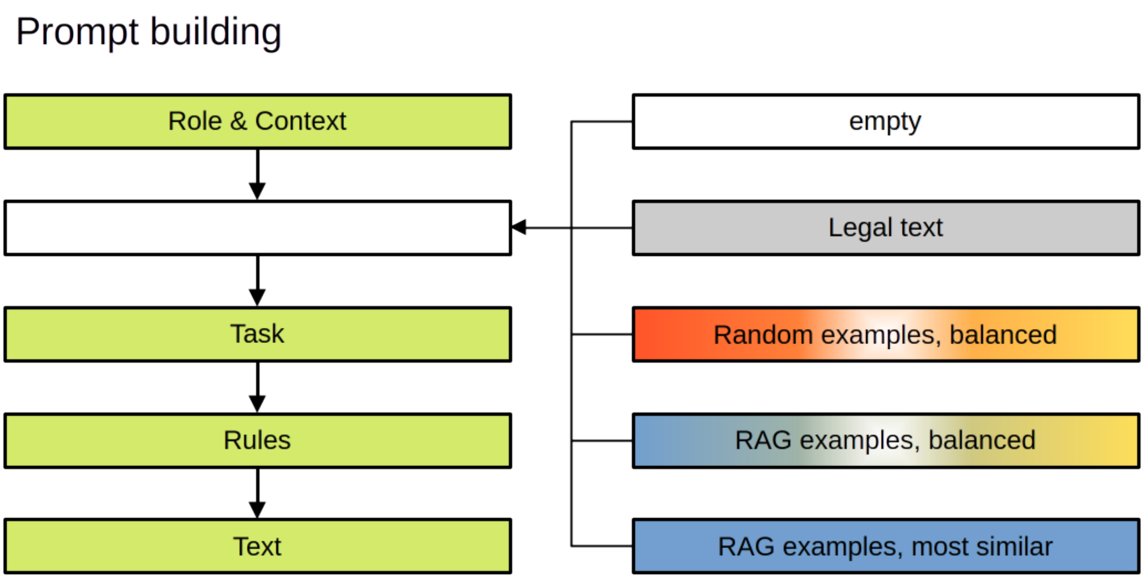


Figure 3.6: Showing the basic structure of the prompts and which strategies are used to pass additional information to the LLM.

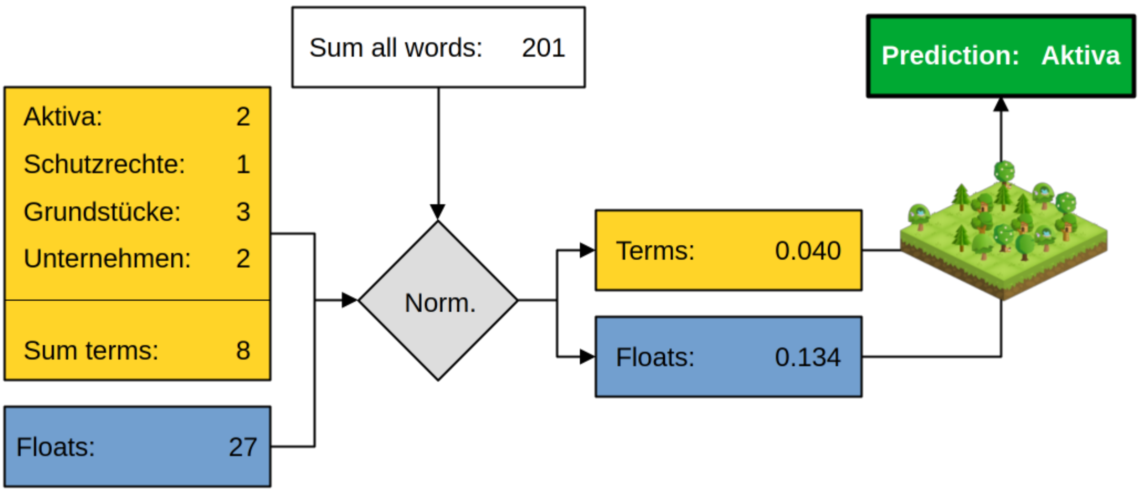


Figure 3.7: Visualizing, how term and float frequency get calculated and used to predict, if a page is of the target class.

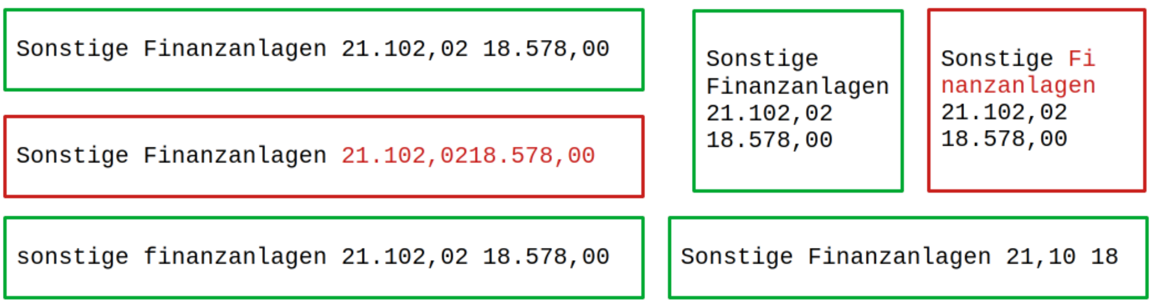


Figure 3.8: Visualizing the extraction results for different text examples. Texts in green boxes are matching our regular expression. Texts in red boxes do not, because of the red text part.

Real tables We use LLMs to extract the numeric values of real **Aktiva** tables with restricted generation. The LLM has to group row identifiers and corresponding numeric values and match the row identifier with the labels of the schema. If a row identifier is unknown, the values have to be discarded. If a label is not present among the row identifiers, the model predicts *null*. All values are extracted in one pass. We do not include any instruction, how to proceed with currency units, that might be given for certain columns.

We test a wide range of open-weight models and compare different prompting techniques. Figure 3.9 shows, how the prompts are composed for the different strategies. Besides a zero shot approach we test few-shot in-context learning with examples that are either chosen randomly or retrieved based on their vector similarity. Finally, we test passing a synthetic **Aktiva** table as example. We test models from OpenAIs GPT family in addition to the open-weight models.

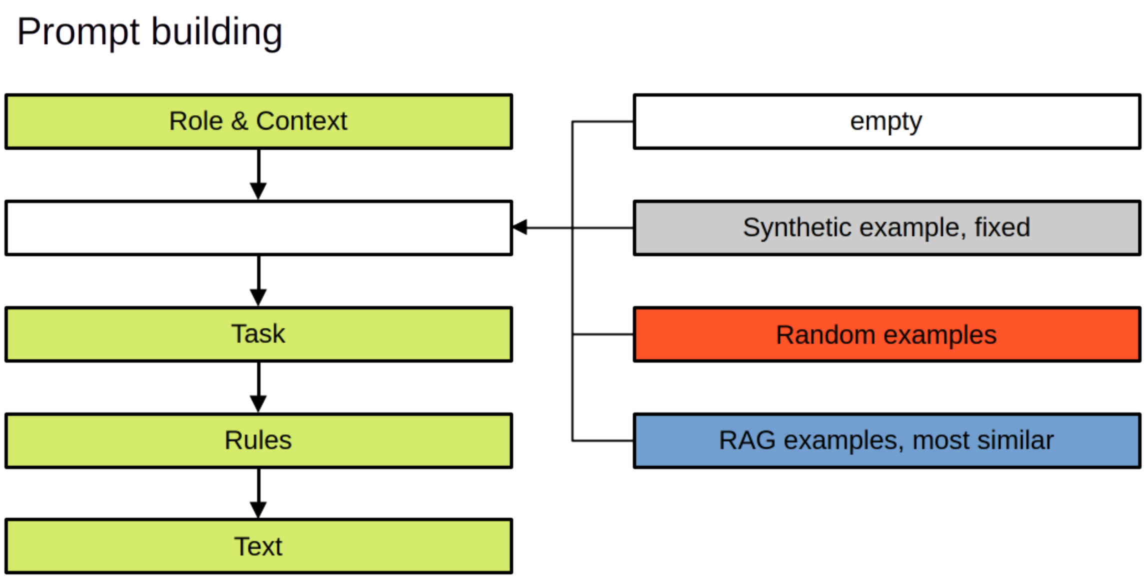


Figure 3.9: Showing the basic structure of the prompts and which strategies are used to pass additional information to the LLM for the information extraction task.

Synthetic tables We use LLMs to extract the numeric values of synthetic **Aktiva** tables with restricted generation. The procedure is identical as with the real **Aktiva** tables. We extract all values with and without an explicit instruction on how to proceed with currency units. We limit our test on the open-weight models.

Hybrid approach We use LLMs to extract the numeric values of real **Aktiva** tables with restricted generation, providing examples from synthetic **Aktiva** tables. The procedure is identical as with the real **Aktiva** tables. We extract all values with and without an explicit instruction on how to proceed with currency units. We limit our test on the open-weight models.

3.5.3 Hardware normalization

To make the runtime of different LLMs running on different amounts and types of GPUs comparable, we conducted a benchmark running the models Qwen2.5-7B and Qwen2.5-32B with different hardware compositions on the Datexis cluster. Figure 3.10 shows the runtime for classifying 100 pages with the multi-class approach, providing three random examples for the in-context learning.

The classification time with Qwen2.5-32B on GPUs of type B200 is a little faster than running Qwen2.5-7B on the same amount of A100 GPUs. We calculate normalized runtimes for our experiments, based on these runtime measures for small and larger LLMs on different types and numbers of GPUs. A minute of computation on a single B200 is comparable to 4:30 minutes of computation on a single A100.

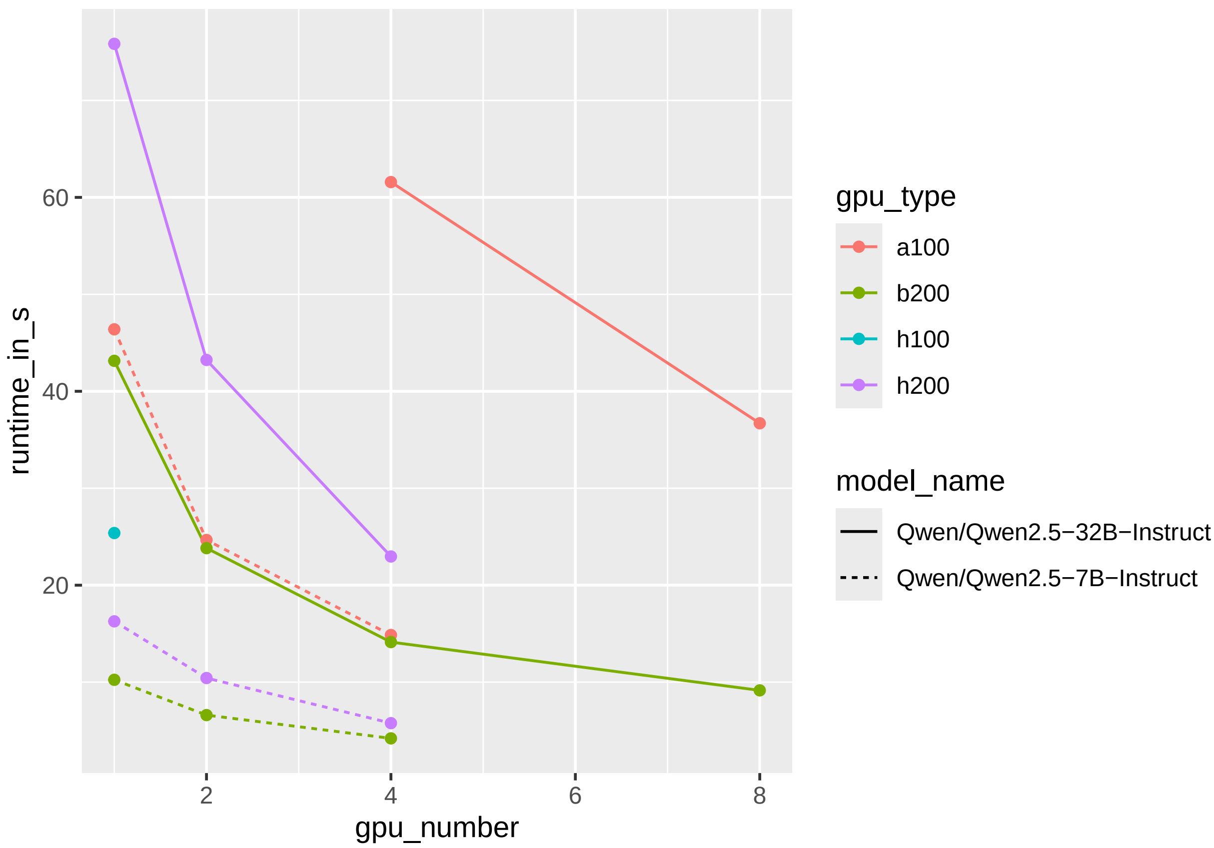


Figure 3.10: Showing the runtime to classify 100 pages with the multi-class approach, providing three random examples for the in-context learning.

3.5.4 Error analysis

The ultimate goal is to fully automate the information extraction task at hand. Thus, it is important to analyse potential errors, to identify obstacles that hinder performance and find ways to further improve the system.

We expect to find issues with wrong extracted or hallucinated numbers, wrong entity recognition and false positive *null* values. Not respected units

Quantitative / stratified: We will compare the error rates based on the different variables of the experiments. For the approaches using LLMs to solve the problem there are model specific, prompting strategy specific and example specific variables.

Qualitative: Finally, we investigate some of the erroneous extracted examples manually, and try to identify the underlying issues.

Tools and criteria

Reporting

Example:

To better understand the limitations of the evaluated models, we will conduct a detailed error analysis. We will first quantify the types of errors (e.g., false positives, false negatives, misclassifications) using confusion matrices and error rate statistics. Additionally, we will manually inspect a sample of erroneous predictions to identify common causes, such as ambiguous table layouts, OCR errors, or model misinterpretations. Errors will be categorized by document type and extraction task to reveal systematic weaknesses. Representative error cases will be documented to illustrate typical failure modes and to inform potential improvements for future work.

99.5 % or 96 % accuracy for extracting financial data from Annual Comprehensive Financial Reports (H. Li, Gao, et al., 2023) In the untabulated test, GPT-4 achieved an average accuracy rate of 96.8%, and Claude 2 achieved 93.7%. Gemini had the lowest accuracy rate at 69%. (ebd.)

found error types: including omissions when the LLM was instructed to extract a list of line items, misjudgment of units (such as thousands or millions), and incorrect identification of rows and columns

failed to extract all of list, Too many hallucinated values when it was NA instead (Gougherty & Clipp, 2024)

(Grandini et al., 2020)

3.5.5 Baseline selection rationale

see section Evaluation research

3.5.6 Evaluation methods

- box plots
- PR-curve
- random forest + SHAP

XGBoost not used finally, because calculation SHAP values for XGBoost model took to long for just a first glimpse on what might influence the extraction. lm also fitted and not used

3.6 Ethical & Practical Considerations (eher am Ende oder weg?)

3.6.1 PDF extraction limitations

Pdfminer informs that the text of some annual reports from *IBB* and *Berlinovo* should not be extracted. This information is given in a meta data field of the PDF. We use the text extract from these documents for our study anyway.

Errors catched by HITL approach before they have down stream implications.

3.6.2 Computational constraints

The extraction with LLMs is computationally demanding and should be run on GPUs. To run model that yields the best results four H200 GPUs are needed.

3.6.3 Generalizability scope

The approach tested here is probably using on other companies annual reports as well. To extract information that is only filling a small part of a page the framework may has to be adjusted. The page identification could be trickier with some approaches if only a single key word is searched.

3.6.4 Ethical considerations

The extraction of numeric information is not the same as making decisions. It probably isn't affected by any bias, that is discriminating humans.

The automatisation of information extraction is potentially replacing low requirements work places. At RHvB there are no jobs for such a task anymore. More free time for other tasks. Shifting to more complex tasks.

AI Act does probably not apply, since decisions are not made on individual level?: Are there restrictions on the use of automated decision-making? Yes, **individuals should not be subject to a decision that is based solely on automated processing** (such as algorithms) and that is legally binding or which significantly affects them.

3

Chapter 4

Implementation

(max 5p)

4.1 Environments

The computations for this thesis are performed in two environments. Task that do not require a GPU are run locally. You can find the specifications of the local device in section E.2. Other tasks are run on the Datexis Kubernetes cluster.

Egal ab hier:

The prototyping for these tasks is performed on the cluster as well. Therefore, a interactive docker image with SSH capabilities and Python has been created based on the vLLM (Virtual Large Language Model) docker image. In rare cases a vLLM server is deployed on the cluster and queried from the local machine during prototyping.

The experiments run using the same images as the prototyping environment and connects to the persistent volume, where the scripts to run and data(bases) to use are located and saves the results on the persistent volume as well. We do backups of the folder holding the scripts and data to process and download the results via SSH (secure shell) protocoll. We use *git* for version control but do not synchronize the data from the persistent volume with *GitHub*.

We used 5 TB persistent storage. Most of the space is used for caching the LLM sefetensors.

Within the local environment we use *git* as well. Except for the gigabytes of result files everything is synchronized with *GitHub*.

Table : what task in what environment? Seems not super important

4.2 Evaluation and Reporting

We mostly use *R* for evaluation, visualization and reporting. We use the *bookdown* library[1], to create a report, that is linked to our data and thus automatically includes new results and updates all figures and tables. This allows us to run small additional experiments until the very end of thesis writing.

Furthermore, this allows us to create a PDF version as well as a HTML (hyper text markup language) version of the thesis at the same time with low additional effort. The HTML version allows to use some helpful interactive elements as paginated tables with search and sorting capabilities, image light boxes and image sliders. Thus , a lot of information can be offered without occupying pages over pages with tables and figures. The HTML version is more machine readable as well. Lacking machine readability is what makes the information extraction from PDFs mandatory in the first place and we want spare others these difficulties.

[1] For the next project we probably will start using *Quarto* instead of *bookdown*. This is the new reporting framework of Posit, we became aware of too late.

4.3 Software Packages

Macht das Sinn, das hier aufzulisten? Wenn ja, wie detailliert? Vielleiche auf eine requirements Datei je Sprache verweisen?

Einmal die großen und was es macht

- Python
  - pandas
  - numpy
  - scikit learn
  - vLLM
  - chroma DB
- R
  - tidyverse

4.4 Speedup with vLLM and batching

We run our final experiments with the vLLM library on Python, using its batch processing capabilities. Our first test used the *transformers* library directly and did not use batch processing. Section E.3.3 shows the runtime reduction that is achieved with the final setup.

4.5 Text extraction

We use *pdfium* for the text extraction for all tasks. Some approaches are run with the texts of other PDF extraction libraries as well.

Table : what task had additional extraction backends? Seems not super important

4.6 Data processing

We start by extracting the text for each page from the annual reports, using PDF extraction libraries like *pdfium*. We do this once for each document and save all text extracts in a json file together with the original file path and pagenumber.

For LLM approaches we embed the texts in the prompt template. The (merged) texts are then processed by the algorithm, predicting, if the text is including a specific type of information or not. The predictions are compared with ground truth.

The results of this check are saved as json. We save the result for every individual check, as well as calculated performance metrics and the runtime needed to process all texts as batch. This allows us to reevaluate or exclude single results and recalculate the aggregated metrics later. All steps from the text extraction to the result saving are implemented in *Python*.

The process for the information extraction is similar. One difference is, that the algorithm makes multiple predictions per text. Thus, we save not a single prediction and evaluation but a data frame with all predictions and all ground truth values per text. Saving the ground truth values in this data frame is not necessary but allows us a more convenient reevaluation.

The (re)evaluation is done in *R* instead of *Python*, because we can seamlessly include it in our reporting engine.

4

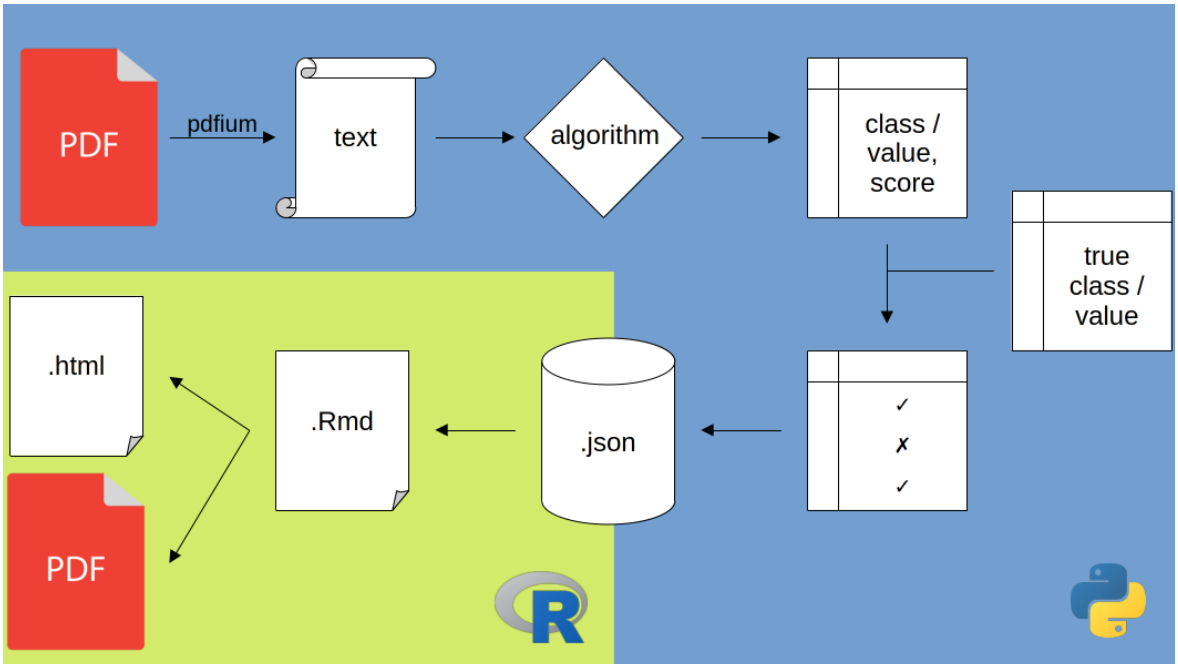


Figure 4.1: Showing the processing steps from input data to the results in this thesis.

Chapter 5

Results

5

This chapter presents the main results for the two main and our side research questions of this thesis:

Q1 How can we use LLMs effectively to locate specific information in a financial report?

Q2 How can we use LLMs effectively to extract these information from the document?

Q3 Can we use additional information from the extraction process, to guide the user which values need to be checked and which can be trusted as they are?

Section 5.1 presents the results for the first research question. Section 5.2 presents the results for the second question. Section 5.3 shows the results for the side research question. Finally, we will summarize all results in section 5.4.

Each section will start with an overview about the specific sub tasks as well as about the models, methods and data used to investigate the research question.

This chapter focusses on the presentation of results, that answer the question, if an approach can be used to solve a task. We discuss additional findings in chapter 6. The presentation of those additional results can be found in the appendix. We refer to the chapters of the appendix, that document our investigation and the results of the sub tasks in detail, at the beginning of each of the following sections.

5.1 Page identification

The first research question asks, how LLMs can be used, to effectively locate specific information in a financial report. The task for this thesis is identifying the pages where the balance sheet (*Bilanz*) and the profit-and-loss-and-statement (*Gewinn- und Verlustrechnung, GuV*) are located. The balance sheet is composed of two tables showing the assets (*Aktiva*) and liabilities (*Passiva*) of a company. Often these two tables are on separate pages. Hereafter, the German terms **Aktiva**, **Passiva** and **GuV** will be used.

H. Li, Gao, et al. (2023) describes two ways to identify the relevant pages (see Figure E.4). For longer documents they propose to use the TOC to determine a page range that includes the information of interest. In addition, they develop target specific regular expressions and rules to filter out irrelevant pages[1]. The result of this "Page Range Refinement" is then passed to the LLM to extract information from.

This section is presenting the results of four approaches to identify the page[2] of interest. The detailed report on all experiments conducted in their results can be found in the appendix:

[1] Personal opinion: Developing well performing regular expressions can be a very tedious and setting appropriate rules requires some domain knowledge. It can be worth the effort if there are a lot of documents with similar information to extract. For this thesis it took multiple months. At least, now there is kind of a pipeline one can reuse, exchanging the rules and key word lists. Thus the next similar task should be solved faster.

[2] In some cases the information of interest is spanning two pages. These rare cases are not covered from the approaches presented here, yet.

- Subsection A.1 presents the findings of a page range refinement using a list of key words with a regular expression.
- Subsection A.2 presents the findings of a TOC understanding approach
- Subsection A.3 presents the findings of a text classification approach using LLMs.
- Subsection A.4 presents the findings of a term-frequency approach.

In subsection 5.1.2 the results get compared and summarized. Subsection @ref() proposes an efficient combination of approaches to solve the task of this thesis and discusses its limitations.

Woanders hin oder weg:

- Thus, we prompt the LLM to classify if the text extract of a given page
- for implementation: As described in E.3.1 open source libraries have been used to extract the text from the annual reports.

Dataset describtion For the page identification task companies (mainly) from the first row of Figure 1.1 have been selected, to build the ground truth from. The idea is that the documents of a companies within a category are more similar to each other, than to documents of companies of other categories. For the chosen companies all available annual reports are selected. Since one of the companies mainly published documents that require OCR preprocessing, we include the documents of a second company for this category.

5.1.1 Approaches

The page identification task is broken down to a classification task for all of the approaches presented in this section but the TOC understanding approach. This subsection briefly describes our approaches. A detailed report can be found in chapter A.

Regular expressions We develop multiple sets of regular expressions and filter out all pages that do not fulfill all regular expressions of a given set. There are different sets for each target type, **Aktiva**, **Passiva** and **GuV**. The sets also differ in how versatile they can cope with additional white space introduced by a imperfect text extraction and how many different words for a given term are accepted.

Table of Contents Understanding We use a LLM to extract the TOC from the first pages from a document or use the embedded TOC and prompt a LLM to identify the pages where the **Aktiva**, **Passiva** and **GuV** are located.

Large Language Model Classification We use LLMs to classify if the text extract of a given page is containing a **Aktiva**, **Passiva** or **GuV** table or something else. We test binary classification and a multi-classification approach. The reported confidence scores can be used to form a ranking, which text extract might be most similar to the target type.

We test a wide range of open-weight models and compare different prompting techniques. Besides a zero shot approach we test few-shot in-context learning with examples that are either chosen randomly or retrieved based on their vector similarity. Finally, we test passing the legal text instead of examples from a annual report.

Term frequency Ranking We use normalized term frequencies and normalized float frequency to as features for a classification using a random forest. The predicted scores are used to build a ranking, which page most probably contains the target pages. Undersampling is used during training, to handle the unbalanced data.

5.1.2 Comparison

This subsection presents the performance and efficiency for all four presented approaches and compare it with the the results a human achieves manually

Prediction performance Table 5.1 shows the best performance achieved by the four presented approaches regarding precision, recall and F1 score.

The best F1 score is reached by Llama 4 Scout for the target types **Akiva** and **Passiva** in the multi-class classification approach. For **GuV** the best F1 score (0.985) is found with Ministral-8B-Instruct in the binary classification approach. Llama 4 Scout reaches a F1 score of 0.971 for target type **GuV** and multi-class classification.

In the dataset preparation for the table extraction task (see section 3.4.1) 107 **Aktiva** pages have been selected. In this manual process we made two mistakes, accidently selecting one **Passiva** and one **GuV** page. Thus the human baseline to compete with is 0.981. Thus, Llama 4 Scout is more precise than us.

5

Furthermore, Llama 4 Scout reached a recall of 1.0 for all target types. This means, the results can be used downstream, even though the precision is not always perfect. The pages classified as target can be double checked by a human, without missing any page.

The performance of approaches not using LLMs is way worse. Only the term-frequency approach's results could be used downstream, because we find a recall of 1.0. Table 5.2 shows the results of the top k recall for the term-frequency and LLM approaches. The LLMs always rate the correct **GuV** page highest. With Llama Scout 4 we find all target pages within the first two ranked pages. For the term-frequency approach a human sometimes has to check up to five pages.

Energy usage and runtime Table 5.3 shows the runtime in seconds per document, estimated energy consumption in Joule per document and costs in **CENTS per 1000 documents**. The runtime for the LLMs was normalized to seconds on a nvidia B200 and thus the TDP of 700 W is used to calculate the energy consumption. For the other approaches, running on my laptop (see section E.2) a TDP of 28 Watts is used. For manual work by a human additional 60 W are added for the screen used. It is assumed that the LLM is hosted locally.

Table 5.3 shows, that the regular expression approach is fastest and consumes least energy. Nevertheless, since the results are not sufficient another approach has to be chosen if the amount of manual labor should be reduced for the human inn the loop.

Second place regarding all these criteria is the term-frequency approach, which guarantees a perfect recall, while reducing the number of pages to investigate to five per target type. This is similar to the number of pages a human has to investigate to find the TOC of the document. And it is a reduction to 7.4 % of the average 67 pages the documents in this dataset have. The costs are still negligible.

The LLM approaches have the highest runtime and energy consumption. This is the case, because they process every page with very computational demanding algorithms. For the TOC approach LLMs are used as well, but they process far less of the documents pages. Thus, their energy consumption is lower.

Since all approaches but the manual identification need the text extract, this runtime and energy consumption are also not listed (but low).

5.2 Information extraction

The second research question asks, how LLMs can be used, to effectively extract specific information from a financial report. The task for this thesis is to extract the numeric values for the assets (*Aktiva*) table, which is part of the balance sheet (*Bilanz*). Hereafter, the German term **Aktiva** will be used. We are limiting the scope even further than in subsection 5.1, because it takes more time to manually create the first reference dataset.

Table 5.1: Comparing page identification perfromance among all four approaches.

approach	strategy	precision	recall	F1
Aktiva				
Regex	exhaustive	0.132	0.997	0.233
TOC	machine readable	0.6	0.256	0.359
TOC	combi	0.338	0.268	0.299
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	0.906	0.939	0.922
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	0.987	0.937	0.961
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	**1**	**1**	**1**
TF	high recall	0.193	**1**	0.324
human	manual	NA	NA	0.981
GuV				
Regex	exhaustive restricted	0.21	**1**	0.35
TOC	machine readable	0.446	0.245	0.316
TOC	combi	0.378	0.363	0.37
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	**0.981**	0.99	**0.985**
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	0.903	**1**	0.949
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	0.944	**1**	0.971
TF	high recall	0.131	**1**	0.232
Passiva				
Regex	exhaustive	0.13	0.993	0.23
TOC	machine readable	0.5	0.21	0.296
TOC	combi	0.281	0.222	0.248
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	0.937	0.914	0.925
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	**1**	0.761	0.864
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	0.985	**1**	**0.993**
TF	high recall	0.21	**1**	0.347

Table 5.2: Comparing the top k recall for the termfrequency and LLM approaches.

approach	strategy	top 1 recall	k for full recall
Aktiva			
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	0.959	2
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	0.932	3
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	**1**	**1**
TF	high recall	0.826	5
GuV			
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	**1**	**1**
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	**1**	**1**
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	**1**	**1**
TF	high recall	0.7	5
Passiva			
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	0.932	**2**
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	0.824	3
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	**0.973**	**2**
TF	high recall	0.808	5

5

Table 5.3: Comparing page identification efficiency among all four approaches.

approach	strategy	runtime per document in s	energy in J	costs in CENTS per 1000 documents
Regex	exhaustive	**0.005**	**0.151**	**0.001**
TOC	machine readable	0.202	141.580	1.062
TOC	text based	1.939	1357.534	10.182
LLM binary	Ministral-8B-Instruct-2410, 3_rag_examples	35.851	25095.946	188.220
LLM multi-class	Ministral-8B-Instruct-2410, 3_rag_examples	18.905	13233.784	99.253
LLM multi-class	Llama-4-Scout-17B-16E-Instruct, 3_rag_examples	60.149	42104.054	315.780
TF	high recall	0.138	3.859	0.029
human	manual	61.000	5368.000	40.260

Structured output We are using a strict schema for the extraction process that is derived from the legal text (HGB, 2025, Section 266). Actually, there are three types of verbosity, that are defined in the law. Smaller companies are permitted to create less detailed balance sheets. Our schema is created based on the most detailed level. This is the form most often found in the document base[3].

Using a strict schema has advantages for processing the results in downstream tasks - i.e. for adding the results to a relational database. It is also easier to compare the results with a ground truth if the names of all rows and their order is fixed. The schema is defined as ebnf (extended Backus–Naur form) grammar and passed as an argument to vLLM.

Gound truth dataset For the information extraction task two datasets are used. First, a collection of 107 real **Aktiva** tables is created, going through two sampling iterations. In the first iteration a single report is selected for each company. In addition, all available reports from the first listed company are chosen, to test an in-company learning approach. In the second iteration more reports of the other companies are added, to increase the ground truth size and allow to test the in-company approach for all companies.

Second, a dataset of 16_504 synthetic **Aktiva** tables is created. These tables are generated based on the extraction schema and filled with random numeric values. Different table characteristics are systematically combined, to investigate potential effects of these features on the extraction performance. The tables are created as PDF, HTML and Markdown files each. This dataset allows to estimate the extraction performance, if there are no unknown row identifiers present.

5.2.1 Approaches

Regular expressions We use regular expressions to extract the numeric values for matching row identifiers. The regular expressions handle line breaks between words in the row identifiers, but not within a word. They can handle multiple signs of white space. Besides that, they try to fully match the labels from the legal text with the text extract, ignoring upper case. They extract numbers with "." as thousands separator.

Real tables We use LLMs to extract the numeric values of real **Aktiva** tables with restricted generation. The LLM has to group row identifiers and corresponding numeric values and match the row identifier with the labels of the schema. If a row identifier is unknown, the values have to be discarded. If a label is not present among the row identifiers, the model predicts *null*. All values are extracted in one pass. We do not include any instruction, how to proceed with currency units, that might be given for certain columns.

[3]Unfortunately, well known companies as BVG and BSR publish a less detailed form. Thus, their documents are not included in the document base for this task.

We test a wide range of open-weight models and compare different prompting techniques. Besides a zero shot approach we test few-shot in-context learning with examples that are either chosen randomly or retrieved based on their vector similarity. Finally, we test passing a synthetic **Aktiva** table as example. We test models from OpenAIs GPT family in addition to the open-weight models.

Synthetic tables We use LLMs to extract the numeric values of synthetic **Aktiva** tables with restricted generation. The procedure is identical as with the real **Aktiva** tables. We extract all values with and without an explicit instruction on how to proceed with currency units. We limit our test on the open-weight models.

Hybrid approach We use LLMs to extract the numeric values of real **Aktiva** tables with restricted generation, providing examples from synthetic **Aktiva** tables. The procedure is identical as with the real **Aktiva** tables. We extract all values with and without an explicit instruction on how to proceed with currency units. We limit our test on the open-weight models.

5.2.2 Comparison

This subsection compares the results for the table extraction tasks. It will discuss the findings about performance and runtime and compare it with the results a human may achieve wit manual labor.

Performance Table 5.4 summarizes the mean percentage of correct predictions total for all approaches and both types of **Aktiva** tables. The highest baseline for the extraction tasks is set by our own manual performance. We achieve 97.6 % correct extracted values on the real **Aktiva** tables. The regex performance on the synthetic **Aktiva** tables comes close but on real **Aktiva** tables it is far off.

The mean performance of Qwen3-235B does not match our baseline on the real **Akiva** tables. But its median performance already is 100 %.

On synthetic tables its mean performance is almost perfect, if currency units get respected. With HTML documents we find 100 % correct predictions. With Markdown documents we find 99.9 % correct predictions as well. Figure G.9 shows, that the better performance on the synthetic tables is found for almost all models.

Qwen3-8B performed best among the small models LLMs but shows over 4 % more wrong predictions than Qwen3-235B.

Using synthetic examples, results in worse performance. But it can be used to show how to handle currency units.

Runtime Extracting the values from all 106 tables took Qwen3-235B around six minutes. Thus, excluding the setup time for the LLM, Qwen3-235B-A22B-Instruct is around 100 times faster than a human.

Table 5.4: Comparing the mean percentage of correct predictions total among all approaches and table types.

approach	strategy	mean_percentage_correct_total
real		
human	manual	**97.6**
regex		68.6
llm	Qwen3-235B, top_5_rag_examples	97
llm	Qwen3-8B, top_5_rag_examples	92.7
llm	Qwen3-235B, top_5_rag_examples, synth examples	91.8
synth		
regex		96.9
llm	Qwen3-235B, top_5_rag_examples, respect_units	**99.9**
llm	Qwen3-8B, top_5_rag_examples	94.6

Hypotheses The predictor that shows a strong effect in all approaches is currency unit. Reflecting this in the table extraction is a key factor to optimize the performance. For the approaches that use LLMs most of the model and method related variables showed a strong effect. Using a versatile model and providing good learning examples is mandatory.

Especially for the approaches that use synthetic tables show that the input format could also have a meaningful effect. It seems important to prevent erroneous text extraction and converting the extracted text in HTML might be helpful to eliminate last unclarities. But the question, if a perfect text extract would be as good as HTML or Markdown, is not answered yet.

5.3 Error rate guidance

The side research question asks, if it is possible to guide the users attention to predictions that have a higher empirical rate of errors. In this thesis we focus the confidence score reported with LLMs responses.

Subsection 5.3.1 presents the results found regarding our side research question for the page identification task. Subsection 5.3.2 presents the results found regarding our side research question for the information extraction task.

5.3.1 Page identification

We find, that the confidence score can be used in the page identification task, to identify confidence intervals, that contain no or only a few errors. The amount of predictions falling in these intervals varies among models and classification task and target class.

Binary classification Distinguishing correct and wrong classifications based on the confidence score is working well for the responses of Ministral-8B-Instruct. But for other models, e.g. from the Qwen family, it works worse. This is possible, because Ministral-8B-Instruct reports confidence scores over a wide range, while models from the Qwen 2.5 family report always high confidence.

Thus, it is possible to define a wide range of confidence intervals, where we find a empirical error rate of zero for Ministral. For Qwen 2.5 32B we find the highest confidence interval containing some mistakes, But it is still good with less 1 %. Most predictions are in the highest confidence score interval for both models.

Multi-class classification Distinguishing correct and wrong classifications based on the confidence score is still working well for the responses of Ministral-8B-Instruct, predicting **Aktiva** and **GuV**. For **Passiva** we find a single wrong prediciton in the highest confidence interval. For Llama 4 Scout it is working for the target classes **Aktiva** and **Passiva**. For Qwen 2.5 32B it works worst among those three - still well perfomring - models.

For Ministral we find a empirical error rate of zero for the highest confidence interval, except for **Passiva** For Llama we find an error rate lesst than 1 % for all classes. For Qwen 2.5 32B only **Passiva** has a high confidence interval with less than 1 % error rate. Most predictions are in the highest confidence score interval for all models again.

5.3.2 Information extraction

We find, that the confidence score can not be used alone in the information extraction task, to identify confidence intervals, that contain no or only a few errors. There are only few exceptions, where we achieve an error rate of under 1 % over all annual reports. We just report the results of the best performing model here.

Real tables For the best predicting model Qwen3-235B-A22B-Instruct, we find an empirical error rate of 1.3 % for predicting a missing value and 3.3 % for predicting numeric values. Almost all predictions fall in the highest confidence interval. Making the interval width smaller, does not result in intervals with lower error rate.

Synthetic tables For the best predicting model Qwen3-235B-A22B-Instruct, we find an empirical error rate below 1 % for predicting a missing value and numeric values, if we explicitly instruct the model to handle currency units. If the input format is not a text extracted from a PDF file, but perfect HTML code the error rate gets 0 %. With perfect Markdown code the error rate is above 0 % but below 1 %.

Hybrid approach For the best predicting model Qwen3-235B-A22B-Instruct, we find an empirical error rate below 4 % for predicting a missing value and around 20 % to 26 % for predicting numeric values. The values is lower, if we explicitly instruct the model to handle currency units.

5.4 Summary

Chapter 6

Discussion

6.1 Page identification

6.1.1 General performance

Results The page identification task is solved with higher F1 scores for every target class than the human reference F1 score. It is solved completely on the created dataset for predicting the class **Aktiva**. In two cases the multi-class classification wit Llama 4 Scout is best. For classifying **GuV** the binary classification with Ministral is even better.

Interpretations To get the best results, a combination of two LLMs would be necessary. A more general approach is using Llama 4 Scout for multi-class classification. If there is little VRAM Ministral-8B also does a decent job in multi-class classifiacation.

Compare with previous work We are able to narrow down the page range to five pages without using a LLM. With the LLM we are guaranteed, to find the correct pages within a range of two pages. Most of the time the first page in the LLM ranking is the correct one. H. Li, Gao, et al. (2023) do not present a concrete number of pages, they have to process after page refinement. The TOC does not work as well as expected from their report.

Implications Introducing new areas of application should be easily possible and manageable even from a regular user. For the term frequency approach we can set up a pipeline, where the user just has to enter a list of keywords and then he gets presented a page ranking, based on TF-IDF values. The user might adjust the key word list or select correct pages to build a ground truth. If there are more measures of interest (e.g. a float frequency as well) we can automatically train a random forest classifier as well.

Another approach is, that the user provides documents and a list on which page the information of interest is located. This can be the base for a retrieval augmented few-shot classifier, that will improve in the process of classifying more pages.

Limitations The term frequency and LLM classification might perform worse, if the information searched for, is just making up a small part of the pages content. If the information is in a table we can use a visual table detection model, to identify all tables. Section E.3.2.2 shows that this is a promising approach. Then we can use the retrieval augmantag few-shot approach to identify, which table is the correct one.

If the information is not even in a table, but part of a regular sentence, it might get difficult to find the correct page with this approach. Maybe the TOC approach could be used for page range refinement in this case.

Unexpected results

- Ministral is performing unexpected well. Is performs better, than other Mistral models, that are newer and have more parameters.
- TOC approach performs not as well as expected by H. Li, Gao, et al. (2023) results.

Recommendations We recommend, if possible, to refine the page range, using a term frequency approach. Afterwards a LLM can be used to perform a multi-class classification those pages. Use the page with the highest score for the information extraction. Keep the ranking.

Do not include a obligatory step, to confirm the selected page, but start the information extraction right away. When the user is checking the results, a wrong page will be noticed immedeatly. Then other pages can be inspected manually, following the order in the ranking.

Save the examples already classified in a vector database and use those in future tasks. Include documents from the same company. Build the database document by document in the beginning, before starting with batch wise processing.

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Possible improvement

- Instead of the simple term frequency the TF-IDF measure could be implemented.
- With more expertise and few shot learning the TOC approach could perform better.

Conclusion

6.1.2 Energy usage and runtime

The fastest and least energy consuming strategy, using only LLMs, is to use a small model as Ministral-8B-Instruct for the multi-class approach. This is more effective than running three binary classifications.

An alternative approach could be to binary predict if the page is of any target type and then perform a classification, which type exactly the page is of. But this would probably consume as much energy as the multi-class approach, because we have to provide a balanced amount of examples for each class. The results of the multi-class strategy are good enough to run it right away.

In both strategies the k required for perfect recall is three, using the Ministral-8B-Instruct model[1].

Nevertheless, it is more promising, to reduce the number of pages, to classify with the LLM in the first place. This can be achieved, by running the term-frequency approach first to refine the page range, and then use the LLM approach.

Compare with manual page identification The manual approach is the slowest. We identified the pages of interest for all target classes in ten random documents for the benchmark. We used the TOC and the search function to find key words like **Aktiva** or **Bilanz**. Anyhow, its almost as fast as the multi-classification using Llama 4 Scout, while consuming eight times less energy. Comparing it to Ministral-8B-Instruct it take three times longer but consumes less then half of the energy.

Not taken into account fo this comparison are factors as:

- costs to buy and maintain hardware (i.e. a GPU cluster).
- higher costs per runtime if the LLM compute is purchased from cloud providers. CLOUD: price if LLM is in the cloud <– print tokens used
  - four classes (3 random examples): 11 k tokens

[1] Potentially smaller fine tuned models can solve the task even more efficient.

  - binary (3 random examples): 6.5 k tokens

- payment and insurance to pay for a human (e.g . student coworker).
- the training time and energy consumption for training either
  - a LLM (probably done by the LLM provider).
  - a human (growing up, getting educated).
- the energy consumed with the food humans eat.

6.2 Information extraction

6.2.1 General performance

Results The best performing model - Qwen3-235B-A22B-Instruct - almost reaches human performance on real **Aktiva** tables, but is much faster. Both measures, percentage of correct numeric predictions (98.0 %) and F1 score (98.1 %) are not perfect yet and could be improved. It achieves perfect results on synthetic tables provided in HTML format.

Interpretations The strong performance observed means, that Qwen3-235B is performing numeric transformations, respecting the currency units, in many cases. Otherwise the upper limit for correct numeric extraction would be 80.8 %, since 19.2 % of all numeric values have *T€* as unit.

Furthermore, we can see that it is possible to achieve perfect output, if the input is perfect structured and without unknown row identifiers. Perfect in, perfect out. Thus, we show that there is no LLM approach inherent mechanism, that prevents perfect information extraction of numeric values.

The 0.1 % incorrect predictions on synthetic tables from the PDF documents could be caused by faulty text extracts by *pdfium*. But the Markdown input is without any flaws and resulted in 0.1 % errors as well.

investigate F1 score

Compare with previous work H. Li, Gao, et al. (2023) achieve a perfect extraction result, after refining their approach, extracting a total of 152 data points from 8 ACFRs reports. Before the prompt adjustments they find 96.1 % correct extracted datapoints.

They included an instruction how to handle missing values but do not report any remarkably higher error rates with missing values.

(probably homogeneous) fuzzy matching instruction 3 values per go, instructions for currency units

98.9 % on ESG reports after refinement, 90 values from 15 documents; heterogeneou (multiple ccompanies)? started at 93.3 % misjudging units between grams, kilograms, and tonnes introduced additional fields to the data points and had LLM extract the units as separate output fields

small in sample extractions => 4000 county year ACFRs: 96 % (80_000 data points)

Implications We have not investigated yet, if the 2 % wrong extracted numeric values are caused by not respecting currency units, or if there is another reason. A potential reason may be numeric values, that get stiched together during text extraction.

- invest more into table extraction?

Checked other extraction libraries as well. Including Azure Document Intelligence and Dpcling, but results not better. In Markdown they get worse.

Checking the extracted values takes up to three minutes. This totals in 300 minutes prediction checking. Thus, selecting a smaller model that is finishing after 2:30 minutes is not speeding up the process a lot. Once we get a sufficient good performance with the big models the prediction checking can be dropped. This would bring th real benefit.

Limitations

- add schemas for different hierarchies
- test guided decoding instead of restricted (open a new list for unmatched entries?)

Unexpected results

- converts currency units without being prompted explicitly

Recommendations

- invest in supply of machine-readable information and good user experience, instead of 100 % perfect extraction
- building a document extraction database document by document can improve performance taking advantage of same-company rag in-context learning

Possible improvement The extraction performance may get higher, if the in-context learning examples show how to deal with columns that have a currency unit.

- explicitly instruct, how to handle currency units
- extend schema or sum rows
- handle non matched rows explicitly

Conclusion

- check if missing value in one col (hand full of those cases) is resulting in hallucinations
- confusion matrix

6.2.2 Company specific results

Figure 6.1 shows, the precision and recall values for predicting a missing value and the percentage of correct numeric predictions for Qwen3-235B for each company. The number after the company name, as well as the color of the boxes indicate, how many of the numeric columns have *T€* as currency unit. The crosses indicate the individual scores per document. The teal crosses represent predictions, if examples from the same company are used for the *top n rag* prompting strategy. Red ones represent predictions, where this is not the case.

One can see, that Qwen3-235B yields perfect predictions for the majority of the companies. This is especially true, if only the teal crosses are considerd. The predictions improve for most companies, if examples from the same company are used for the few-shot learning. It is especially helpful for handling the single numeric column with *T€* for *Deutsche Klassenlotterie*. It is also helping with the two columns with *T€* for *Gewobag*, even though the other examples have not *T€* present.

It seems a little harmful for *WBM GmbH* and can not solve the problems for numeric prediction for *Helmholtz Zentrum GmbH* and *Berliner Stadtgüter*. It improved the precision for *Rundfunk Berlin-Brandenburg* and the recall of *Stadt und Land GmbH* and *Partner für Deutschland*.

Table 6.1 shows the performance of Qwen3-235B for the *top n rag* and *n random* example strategies and distinguishes based on the fact, if examples from the same company can be used for in-context learning. The achieved percentage of correct predictions total is highest, if examples form the same company are used. It is even higher than the human reference score.

If using examples form the same company is not allowed, it seems better to use random examples. This is probably the case, because this comes with a higher heterogeneity. High homogeneity among the learning examples from other companies might demonstrate patterns, that are not correct for the company the

Figure 6.1: Comparing the F1 score for predicting the missingness of a value for OpenAi's LLMs with some Qwen 3 models. The green crosses indicate results where a model has predicted only numeric values even though there have been missing values.

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target document comes from. The pattern, that the same company in-context learning yields best results is true for all models. The order of the results with random examples or examples from other companies varies among the models.

In general the approach seems not be prone to hallucinations. When we accidentally tried to extract values from a **Passiva** and **GuV** table, no prediction was made, because non of the row identifiers matches our strict schema.

predictions for barrierefreie documents of WBM empty

An odd text marking order in a PDF by dragging the mouse is no indicator for a bad text extract.

6.2.3 Error analysis

- new lines / splitted lines
- test synthetic hypothesis with pymupdf extract
- 2.4 % wrong gold standard creation
- errors from wrong formatted numbers
- errors from wrong / unclear entity mapping

6.2.3.1 Ground truth creation

During the second pass of the ground truth creation we find, that 2.4 % of the values differ among the previously created gold standard and the results of the second pass. In the first pass the values are copied manually, while the results of the second pass are LLMs predictions, that we double checked. We find 75 values differing in the 24 documents that are part of both data collections. Table 6.2 shows the nature of errors and their counts. Most errors are distributed in the *omission* classes.

Errors of this type result from an inconsistent coding process. In one pass a value might have been included, while it is not included in the other pass. Or the value is matched to different row identifiers during the two passes. To resolve this kind of errors a strict and detailed coding manual is necessary. Additionally, the coding should be done from experts of the field instead of the data scientist.

6.2.3.2 Regular expression approach

We find, that the regular expression approaches performance on the synthetic dataset is highly influenced by the extraction library used. For the real data we find no difference. Figure B.1 B shows, that the regex approach on text extracted with *pdfium* especially has a wider precision range. The number of wrong extracted numeric values is a little as well.

A reason for this might be incorrect extracted texts. We find, that there are issues with missing (or additional) white space, misplaced line breaks and an extraction of the text column first, followed by the numeric columns. You can find examples for those types of incorrect extracted texts by three different PDF

Table 6.1: Comparing the performance of Qwen3235B for the best approaches depending on the circumstance if examples from the same company can be used for learning.

model	method	same company	mean numeric	mean F1	mean total
Qwen3-235B-A22B-Instruct-2507-FP8	top_3_rag_examples	FALSE	0.972	0.972	0.959
Qwen3-235B-A22B-Instruct-2507-FP8	top_5_rag_examples	TRUE	**0.990**	**0.987**	**0.982**
Qwen3-235B-A22B-Instruct-2507-FP8	5_random_examples	NA	0.982	0.975	0.966

Table 6.2: Showing the nature of errors and their counts. Errors with multiple difference have Levenshtein distance greater one.

error_type	count
ommited in first pass	29
ommited in second pass	20
multiple differences	13
missing digit	10
swapped digits	2
comma instead of dot	1

extraction libraries in section E.8. One of the examples is found with the real table dataset, while two are found with the synthetic tables.

The random white space and line breaks could be handles by adjusting the regular expression for the label matching. Missing white space between numeric values could also be handled by adjusting the regex. The misplaced columns would need more advanced reprocessing strategies. But all those error ypes shouel influence the recall and not the precision.

A possible explanation for a small spread in precision with both PDF extraction backends could be the duplicated row identifier *Geleistete Anzahlungen*. Our simple approach matches this row always with the first occurrence. This means, if the second occurrence is given in the ground truth, but not the first one, our approach would create a false positive result. The percentage of false positive example is then determining the precision value and is linked to the number of total rows in the ground truth. But we do not see sucha pattern for the *pymupdf* results at all.

A reason for wrong numeric values are rows, where the summed value is given in the next column, but same row, as the individual values. In this case the approach selects one individual value and a sum, instead of two individual values.

- synthetic tables have been generated with cell lines because this should have improved the performance of a table extraction approach (not conducted)- maybe this is confusing pdfium? Or the zoom level?

6.3 Error rate guidance

Results Confidence score can be used to determine empirical error rate for confidence intervals. For well performing models we find most predictions in the highest confidence interval.

Ministral shows good spread over confidence range for page identification task. We can find confidence intervals with zero error rate for the page identification task and the information instruction task on synthetic data.

We do not find confidence intervals with a error rate below 1 % for real **Aktiva** tables. Explicitly instructing to respect currency units, reduces errors.

Interpretations Confidence score can be used to guide attention for page identification task, but hardly for information extraction task.

Compare with previous work

Implications Additional segementation could be necessary, to find values that are predicted well enough.

confidence intervals based on company (know which formats are tricky)

Limitations

Unexpected results Most models predict high confidence, even for wrong predictions.

Recommendations 0 % empirical error rate unstable. Chose cutoff or show error rate continuously?

Possible improvement Testing normalized confidence.

Conclusion Discussion:

An additional feature to narrow down the selection and get a more concrete error rate scores for similar texts could be the the company.

Check perfect text?

Learning benefit of real examples higher for numeric value extraction as for lable matching.

works only well for page identification, where it is not really needed (perfect results, low checks, implicit found in extraction window)

additional segmentation might help

HTML might help => document parsing and table extraction

6.4 Feature effect analysis

6.4.1 General performance

Results

Interpretations

Compare with previous work

Implications

Limitations

Unexpected results

Recommendations

Possible improvement

Conclusion

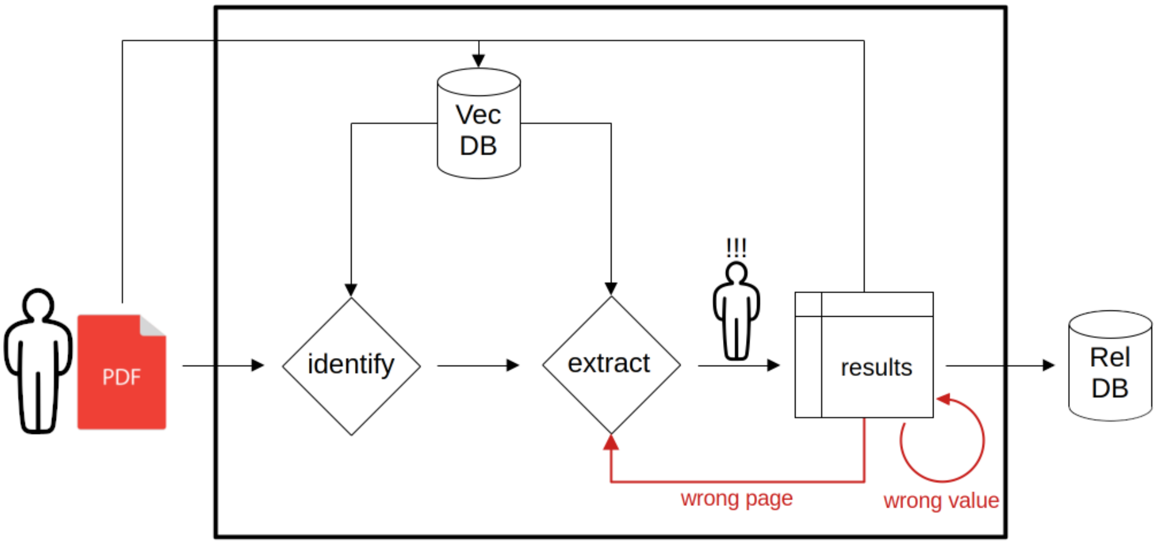

Figure 6.2: Showing the information extraction process in a HITL application. We propose to include user action only after the information extraction. If a wrong page is selected, this can be fixed and extraction runs again. Wrong extracted values and handling unknown row identifiers should be done in one place.

6.5 Summary

6.6 Limitations

6.6.1 Context rot

We reported the worsening performance of Llama 4 Maverick, when it gets to many examples presented in both main tasks. Since we used the FP8 version, we tested if this is a problem of to low precision in the calculation. But we find the same behavior with the FP16 version. It is the only model we detect the issue of *context rot* for.

Context rot is a term introduces in (Kelly Hong & Anton Troynikov, 2025) technical report. The investigated an advanced *Needle in the Haystack* problem, including distractors and requiring the LLMs to find semantic similarity instead of exact term matching. They find that the accuracy often starts to decrease with 10 k input tokens and more.

Meta claims that Llama 4 Maverick has a context length 1 M (Llama 4 Scout even 10 M), where other models often ar limited to 128 k or 32 k or less. We limited our input token length to 32 k in most cases and reached this limit multiple times. We find it remarkable, that Llama 4 Maverick already shows *context rot* at inputs of length 10 k - 100 times shorter than their context window.

Levy et al. (2024) show a notable degradation in LLMs' reasoning performance at much shorter input lengths than their technical maximum. They also show, that Mistral achieves the highest accuracy, when the relevant information is at the end of the prompt. We are not sure, how to relate these findings, since we do not include irrelevant information.

6.6.1.1 Page identification

Figure 6.3 shows the amount of correct (matching) and incorrect classifications by Llama 4 Maverick for the binary classification tasks ordered by target type and method. One can see, that the *n_rag_example* strategy starts predicting the target class too often with increased number of examples. This behavior is not observed for the *n_random_examples* strategy.

Figure 6.4 is showing the confusion matrices for the multi-class classification with Llama 4 Maverick grouped by *method_family* and *n_examples*. Teal bordered tiles are correct predictions and red bordered

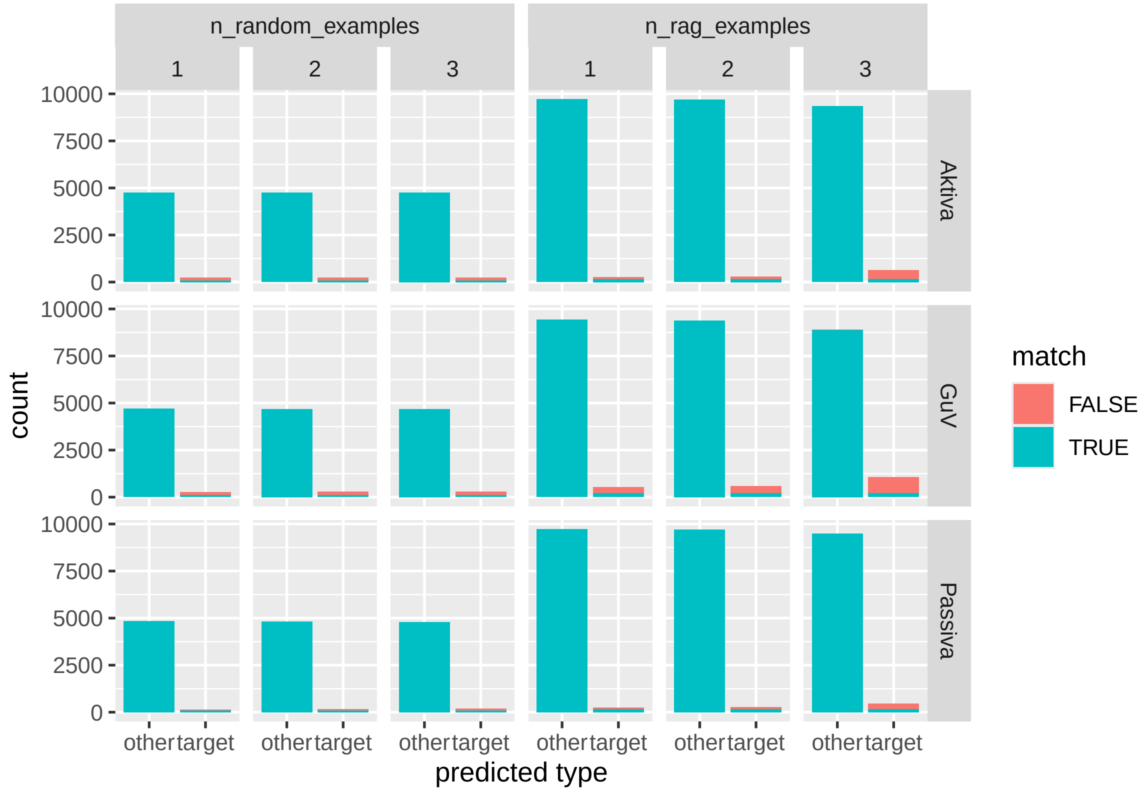

Figure 6.3: Comparing the amount of correct classifications by Llama 4 Maverick for the binary classification tasks ordered by target type and method. With increased number of examples the n-rag-example strategy starts predicting the target class too often.

tiles represent wrong predictions. The number is showing the percentage of classifications by the LLM of a certain type (*predicted_type*) based on the true count of observations with that type (*type*). They sum up to one column-wise.

We can see, that the *n_rag_example* strategy starts to predict **GuV** too often, when presented with two or more examples. We observe the same for the *n_random_examples* strategy starting from three provided examples. The LLM is not just over-predicting **GuV**, but also other target classes. The over-prediction rate for *other* is lowest. Those pages often have no page filling table and thus are more different from the target classes and easier to distinguish (for a human).

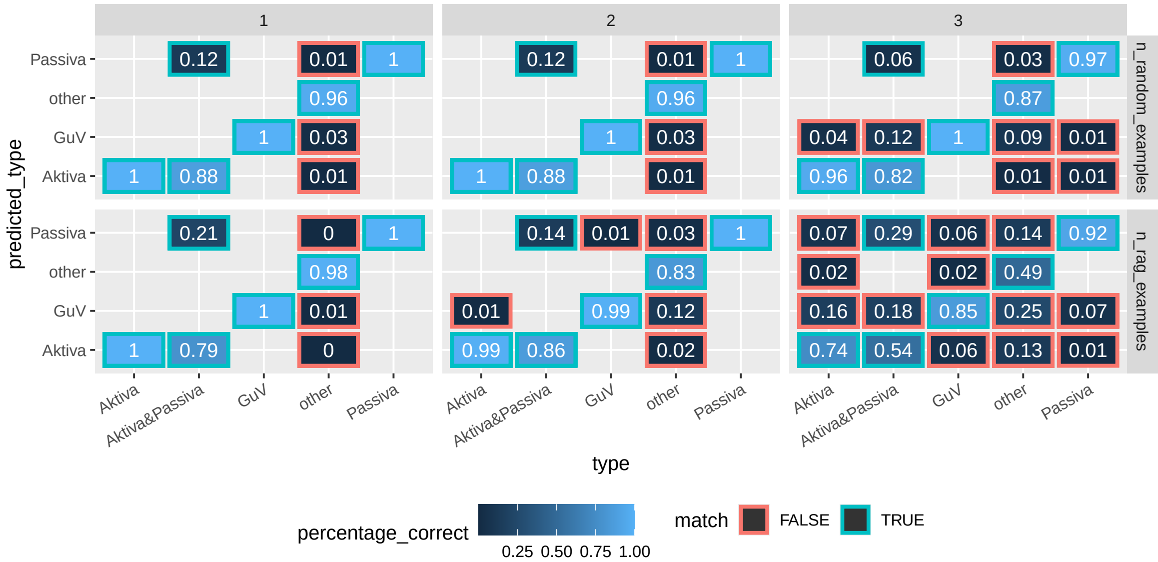

Figure 6.4: Showing the confusion matrices for the multi-class classification with Llama 4 Maverick grouped by method-family and n-examples.

A possible explanation fro over-predicting **GuV** most might be, that the examples for **GuV** are presented first, because we just iterate over the *phrase_dict* dictionary (see code below). Liu et al. (2023) describe a behavior of LLMs, that they are better with identifying relevant information, when it is placed in the beginning or end of the context. Since all examples are provided in the same manner, examples for classes other than the target class, could be interpreted as distractors with a high similarity. Kelly Hong & Anton Troynikov (2025) shows, that in the presence of similar LLMs' performance can degrade quickly. They do not present results, if the position of the picked distractor is important. Thus, we formulate the hypotheses for future investigation:

1. LLMs tend to choose distractors at the beginning or end of the prompt.
2. LLMs tend to choose distractors that apprear first or last.
3. There is an interaction effect, with the position, where the task itself is specified.

```
phrase_dict = {
  "GuV": "a 'Gewinn- und Verlustrechnung' (profit and loss statement) table",
  "Aktiva": "a 'Aktiva' (assets) table",
  "Passiva": "a 'Passiva' (liabilities) table",
  'other': "a text that does not suit the categories of interest",
}
```

6.6.1.2 Information extraction

Figure 6.5 shows the confusion matrix for the information extraction task with Llama 4 Maverick and five examples. It shows, that the LLM starts to predict numeric values for every row instead of prediction *null* if a row is missing. Figure 6.6 shows, what kind of numeric values are predicted. We find two peaks for predicting floating point numbers close to zero or close to 30, while the true values (and values from the examples provided) are in a range of 1_000 and 10_000_000. Thus, we assume the values are hallucinated and not wrongly picked from the examples provided.

Local and global context window / attention (Khowaja, 2025). Trained on 256 k tokens with FP8 precision.

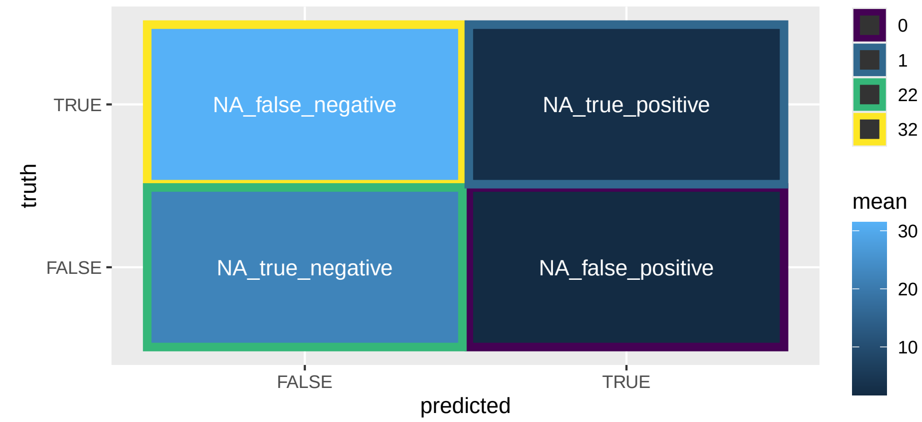

Figure 6.5: Showing the confusion matrix for the information extraction task with Llama 4 Maverick and five in-context learning examples.

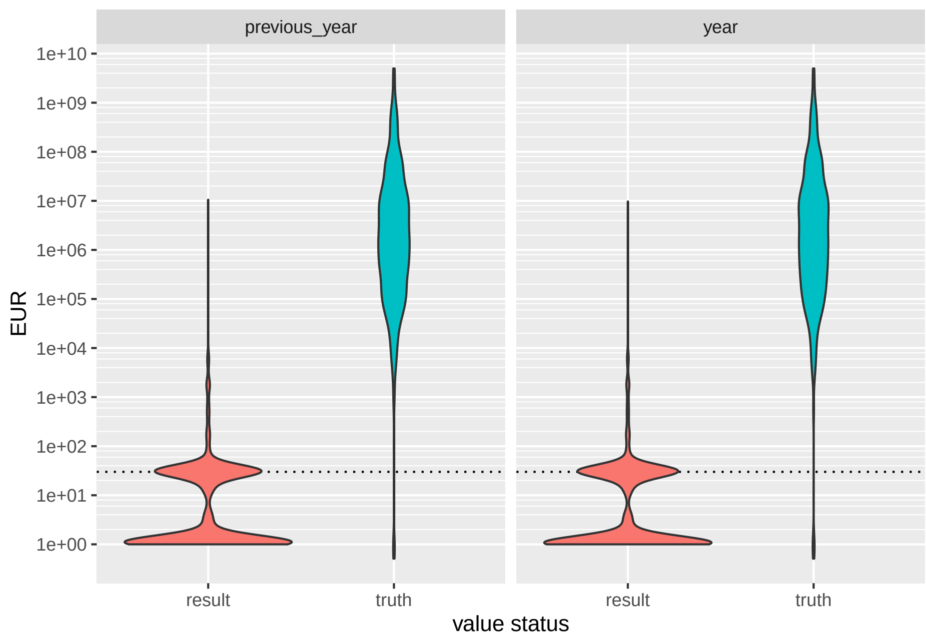

Figure 6.6: Comparing the predicted numeric values with the true value distribution for the information extraction task with Llama 4 Maverick and five in-context learning examples. The dotted line is marking the value 30 EUR.

6.6.2 classification

- Qwen 2.5 hat zweiseitige GuV von IBB entdeckt und zur Anpassung der Ground Truth
- predictor: n_big_tables (tf or llm relevant?)
- Why it is important to have a good recall (or top n accuracy)
-

6.7 Not covered

- OCR
- fine-tuning
- using something smaller (e.g. LSTMs) instead LLMs
- building application, UX design (ref Ambacher 2024)
- table extraction (either VLLMs (visual) or classic approaches <– tried tabula but was not successful (because of missing visual traits)?) to prevent wrong text flow and have clear cell borders
- classification oriented models with softmax

in company document next / previous year more helpful than years further away?

6.7.1 Table detection / extraction

Can be used to narrow down set of possible pages

Can be used to focus only on the table content (measure if correct area was identified would be necessary)

Vision model as baseline

6

6.8 Outlook

- ensemble from multiple models or are errors systematic? (e.g. Wohnungsbaugenossenschaften splitting some rows in multiple and none is picked?)
- check for halluzination vs wrong placed / repeated numbers
- no perfect score even with synthetic data
- flexible extraction (name something, find it, get it)
- UI
  - checking results / correct errors; col by col; match entities
  - add unused entries (backlog? extra table?)
  - possibilities for rerun / flagging the source of issue
- ml health check / benchmark framework
  - test new models performance
  - check if new examples might be harmful (repredicting)

Ad-hocs for monitoring during the year

6.9 Tools

Vlt egal oder outlook

6.9.0.1 Vision Grid Transformer

6.9.0.2 TableFormer

SynthTabNet <– has it: - nested / hierarchical tables, where rows add up to another row? - identifying units and unit cols/rows

6

Chapter 7

Conclusion

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Glossary

LLM large language model
AI artificial intelligence
PDF Portable Document Format
RHvB Rechnungshof von Berlin
GPT generative pre-trained transformers
HITL human-in-the-loop
regex regular expression
TOC table of contents
MoE mixture of experts
RAG retrieval augmanted generation
SHAP SHapley Additive exPlanations
TF-IDF Frequency-Inverse Document Frequency
BM25 best matching 25
IDF Inverse Document Frequency
FFN feed forward network
PLE Per-Layer Embedding
XGBoost Extreme Gradient Boosting
XAI explainable artificial intelligence
UX user experience
json JavaScript Object Notation
GPU graphics processing unit
BHT Berliner Hochschule für Technik
OCR optical character recognition
vLLM Virtual Large Language Model
SSH secure shell
HTML hyper text markup language
ebnf extended Backus–Naur form
ACFR Annual Comprehensive Financial Report
mcc multi-class classification
AUC area under the curve
UI user interface

Appendix A

Appendix A - Page identification report

The first research question asks, how LLMs can be used, to effectively locate specific information in a financial report. The task for this thesis is identifying the pages where the balance sheet (*Bilanz*) and the profit-and-loss-and-statement (*Gewinn- und Verlustrechnung, GuV*) are located. The balance sheet is composed of two tables showing the assets (*Aktiva*) and liabilities (*Passiva*) of a company. Often these two tables are on separate pages. Hereafter, the German terms **Aktiva**, **Passiva** and **GuV** will be used.

A.1 Baseline: Regex

The first approach presented in this section is, to use a key word list and regex (regular expression) to filter out irrelevant pages. It is setting the performance baseline for the following approaches. Building a sound regular expression often is an iterative process. In a first approach a very *simple regex* was implemented. To increase the recall to 1.0 the regular expression was extended[1]. This second regex is called *exhaustive regex*. In a third attempt minor changes have been made to the *exhaustive regex* to increase the precision without decreasing the recall. This regular expression is called *exhausitve regex restricted*. The regular expressions can be found in the appendix (see section E.5).

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Table A.1 shows the mean performance for precision, recall and F1 for the three regular expressions for the three types of pages to identify[2]. It was possible to create a regular expression that has a high recall for all target types. The precision is low for all tested regular expressions and target types. Figure A.1 gives insight into performance differences between the companies. There is only one document from *Berlin Energie und Netzholding* where the **GuV** is not identified except with the *exhausitve regex restricted*[3].

The regular expressions have been tested on the texts extracted with multiple Python libraries. The reported standard deviations are very small. This means that there are no substantial differences in the extracted texts on a word level[4]. But table E.1 in section E.3.1 shows that there are differences in the extraction speed.

Code can be found at "benchmark_jobs/page_identification/page_identification_benchmark_regex.ipynb"

Todo: * look into details where they differ and if it is because of a line break or whitespace?

Summary Nothing works well

[1] The idea is that the regular expression approach is computationally cheap. If we can rely on the fact, that it keeps all relevant pages we can use additional, computationally more expensive approaches to further refine the page range.

[2] See Figure G.2 for a graphical representation.

[3] I don't understand why the restricted version is finding the page but the non-restricted regex is not.

[4] Since the results are not depending on the text extraction library, the *exhaustive regex restricted* ran only with the text extracted by the fastest extraction library: *pdfium*. This library is used for the most tasks in this thesis. Later faced issues with the text extracted by *pdfium* are discussed in @ref().

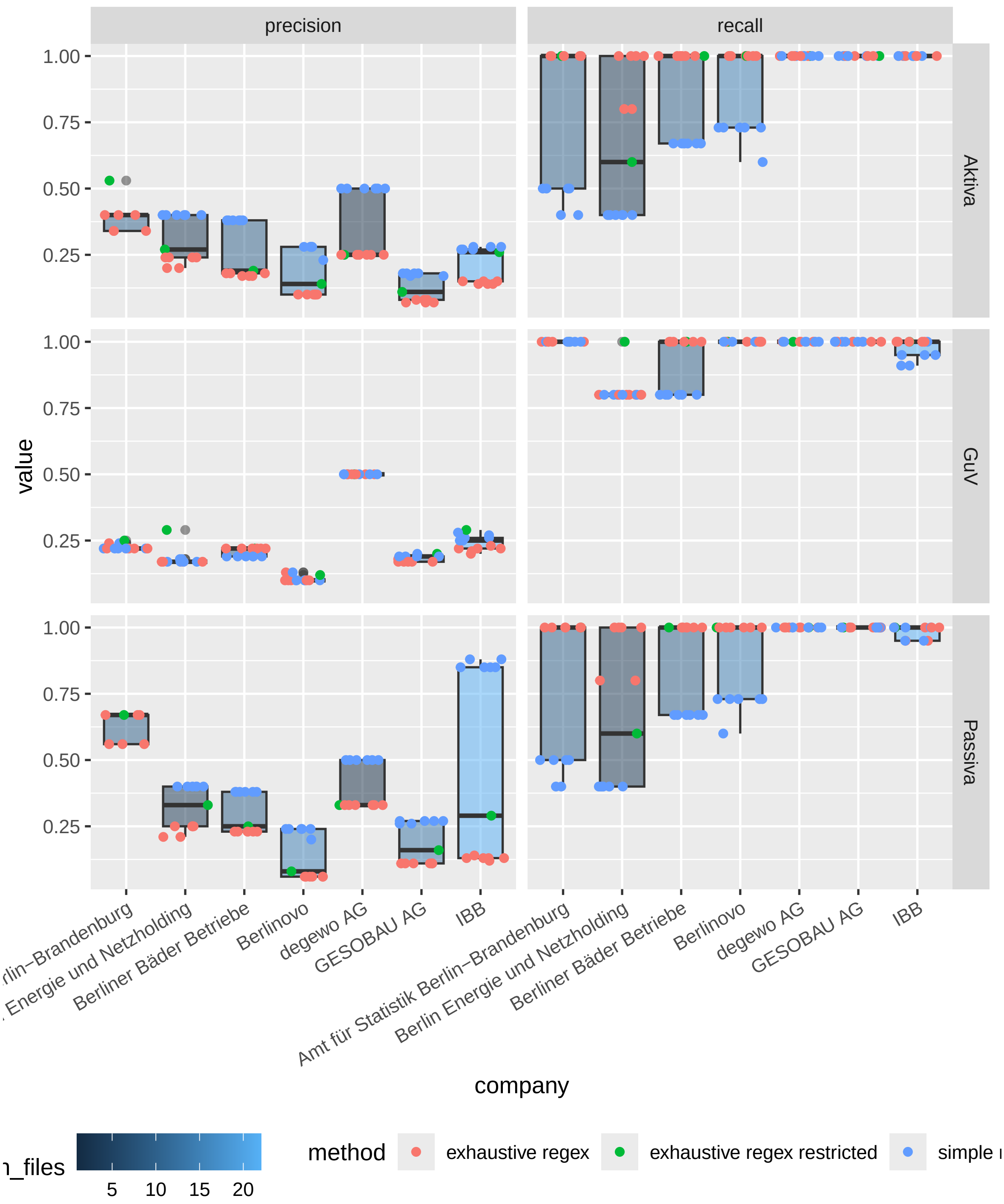

Figure A.1: Comparing the performance among different companies.

Table A.1: Comparing page identification metrics for different regular expressions for each classification task by type of the target table.

method	type	precision	recall	F1
Aktiva				
simple regex	Aktiva	**0.273** ± 0.005	0.788 ± 0.010	**0.403** ± 0.005
exhaustive regex restricted	Aktiva	0.190	0.990	0.320
exhaustive regex	Aktiva	0.132 ± 0.004	**0.997** ± 0.005	0.233 ± 0.008
Passiva				
simple regex	Passiva	**0.400** ± 0.009	0.780 ± 0.009	**0.530** ± 0.009
exhaustive regex restricted	Passiva	0.190	0.980	0.320
exhaustive regex	Passiva	0.130 ± 0.000	**0.993** ± 0.010	0.230 ± 0.000
GuV				
simple regex	GuV	0.180 ± 0.006	0.938 ± 0.008	0.302 ± 0.010
exhaustive regex restricted	GuV	**0.210**	**1.000**	**0.350**
exhaustive regex	GuV	0.173 ± 0.008	**1.000** ± 0.000	0.295 ± 0.012

A.2 Table of Contents understanding

The second approach presented in this section leverages the TOC understanding capabilities of LLMs. H. Li, Gao, et al. (2023) use this approach with long documents as a first step to determine a page range of interest. If the predicted page range is correct and narrow, this approach is more efficient than processing the whole document with a LLM directly. The TOC in a PDF document can be embedded in a standardized, machine readable format or be presented in varying, human readable forms of text on any page. Of course there are documents without any TOC.

Thus, the task is investigated based on two different input data formats In one case the LLM is provided with text extracted from the beginning of the document. In the other case the LLM is provided with the Markdown formatted version of the machine readable TOC embedded in the document. Subsection A.2.1 shows the results for the text based approach. Subsection A.2.1 shows the results for the approach, using the embedded TOC.

Additionally, each approach is performed three times with minor changes in the prompt. The prompts used for both approaches can be found at E.4.1. The prompt was adjusted two times to tackle shortcomings in the results. The first change adds the information, that assets and liabilities are part of the balance sheet. It is the balance sheet, that is listed in the TOC - not the assets or liabilities itself. The second change specifies the information, that assets and liabilities are often on separated pages, into, liabilities often are found on the page after the assets.

The code can be found in:

- “benchmark_jobs/page_identification/toc_extraction_mistral.ipynb”
- “benchmark_jobs/page_identification/toc_extraction_qwen.ipynb”

Discussion:

- H. Li, Gao, et al. (2023) did not report any issues with this approach. They use few-shot learning and Chain-of-Thought techniques to help the LLM to understand the task. They ask just for one information at a time.
- ChatGPT 4 vs Mistral 2410 8B (huge parameter difference)
- For a lot of short annual reports one can find the tables of interest within the first eight pages as well.

A.2.1 Details for the approaches

Text based H. Li, Gao, et al. (2023) used the TOC to identify the pages of interest. In their approach the table of contents is extracted from the text. Based on their observation, that the TOC in ACFR (Annual

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Comprehensive Financial Report)s is found within the initial 165 lines of the converted document (H. Li, Gao, et al., 2023, p. 20), they use the first 200 lines of text.

My initial expectation was to find the TOC within the first five pages. Often there are way less than 200 lines of text on the five first pages (see Figure A.2). In my approach the first step is to prompt the LLM to identify and extract the TOC in a given text extract^[The prompt can be found in section E.4.1]. For the same documents Mistral 2410 8B finds^[The strings extracted in this step have not been checked in detail.]

- 63 strings that should represent a table of contents among the first five pages.
- 68 strings that should represent a table of contents among the first 200 lines.

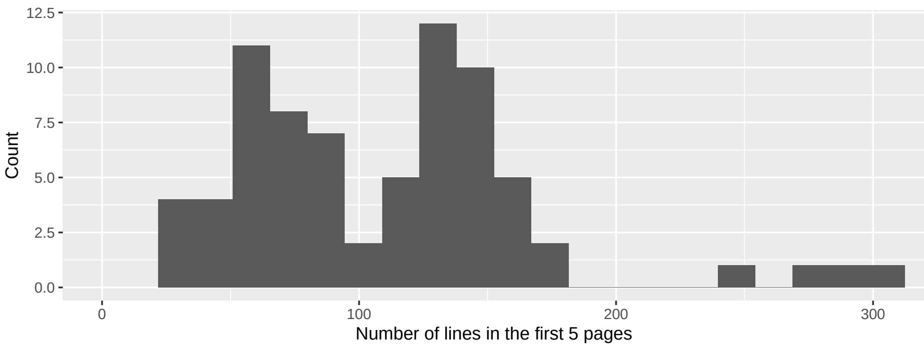

Figure A.2: Histogram of the number of lines in the first 5 pages of the annual reports

Machine readable TOC based I also tested to use the TOC representation embedded within the PDF files. First, this limits the text amount to process. Second, this hopefully increases the quality of the data passed to the LLM. 43 of the 80 annual reports have a machine readable embedded TOC. The embedded TOC is converted into markdown format before it gets passed to the LLM. Here is an example:


```
## |   hierarchy_level | title                       |   page_number |   enumeration |
## |------------------:|:----------------------------|--------------:|--------------:|
## |                 1 | Lagebericht                 |             5 |             1 |
## |                 1 | Bilanz                      |             7 |             2 |
## |                 1 | Gewinn- und Verlustrechnung |            10 |             3 |
## |                 1 | Anhang                      |            13 |             4 |
## |                 1 | Lagebericht                 |            17 |             5 |
## |                 1 | Bilanz                      |            25 |             6 |
## |                 1 | Anhang                      |            31 |             7 |
## |                 1 | Anlagenspiegel              |            39 |             8 |
## |                 1 | Bestätigungsvermerk         |            42 |             9 |
```

A.2.2 Results

Comparison of the different approaches: base prompt Table A.2 shows that the machine readable TOC approach has the highest rate of correct page ranges for all types with the base prompt. It also predicts the most correct page ranges in absolute numbers for **Aktiva** and **GuV**. Thus, it also has the highest rate of correct page ranges based on the total number of page ranges to identify over all documents - no matter, if there was a TOC of any type in the document or not - for **Aktiva** and **GuV** of around 27 %.

Figure A.3 shows that the amount of correct predicted page ranges for **Passiva** is lowest for all approaches but can be improved by simply extending the predicted end page number by one the most. This improvement would be best for the machine readable TOC approach. This approach is the only one, where the number of correct page ranges **Aktiva** would not increase if we extend its range by one. Table A.3 shows that this is the case, because the machine readable TOC approach predicts the same end page for **Passiva** as for **Aktiva** in 84.8 % of the cases, even though the prompt for all approaches included the information, that **Aktiva** and **Passiva** are on separate pages.

Table A.2: Comparing the number and percentage of correct identified page ranges among the approaches.

benchmark_type	type	n_correct	n	n_total	perc_correct	perc_correct_total
200 lines	Aktiva	9.0	63	82	14.3	11.0
200 lines	GuV	22.0	95	102	23.2	21.6
200 lines	Passiva	**6.0**	62	81	9.7	**7.4**
5 pages	Aktiva	7.0	58	82	12.1	8.5
5 pages	GuV	15.0	89	102	16.9	14.7
5 pages	Passiva	3.0	57	81	5.3	3.7
machine readable	Aktiva	**22.0**	35	82	**62.9**	**26.8**
machine readable	GuV	**28.0**	56	102	**50.0**	**27.5**
machine readable	Passiva	4.0	34	81	**11.8**	4.9

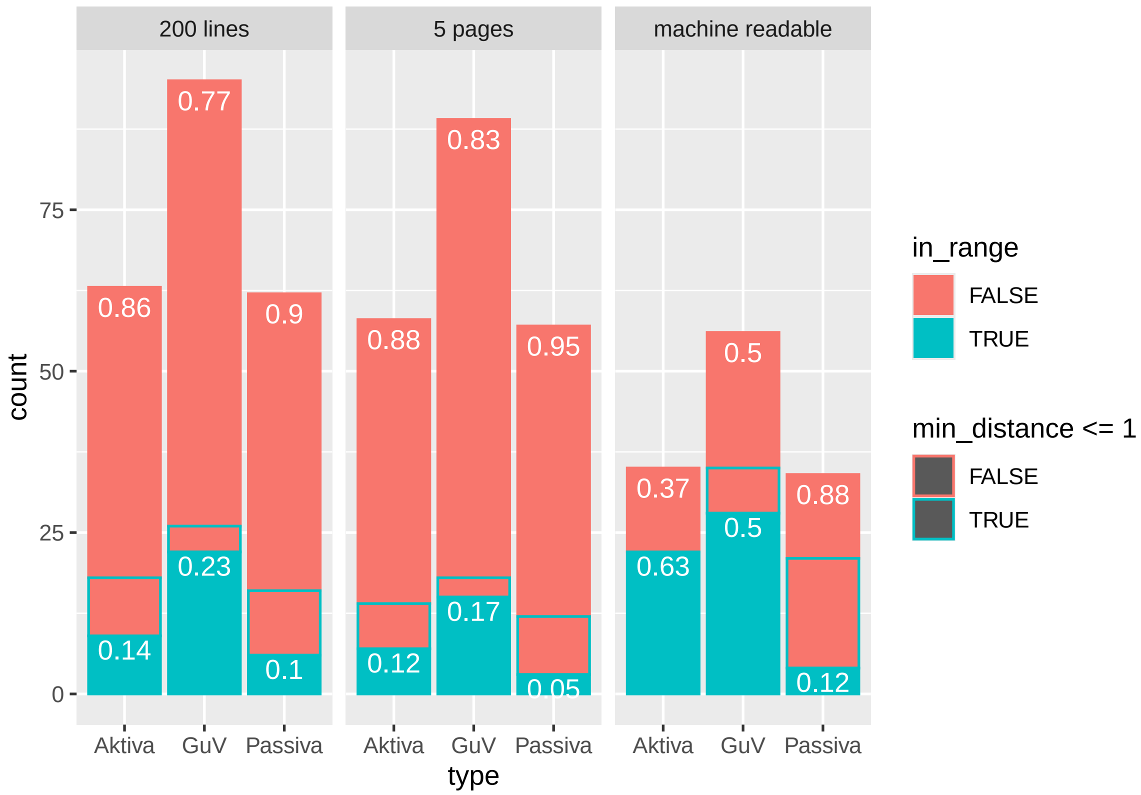

Figure A.3: Comparing number of found TOC and amount of correct and incorrect predicted page ranges

Table A.3: Comparing the number and percentage end pages prediction for Aktiva and Passiva that are equal.

benchmark_type	equal_end_page	n	perc_equal_end_page
200 lines	20	58	34.5
5 pages	26	53	49.1
machine readable	28	33	84.8

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Comparison of the different approaches: advanved prompts As a first attempt, to increase the correct page range rate for **Passiva** I tried to specify, that assets and liabilities are part of the balance sheet. This did work for the text based approaches, but not for the machine readable approach (see Figure G.3). Figure A.4 shows that it is more successful, to explicit tell the LLM that the liabilities table is often on the page, after the assets table.

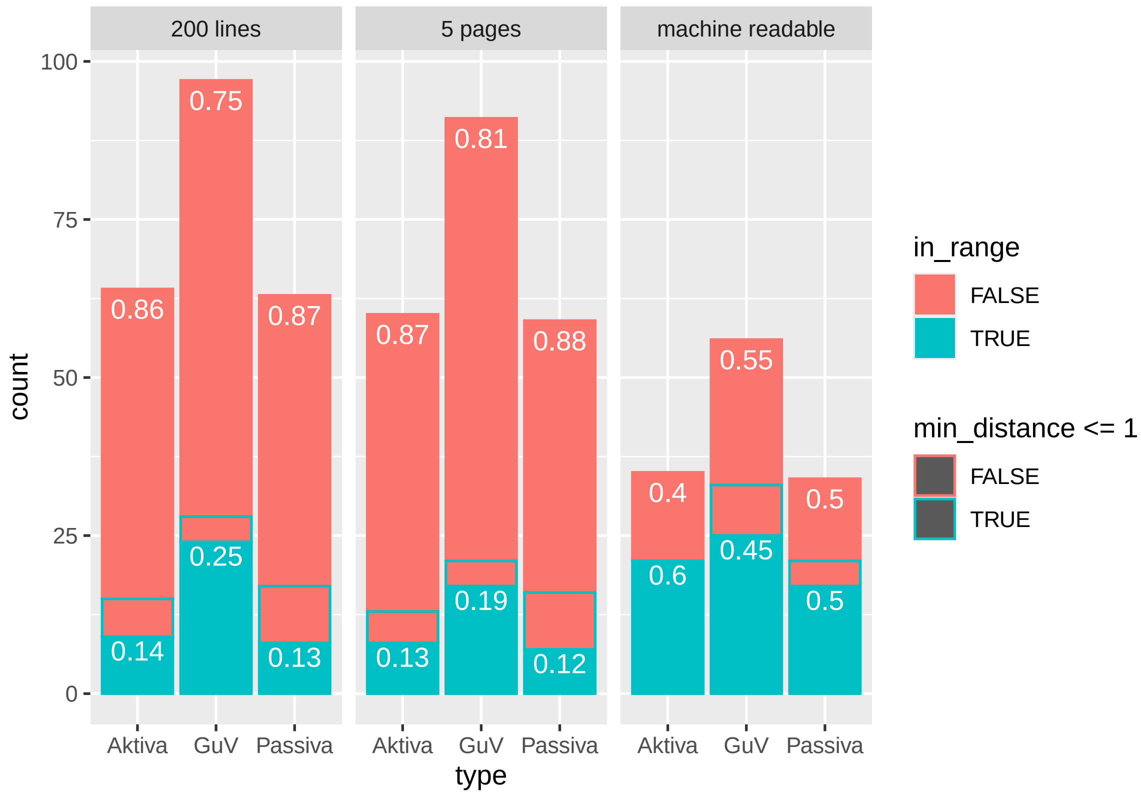

Figure A.4: Comparing number of fount TOC and amount of correct and incorrect predicted page ranges

Table A.4 shows the results from the final zero shot prompt. The machine readable TOC approach is now predicting best for all types. Nevertheless, a correct page range prediction rate below 60, 45, 50 % is still unsufficient to build downstream task on withou human checkups. Table A.5 shows, that the machine readable TOC approach is the fastest as well.

Table A.6 shows, that this advantage of the machine readable TOC approach is not coming from wide predicted page ranges. It has the smallest median range size among all approaches. Figure A.5 shows, that especially the ranges for **GuV** are not normally distributed. Some far off lying range sizes are shifting the mean off from the median.

Table A.4: Comparing the number and percentage of correct identified page ranges among the approaches.

benchmark_type	type	n_correct	n	n_total	perc_correct	perc_correct_total
200 lines	Aktiva	9.0	64	82	14.1	11.0
200 lines	GuV	24.0	97	102	24.7	23.5
200 lines	Passiva	8.0	63	81	12.7	9.9
5 pages	Aktiva	8.0	60	82	13.3	9.8
5 pages	GuV	17.0	91	102	18.7	16.7
5 pages	Passiva	7.0	59	81	11.9	8.6
machine readable	Aktiva	**21.0**	35	82	**60.0**	**25.6**
machine readable	GuV	**25.0**	56	102	**44.6**	**24.5**
machine readable	Passiva	**17.0**	34	81	**50.0**	**21.0**

Table A.5: Comparing GPU time for page range prediction and table of contents extraction. Time in seconds per text processed.

Benchmark Type	Page range predicting	TOC extracting
200 lines	0.57	3.8
5 pages	**0.56**	**2.19**
machine readable	0.63	NA

Table A.6: Comparing the mean and median page range sizes.

benchmark_type	type	mean_range	SD_range	median_range	MAD_range
200 lines	Aktiva	2.11	1.09	2	1.48
200 lines	GuV	4.25	3.29	4	2.97
200 lines	Passiva	1.7	0.59	2	0
5 pages	Aktiva	2.03	1.29	2	1.48
5 pages	GuV	3.15	2.17	2	1.48
5 pages	Passiva	1.64	0.89	2	0
machine readable	Aktiva	1.6	2.56	**1**	0
machine readable	GuV	3.89	5.75	**1**	0
machine readable	Passiva	1.24	0.74	**1**	0

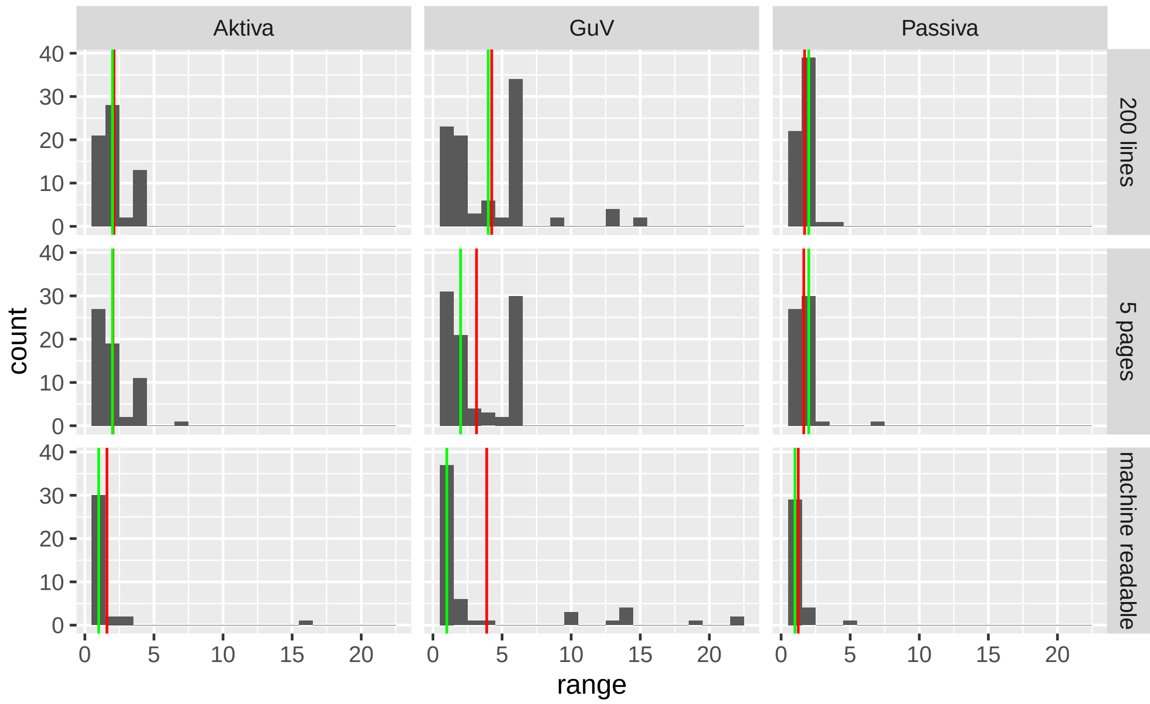

Figure A.5: Comparint the predicted page range sizes. The red vertical line shows the mean and the green one shows the median of these sizes.

Figure A.6 shows that the confidence of the LLMs responses is higher for the machine readable TOC approach as well. Besides a single group that was predicted far off, the page ranges are closer to the correct pages too. A linear regression of the correlation between minimal page distance and logistic probability shows that is has a similar slope for all approaches and target types.

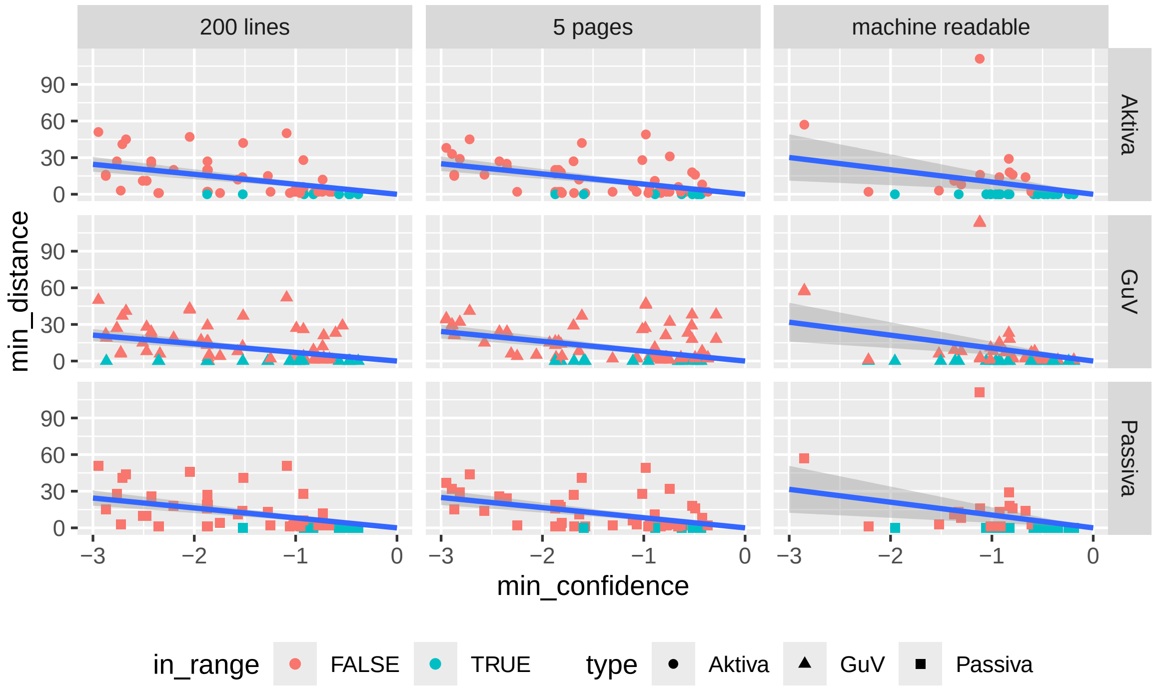

Figure A.6: Showing the minimal distance of the predicted page range to the actual page number overthe logprobs of the models response confidence.

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A.2.3 Machine readable TOC approach specific results

Figure A.7 shows, that correct predictions for the page range are more probable when the embedded TOC has a medium number of entries. It is possible to drop documents with less than 9 without loosing a single correct prediction. This means that the LLM was not able to make a correct prediction for documents with TOC, that have less then 9 entries. This is not surprising since neither **Bilanz** nor **GuV** are mentioned there explicit.

It has no big influence on the predictions, if the TOC is passed formatted as markdown or json. With the json formatted TOC it found two more correct page ranges[5]. This was tested because the relation between heading and value for the column *page_number* might have been clearer[6] in json for a one-dimensional working LLM.

Delete or place somewhere else?:

- Thus it is safer to go with the 200 lines approach. But it also takes longer. A.5
- Values can be higher than 80, the total number of PDF files, since there can be multiple tables of interested for the same type in a single document or a table of interest can span two pages.

[5]This result is based on a single test run.

[6]With json the key *page_number* gets repeated every line, while it is just mentiones once in the beginning of the markdown formatted tables.

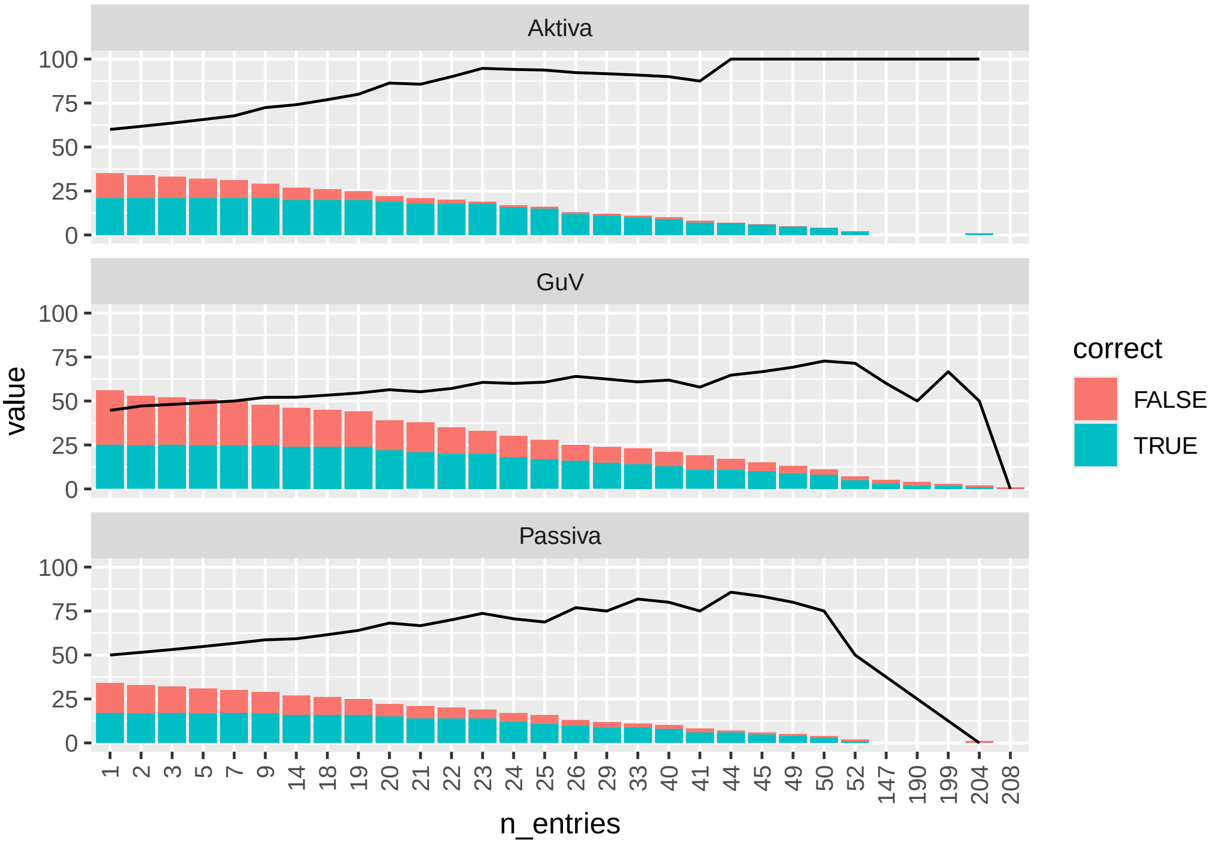

Figure A.7: Showing the amount of correct and incorrect predicted page ranges (bars) and the percentage of correct predictions (black line).

A.3 Classification with LLMs

The third approach we present in this section, uses pretrained LLMs to classify, if a given text extract is including any of the target tables. Two classification approaches are presented.

On the one hand, a binary classification is used three times, to predict, if the text extract is including an **Aktiva**, **Passiva** or **GuV** table, once at a time. In this case the LLM is forced to answer with either *yes* or *no*. On the other hand, the LLM performed a \acr{mcc}. For the mcc (multi-class classification) the LLM is forced to answer *Aktiva*, *Passiva*, *GuV* or *other*. The prompts can be found in appendix in section E.4.2.

The different classification tasks are combined with different prompting strategies. A zero shot approach is setting the baseline. In a second approach the excerpt of the relevant law is provided with the context. Additionally, three few shot approaches are used.

In the few shot approaches text examples and a correct classification for the text examples are provided. Figure A.8 shows how many examples the LLM gets provided, depending on the classification type and chosen parameter *n_example*[7]. For both approaches three example selection strategies are implemented. First, random examples for each page type get sampled from the truth dataset. Second, a vector database provides the entries that are closest to the target text for each page type. Third, the vector database just provides the texts that are closest to the target text without considering the page type of the examples returned.

For the binary classification task the LLM is provided with more examples for the target type than for other types. Thus, the number of examples and tokens is reduced. This should reduce the runtime as well. On the same time the LLM should get enough information about the structure and contents of the target class and some information how it differs from other big tables or general text pages.

For the mcc the same amount of every possible class is provided. Thus, the relation between the parameter *n_examples* and the number of tokens to process is stronger for the *n_random_examples* and *n_rag_examples* strategies.

Table A.7 shows, which models have been used in the classification benchmarks. Overall 21 models from 7 model families have been tested. Prerequirement for a model to be tested is, that it can be used with the vLLM library, accessed via hugging face and fits into the combined VRAM of 8 nvidia B200 graphic cards (1.536 TB). The models cover a wide range of (active) parameter sizes. Especially for the Qwen family many models of different parameter sizes are used in the benchmark, to investigate if there is a clear minimum amount of parameters needed, to solve the classification task.

A

The results of the benchmarks have been logged as json files totaling in 2.1 GB of data for the final results.

To do:

- compare out of company vs in company rag

A.3.1 Binary classification

Table A.8 shows the best performing combination of model family and prompting method for each classification target type. The classification of **GuV** tables works best and is solved almost perfectly. The F1 score for **Aktiva** and **Passiva** are 0.07 lower for the top performing model. The median F1 score of **GuV** is 0.81 0.1 higher than the median F1 score for **Aktiva** (0.84) and 0.2 higher than the median F1 score for **Passiva** (0.79).

Mistral 8B Instruct 2410 is performing best for the binary classification task for each target type. Llama-4-Scout-17B-16E-Instruct is performing second best for **Aktiva** and **GuV** and is close to the second best for **Passiva** as well. The runtime of Mistral 8B Instruct 2410 is four times lower than the runtime of Llama-4-Scout-17B-16E-Instruct. In addition, the time to load Llama-4-Scout-17B-16E-Instruct into the VRAM is much longer[8], because it has a total of 109B parameters. It was surprising that Googles gemma models perform so bad[9].

[7] See also Table F.1.

[8] It takes around 30 minutes to setup a vllm instance with Llama-4 Scout compared to 4:30 minutes setuptime for Mistral 8B 2410.

[9] This is not due to a temporary technical problems caused by a bug in the transformers version shipped with the vllm 0-9-2 image. Those problems have been overcome. The performance stays bad.

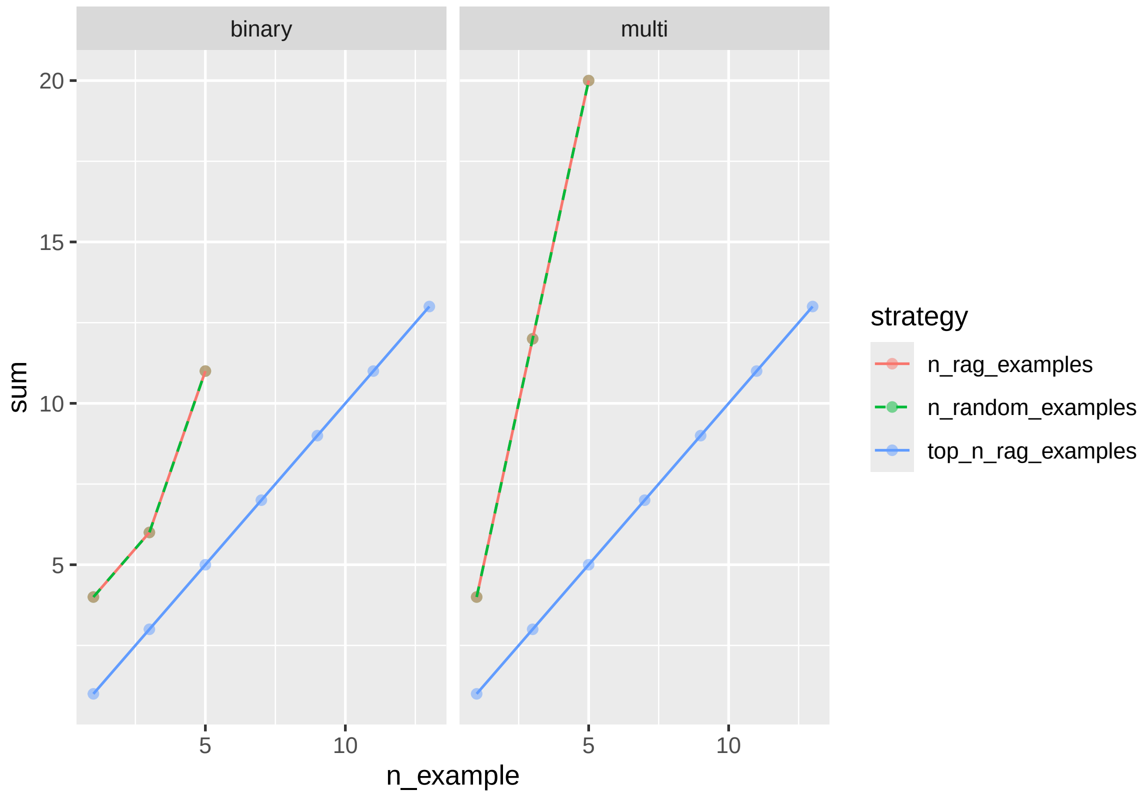

Figure A.8: Comparing the actual number of provided examples depending on the classification type, example selection strategy and chosen parameter n-examples. The slope for the top-n-rag-examples strategy is the same for both approaches. The line for the strategies n-random-examples and n-rag-examples is equal within each approach.

Table A.7: Overview of benchmarked LLMs for the classification tasks.

model_family	model	parameter_count
Falcon3-10B-Instruct	Falcon3-10B-Instruct	10
Llama-3	Llama-3.1-8B-Instruct	8
Llama-3	Llama-3.1-70B-Instruct	70
Llama-3	Llama-3.3-70B-Instruct	70
Llama-4	Llama-4-Maverick-17B-128E-Instruct-FP8	17
Llama-4	Llama-4-Scout-17B-16E-Instruct	17
Ministral-8B-Instruct-2410	Ministral-8B-Instruct-2410	8
Mistral-Large-Instruct-2411	Mistral-Large-Instruct-2411	124
Mistral-Small-3.1-24B-Instruct-2503	Mistral-Small-3.1-24B-Instruct-2503	24
phi-4	phi-4	15
Qwen 2.5	Qwen2.5-0.5B-Instruct	0.5
Qwen 2.5	Qwen2.5-1.5B-Instruct	1.5
Qwen 2.5	Qwen2.5-3B-Instruct	3
Qwen 2.5	Qwen2.5-7B-Instruct	7
Qwen 2.5	Qwen2.5-14B-Instruct	14
Qwen 2.5	Qwen2.5-32B-Instruct	32
Qwen 2.5	Qwen2.5-72B-Instruct	72
Qwen 3	Qwen3-8B	8
Qwen 3	Qwen3-30B-A3B-Instruct-2507	30
Qwen 3	Qwen3-32B	32
Qwen 3	Qwen3-235B-A22B-Instruct-2507	235

Table A.8: Overview of benchmarked LLMs for the binary classification tasks. Limiting the number of examples provided for the few shot approach to 3.

model_family	model	classification_type	method_family	n_examples	f1_score
mistralai	Ministral-8B-Instruct-2410	GuV	n_rag_examples	3	0.99
Llama-4	Llama-4-Scout-17B-16E-Instruct	GuV	n_rag_examples	3	0.98
Qwen 2.5	Qwen2.5-32B-Instruct	GuV	n_rag_examples	1	0.93
mistralai	Ministral-8B-Instruct-2410	Passiva	n_rag_examples	3	0.92
mistralai	Ministral-8B-Instruct-2410	Aktiva	n_rag_examples	3	0.92
Llama-4	Llama-4-Scout-17B-16E-Instruct	Passiva	n_rag_examples	3	0.86
Qwen 2.5	Qwen2.5-32B-Instruct	Aktiva	n_rag_examples	1	0.85
Qwen 3	Qwen3-235B-A22B-Instruct-2507	Aktiva	n_rag_examples	3	0.85
Llama-4	Llama-4-Scout-17B-16E-Instruct	Aktiva	n_rag_examples	1	0.84
Llama-4	Llama-4-Scout-17B-16E-Instruct	Aktiva	n_rag_examples	3	0.84
Qwen 2.5	Qwen2.5-32B-Instruct	Passiva	n_rag_examples	1	0.81
Qwen 3	Qwen3-235B-A22B-Instruct-2507	Passiva	n_rag_examples	3	0.79
Llama-3	Llama-3.1-70B-Instruct	Aktiva	n_rag_examples	1	0.79
Llama-3	Llama-3.1-70B-Instruct	Aktiva	n_rag_examples	3	0.79
Llama-3	Llama-3.1-70B-Instruct	Passiva	n_rag_examples	1	0.76
microsoft	phi-4	Aktiva	law_context	1	0.7
Llama-3	Llama-3.1-70B-Instruct	GuV	law_context	1	0.69
Qwen 3	Qwen3-30B-A3B-Instruct-2507	GuV	n_rag_examples	3	0.68
microsoft	phi-4	Passiva	law_context	1	0.66
tiiuae	Falcon3-10B-Instruct	Passiva	n_random_examples	1	0.5
tiiuae	Falcon3-10B-Instruct	Aktiva	n_rag_examples	1	0.45
tiiuae	Falcon3-10B-Instruct	GuV	top_n_rag_examples	1	0.34

Figure A.9 shows, the classification performance for Mistral 8B 2410 in detail. It shows the F1 score for each target type over the models runtime. It shows the results for the different prompting strategies (*method_families*) with differently colored shapes. The *zero_shot* strategy performs worst with a F1 score below 0.6. Next come the *law_context* and *top_n_rag_examples* strategy. Above those the *n_random_examples* and finally the *n_rag_examples* strategy perform best.

The shape is giving information, if the example proveded to the LLM are selected from other companies than the target table comes from only, or if they can also be selected from documents of the same company. This is only relevant for strategies that get the examples picked by the documents vector embedding distances. The LLM performs better[10], if examples from documents of the same company can be used. If this is not permitted, the *n_random_example* approach performs better than the *n_rag_example* for the classification of **GuV** and **Passiva** tables.

The number inside of the shapes is referring to the *n_examples* function parameter. Most models got benchmarked with an *n_examples* value of up to three. The actual number of examples provided to the models is depending on the method family / example selection strategy and can be looked up in Table F.1.

The best performing model, Mistral 8B 2410, was provided with mode examples to investigate the effect of a richer context. The predictions do not get better by providing more and more examples. Figure A.9 shows, that the improvements get smaller naturally going from three to five examples while approaching an F1 score of 1.0.

But for the *n_rag_example* strategy we find a significant drop in the F1 score, if we set the *n_examples* to five[11] and examples pages come from annual reports of other companies. This is caused by a sever recall drop. For the *n_random_example* strategy we see a small drop with the F1 score for the class **Passiva** as well. Taking into account that the runtime also almost is twice as high, this is very inefficient.

[10] It has a better F1 score, when examples from the same company are permitted. The recall is better with examples from same company. The precision is better without. The improvement in the recall is stronger.

[11] In this case five examples for the target table type and two examples for each other type are provided, totaling at twelve examples.

Figure A.9 also shows, that the results are stable[12]. Running the benchmark three times shows similar results in the F1 score for each strategy. This is reflected by closely overlapping shapes of the same color with the same number within.

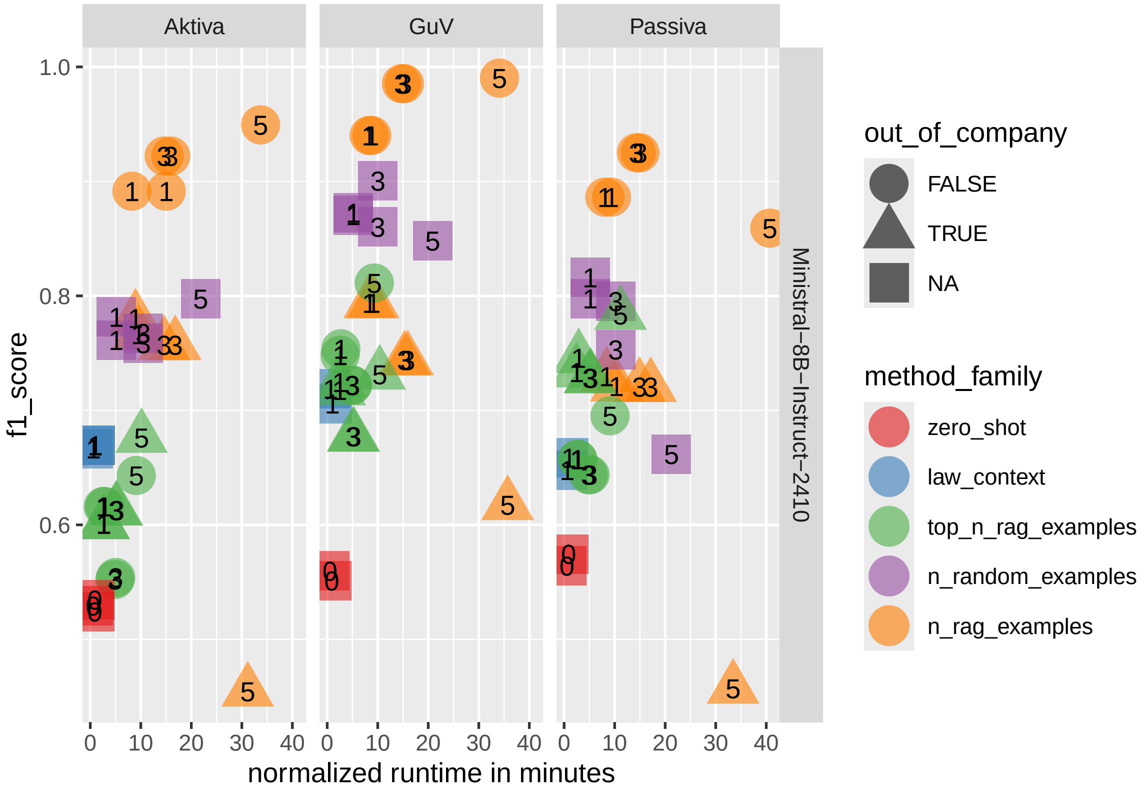

Figure A.9: Showing F1 score performance over normalized runtime for binary classification for Mistral-8B-Instruct-2410.

Figure A.10 shows the experiments for Ministral-8B-Instruct-2410 with *n_examples* greater or equal three. This time the actual number of examples provided to the LLM are shown in the shapes to increase the comparability among the different strategies. Additionally, it shows results for the *top_n_rag_example* strategy with *n_examples* up to 13. The F1 score of the *top_n_rag_example* strategy stays lower than the F1 score of the *n_rag_examples* strategy, even though there are more examples used. This is mainly caused by lower precision scores, probably because there are no contrasting examples provided.

Figure G.4 and Figure G.5 shows the F1 performance over normalized rundtime for all benchmarked models. Comparing Mistral-8B-Instruct-2410 with Mistral-124B-Instruct-2411 shows that one can spend over tenfold amount of computation power without getting better results.

It also shows, that with Qwen 2.5 it needs at least the 3B parameter model to achieve good results. Comparing the 32B and 72B parameter models shows, that th performance does not increase anymore, but starts to decrease. For Qwen 3 it shows, that only the newer mix of experts models give reasonable results.

The mix of expert models show good performance for the Llama 4 family as well and reduce the compute time compared with the 72B models of LLama 3. But for LLama 4 Maverick the performance drops using the *n_rag_examples* strategy with three *n_examples*. The performance of Llama 3.1 70B was higher than the performance of Llama 3.3 70B.

Summary:

Neither do newer generations always improve the performance for the binary classification task, nor do more parameters always improve or at least show stable performance.

[12]Earlier experiments on a subset of the pages have been run five times indicating stable results. Running the experiments up to tree times in this very task indicate this as well.

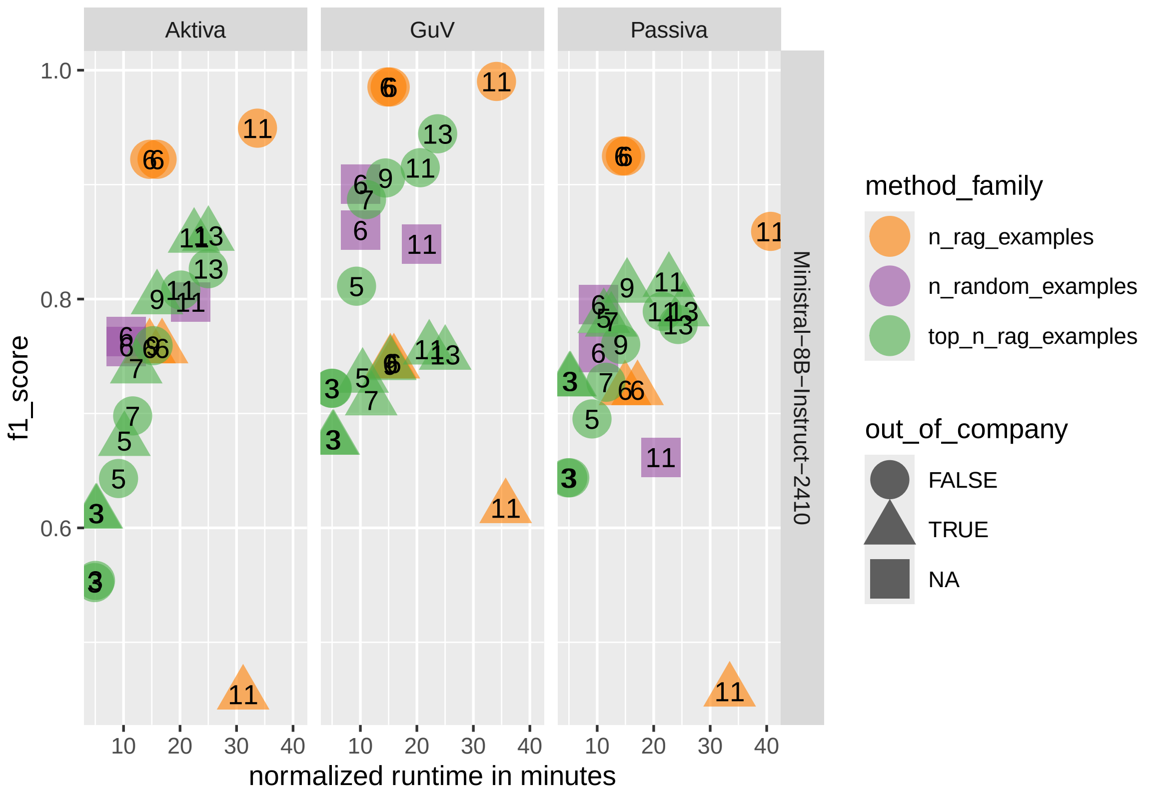

Figure A.10: Showing F1 score performance over normalized runtime for binary classification for Mistral-8B-Instruct-2410. Comparing the performance based on the real number of provided examples.

A.3.2 Multi-class classification

Table A.9 shows that Llama-4-Scout solves the mcc task almost perfect for all classes. Mistral-Large-Instruct-2411 performs second best. In contrast to the binary classification task no order is visible, what class was easiest to predict. Googles gemma models perform much better in the mcc task with F1 scores of 0.89 instead of 0.58 for the binary classification task.

Table A.10 shows that the smaller models do perform good, too. Ministral-8B performs good but is around tenfold faster than Mistral-Large and Llama-4 Scout. For the larger models the *n_rag_examples* strategy is performing best. For the smaller models the *top_n_rag_examples* strategy is performing good as well and is faster because of shorter contexts.

Figure A.11 shows, the micro averaged F1 score for the three minority classes over the normalized runtime for two models. It shows the results for the different prompting strategies (*method_families*) with differently colored shapes.

The shape is giving information, if the examples provided to the LLM, are exclusively selected from other companies than the target table comes from, or if they can also be selected from documents of the same company. This is only relevant for strategies that get the examples picked by the documents vector embedding distances (*top_n_rag_examples* and *n_rag_examples*). The LLM performs better, if examples from documents of the same company can be used.

The number inside of the shapes is referring to the *n_examples* function parameter. Most models got benchmarked with an *n_examples* value of up to three. The actual number of examples provided to the models is depending on the method family / example selection strategy and can be looked up in Table F.1.

n_rag_examples better for Llama 4 Scout than *n_random_examples* ; For Ministral it is depending on the *out_of_company* setting

On can see, that Ministral–8B 2410 reaches a good performance already with few examples, but only if *out_of_company* is false. It performs moderate with the *law-context* strategy and *zero_shot*, too. Adding more examples does not improve the performance. Best with *top_n_rag_examples*

Table A.9: Overview of benchmarked LLMs for the multiclass classification tasks. Limiting the number of examples provided for the few shot approach to 3.

model_family	model	metric_type	method_family	n_examples	f1_score	runt
Llama-4	Llama-4-Scout-17B-16E-Instruct	Aktiva	n_rag_examples	3	1	
Llama-4	Llama-4-Scout-17B-16E-Instruct	GuV	n_rag_examples	1	1	
mistralai	Mistral-Large-Instruct-2411	Passiva	n_rag_examples	1	0.99	
Llama-4	Llama-4-Scout-17B-16E-Instruct	Passiva	n_rag_examples	3	0.99	
mistralai	Mistral-Large-Instruct-2411	Aktiva	n_rag_examples	3	0.98	
Qwen 2.5	Qwen2.5-32B-Instruct	Aktiva	n_rag_examples	3	0.98	
Qwen 3	Qwen3-235B-A22B-Instruct-2507	GuV	n_rag_examples	3	0.97	
Qwen 2.5	Qwen2.5-72B-Instruct	Passiva	n_rag_examples	1	0.97	
Qwen 3	Qwen3-30B-A3B-Instruct-2507	Aktiva	n_rag_examples	3	0.96	
Llama-3	Llama-3.1-70B-Instruct	Aktiva	top_n_rag_examples	3	0.96	
mistralai	Mistral-Large-Instruct-2411	GuV	n_rag_examples	1	0.96	
Llama-3	Llama-3.1-8B-Instruct	Passiva	n_rag_examples	1	0.95	
Qwen 3	Qwen3-235B-A22B-Instruct-2507	Passiva	n_rag_examples	3	0.95	
Qwen 2.5	Qwen2.5-72B-Instruct	GuV	n_rag_examples	3	0.91	
tiiuae	Falcon3-10B-Instruct	GuV	n_rag_examples	1	0.71	
tiiuae	Falcon3-10B-Instruct	Aktiva	n_rag_examples	3	0.71	
microsoft	phi-4	Passiva	n_rag_examples	2	0.67	
Llama-3	Llama-3.1-8B-Instruct	GuV	top_n_rag_examples	1	0.65	
microsoft	phi-4	Aktiva	n_random_examples	1	0.6	
tiiuae	Falcon3-10B-Instruct	Passiva	top_n_rag_examples	3	0.59	
microsoft	phi-4	GuV	n_rag_examples	1	0.46	

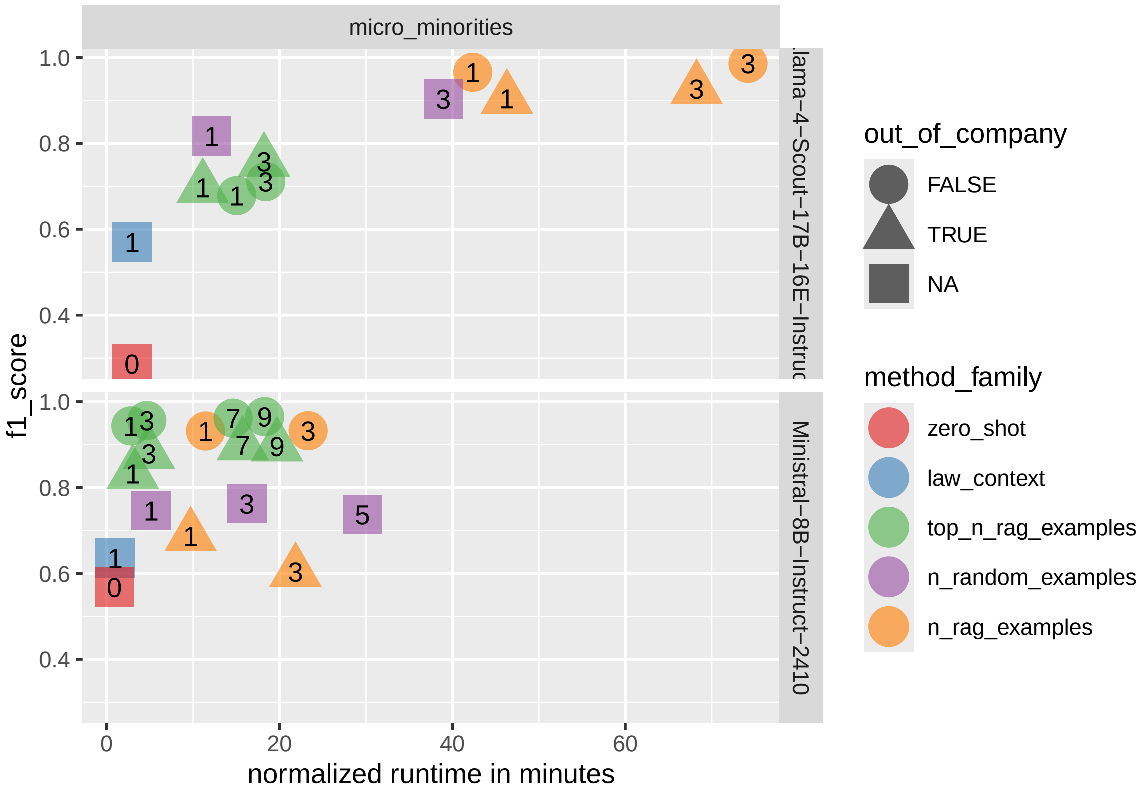

Figure A.11: Comparing F1 score micro averaged for the minority classes for two models over their normalized runtime.

Table A.10: Overview of benchmarked LLMs for the multiclass classification tasks focussing on models with less than 17B parameters. Limiting the number of examples provided for the few shot approach to 3.

model_family	model	metric_type	method_family	n_examples	f1_score	runtime in s
mistralai	Ministral-8B-Instruct-2410	Aktiva	n_rag_examples	1	0.98	686
mistralai	Ministral-8B-Instruct-2410	Passiva	top_n_rag_examples	3	0.96	279
mistralai	Ministral-8B-Instruct-2410	GuV	top_n_rag_examples	3	0.95	279
Llama-3	Llama-3.1-8B-Instruct	Passiva	n_rag_examples	1	0.95	593
Qwen 2.5	Qwen2.5-3B-Instruct	Aktiva	n_rag_examples	1	0.86	492
Llama-3	Llama-3.1-8B-Instruct	Aktiva	top_n_rag_examples	3	0.86	269
Qwen 2.5	Qwen2.5-3B-Instruct	Passiva	top_n_rag_examples	1	0.83	187
Qwen 2.5	Qwen2.5-3B-Instruct	GuV	n_rag_examples	1	0.76	492
tiiuae	Falcon3-10B-Instruct	GuV	n_rag_examples	1	0.71	868
tiiuae	Falcon3-10B-Instruct	Aktiva	n_rag_examples	3	0.71	2393
microsoft	phi-4	Passiva	n_rag_examples	2	0.67	1660
Llama-3	Llama-3.1-8B-Instruct	GuV	top_n_rag_examples	1	0.65	205
microsoft	phi-4	Aktiva	n_random_examples	1	0.6	493
tiiuae	Falcon3-10B-Instruct	Passiva	top_n_rag_examples	3	0.59	494
microsoft	phi-4	GuV	n_rag_examples	1	0.46	1725
Qwen 3	Qwen3-8B	Aktiva	law_context	1	0.07	63
Qwen 3	Qwen3-8B	Passiva	n_rag_examples	3	0.07	1346
Qwen 3	Qwen3-8B	GuV	n_rag_examples	1	0	680
Qwen 3	Qwen3-8B	GuV	n_rag_examples	1	0	636
Qwen 3	Qwen3-8B	GuV	n_random_examples	1	0	318
Qwen 3	Qwen3-8B	GuV	n_rag_examples	3	0	1346
Qwen 3	Qwen3-8B	GuV	n_rag_examples	3	0	1300
Qwen 3	Qwen3-8B	GuV	n_random_examples	3	0	973
Qwen 3	Qwen3-8B	GuV	law_context	1	0	63
Qwen 3	Qwen3-8B	GuV	top_n_rag_examples	1	0	178
Qwen 3	Qwen3-8B	GuV	top_n_rag_examples	1	0	330
Qwen 3	Qwen3-8B	GuV	top_n_rag_examples	3	0	299
Qwen 3	Qwen3-8B	GuV	top_n_rag_examples	3	0	329
Qwen 3	Qwen3-8B	GuV	zero_shot	0	0	55

A

A.4 Term frequency based classifier

The fourth approach uses term frequencies for a key word list and the number of floats to rank pages. The approach is inspired by TF-IDF - a technique commonly used for information retrieval. It is similar to the baseline approach, because it uses a key word list and regular expressions to count terms and floats. But it is more flexible because the works in the key word list are not mandatory. This makes the approach robust against issues in the text extracts for single key words.

The key word list is generated removing the stop words from the law about **Aktiva**, **Passiva** and **GuV**. The key words from the regex approach are added, e.g. *GuV* and *Gewinn- und Verlustrechnung*. Since real life representations of those target types never contain all entries, it is not possible to include most of those words in a strict regex search as presented in the first approach.

This approach sums the counts of each word from the key word list per page in a first variable. In a second variable it counts the number of floats on each page. These two variables are then divided by the number of words found on the page. These densities are used to rank all pages from a single document. This is done with a unique key word list for each target type.

A random forest is trained to determine which density should be weighted to what amount. Because of the imbalanced data set undersampling is used when the training data set is created[13]. A single random forest is trained because the density of floats and specific words is assumed to be similar. The actual type of the page is not taken into account. The model just knows if the page is a page of any target type, based on the term and float density. This trippels the data points of the target class.

This single random forest performs much better than random forests that are trained using the dataset for each target type separatly. The performance is tested on all data points not included in the undersampled train dataset. Thus the test dataset is again highly imbalanced.

The random forest performs a binary classification task. But instead of the actual classifications, the predicted scores are used to rank the pages. Instead of precision or recall the metric used for the evaluation is top k recall. It is of interest which value of k is required to get a recall of 100 %.

The code can be found at: "benchmark_jobs/page_identification/term_frequency.ipynb"

- top 1
- top k

low precision llm linked to position of correct page? numeric frequency?

Figure A.12 shows how the test data points are distributed in the two dimensional value map for the random forest with two predictors. The target pages have a *float_frequncy* between 0.2 and 0.5 and pages with a *term_frequency* value over 0.07 get classified as target. One target page shows a lower *term_frequency* and thus does not get ranked correct. (recall, precision?)

A second random forest is trained supplementing the two predictors *term density* and *float density* with two additional predictors: *date count* and *integer count*. Figure A.13 shows the top n recall for both random forests. On the left side the top n recall on the imbalanced test dataset is shown. On the right side the performance on the train dataset.

Both random forests perform similar on the train dataset. The random forest with four predictors reaches perfect recall faster for **Aktiva** on the test dataset. Thus, with $n = 5$ 100 % recall is reached for the random forest with four predictors. With the random forest with two predictors it needs $n = 7$.

Figure A.14 shows that the two additional predictors *date_count* and *integer_count* have little importance. But since it is computationally cheap to determine their value and the effiency of a random forest classifier, there is little reason not to use them.

Fianlly, figure A.15 shows the precision-recall-curves for the term frequency approach for all three target types. The AUC (area under the curve) for all types is below 0.5. The precision and F1 score stay below 0.5 as well. A high recall can be maintained for all types for threshold values up to at least 0.72.

[13] The random forest build with undersampling performs much better as a classifier, that is trained using n oversamples train dataset.

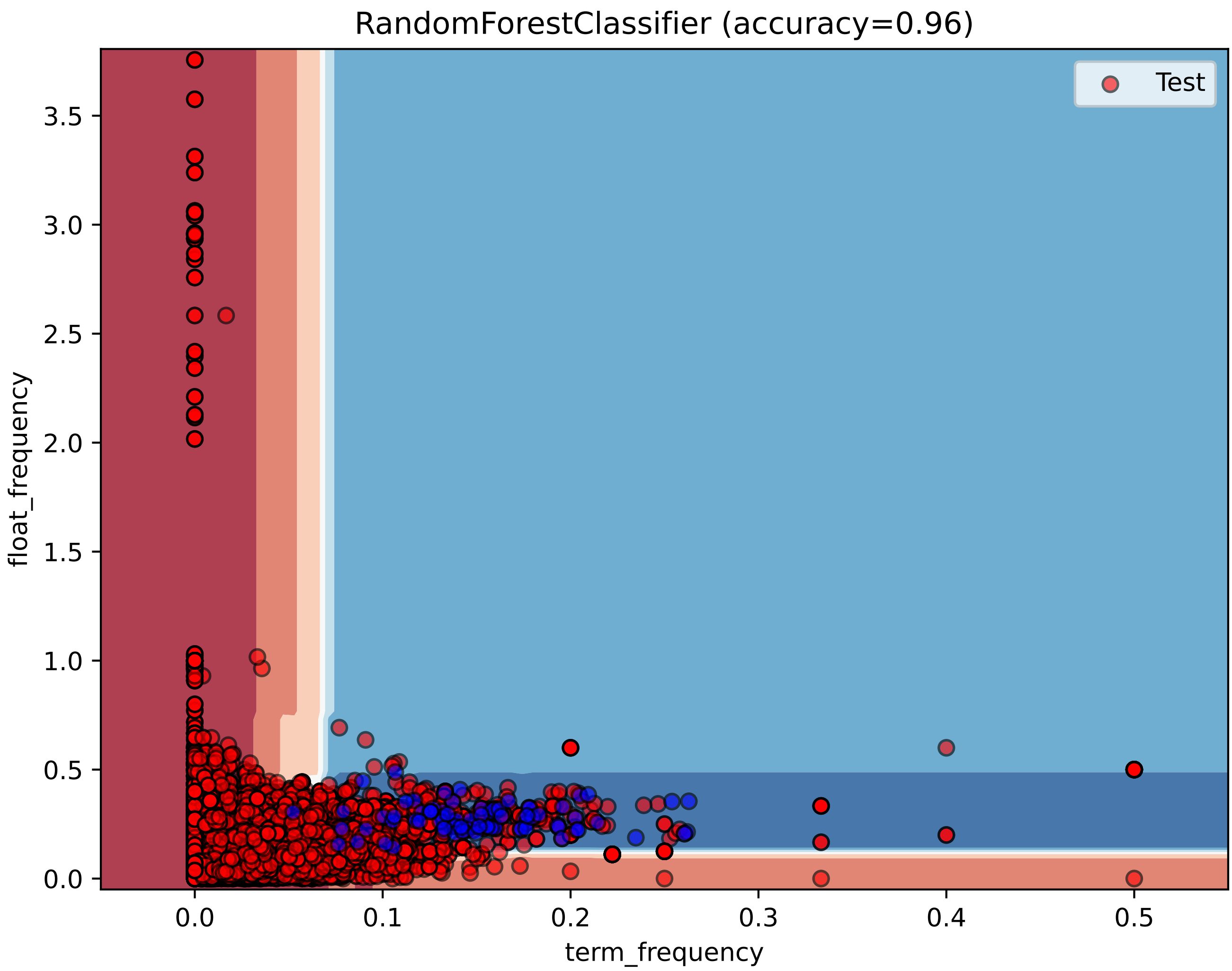

Figure A.12: Classification map showing which score a data point gets based on its term and float frequency and which type the data points in the test dataset actually have.

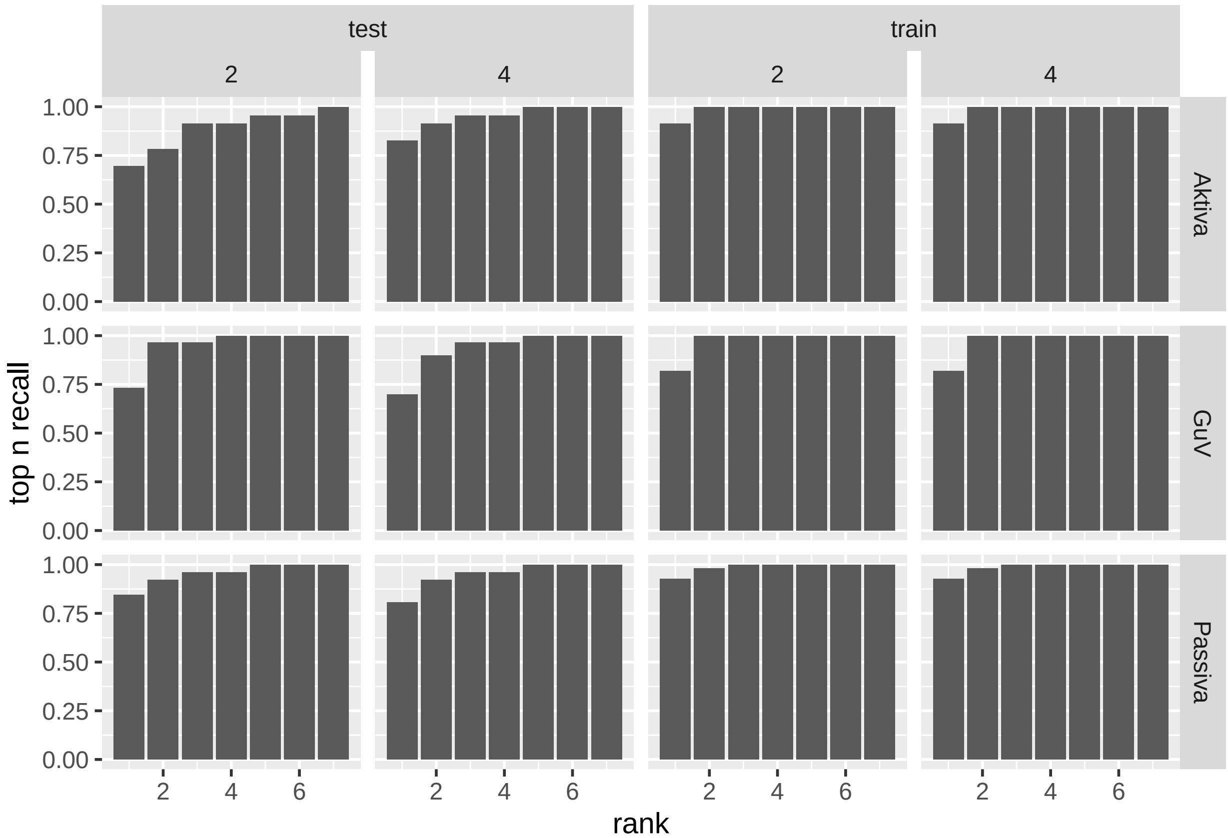

Figure A.13: Comparing the top n recall on training and test dataset among the random forest with two and four predictors.

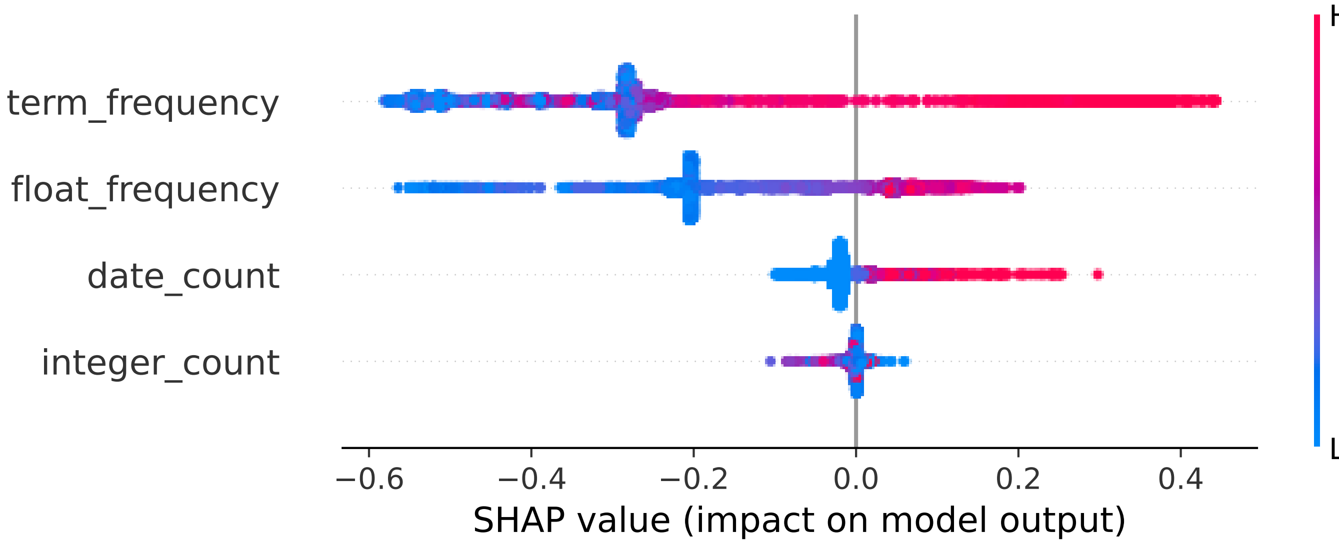

Figure A.14: Beeswarm plot of SHAP importance values for the four predictors of the second random forest classifier.

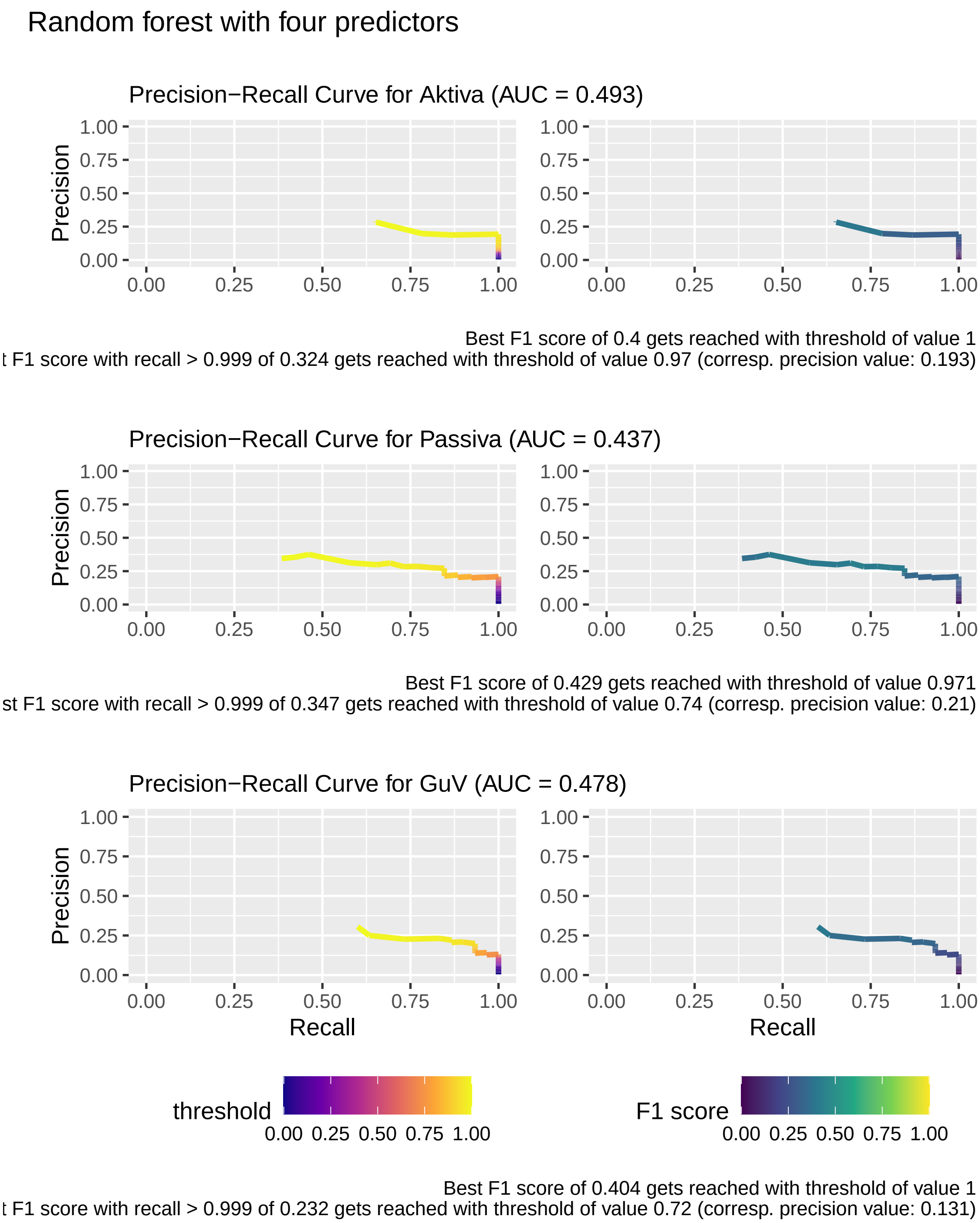

Figure A.15: Showing the precsion-recall-curve for the random forest with four predictors.

A.5 Summary

A

Appendix B

Appendix B - Information extraction report

The second research question asks, how LLMs can be used, to effectively extract specific information from a financial report. The task for this thesis is to extract the numeric values for the assets (*Aktiva*) table, which is part of the balance sheet (*Bilanz*). Hereafter, the German term **Aktiva** will be used. We are limiting the scope even further than in subsection 5.1, because it takes more time to manually create the first reference dataset.

B.1 Baseline: Regex

The baseline for the table extraction task is set by an approach using regular expressions on the text extract. Figure B.1 shows the performance of this approach. In the first row (A) the percentage of correct predicted numeric values and the percentage of total correct responses is shown. The second row (B) shows the precision, recall and F1 score for identifying a value as missing and thus predicting *null*. The percentage of total correct responses is calculated as

$$percentage\_correct\_total = \frac{n_{correct\_numeric} + n_{missing\_true\_positive}}{n_{total\_entries}}$$

with $n_{total\_entries} = 58$. This implies that the correct prediction of missing values has more influence for tables, that have only a few numeric values in the ground truth. The minimal number of numeric values in a tables is ten. Figure G.1 shows, that the percentage of total correct responses is not a sufficient metric, because responses that only predicted *null* can have a high score if there are only a few numeric values in the ground truth table.

Performance In each frame there are two groups of two box-plots. The left group is showing the performance on real **Aktiva** tables. The right group shows the performance on synthetic **Aktiva** tables. Within the group the green (left) box shows the performance on text extracted with the *pdfium* library. The peach colored (right) box shows the performance on text extracted with the *pymupdf* library.

Figure B.1 shows, that the regex approach performs better[1] on the synthetic tables compared to the real tables. Even though, the performance is not perfect and more consistent on the text extracted with *pymupdf* compared to *pdfium*. In contrast, the used text extraction library has no noticeable influence on the real **Aktiva** tables.

The performance for the regex based table extraction is much better than the regex based page identification performance. The median performance scores of the regex approaches will be reflected by a dashed line in the box-plots in subsequent sections. The scores for the real **Aktiva** table extraction are:

[1] A comparison of the numeric values over all methods can be found in section 5.2.2.

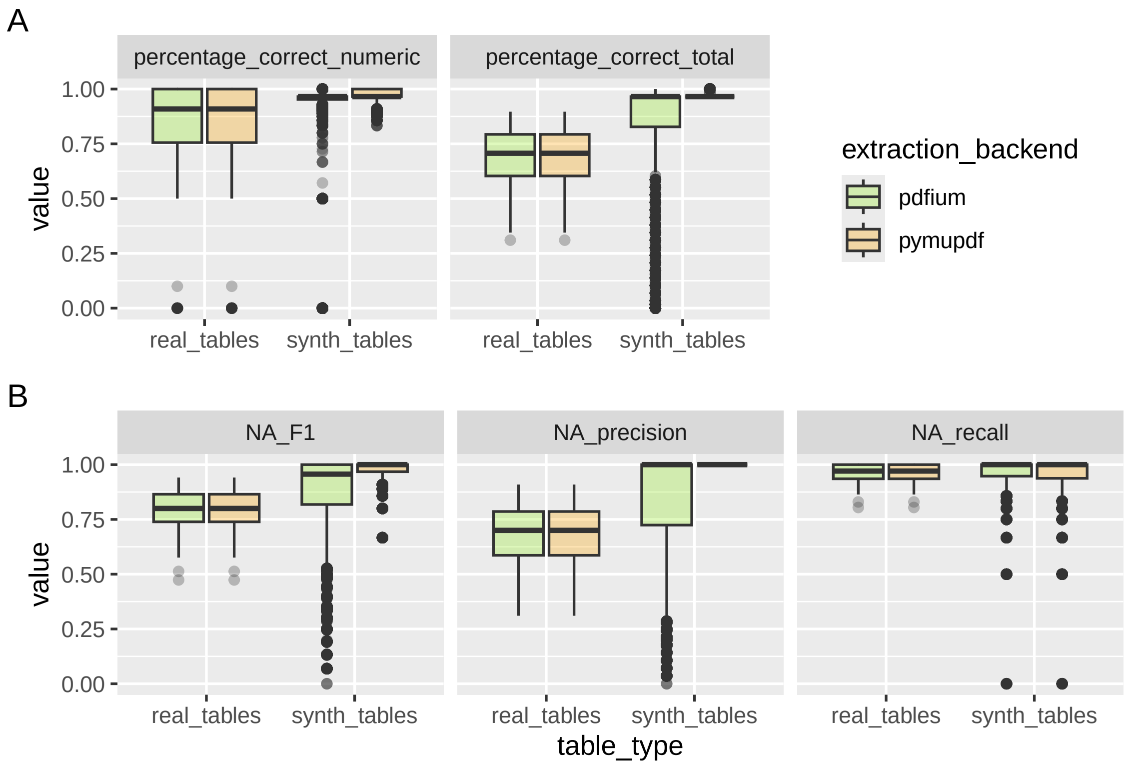

Figure B.1: Performance overall and on numeric value extraction with regular expressions.

B

Table B.1: Summarizing the median performance of the regex approaches for the real and synthetic table extracion task.

measure	real_mean	real_median	synthetic_mean	synthetic_median
percentage of correct predictions total	0.686	0.707	0.969	0.966
percentage of correct numeric predictions	0.778	0.909	0.973	0.966
F1 score	0.789	0.800	0.979	1.000

The difference in the precision scores for the regex approach on synthetic tables is discussed in section 6.2.3.2.

B.2 Extraction with LLMs

This section presents the results for the table extraction task performed with LLMs on **Aktiva** tables. Subsection B.2.1 compraes the performance of open source models on real tables. It also compares those results with the table extraction performance achieved with models by OpenAI.

Subsection B.2.2 presents the results on synthetic **Aktiva** tables. Subsection B.2.3 shows a hybrid approach, where synthetic tables are used for the in-context learning, to extract real **Aktiva** tables. Finally, we summarize the results for all approaches in subsection 5.2.2.

- confidence usable to head for user checks?
- not handled new entries
- five examples bring not much more, but a little

Explain *static_example* method.

B.2.1 Real tables

Performance For the table extraction task 32 open source models from 9 model families have been benchmarked[2]. Table B.2 shows the best performing combination of LLM and prompting strategy for each model family. The results are sorted by their mean percentage of total correct predictions. It also shows the normalized runtime in seconds and the parameter number of the model.

Qwen3-235B-A22B-Instruct performed best with a mean score of 0.97. This is equal with the performance that we achieved building the ground truth dataset. There are other models that perform almost as good with a score of 0.96 and more, but that don't match the human performance. These models show a median score of 1.0. Qwen3-235B-A22B-Instruct is the second fastest of those well performing models and needs less than six minutes. Only Llama 4 Maverick is faster. It needs half the time to extract the information.

Table B.3 shows the performance of models with less than 17B parameters, that have not been listed above. Qwen3-14B performs best among the smaller models achieving a mean of 0.93 and median of 1.0. It takes 1:49 minutes to extract the information from all **Aktiva** tables. Ministral-8B-Instruct does not perform as good as in the page identification task.

Most models need a context learning approach to beat the performance of the regular expression approach at total and numeric correctness rate and F1 score. Table B.4 shows, that 3 models perform better without

[2] The models *deepseek-ai_DeepSeek-R1-Distill-Qwen-32B* and *google_gemma-3n-E4B-it* have been tested as well but don't get presented as they never performed anywhere beyond random guessing.

Table B.2: Comparing best table extraction performance with real 'Aktiva' dataset for each model family

model_family	model	method_family	n_examples	parameter_count	m
Qwen 3	Qwen3-235B-A22B-Instruct-2507-FP8	top_n_rag_examples	5	235	
mistralai	Mistral-Large-Instruct-2411	top_n_rag_examples	5	124	
Qwen 2.5	Qwen2.5-72B-Instruct	top_n_rag_examples	5	72	
Llama-4	Llama-4-Maverick-17B-128E-Instruct-FP8	top_n_rag_examples	1	402	
Llama-3	Llama-3.1-70B-Instruct	top_n_rag_examples	5	70	
microsoft	phi-4	top_n_rag_examples	2	15	
openai	gpt-oss-120b	top_n_rag_examples	5	120	
tiiuae	Falcon3-10B-Instruct	top_n_rag_examples	3	10	
google	gemma-3-27b-it	top_n_rag_examples	3	27	

Table B.3: Comparing best table extraction performance with real 'Aktiva' dataset for each model family for models with less than 17B parameters. Models that have been listes in the previous table are not listed again.

model_family	model	method_family	n_examples	parameter_count	mean_total	media
Qwen 3	Qwen3-8B	top_n_rag_examples	5	8	0.927	
Qwen 2.5	Qwen2.5-14B-Instruct	top_n_rag_examples	5	14	0.925	
mistralai	Ministral-8B-Instruct-2410	top_n_rag_examples	5	8	0.895	
Llama-3	Llama-3.1-8B-Instruct	top_n_rag_examples	5	8	0.832	
google	gemma-3-12b-it	top_n_rag_examples	3	12	0.811	

any guidance[3]. 6 models achieved an performance better than the regex baseline using the approach to learn with a fixed example from the synthetic dataset.

In contrast: most of the models achieved a better performance than the regex baseline when they were provided with one or more examples from real **Aktiva** tables. Table B.5 shows, that 11 don't consitently achieve a better score, when provided with three or five real **Aktiva** table examples. Here we find the smallest models with less than 2B parameters which don't achieve a consistence performance no matter how many examples they get. But we also find models that start to perform bad if they get a too long context with too many examples like the very recent and large model Llama 4 Maverick.

The results for all models are presented in Figure G.15, G.16 and G.17. In general the performance within a model family is positive correlated with the models number of parameters, if we provide real **Aktiva** examples. Once the 4B parameters are passed, the improvements get less and less, approaching the perfect performance. But no model achieves sperfect result on all documents. The *zero_shot* and *static_example* approach show some unpredicted performance drop, i.e. for Qwen3-14B.

OpenAI models Even though a lot of documents to process at RHvB will not be public and thus must not be processed on public cloud infrastructure, the performance of models like OpenAI's GPT are interesting benchmark references within this thesis and for comparing these findings with other papers results. Therefore for this thesis the public available versions of annual reports have been used instead of the ones used internally or for public administration purposes. Those public available reports often are visually more appealing and more heterogeneous in their structure.

Table @ref(tab.table-extraction-llm-performance-total-gpt-ranking) shows the ranking for the best model-method combinations Qwen3 235B is performing best. gpt-4.1 and gpt-5-mini perform equally well and are almost as good as Qwen3 235B. All models but gpt-4.1-nano, gpt-5-nano and Qwen3-0.6B manage to beat the regex threshold. Qwen3-0.6B performs better than the nano models once it gets provided with an example.

Table B.7 shows the accumulated costs for the table extraction task for the models provided by Azure. Using gpt-4.1 is most expensive, followed by gpt-5-mini. Next is gpt-5-nano. This is caused by an unexpected

[3] There is an external guidance through the provided xgrammar template but it is not communicated to the model in form of a promt.

Table B.4: Comparing table extraction performance with real 'Aktiva' dataset for models that perform well without or with little context learning

model	median_total_zero_shot	median_total_static_example
Llama-4-Maverick-17B-128E-Instruct-FP8	**0.897**	0.922
Qwen3-235B-A22B-Instruct-2507-FP8	**0.897**	**0.931**
gpt-oss-120b	**0.897**	0.897
Qwen2.5-32B-Instruct	NA	**0.931**
Qwen2.5-72B-Instruct	NA	0.897
Qwen3-30B-A3B-Instruct-2507	NA	0.879

Table B.5: Comparing table extraction performance with real 'Aktiva' dataset for models that perform worse than the regex baselin with 3 or 5 examples for incontext learning

model	method	parameter_count	median_total
Llama-3.1-8B-Instruct	3_random_examples	8	0.81
Llama-4-Maverick-17B-128E-Instruct-FP8	5_random_examples	**402**	0.017
Qwen2.5-0.5B-Instruct	3_random_examples	0.5	0.586
Qwen2.5-1.5B-Instruct	3_random_examples	1.5	0.724
Qwen2.5-3B-Instruct	3_random_examples	3	0.759
Qwen2.5-7B-Instruct	3_random_examples	7	0.862
Qwen3-0.6B	3_random_examples	0.6	0.612
Qwen3-1.7B	3_random_examples	1.7	0.776
gemma-3-12b-it	3_random_examples	12	0.793
gemma-3-4b-it	3_random_examples	4	0.664
gpt-oss-20b	3_random_examples	20	**0.897**

high cost for output tokens. In general we find, that the ratio of output costs to input costs is much higher for gpt-5 models. Since gpt-5-mini gives consistently good results already with one provided example, this could be the most cost efficient strategy. But it takes gpt-5-mini more than three times longer to respond than gpt-4.1.

Discussion?:

Since the output token costs are not that different (2 $ for 1M output tokens with gpt-5-mini vs 1.6 $ with gpt-4.1-mini), the generated output token number has to be much higher for the gpt-5-mini models. But since the responses are based on the same schema and required the same numeric values there shouldn't be a big difference[4].

Figure B.2 shows the distribution of F1 score for up to three examples. It shows green crosses at the bottom of the abscissa that indicate prediction, where no *null* value is reported. This means, the model hallucinates many numeric values. This is only the case for OpenAI's models but not for Qwen3 models. This behaviour persists up to five examples for the nano as well the gpt-oss 20b model. For gpt-4.1 and gpt-4.1-mini these cases vanish when we provide three or more examples and never appeared for gpt-5-mini.

One can find the full plots in Figures G.19, G.20 and G.21).

[4]With the gpt-oss models we found the new Harmony response format to produce a lot of tokens in the chain of thought stream, we discarded, because we only need the json in the final stream Maybe this is similar for gpt-5 models as well but the chain of thought stream is kept on Azures side?

B

Table B.6: Comparing table extraction performance with real 'Aktiva' dataset for OPenAIs GPT models with a selection of Qwen3 models.

model	method	mean_percentage_correct_total	median correct total
Qwen3-235B-A22B-Instruct-2507-FP8	5_random_examples	0.97	1
gpt-4.1	top_5_rag_examples	0.95	0.97
gpt-5-mini	top_5_rag_examples	0.95	0.97
Qwen3-30B-A3B-Instruct-2507	top_5_rag_examples	0.92	0.97
gpt-4.1-mini	top_3_rag_examples	0.91	0.96
Qwen3-8B	top_5_rag_examples	0.89	0.93
gpt-oss-120b	5_random_examples	0.88	0.93
gpt-oss-20b	3_random_examples	0.84	0.9
Qwen3-0.6B	5_random_examples	0.65	0.65
gpt-5-nano	3_random_examples	0.3	0.24
gpt-4.1-nano	zero_shot	0.21	0.14

Table B.7: Comparing the costs for OpenAIs GPT models provided by Azure. Notice the high output cost for GPT 5 Nano.

model	cost_input	cost_output	cost_total	median runtime in minutes
gpt-4.1	18.07	10.35	28.42	29:53
gpt-5-mini	1.93	10.28	12.21	110:50
gpt-5-nano	0.41	6.99	7.4	135:37
gpt-4.1-mini	3.76	2.02	5.78	31:48
gpt-4.1-nano	0.08	0.06	0.14	10:28

We were not able to get OpenAI's models to stick to the provided json schema strictly. Passing the ebnf grammar did not work at all. This means that with gpt-4.1-nano there have been 88 predictions that have been completely empty. For gpt-5-nano we find 6 such predictions. Figure @red(fig:table-extraction-llm-prediction-count-gpt) shows the distribution of responses with a wrong number of predictions (including *null* and numeric predictions). Overall there have been 34.3 % of the responses of OpenAI's models that were compatible with the schema but had a wrong number of rows predicted. The maximum number of returned values (by gpt-5-nano) is 714.

Using gpt-5-chat for the table extraction task with structured output is not working, returning an error informing that a *json_schema* can't be used with this model. Figure B.4 shows, where other models produced an answer that could not be parsed as valid json.Most errors occured for gpt-oss-20B and the *static_example* method. Over half of all tables could not be transcripted in json with in the 40_000 response token limit[5]. Only with gpt-5-mini we had no json parsing error.

Examples from same company performance Table B.8 shows the improvement for the percentage of correct predictions total, when **Aktiva** tables from the same company as the target tables company are provided for the in-context learning. It shows that this improvement is biggest for goolge and Qwen and smallest for Llama models.

Figure G.18 shows, that using **Aktiva** in-company examples improves the performance, mainly by reducing the number of bad predictions. The found improvement is present for all models but Llama 4 Maverick. Here the number of bad predictions gets larger if we provide three or more examples. With five examples the performances totally collapses.

B

The perfromance improvement for GPT-4.1-mini and GTP-4.1 with only one provided example seems to be big, because the box is getting much more narrow. But the median shifts not more than for other models.

Check results for openai, when 5 nano finished

[5] Without the Harmony format 4_000 are enough.

Table B.8: Comparing the extraction performance when Aktiva tables from the same company can be used for incontext learning or not.

model_family	improvement_mean	improvement_median
google	0.13	0.14
Qwen 3	0.12	0.07
chat-gpt	0.12	0.17
Qwen 2.5	0.1	0.12
tiiuae	0.09	0.07
mistralai	0.08	0.07
Llama-3	0.07	0.05
microsoft	0.07	0.06
openai	0.05	0.07
Llama-4	0.03	0

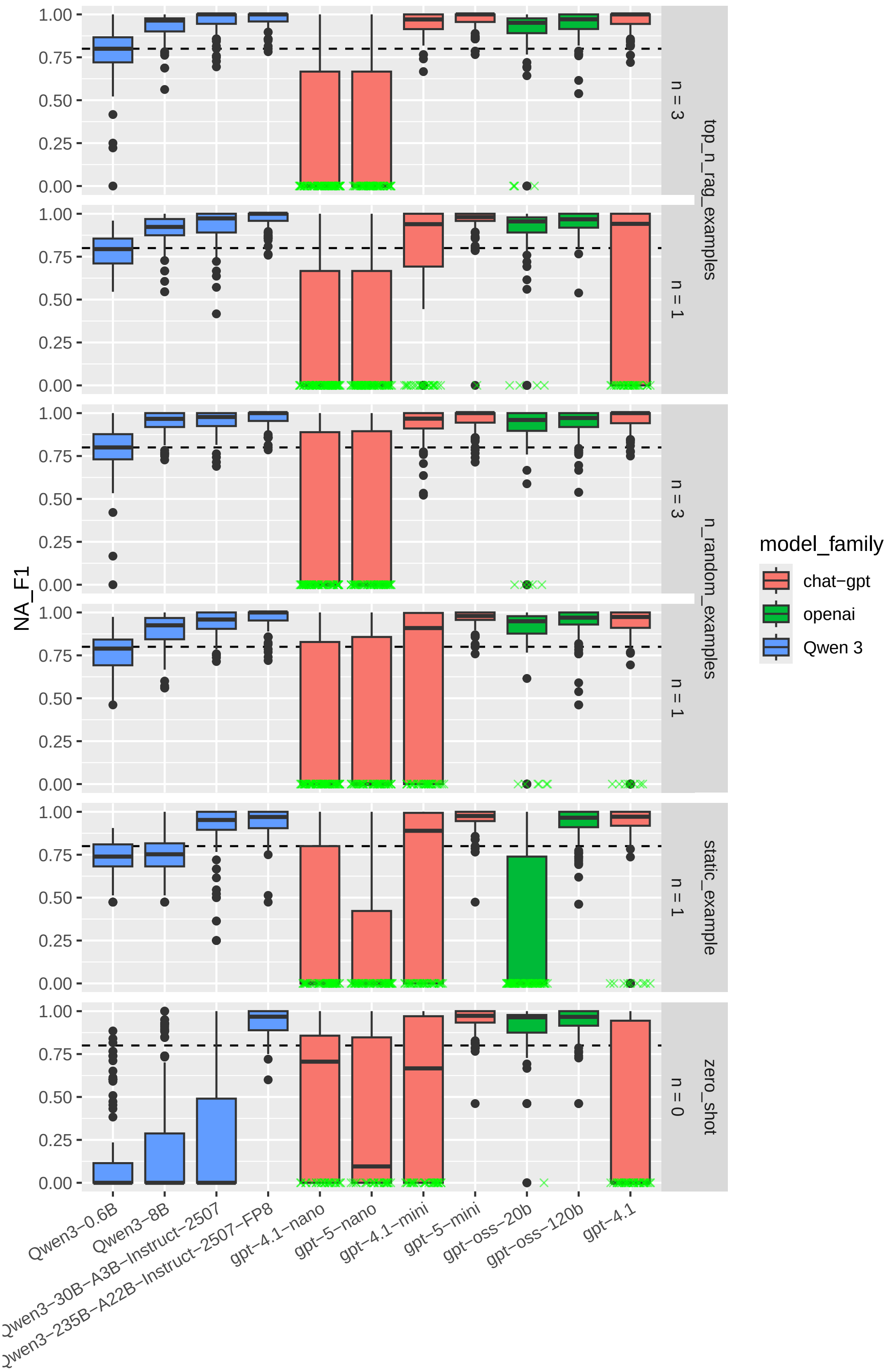

Figure B.2: Comparing the F1 score for predicting the missingness of a value for OpenAi's LLMs with some Qwen 3 models. The green crosses indicate results where a model has predicted only numeric values even though there have been missing values.

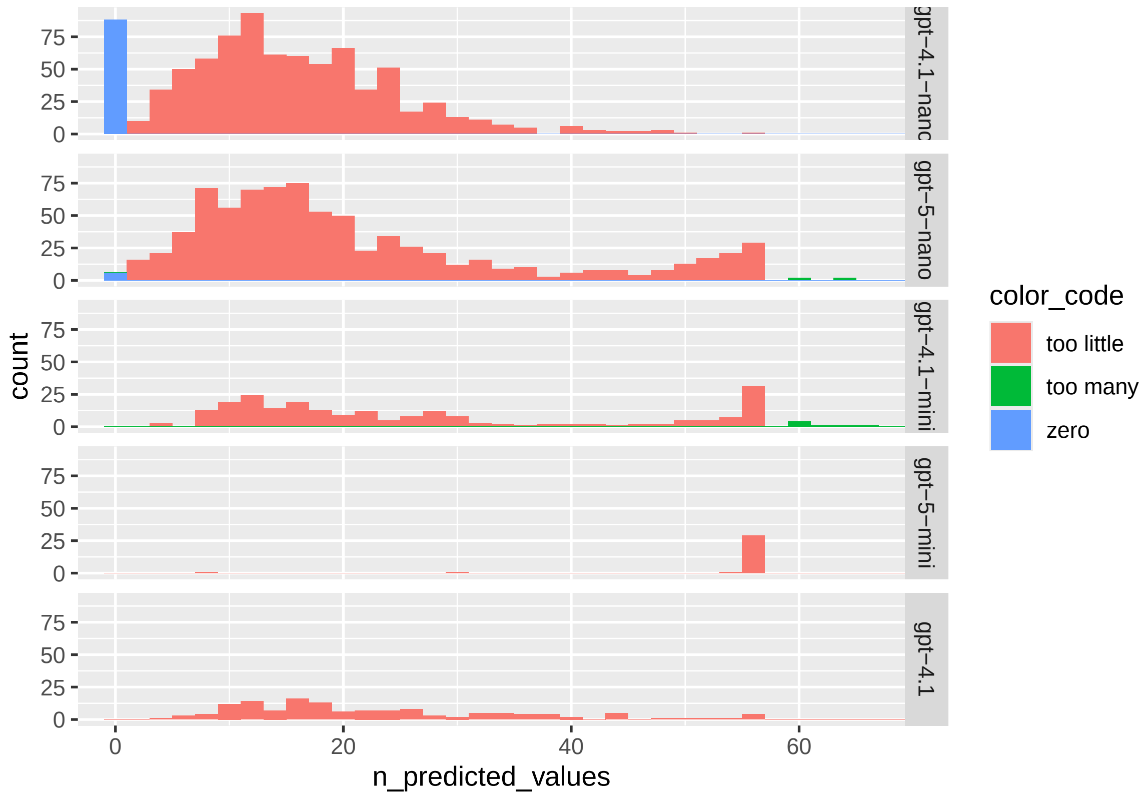

Figure B.3: Showing the number of predictions OpenAI's models made.

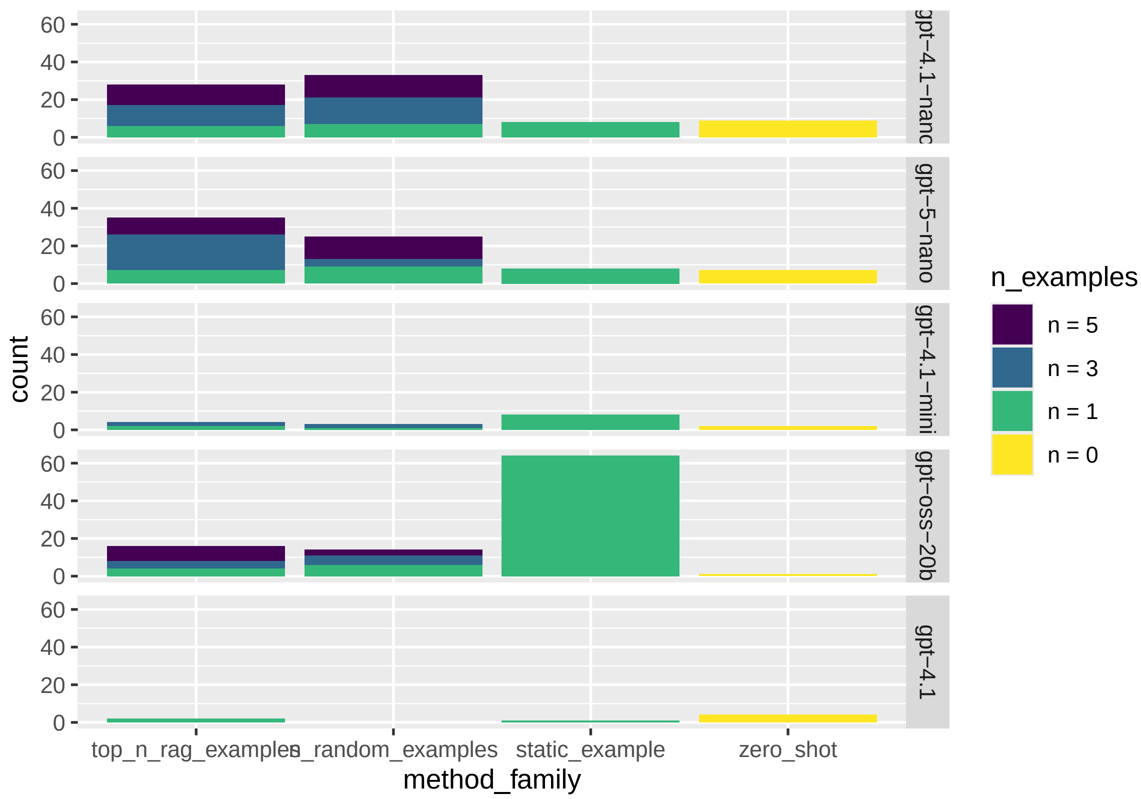

Figure B.4: Showing the number of predictions OpenAI's models made.

B

B.2.2 Synthetic tables

Ground truth dataset For this task we created synthetic **Aktiva** tables that should allow to investigate the influence certain characteristics of tables on the extraction task. We systematically created **Aktiva** tables that vary over the following characteristics:

1. n_columns: Number of columns the numeric values are distributed over ranging from 2 to 4.
2. header_span: Span in the header rows.
3. thin: Including just a subset of all possible entries for a **Aktiva** table.
4. unit_in_first_cell: Is the currency unit (e.g. T€) given in the beginning of the table instead for each column.
5. enumeration: Are the rows numerated following the schema in the legal text.
6. many_line_breaks: Limiting the character length for the row descriptions to 50 to introduce line breaks.
7. shuffle_rows: The order of the rows within lower hierarchies can vary.
8. text_around: There is some random text before and after the table on the generated page.
9. sum_same_line: Summed values are in the same line as single values if there are more than two columns.
10. unit: Eight different currency units from. E.g.: €, TEUR, Mio. €
11. input_format: Table is exported as PDF, HTML or Markdown document.

This results in 49152 tables. A sample of 10 % is used for the extraction task. The *header_span* and *text_around* are only varied for the PDF format.

Extraction task overview For the table extraction task with synthetic **Aktiva** tables 17 open source models from 6 model families have been benchmarked. There have been the same seven methods tested with each LLM as described in section B.2. Each method was used twice, because in one trial the LLM is prompted to respect the currency units and in the other trail it is not.

This results in 531 files, that hold the results of 4_915 table extractions each. For the investigation of potential predictors influences the random forest is generated with a sample of 50_000 of these 68_810 results and finally, the SHAP values are calculated with 2_000 rows of data.

Performance Table B.9 shows the best performing combination of LLM and prompting strategy for each model family. The results are sorted by their mean percentage of total correct predictions. We only compare results for table extractions that work with a PDF document based table here.

For every model family there is at least one model-method combination that performed better than the regex baseline. For the synthetic table extraction task the baseline is 0.966. 67 from 129 model-method combinations perform better than this baseline. There has been no model that performed better than this baseline with the *zero_shot* or *static_example* method.

Table B.9 shows, that Qwen3-235B-A22B-Instruct performs best. Llama 4 Scout also performs very good but is three times faster. Table B.10 shows three small LLMs that also beat the median threshold for the synthetic table extraction task. But we would not prefer the Qwen3-8B model over the Llama Scout model, because its speed advantage is to small, compared to the performance decrease. But if there is limited VRAM available the Qwen3 model is a good choice. It can run well with 40 GB VRAM. The Llama Scout needs 640 GB VRAM to run well[6].

Detail:

Figure G.24 shows, that Llama 3.3 70B never manages to reduce the spread in the numeric prediction performance.

[6]When we say, it runs well, it gets rated as *okay* on the LLM Inference: VRAM & Performance Calculator.

Table B.9: Comparing best median table extraction performance with synthetic 'Aktiva' dataset for each model family

model_family	model	method_family	n_examples	mean_total	median_total	me
Qwen 3	Qwen3-235B-A22B-Instruct-2507	n_random_examples	5	0.991	**1**	
Qwen 2.5	Qwen2.5-72B-Instruct	top_n_rag_examples	5	0.988	**1**	
mistralai	Mistral-Large-Instruct-2411	top_n_rag_examples	5	0.987	**1**	
Llama-4	Llama-4-Scout-17B-16E-Instruct	top_n_rag_examples	3	0.974	**1**	
google	gemma-3-27b-it	top_n_rag_examples	5	0.914	0.931	
Llama-3	Llama-3.1-8B-Instruct	top_n_rag_examples	3	0.873	0.931	

Table B.10: Comparing best median table extraction performance with synthetic 'Aktiva' dataset for each model family for models with less than 17B parameters

model_family	model	method_family	n_examples	mean_total	median_total	median_r
Qwen 3	Qwen3-8B	top_n_rag_examples	3	0.944	**1**	18:38
Qwen 2.5	Qwen2.5-7B-Instruct	top_n_rag_examples	5	0.919	**0.966**	15:26
mistralai	Ministral-8B-Instruct-2410	top_n_rag_examples	3	0.908	**0.983**	31:12
Llama-3	Llama-3.1-8B-Instruct	top_n_rag_examples	3	0.873	0.931	14:8
google	gemma-3-12b-it	top_n_rag_examples	5	0.858	0.931	26:28

Hypotheses Table B.11 shows some unsupported hypotheses for predictors with strong effects. The observations suggest, that prompting the model to respect the currency units is decreasing its performance to predict the correct numeric values. This is understandable, if the task is reflected properly and we made a mistake there, when we formulated our hypothesis.

If the model is not prompted to respect the currency units, it is presented with examples that just copy over the numeric values. And it gets evaluated if it copied the values correctly. If the model is prompted to respect the currency units, it is presented with examples, where the values not only get copied but also transformed. And they get evaluated if they do the transformation correct as well. Thus the task is harder, if numeric values should be respected and the effect is having a negative direction.

Figure B.5 shows that the transformation task is handled best, if the examples are provided with the *top_n_rag* strategy. It does not work with the *zero_shot* strategy. It also shows, that the performance is lower with the PDF *input_format* and that the models have difficulties, if the *unit_multiplier* is one million. This also shows a strong effect and is strongest for the PDF *input_format*. This is a general effect. We see in C.13 that it can be different for single models like Qwen3-235B.

old:

HTML and Markdown better but expected interaction effects mostly not found - except: - columns help pdf - thinning least bad for pdf - pdf worst with numbers that have currency units (short numbers, maybe no 1000er delimiter) - enumeration positive for pdf (and interaction with log10 mult)

line breaks are no problem

zero shot gets confused by text around

Markdown might be even better than HTML

respecting units was bad - except for: Top n rag finds examples with same currency units (shorter numbers more important than currnency in header?)

log10 multiplier has many interaction effects

LLama 4 Maverick again problem with five examples

Positive column count effect (different for real data)

Table B.11: Comparing the formulated hypotheses and the found results for the table extraction on synthetic Aktiva tables with the LLM approach.

	F1		
predictor	Hypothesis	Result	Hypothesis
model_family	**unknown**	google worst	**unknown**
parameter_count	**positive**	positive	**positive**
method_family	**top_n_rag & n_random best**	zero shot worst	**top_n_rag**
n_examples	**positive**	positive (except for Llama 4 Maverick)	**positive**
n_columns	3 is worse	positive	neutral
n_columns:input_format	less for html and md	neutral	less for htm
sum_same_line	neutral	neutral	negative
sum_same_line:input_format	neutral	neutral	better for h
header_span	neutral	neutral	neutral
header_span:input_format	Can't be evaluated		Can't be ev
header_span:respect_units	neutral	neutral	negative
thin	Can't be evaluated		neutral
respect_units	neutral	negative	**positive**
respect_units:input_format	neutral	neutral	better for h
input_format	**md and html better**	md and html better	**neutral**
year_as	neutral	neutral	neutral
unit_in_first_cell	neutral	neutral	negative
unit_in_first_cell:input_format	neutral	neutral	neutral
log10_unit_multiplier	neutral	neutral	**positive**
log10_unit_multiplier:input_format	neutral	negative for pdf	neutral
enumeration	positive	neutral	neutral
shuffle_rows	neutral	neutral	neutral
text_around	neutral	neutral	neutral
many_line_breaks	negative	neutral	neutral
many_line_breaks:input_format	better for html and md	neutral	neutral
label_length			
label			
missing			
confidence			

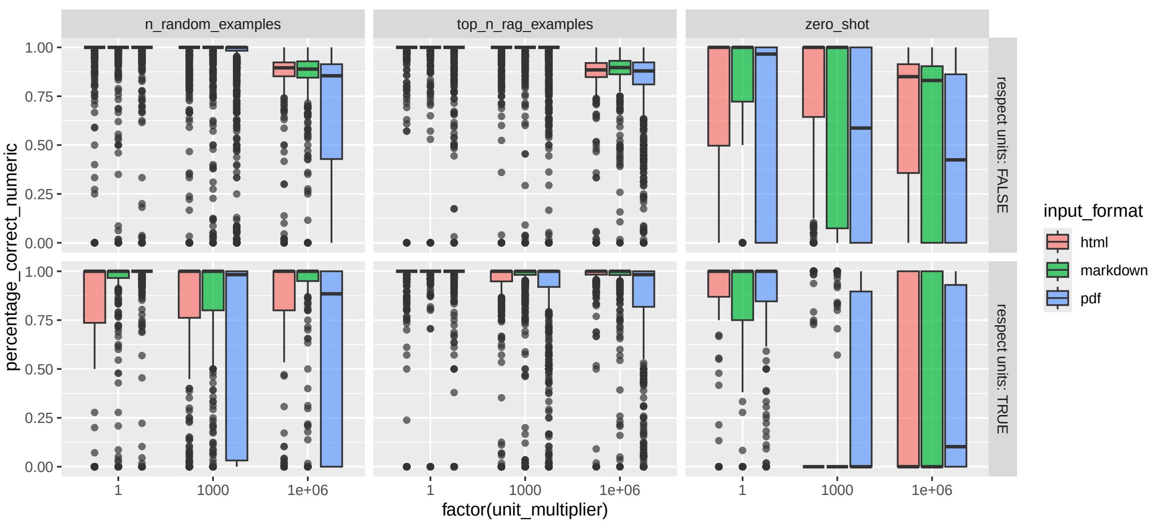

Figure B.5: Comparing the percentage of correct extracted numeric values grouped by input format, method family and the fact, if currency should be respected.

B.2.3 Hybrid approach

In this section we present the results of using synthetic **Aktiva** tables for the in-context learning to extract information from real **Aktiva** tables. We show that even such a hybrid approach can be used, to extend the extraction task by a unit conversation task.

Performance Table B.12 compares the overall performance for the extraction task of the best model-method combination in the hybrid approach per model with the *zero_shot* and real example training performance. Using real examples for in-context-learning for those model-method combinations is better than using the generated synthetic data. Qwen3-8B and gemma3-12b can improve the most using real examples instead of sythetic examples, normalized on the possible improvement from the synthetic learning results using this formula:

$$delta\_rate_{synth} = \frac{median(real) - median(synth)}{1 - median(synth)}$$

On the same time, gemma3-12b shows the lowest *delta_rate* with under 10 %, when the improvement of using synthetic examples is compared with the *zero_shot* method. For the other models this is more tan 48 % and highest for Llama Scout 4 with 87.5 % improving from 0.45 to 0.93. Qwen-235B score as high with both learning approaches, but scored best with just using a single synthetic example. Table F.2 shows that these observations are valid for the improvement with in the models independent from the selected method. Figure G.27 shows, that the improvement for using one or three synthetic examples is biggest for Qwen3-8B.

Learning to respect currency units Table B.13 shows, the difference in the percentage of correct predicted numeric values, if the LLM is prompted to respect currency units and gets synthetic **Aktiva** tables that show how to cope with different currency units, separate for the number of columns with currency units. There are 17 tables that have *T€* in the previous year column and 9 tables that have all columns listed in *T€*.

It shows, that Qwen3-235B, Llama 4 Scout, Mistral-Large and Ministral-8B all can apply the demonstrated numeric transformation for most of the values, if both columns have the *T€* unit. Qwen3-235B, Llama 4 Scout and Mistral-Large also can apply this, if only one columns has a unit corrency. This works best for Qwen3-235B. The target value to archive here is 0.5 instead of 1.0. This is worth to mentioning because there are no synthetic examples that haf different currency units for different columns. Ministral can not generalize this skill. It seems, that Qwen3 apllies numeric transformations regardles the fact, if there are currency units given for a column. Thus, it performs noticeably worse on the majority of all tables. Figure B.6 shows, that the performance of Llama 3.1 8B and gemma3 27B on colums with currency units does not change.

G.28, G.29 and G.30

Thus, synthetic data can be used to solve new tasks and substitute missing data for rare classes.

Table B.12: Comparing extraction performance for real Aktiva extraction task with synthetic and real examples for incontext learning with a zero shot approach for the best performing modelmethod combination in the hybrid

model	method	median_real	median_synth	median_zero_shot	delta_r
Qwen3-235B-A22B-Instruct-2507-FP8	1_random_examples	**0.966**	**0.966**	**0.897**	
Llama-4-Scout-17B-16E-Instruct	5_random_examples	**0.966**	0.931	0.448	
Mistral-Large-Instruct-2411	5_random_examples	**0.966**	0.922	0.776	
Qwen3-8B	5_random_examples	0.94	0.802	0.336	
Llama-3.1-8B-Instruct	5_random_examples	0.836	0.776	0.552	
Ministral-8B-Instruct-2410	5_random_examples	0.897	0.767	0.552	
gemma-3-27b-it	3_random_examples	0.828	0.724	0.207	
gemma-3-12b-it	top_1_rag_examples	0.862	0.586	0.543	

Table B.13: Comparing extraction performance for real Aktiva extraction task dependent on the promt addition to respect currency units

model	n_cols_T_EUR_0	n_cols_T_EUR_1	n_cols_T_EUR_2
Llama-3.1-8B-Instruct	-0.03	-0.02	0.01
Llama-4-Scout-17B-16E-Instruct	**0**	0.28	0.89
Ministral-8B-Instruct-2410	-0.08	0	0.79
Mistral-Large-Instruct-2411	**0**	0.39	0.9
Qwen3-235B-A22B-Instruct-2507-FP8	**0**	**0.44**	**0.96**
Qwen3-8B	-0.48	0	0.28
gemma-3-12b-it	-0.03	0.17	0.48
gemma-3-27b-it	**0**	0.06	0.02

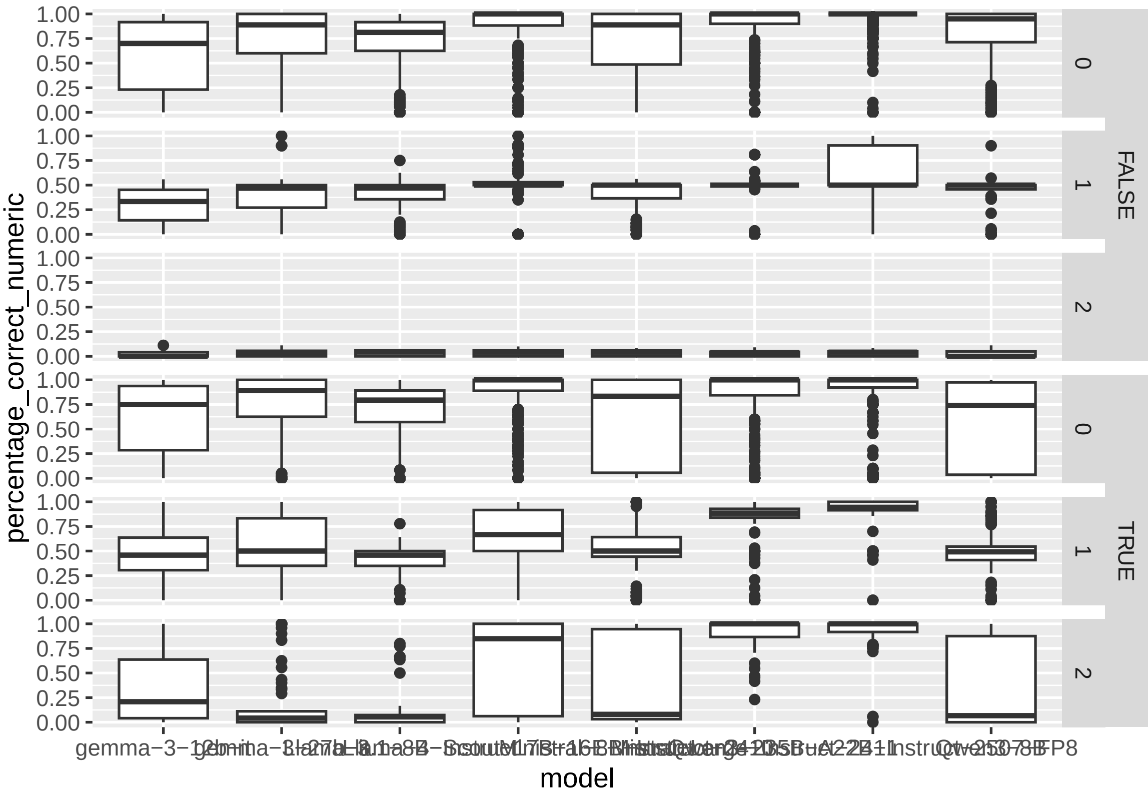

Figure B.6: Comparing the numeric prediction performance for the hybrid approach, based on the fact, if the LLM is prompted to respect currency units.

B.3 Summary

B

Appendix C

Appendix C - Error rate guidance report

The side research question asks, if it is possible to guide the users attention to predictions that have a higher empirical rate of errors. In this thesis we focus the confidence score reported with LLMs responses.

The formula for the confidence score is given in Equation (3.1).

C.1 Page identification

C.1.1 Binary classification

We investigate the relation between the reported confidence for an answer and its correctness, to check if it is possible to inform humans in the loop about results they should double check and which results they can trust. The LLM just returns one prediction and its confidence[1] for the binary classification task. We calculate its confidence as $confidence = exp(logprob)$, if the answer is *yes*. And we calculate its confidence as $confidence = 1 - exp(logprob)$, if the the answer is *no*,

Figure C.1 shows the distribution of reported confidence score for the binary classification with target type **Aktiva** for all table types grouped by their correctness for Ministral-8B-Instruct-2410. One can see that the predictions are very accurate making just 13 mistakes for 4981 predictions.

The reported confidence for answer *yes* is showing a wide spread from around 0.25 to 1.0. This is true for the answer *no* as well. Most wrong decisions are made for responses that have a reported confidence in the range from 0.25 to 0.75. But there are more correct answers in this range as well. It never misclassifies **GuV** or **Passiva**[2] as **Aktiva**. But it with shows some not recalled **Aktiva** tables and is predicting some of the pages of majority class, with not further described content and structure, as **Aktiva**.

This is different for models of most other model families. Figure C.2 shows, that Qwen2.5-32B-Instruct returns always high confidence scores, even when it is wrong. The model shows perfect recall but its precision is worse than the precision of the Mistral model.

Figure C.3 shows the precision-recall-curve for the best performing model twice for each target type. On the left plots the line color represents the threshold score one could use to decide when to accept a response as it is. On the right plots the line color is showing the F1 score that results with a chosen threshold.

The AUC value is lowest for **Aktiva**. Here the F1 score is highest for a threshold value of 0.73. This prevents to classify the pages of type *other* to get classified as **Aktiva**. If it is required to have a very high recall value a threshold of 0.44 should be chosen.

[1] The model could be forced to return multiple answers, but it was not. The confidence score is given as log probability. The exponential function was applied to show the results on the more common scale of 0 to 1.

[2] There was a single prediction where LLM predicts **Aktiva** with high confidence, when the truth is **Passiva** instead. Because Qwen was showing the same wrong prediction for one **Passiva** table, I double checked the ground truth. I found, that the page shows **Aktiva** and **Passiva** simultaneously and was not correct codified. This was not the only time, where a mistake in the gold truth was found, by examining potential LLM mistakes.

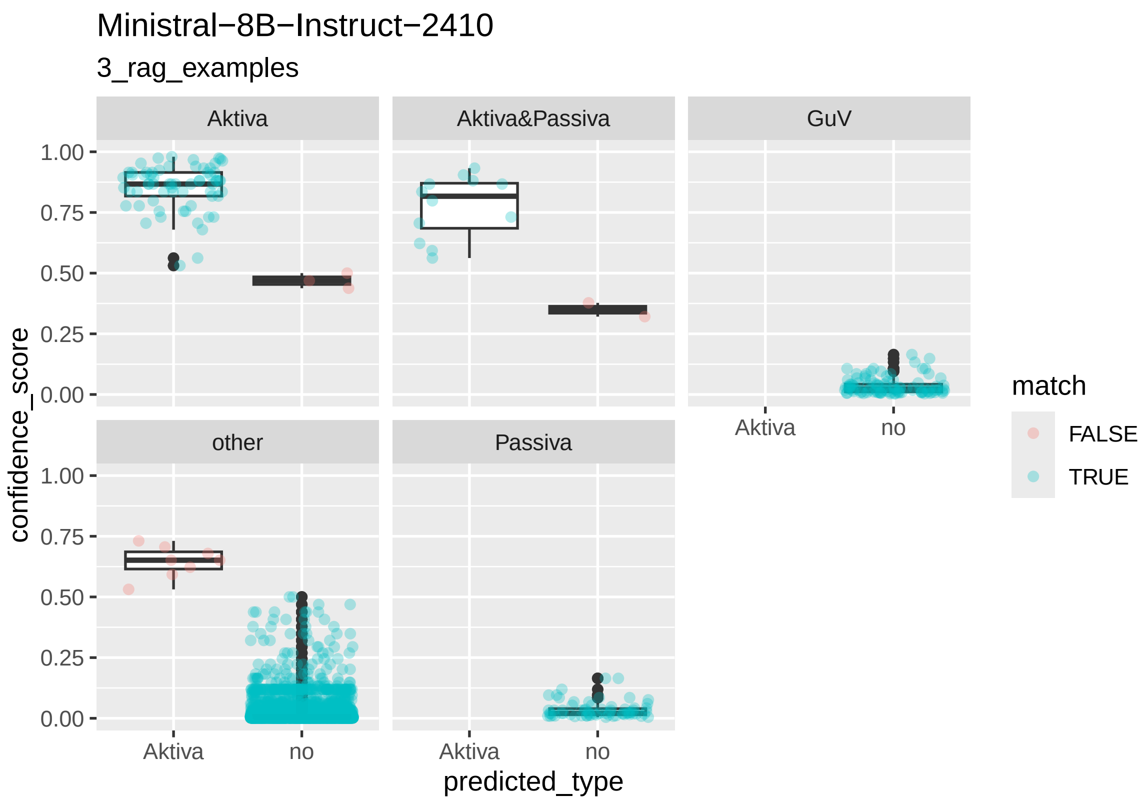

Figure C.1: Showing the confidence score for the Aktiva classification task grouped by table type and correctness for Mistral-8B-Instruct-2410.

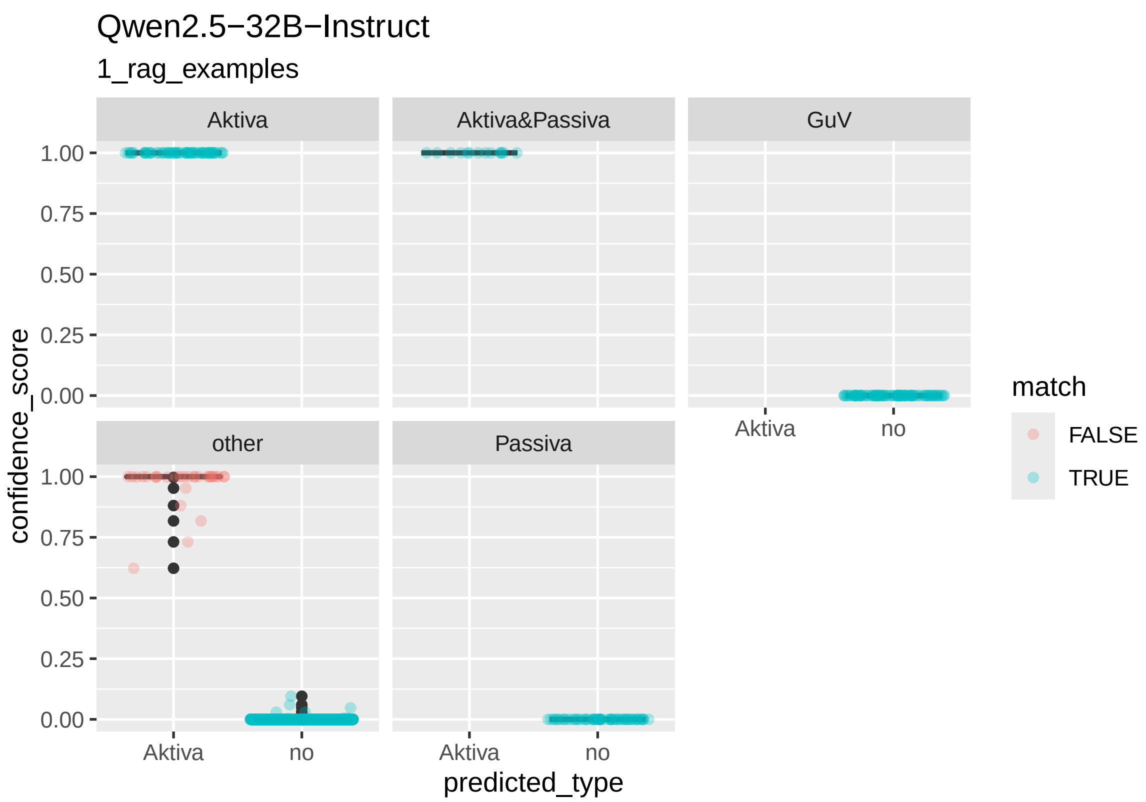

Figure C.2: Showing the confidence score for the Aktiva classification task grouped by table type and correctness for Qwen2.5-32B-Instruct.

C

The precision-recall-curve for **Passiva** is very similar but there is a step close to the recall value of 1.0. This has the effect that for a a guaranteed high recall a very low precision (0.24) and F1 (0.38) has to be accepted[3].

The shape of the precision-recall-curve for **GuV** almost perfectly reaches the top right corner. The highest F1 score is found with a threshold value of .56. With a threshold value of 0.5 a very high recall is guaranteed and the F1 score is just a little lower.

Figure C.4 summarizes the relation between reported confidence and correctness of the classification for all target types and compares it among the best performing model-strategy combinations for Ministral-8B-Instruct-2410 and Qwen3-8B. One can see, that the reported confidence for correct and incorrect classifications are separable in most cases for Mistral-8B. This separation is worse for Qwen3-8B and worst for target type **Passiva**.

Figure C.5 shows, that for Ministral-8B values with a confidence of 0.7 and more, a human don't has to double check the classification for target type **GuV**. This interval is smallest for **Passiva** where only confidences above 0.9 can be fully trusted. These empirical intervals might shrink, once more data is evaluated. If one is less strict and accepts misclassifiaction rates of 1 % the found interval for **Passiva** starts at 0.8 and is probably less depended on the sample evaluated. The percentage of predictions that can be trusted without risk is greater than 93 % even for target type **Passiva**.

For Qwen3-8B we find almost no range without any wrong classifications. For **GuV** this range includes 35 % of all predictions. The ranges that allow for 1 % of wrong classifications cover 57 % of all predictions at least.

Discussion:

- Could be more efficient to predict "is any of interest" and then which type, because dataset is highly imbalanced.
- Why takes n_rag_examples so much longer?
- **Aktiva** and **Passiva** sometimes on the same page and more similar than **GuV**?
- Recall = 1 for human in the loop (looking at selection of pages that could be target and none else, if the number of wrong pages are few => what says F1 with recall 1?)
- Confidence range to error rate

C.1.2 Multi-class classification

Confidence Figure C.6 shows the reported confidence scores for the predictions for the best performing model-strategy combination, Llama 4 Scout with *3_rag_examples*. It is confident for most correct predictions and only misclassifies some of the pages with unknown characteristics. The target types are all recognized correct. All confidences are greater than 0.5. Probably because there is no case where the confidences for all possible classes is below 0.5 and there always is a most probable class. It would have been interesting to use the classification framework of vLLM to get predictions for all competing classes. But this requires special trained models with pooling capability[4].

Figure C.7 shows the reported confidence scores for the predictions for the best performing model-strategy combination among the small models limited to *n_examples* with n smaller five[5], Ministral-8B-Instruct-2410 with *3_rag_examples*. One can see there are some wrong classifications for the minority classes as well. Especially, the **Passiva** target type is often classified as *other*. This is problematic for a smooth workflow (see discussion chapter?)

Figure C.8 shows the precision-recall-curve for Ministral-8B-Instruct-2410 with *3_rag_examples* twice for each target type. On the left plots the line color represents the threshold score one could use to decide when to accept a response as it is. On the right plots the line color is showing the F1 score that results with a chosen threshold.

[3] Thus, a human has in average to check four pages and select the correct **Passiva** page among them.

[4] It might be possible to request the n most probable answers to get confidence scores for all different predictions. But this was not investigated.

[5] The best performance results with *top_11_rag_examples* but the plot was less interesting and its F1 score was not listed in Table A.10.

C

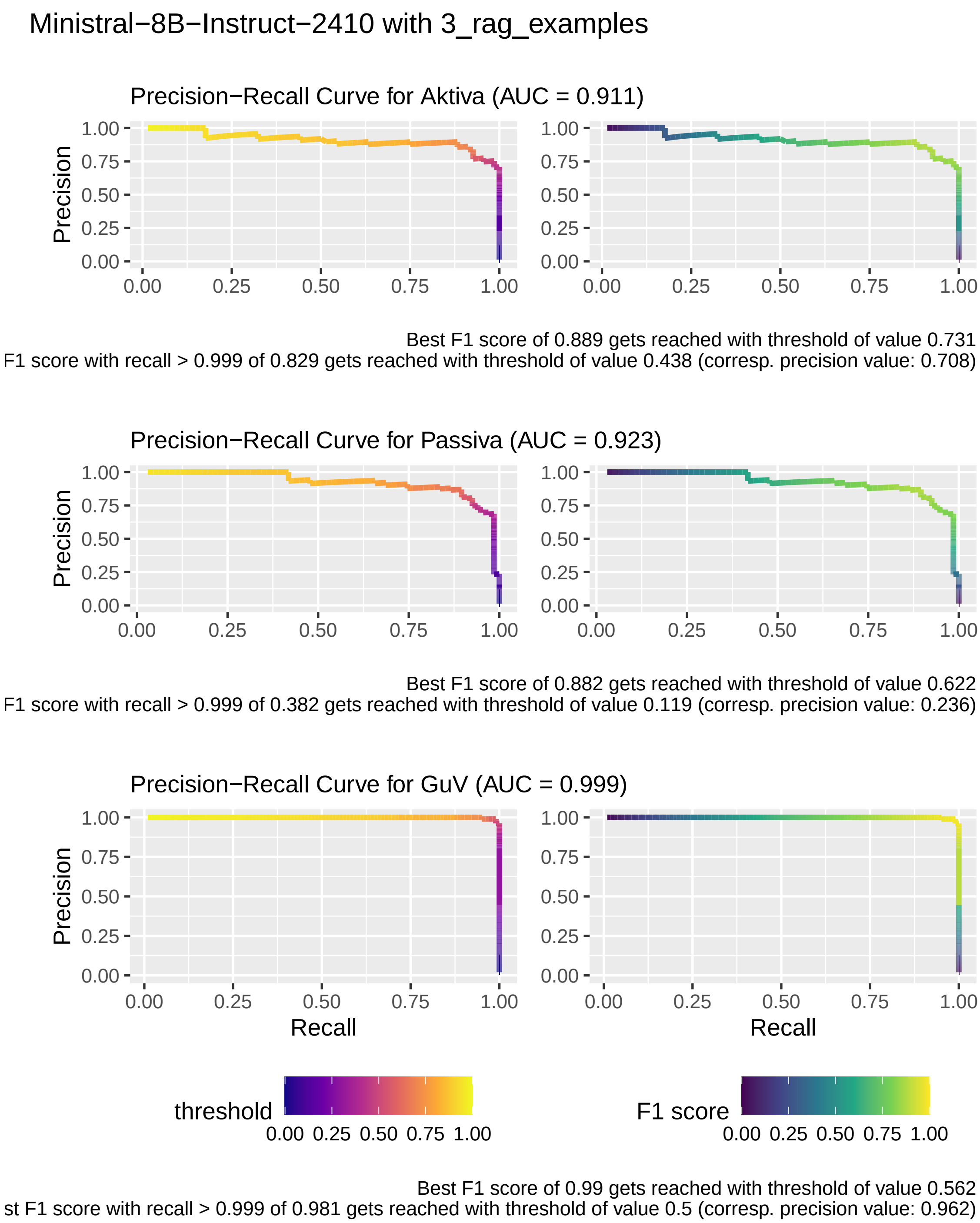

Figure C.3: Showing the precsion-recall-curve for the best performing model.

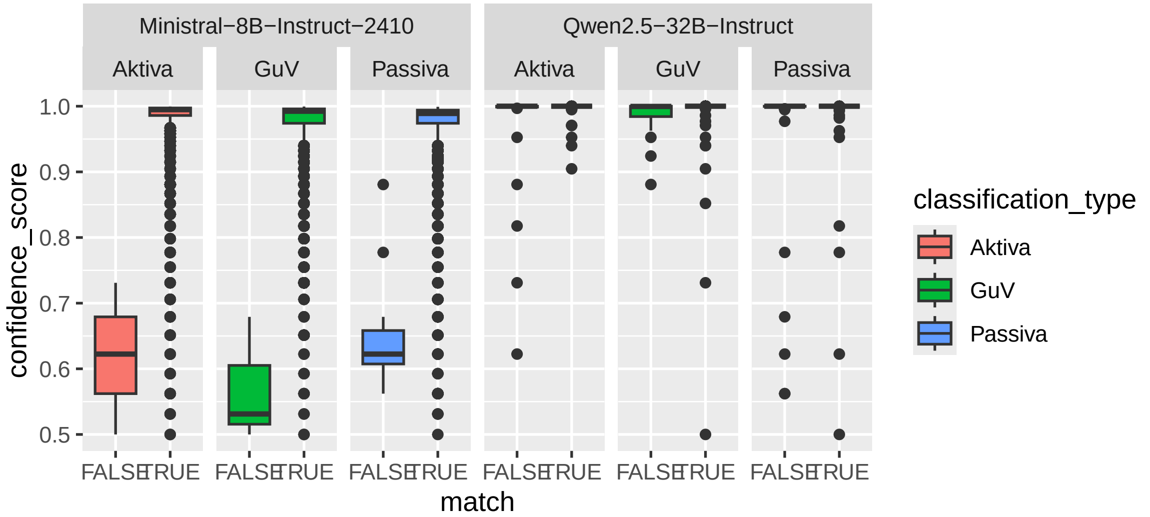

Figure C.4: Comparing the reported confidence scores for the page identification task for the Mistral and Qwen 3 with 8B parameters.

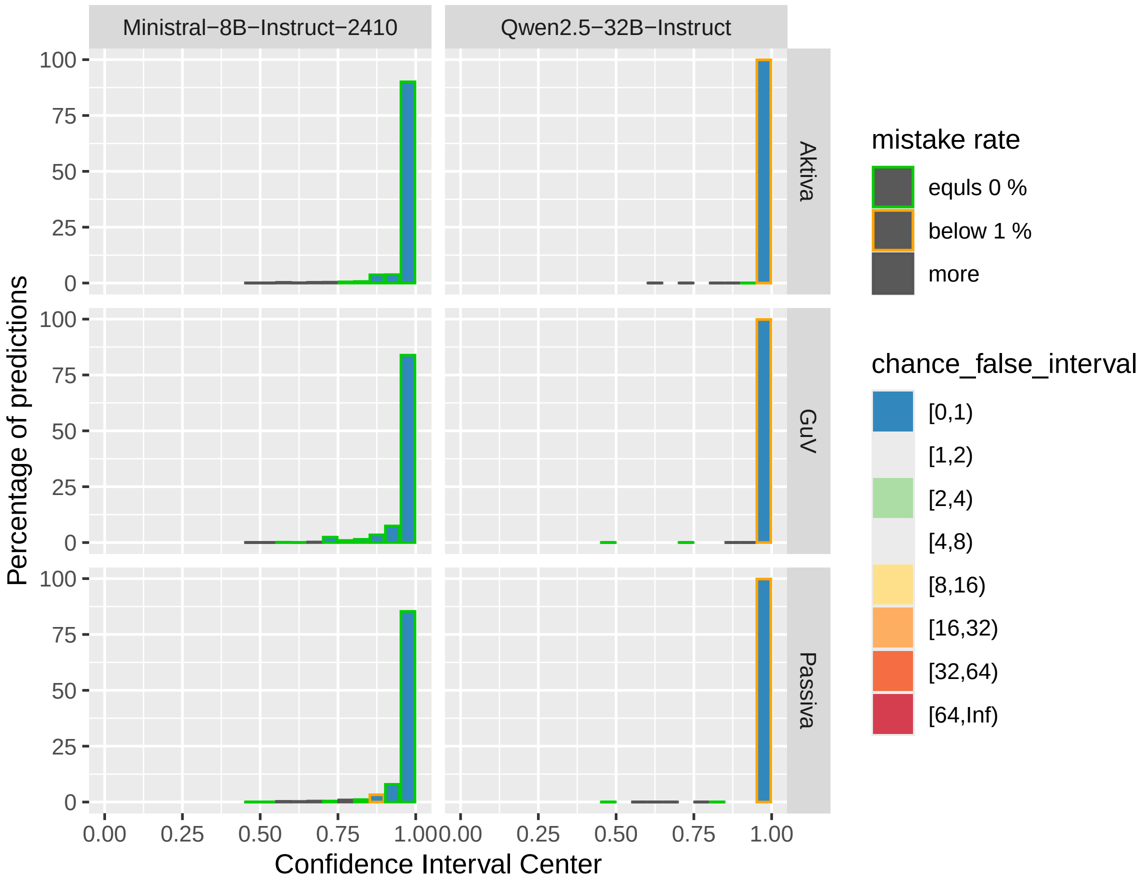

Figure C.5: Estimating the relative frequency to find a wrong classification over different confidence intervals

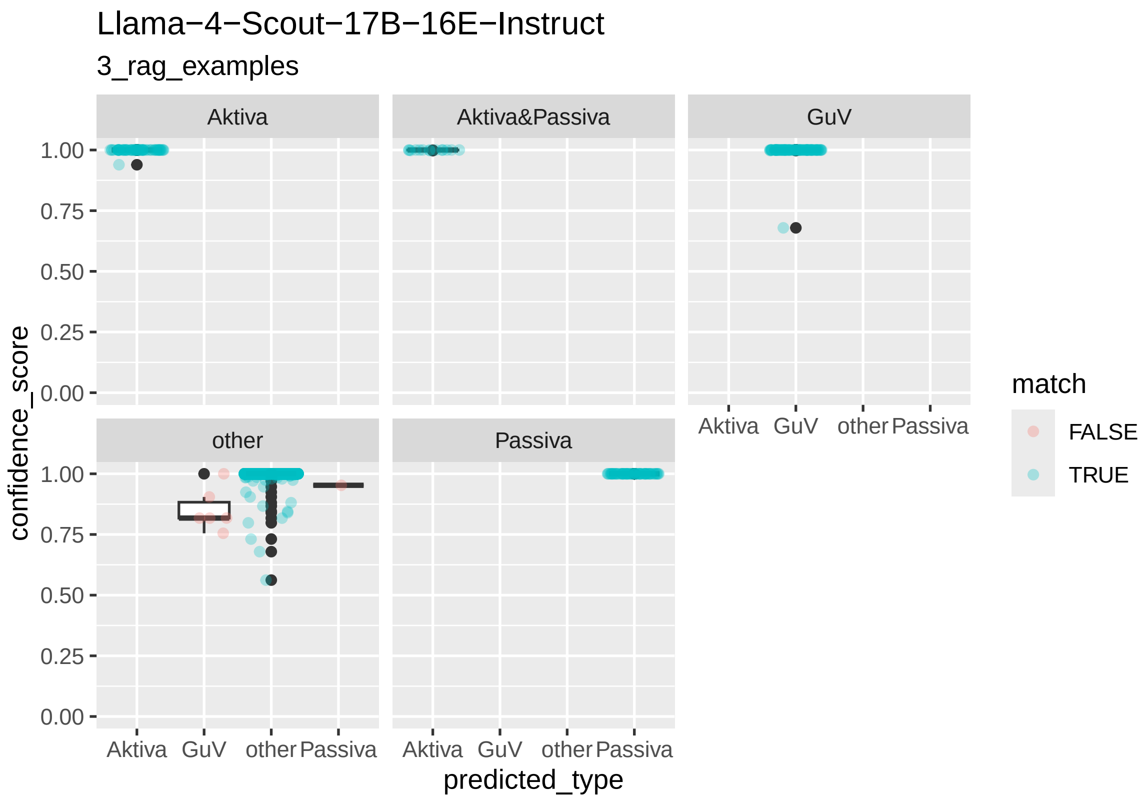

Figure C.6: Showing the reported confidence scores for all predictions of Llama 4 Scout grouped by the true target type. Errors have only been made within the majority class.

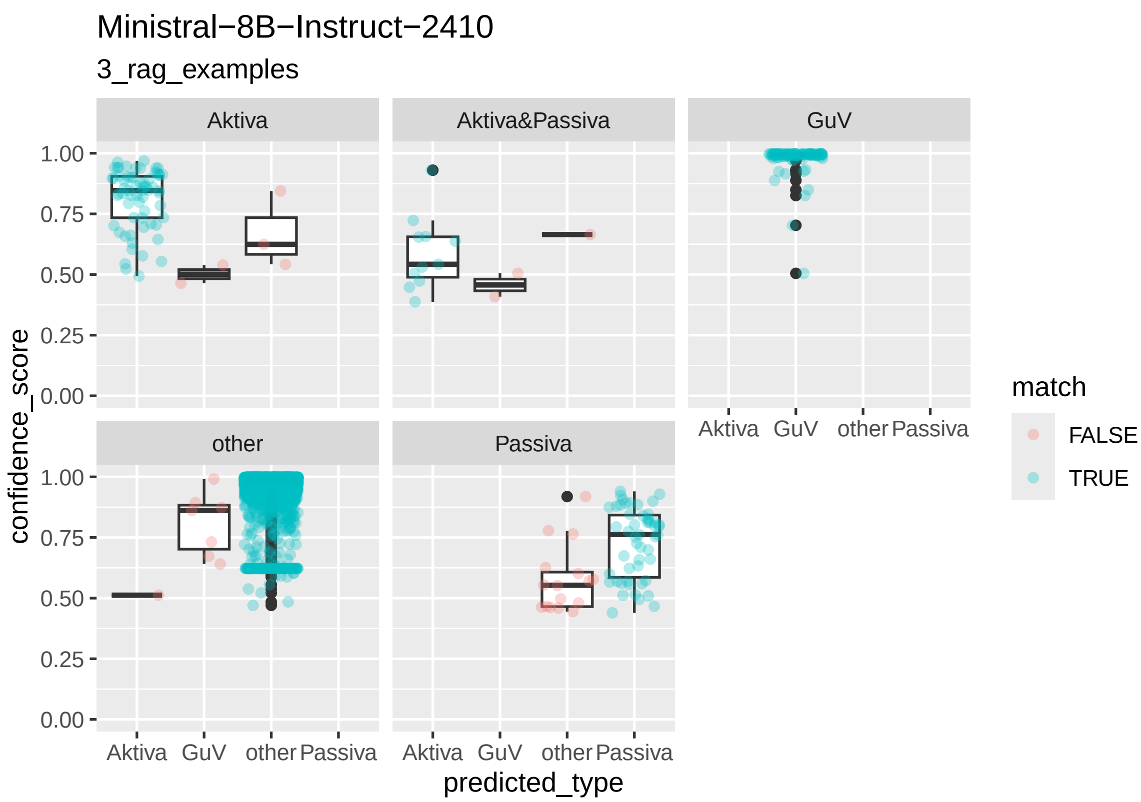

Figure C.7: Showing the reported confidence scores for all predictions of Ministral 8B grouped by the true target type. Errors have only been made within the majority class.

C

The AUC is highest for **GuV** again. But for the multi-class classification **Passiva** shows the lowest AUC, not **Aktiva** as it was in the binary classification task. The precision-recall-curve for **Aktiva** and **Passiva*+ show a "step" in the area of high recall. This has a strong effect on the threshold one should choose, if one wants to guarantee a high recall. The corresponding precision values of 0.2 and 0.13 mean that a human has to check five to eight pages in average to get a correct classified page of type **Aktiva** and **Passiva**.

The corresponding plot for the best performing model, Llama-4-Scout-17B-16E-Instruct, can be found in Figure G.8. Here the precision-recall-curve for **Passiva** and **GuV** is almost perfect. Just the single prediction for **Aktiva** wit a lower confidence shows an influence on the precision-recall-curve.

Figure C.9 summarizes the relation between reported confidence and correctness of the classification for all target types and compares it among the best performing model-strategy combinations for Llama-4-Scout-17B-16E-Instruct, Ministral-8B-Instruct-2410 and Qwen3-8B. It seems, as the reported confidence for correct and incorrect classifications are separable in most cases for Mistral-8B. For Llama 4 Scout this seems not true for the target type **GuV**. For Qwen3-8B there is almost no separation at all.

Figure C.10 shows, that there is almost no area, where the empirical rate of wrong classifications is zero[6]. Only for Ministral-8B we find intervals, where a human don't has to double check the classification for target types **Aktiva** and **GuV**. These intervals include 90 % of all predictions. If error rates of 1 % are accepted almost all predictions by Llama Scout 4 and about 96 % of the predictions by Ministral-8B are included in the corresponding intervals. For Qwen3-8B we find no interval without an error rate below 1 %.

C.2 Extraction with LLMs

C.2.1 Real tables

Confidence Figure C.11 shows, that the distrubution of the models reported confidence is heterogeneous. Again, Qwen3-8B reports very high confidence values no matter if the results are correct or not. Qwen3-235B-A22B-Instruct (and Qwen3-14B) report some lower confidence scores for predictions, where they are wrong. The Mistral model again reports a wider range of confidences and for wrong results the reporetd confidence is lower. But no real separation can be observed for any of the models.

Figure C.12 helps answering the question, if the reported confidence score of the responses can be used, to alert a human that certain predictions might be wrong. In contrast to the page identification task, we find no confidence intervals where the mistake rate is equal 0 or less than 1 %. The majority of the predictions has a very high reported confidence. For the best performing model Qwen3-235B-A22B-Instruct we find error rates of 3.3 % for numeric predictions and 1.3 % for predicting a missing value.

Thus, we can inform the human about the empirical found error rates but do not flag some values to be realy trustworthy. In defense for the model: with manual transcription the error rate is not lower. But we can inform the human about values that have shown a higher rate of mistakes, especially for the Ministral model.

C

C.2.2 Synthetic tables

Confidence Figure C.13 shows, that we do not find a high confidence interval containing a majority of the predictions with 0 % error rate. But for Qwen3-235B we find, that the error rate is below 1 %, except for predicting numeric values, while ignoring their currency units.

Figure G.26 groups the responses additonally by the *input_format* of the documents. It shows, that with HTML documents Qwen3-235B achieves 0 % error rate for the prediction of missing values and predicting numeric values, if currency units get respected.

C.2.3 Hybrid aproach

Confidence Figure C.14 shows the rate of wrong predictions for given confidence intervals. Again, the confidence for predicting a missing value is higher than for predicting a numeric value. One can't see much

[6] The size of intervals has been narrowed down to 0.1 % and still there was no range without wrong classification for Llama 4 Scout.

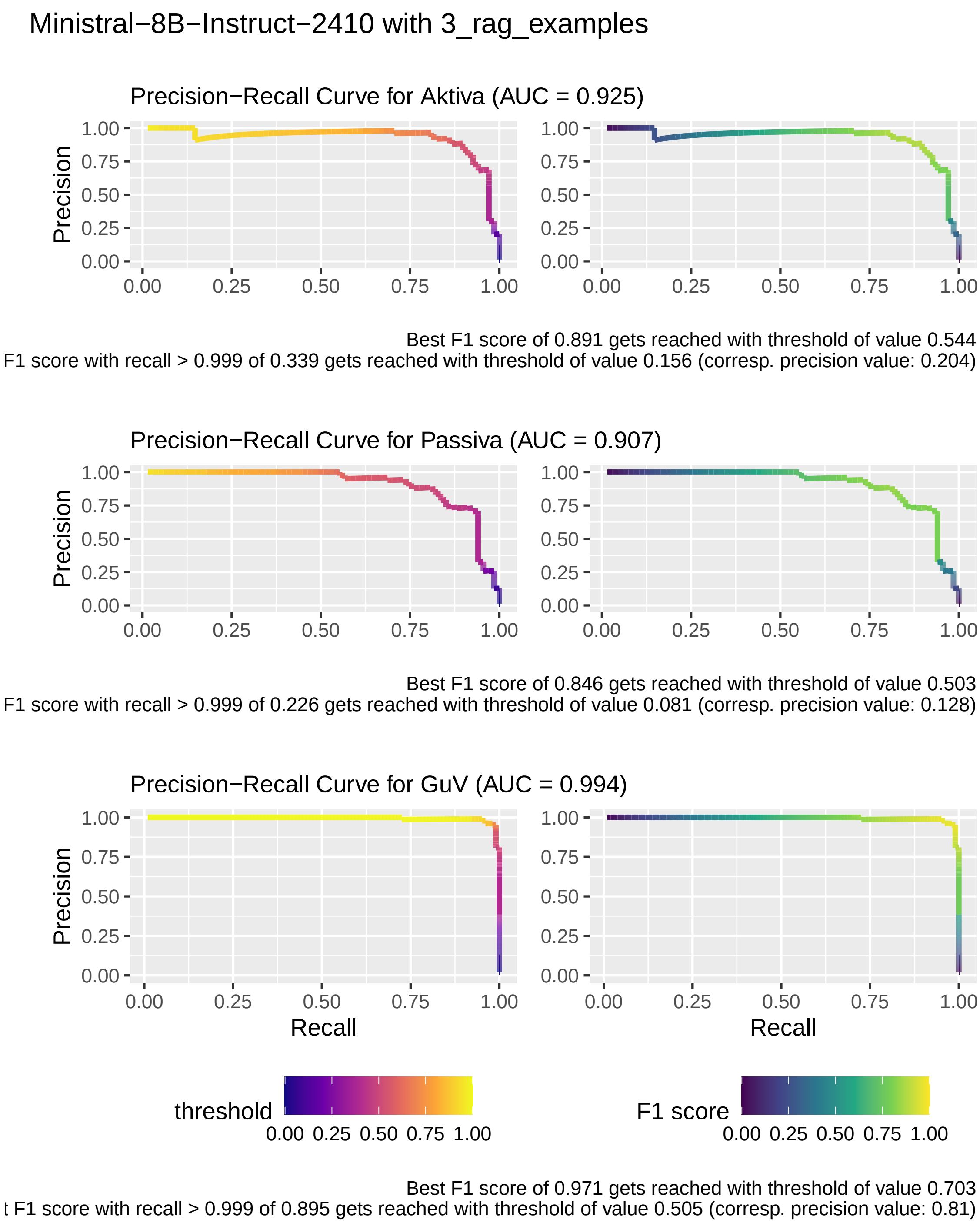

Figure C.8: Showing the precsion-recall-curve for Ministral-8B-Instruct-2410.

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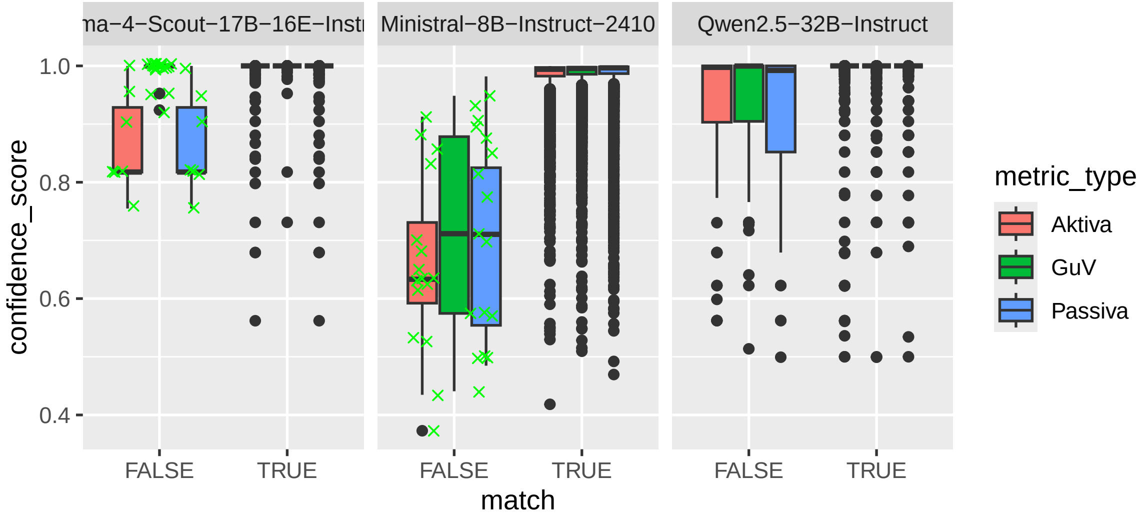

Figure C.9: Comparing the reported confidence scores for the multi-class page identification task for the Mistral and Qwen 3 with 8B parameters. Showing individual scores for groups with less than 20 observations.

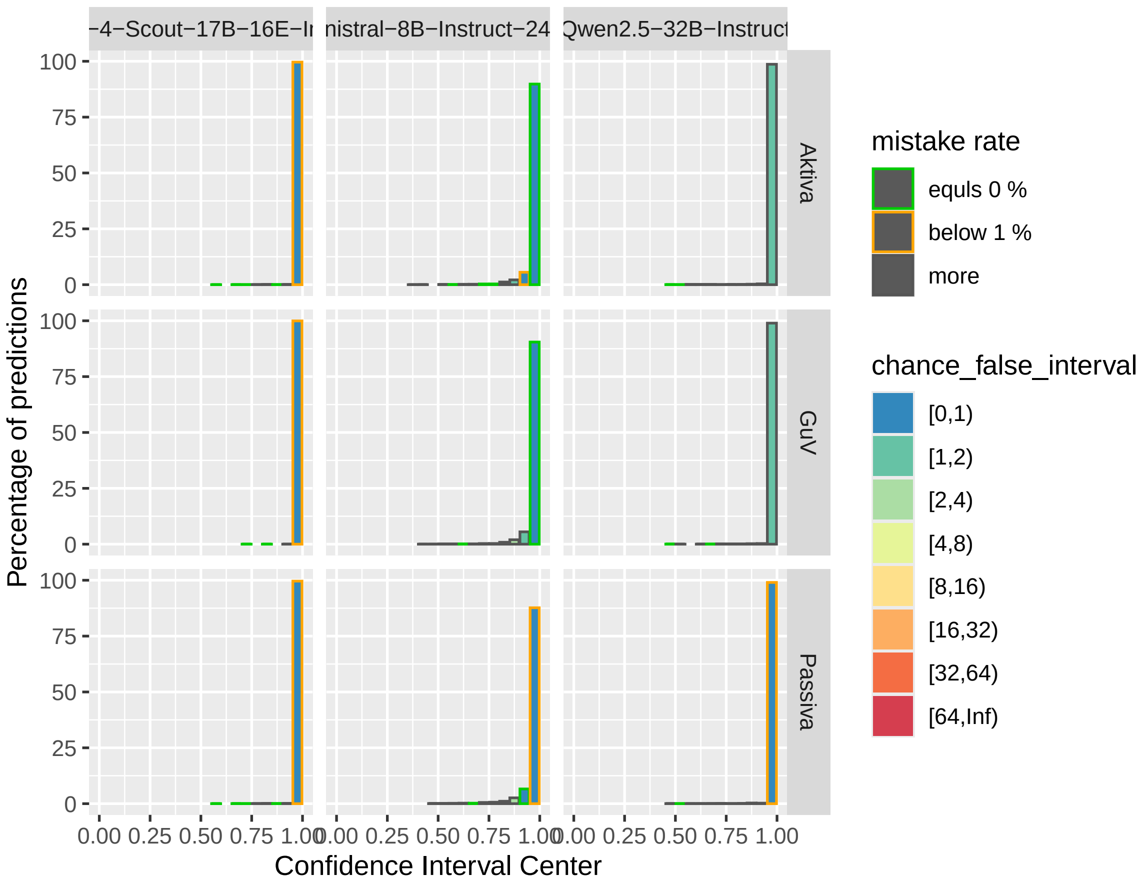

Figure C.10: Estimating the relative frequency to find a wrong classification over different confidence intervals for the multi-class classification task.

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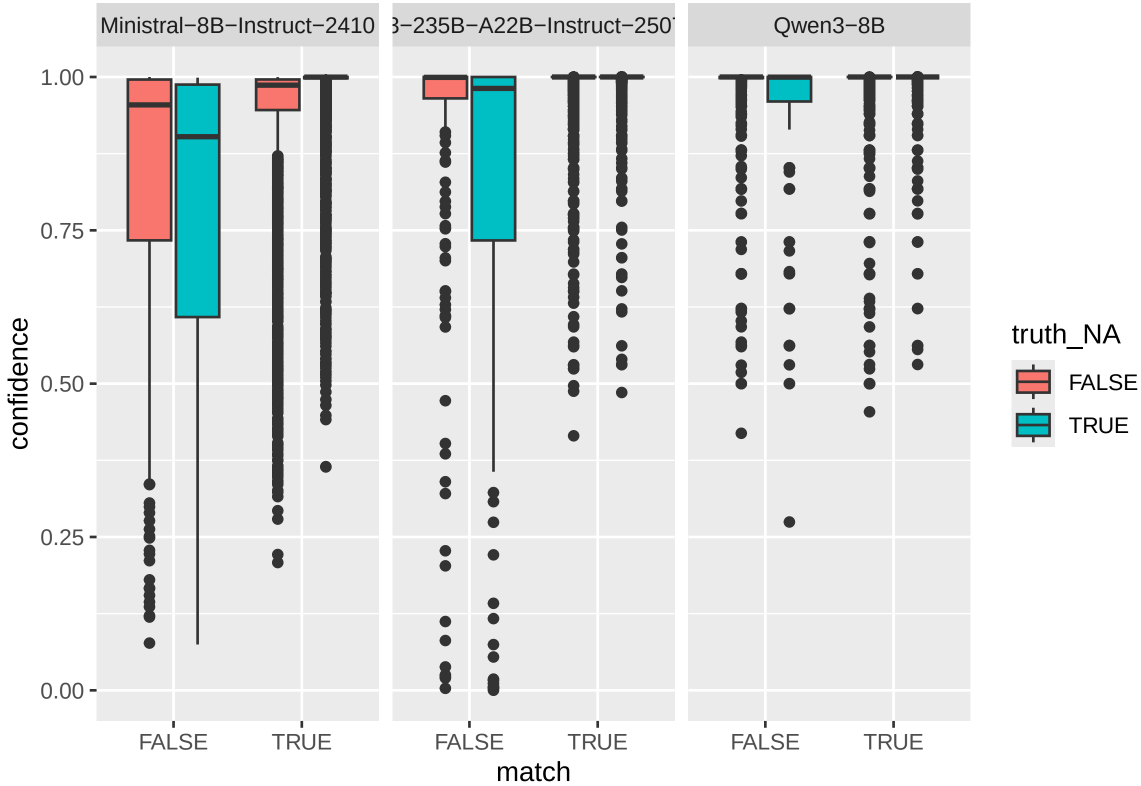

Figure C.11: Comparing the reported confidence scores for the table extraction task on real dataset for the Mistral and Qwen 3 with 8B parameters.

difference, but for the best performing model Qwen3-235B the error rate for numeric values is lower, when currency units are respected (20 % vs 26 %). But the error rate is still to high to mark any numeric value as trustful.

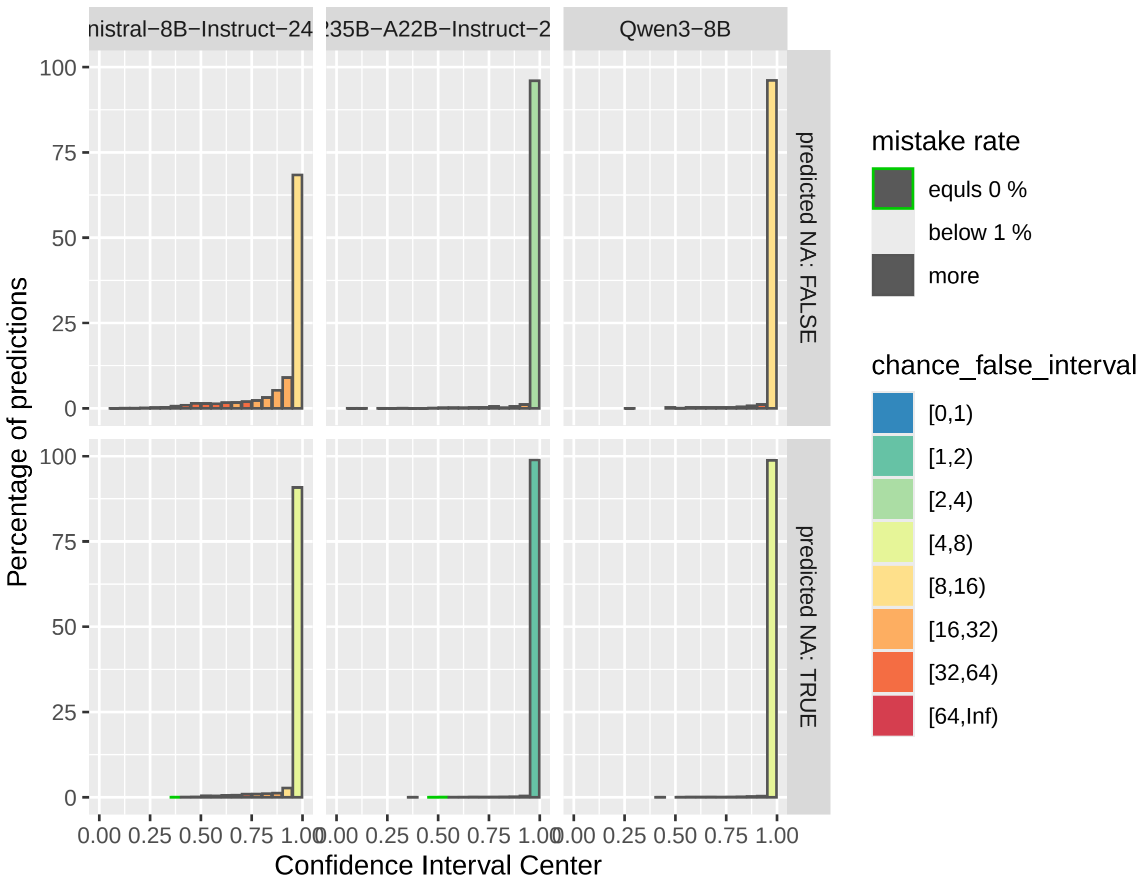

Figure C.12: Estimating the relative frequency to find a wrong classification over different confidence intervals.

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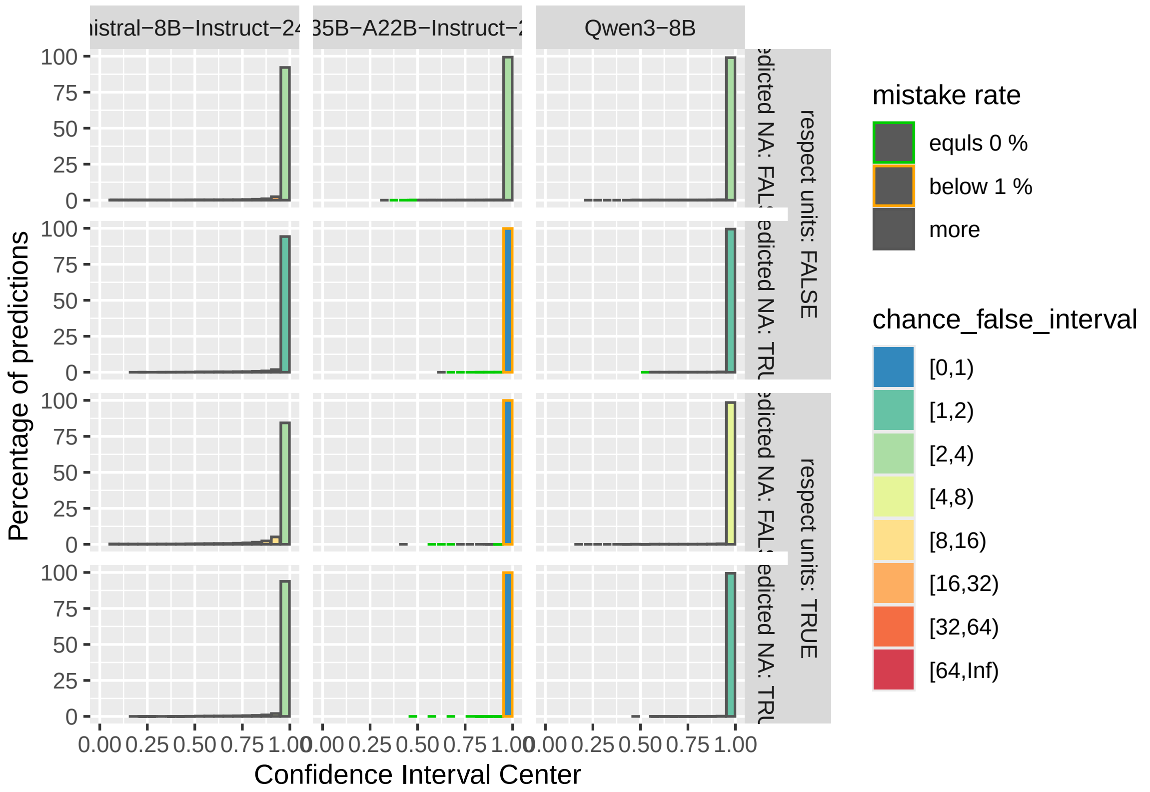


Figure C.13: Estimating the relative frequency to find a wrong extraction result over different confidence intervals for predictions for the synthetic table extraction task.

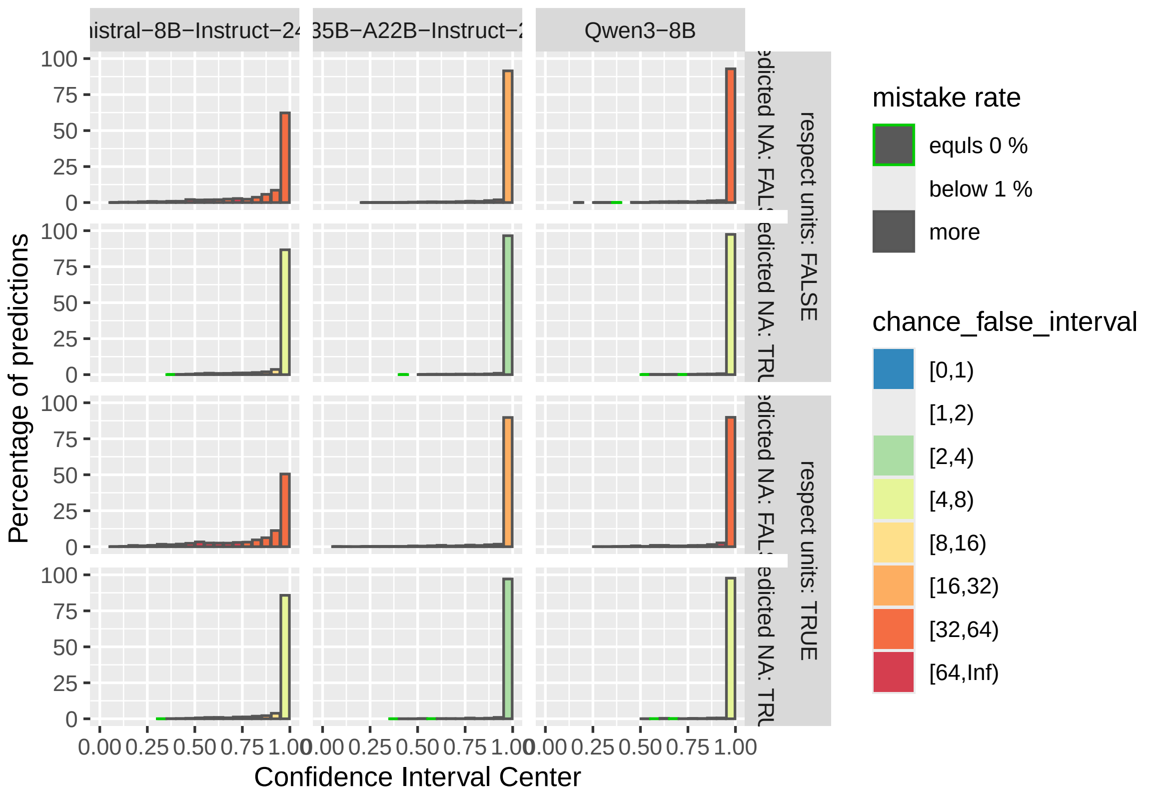


Figure C.14: Estimating the relative frequency to find a wrong extraction result over different confidence intervals for predictions based on synthetic examples for in-context learning.

Appendix D

Appendix D - Feature effect analysis

D.1 Regular expressions

Hypotheses The formulated hypotheses have been evaluated visually using the dependence and beeswarm plots from the *shapviz* library based on the SHAP values calculated for a random forest.

Real dataset The formulated hypotheses have been evaluated visually using the dependence and beeswarm plots from the shapviz library based on the SHAP values calculated with a random forest.

Table D.1 shows in the first column the predictors included in the random forests. Subsequent groups of two columns show the hypotheses and the found effects of those predictors for two aggregated measures (F1 score and percentage of correct numeric predictions) and one value based measure (binomial correctness rating).

Predictors that are marked with an asterisk only have five or less representatives. Thus, those results are not reliable. Bold set hypotheses show the predictors, that showed the highest mean SHAP values. For all measures but the binomial this means the effect is at least 0.025. For the binomial measure the effect of a predictor with bold hypothesis is at least 0.05. Results with red text highlight hypotheses that are not supported by the visual evaluation.

Table D.1 shows many red results, meaning the corresponding hypothesis is getting no support. Since most of these findings show only minor effect strength we don't interpret them as strongly challenging those hypotheses. Only three findings regarding the F1 score show a strong effect and findings that do not align with our hypotheses. First, it seems, that finding a sum in the same row, has a negative effect of finding any valid number there. Second, it has negative effect, if the previous year column is given as *T€*. Third, it has negative effect, if the columns are visually separated.

see Figure G.10

Synthetic dataset Table D.2 shows, many red results as well, meaning the corresponding hypothesis is getting no support. We find more predictors with a strong effect compared to the real **Aktiva** table extraction task. The results are based on 24_576 extracted tables and the SHAP values have been calculated on 2_000 examples each.

Contrary to our assumption, does the *extraction_backend* have a strong effect on all measures. We find, that *pdfium* is struggling with some of the table characteristics while *pymupdf* is not influenced by them. Figure D.1 A shows this exemplary for the characteristic *header_span*. An example for a erroneous text extraction with *pdfium* can be found in section @ref(#regex-extraction-mistakes). Actually, all results that are marked with an asterisk are showing this effect if *pdfium* is used as extraction backend. This can be inspected in Figure G.12.

Furthermore, does the number of columns is have a positive effect overall. Figure D.1 B shows, that this effect has inverse direction for the two libraries.

Table D.1: Comparing the formulated hypotheses and the found results for the table extraction on real Aktiva tables with the regular expression approach.

	F1		% correct numeric		binomial	
predictor	Hypothesis	Result	Hypothesis	Result	Hypothesis	Result
extraction_backend	neutral	neutral	neutral	pymupdf better	neutral	neutral
n_columns	neutral	2 is better	neutral	neutral	neutral	2 is better
sum_same_line	**neutral**	**negative**	**negative**	negative	negative	neutral
sum_in_header*	**neutral**	positive	neutral		neutral	neutral
header_span	neutral	negative	neutral	negative	neutral	negative
unit_first_cell*	neutral		negative	neutral	negative	neutral
T_in_previous_year	**neutral**	**negative**	**negative**	negative	negative	negative
T_in_year*	neutral	negative	**negative**	negative	negative	negative
passiva_same_page	negative	positive	negative	positive	negative	neutral
vorjahr	neutral	negative	neutral	negative	neutral	negative
vis_separated_cols	**neutral**	**negative**	neutral	negative	neutral	negative
vis_separated_rows	neutral	neutral	neutral	neutral	neutral	neutral
label_length					negative	negative
label					**unknown**	
missing					**positive**	positive

It might be worth noting, that the row for *Anteile an verbundenen Unternehmen* was rated to have a clear negative effect on the chance to extract the correct value.

The question, if visual separation of columns is having an effect, as found for the real data, is not studied here, because in the synthetic tables all columns are visually separated. But this could be investigated in future work. It is possible, that the visual separation is causing the faulty text extractions of *pdfium*.

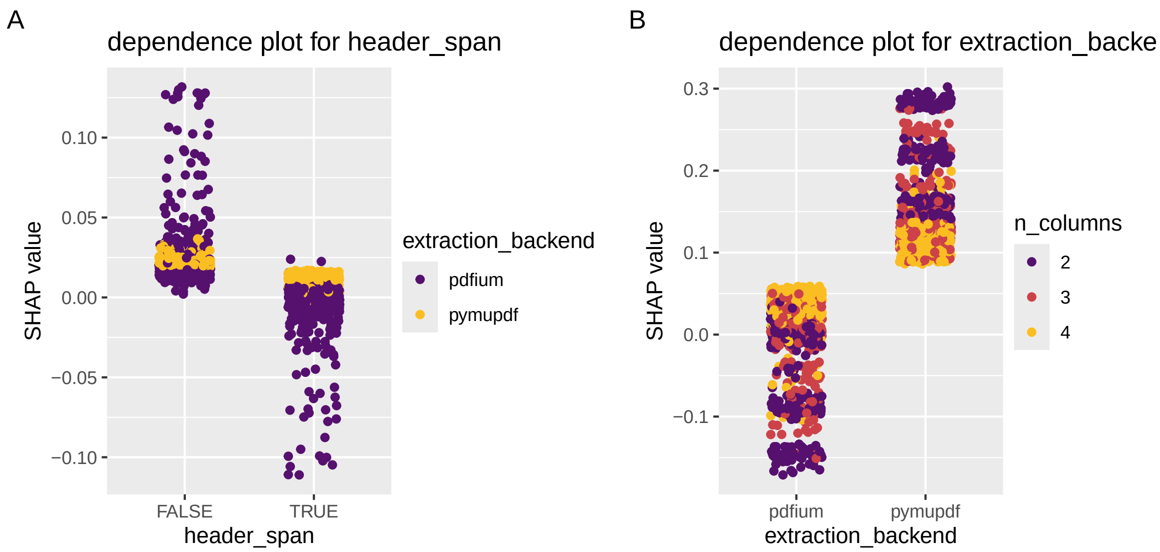


Figure D.1: Showing the influence of the extraxtion library on the numeric text extraction task with synthetic data for the percentage of correct numeric predictions.

D.2 Real tables

Hypotheses The formulated hypotheses have been evaluated visually using the dependence and beeswarm plots from the shapviz library based on the SHAP values calculated with a random forest.

Table D.2: Comparing the formulated hypotheses and the found results for the table extraction on synthetic Aktiva tables with the regular expression approach.

	F1		% correct numeric		binomial	
predictor	Hypothesis	Result	Hypothesis	Result	Hypothesis	Result
extraction_backend	**neutral**	pymupdf better	**neutral**	pymupdf better	**neutral**	pymupdf better
n_columns	**neutral**	**positive**	**neutral**	**positive**	**neutral**	**positive**
sum_same_line	neutral	neutral	negative	negative*	negative	neutral
header_span	neutral	negative*	neutral	negative*	neutral	negative*
thin	negative		neutral	positive*	neutral	neutral
year_as	**neutral**	positive*	neutral	positive*	neutral	positive*
unit_in_first_cell	negative	negative*	negative	negative*	negative	negative*
log10_unit_multiplier	**neutral**	negative*	**positive**	negative*	positive	negative*
enumeration	**positive**	positive*	**neutral**	positive*	**neutral**	positive*
shuffle_rows	neutral	neutral	neutral	neutral	neutral	neutral
text_around	neutral	neutral	neutral	neutral	neutral	neutral
many_line_breaks	negative	neutral	neutral	neutral	neutral	neutral
label_length					negative	neutral
label					**unknown**	
missing					positive	positive

Table D.3 shows in the first column the predictors included in the random forests. Subsequent groups of two columns show the hypotheses and the found effects of those predictors for two aggregated measures (F1 score and percentage of correct numeric predictions) and two value based measures (binomial correctness rating and reported confidence for the prediction).

Predictors that are marked with an asterix only have five or less representatives. Thus, those results are not reliable. Bold set hypotheses show the predictors, that showed the highest mean SHAP values. For all measures but the binomial this means the effect is at least 0.025. For the binomial measure the effect of a predictor with bold hypothesis is at least 0.05. Results with red text highlight hypotheses that are not supported by the visual evaluation.

For most measures the model and method related predictors (*model_family*, *parameter_count*, *method_family* and *n_examples*) show the strongest effects. Worth mentioning is, that *method_family* and *n_examples* show no strong effect on the reported confidence score. From the table related characteristics most strong effects show the hypothesized direction. Not predicted was the negative effect of label length on the reported confidence score. The visual separation of columns and rows shows small effects. We find no support for a negative effect of the fact that the **Passiva** table is on the same page as the **Aktiva** table.

see Figure G.22

D.3 Hybrid approach

Hypotheses Table D.4 shows only one unsupported hypothesis for a predictor with a strong effect: *method_family*. Figure D.2 shows the dependence plot for the this predictor. The prompting strategy *static_example* shows the highest SHAP values. This is surprising, because the the *static example* is equivalent to providing a single random example.

Table D.3: Comparing the formulated hypotheses and the found results for the table extraction on real Aktiva tables the LLM approach.

	F1		% corre	
predictor	Hypothesis	Result	Hypothesis	Res
model_family	**unknown**	google worst	**unknown**	goo
parameter_count	**positive**	positive	**positive**	pos
method_family	**top_n_rag & n_random best**	zero shot worst	**top_n_rag & n_random best**	top
n_examples	**positive**	1 and 3 best (five bad for Llama4)	**positive**	1 ar
n_columns	neutral	neutral	neutral	neu
sum_same_lin	neutral	negative (i.e. if prev year not T€)	negative	neg
sum_in_header*	neutral	neutral	neutral	neu
header_span	neutral	neutral	neutral	neu
unit_first_cell*	neutral	neutral	neutral	neu
T_in_previous_year	neutral	neutral	**negative**	neg
T_in_year*	neutral	negative	**negative**	neg
passiva_same_page	negative	neutral	negative	neu
vorjahr	neutral	neutral	neutral	neu
vis_separated_cols	neutral	negative	neutral	neg
vis_separated_rows	neutral	neutral	neutral	pos
label_length				
label				
missing				
confidence				

Table D.4: Comparing the formulated hypotheses and the found results for the table extraction on real Aktiva tables with the hybrid LLM approach.

	F1		% correc
predictor	Hypothesis	Result	Hypothesis
model_family	**unknown**	Google & Qwen3 worst	**unknown**
parameter_count	**positive**	positive	**positive**
method_family	**top_n_rag & n_random best**	static_example best	**top_n_rag & n_random best**
n_examples	**positive**	positive	positive
n_columns	neutral	interaction with passiva_same_page	neutral
sum_same_lin	neutral	negative if header_span	negative
sum_in_header*	neutral	neutral	neutral
header_span	neutral	neutral	neutral
unit_first_cell*	neutral	neutral	neutral
T_in_previous_year	neutral	neutral	**negative**
T_in_year*	neutral	negative	**negative**
passiva_same_page	negative	neutral	negative
vorjahr	neutral	neutral	neutral
vis_separated_cols	neutral	negative (if T_in_prev year)	neutral
vis_separated_rows	neutral	positive (if header_span)	neutral
respect_units	neutral	neutral	positive
label_length			
label			
missing			
confidence			

Figure D.2: Estimating the relative frequency to find a wrong extraction result over different confidence intervals for predictions based on synthetic examples for in-context learning.

D

Appendix E

Appendix E - Miscellaneous

E.1 Human in the loop application

Using LLMs has become a lot easier in the past years. *Python* frameworks as vLLM make it easy to deploy open-source models for developers. *Open WebUI* allows us to set up a sophisticated chat bot UI with ease. *Dify* promises to create no-code AI agents via a graphical flowchart. But the regular employee at RHvB will just use a provided application. And to solve the task, to extract (tabular) information for loading it into a relational database, a chat UI seems not the perfect match.

For the planned application we have two requirements: First, it should be able to accurately extract information. Second, it has to provide a good user experience.

Extracting the information of the assets table accurately means:

- Numeric values have to be extracted and transformed according to potentially given currency units, e.g. *T€*.
- The row labels should be matched with a limited set of labels in the target database.
- Unknown row labels and their values have to treated in a appropriate way.

To ensure, that there are no mistakes, a HITL approach should be implemented. Figure E.1 shows that the employee should initiate the extraction, by providing the document to extract information from and potentially choose, what to extract. The employee should also double check the results, before they are saved for future usage in down stream tasks.

Why do we aim to build an application that assists the process instead of fully automating it? On one hand, building a system that makes no mistakes might be impossible. And it would be more efficient, to ensure machine-readable data provision in the first place.

On the other hand, building a HITL application, could increase the employees acceptance for the product and trust in the results. An assisting application is not as threatening as an application, that fully automates a process, making the human redundant and potentially leading to job cuts. Programms building on the machine learning paradigm are rarely making decisions that are not seen as correct by a human. And humans make errors as well. Teaming up with an AI to reduce the error rate, should increase the trust in the results, if this story is sold right. (change management)

We believe, that the UX would improve, if we can guide the user, which values to check and which he can trust. This would reduce the work load and might increase the feeling to spend the time meaningful, by finding the same amount of mistakes, while checking less values. Thus, we formulate our side research question:

Q4 Can we use additional information from the extraction process, to guide the user which values need to be checked and which can be trusted as they are?

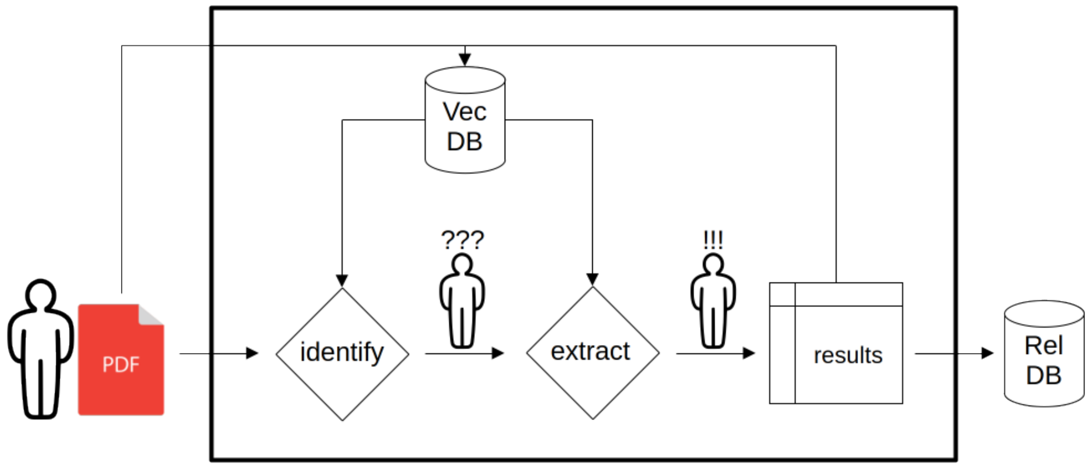
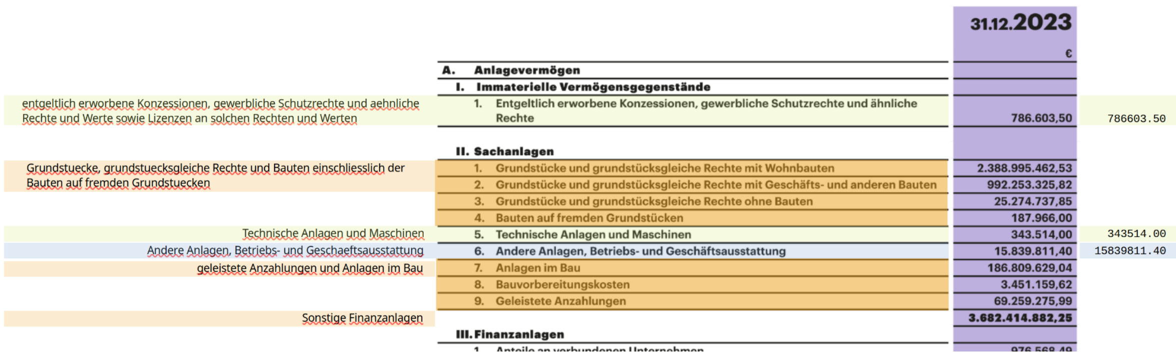


Figure E.1: Showing the information extraction process in a HITL application. The fed in document and results are saved in a database, that is used for the in-context learning RAG approaches for future extractions. The results are saved in the relational company database as well, e.g. as information to present in dashboards.

Of course, mistakes not only happen by extracting a wrong value, but by matching the values row with the wrong row labels from the predefined set. This can happen, because they are similar but not equal or because the row label at hand is not present in the predefined set yet. Having a human in the loop, seems to be a good way to handle such unknown row labels as well.

The UI (user interface) should assist in all cases. Comparing numeric values, checking the row label matching and showing, which rows have not been handled yet and need human decisions. Figure E.2 shows a first mockup, about what has to be compared focussing on a single years numeric values and the row lable matching. A UX study should answer questions, how exactly the UI should look like and if the employee prefers to check the identified page, before the extraction begins (see the human shape with question marks in Figure E.1).



		31.12.2023 €	
	A. Anlagevermögen		
	I. Immaterielle Vermögensgegenstände		
entgeltlich erworbene Konzessionen, gewerbliche Schutzrechte und aehnliche Rechte und Werte sowie Lizenzen an solchen Rechten und Werten	1. Entgeltlich erworbene Konzessionen, gewerbliche Schutzrechte und ähnliche Rechte	786.603,50	786603.50
	II. Sachanlagen		
Grundstuecke, grundstuecksgleiche Rechte und Bauten einschliesslich der Bauten auf fremden Grundstuecken	1. Grundstücke und grundstücksgleiche Rechte mit Wohnbauten	2.388.995.462,53	
	2. Grundstücke und grundstücksgleiche Rechte mit Geschäfts- und anderen Bauten	992.253.325,82	
	3. Grundstücke und grundstücksgleiche Rechte ohne Bauten	25.274.737,85	
	4. Bauten auf fremden Grundstücken	187.966,00	
Technische Anlagen und Maschinen	5. Technische Anlagen und Maschinen	343.514,00	343514.00
Andere Anlagen, Betriebs- und Geschaeftsausstattung	6. Andere Anlagen, Betriebs- und Geschäftsausstattung	15.839.811,40	15839811.40
geleistete Anzahlungen und Anlagen im Bau	7. Anlagen im Bau	186.809.629,04	
	8. Bauvorbereitungskosten	3.451.159,62	
	9. Geleistete Anzahlungen	69.259.275,99	
Sonstige Finanzanlagen		3.682.414.882,25	
	III. Finanzanlagen		

Figure E.2: Showing the information that need to be compared by the user after the information extraction. Unmatched rows could be highlighted in another color.

human in the loop (Mosqueira-Rey et al., 2023; Natarajan et al., 2024; Wu et al., 2022)

- allowing in place adjustments to the extracted data.

E.2 Local machine

One can find the specifications of the local machine used to run the tasks that do not require a GPU below. It is a lightweight laptop device. Its performance cores support hyper-threading and have a clock range between 2.1 and 4.7 GHz. Due to its slim design, there is little active cooling. Thus, thermal throttling starts quickly. It is a reasonable assumption that most local benchmarks are running at 2.1 GHz. Despite this handicap, it has a sufficiently large RAM of 32 GB and 3 TB of NVMe disk space.

System Details Report

Report details

- **Date generated:** 2025-07-19 13:56:16

Hardware Information:

- **Hardware Model:** LG Electronics 17ZB90Q-G.AD79G
- **Memory:** 32.0 GiB
- **Processor:** 12th Gen Intel® Core™ i7-1260P × 16
- **Graphics:** Intel® Graphics (ADL GT2)
- **Disk Capacity:** 3.0 TB

Software Information:

- **Firmware Version:** A2ZG0150 X64
- **OS Name:** Ubuntu 24.04.2 LTS
- **OS Build:** (null)
- **OS Type:** 64-bit
- **GNOME Version:** 46
- **Windowing System:** Wayland
- **Kernel Version:** Linux 6.11.0-29-generic

E.3 Benchmarks

E.3.1 Text extraction

All our experiments use the text extracted from PDF files. The available open-source libraries differ in their speed, quality of results and restrictiveness of licensing (Auer et al., 2024). We have tested multiple libraries in this thesis, because Auer et al. (2024) published no quantitative results. The benchmark runs on the local machine described in section E.2. There are 5256 pages to extract the text from.

Table E.1 shows, that *pdfium* and *pymupdf* extract the text fastest. For implementation in a system where the text has to get extracted live or frequently the speed of the library might be paramount. Since the AGPL license of *pymupdf* might not be met with the application, that will be created for RHvB, *pdfium* is an interesting candidate for the PDF parsing library to use.

Auer et al. (2024) reports, that *pdfium* occasionally merges text cells that are not close o each other, resulting in unrecoverable quality issues. Thus we checked some of the extracted texts manually and include the PDF extraction backend as a variable in our experiments. The page identification experiment, using the regex approach, shows no effect of the text extraction library. In contrast, we find an effect in the later performed information extraction experiment on synthetic **Aktiva** tables with the regex approach.

Some examples for errorneous extracted texts with *pdfium* and *pdfminer* can be found in section E.8.

time to ocr 107 images with pdf2image and pytesseract: 1:28+11:41

E

Table E.1: Comparing extraction time (in seconds) for different Python package

package	runtime in s
pdfium	**14**
pymupdf	22
pypdf	218
pdfplumber	675
pdfminer	752
docling-parse	1621

E.3.2 Table detection

E.3.2.1 old classification with llm

First experiments for the page identification task ran on a smaller dataset. The pages used for this setup are the pages, that are classified as target class by the regular expression approach. Without batch processing and the vLLM framework classifying these 727 pages already takes very long. This motivated the test, if image detection models can be used for the page refinement by detecting tables. Subsection E.3.2.2 shows the results of this attempt.

benchmark and n-shot base for llm classification (contrasts)

E.3.2.2 yolo benchmark and table transformer

We test three visual models, trained for table detection. One is based on Microsofts table transformer. The other two are based on Ultralytics Yolo 12 and differ in their parameter size:

- microsoft/table-transformer-detection
- yolo12l-doclaynet
- yolo12n-doclaynet

The Yolo models performed much better. Up to a threshold of 0.5 they show a recall of around 1 and a precision over 0.95. Thus, they can be used to refine the page range, by identifying all pages that have a table. The table transformer model has a worse precision of around 0.7

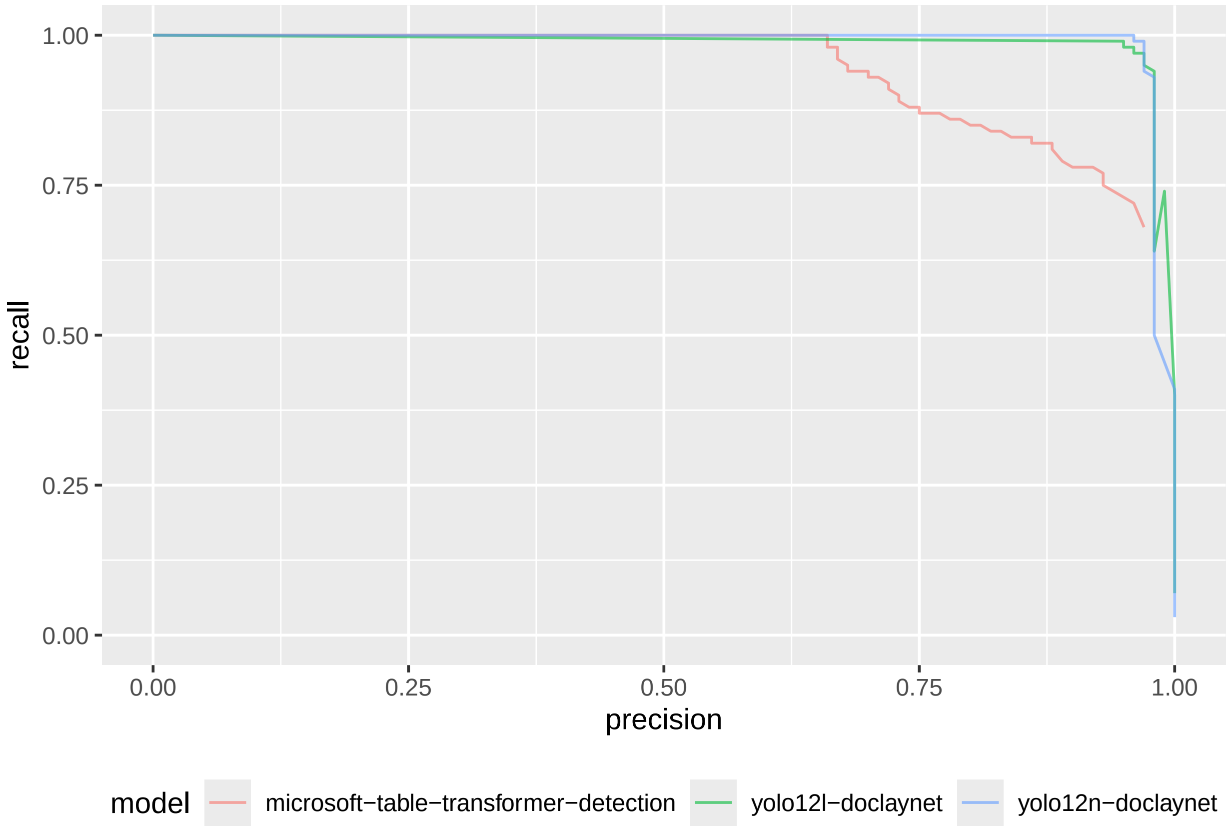
microsoft 5:55 min yolo large 20:6 min yolo nano 3:20 min

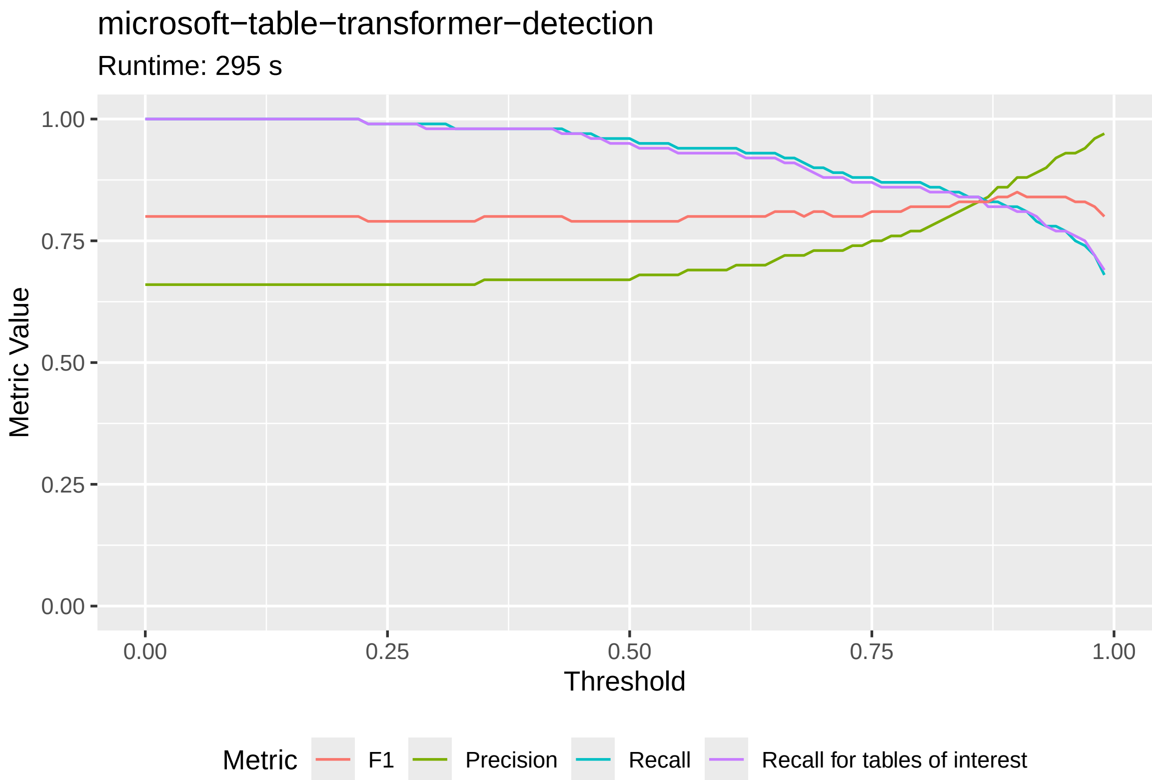
```
df_table_detection_result %>%
  select(model, runtime, pr_auc) %>%
  mutate(pr_auc = format_floats(pr_auc, 3))
```

```
## # A tibble: 3 x 3
##   model                              runtime pr_auc
##   <chr>                              <chr>   <chr>
## 1 microsoft-table-transformer-detection 5:55    0.920
## 2 yolo12l-doclaynet                  20:6    0.986
## 3 yolo12n-doclaynet                  3:20    0.989
```

```
table_detection_result_list %>% rowwise() %>%
  mutate(metrics = list(bind_rows(metrics, c(precision = 0, recall = 1)))) %>%
  unnest(metrics) %>%
  ggplot() +
  geom_line(aes(x = precision, y = recall, color = model), alpha = 0.6) +
  theme(
    legend.position = "bottom"
  )
```

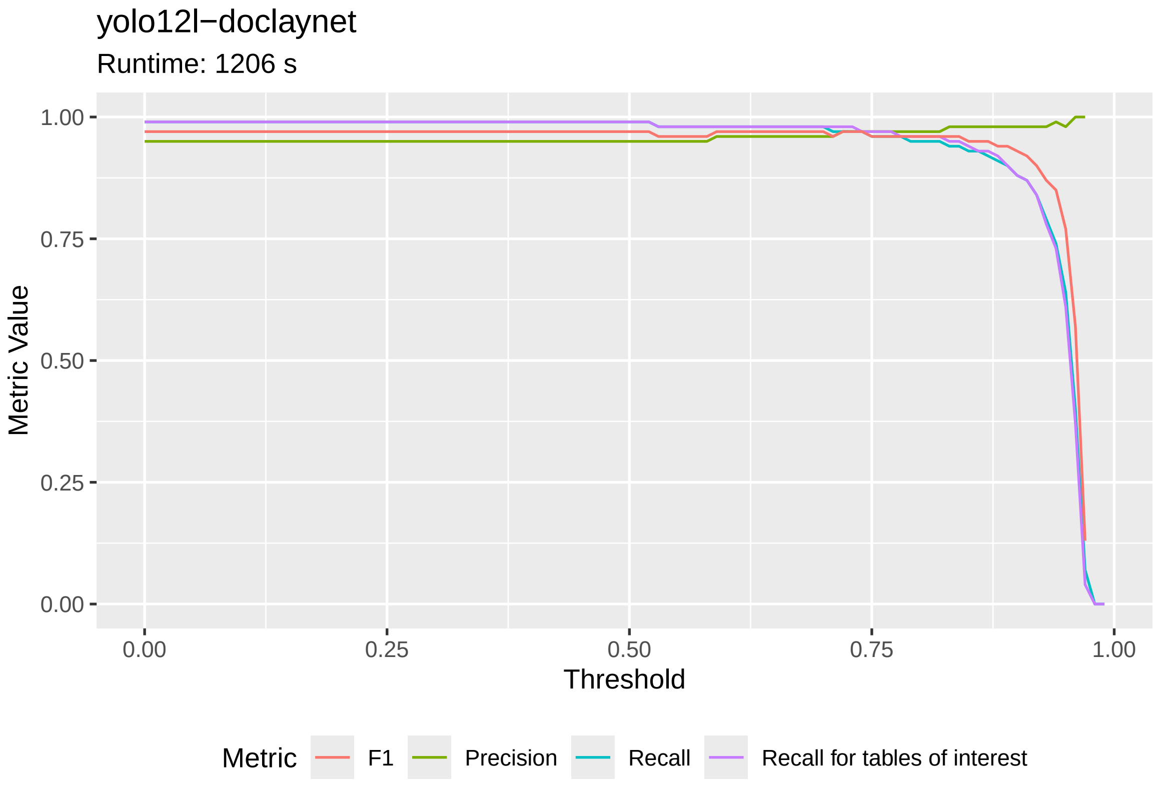
```
## Warning: Removed 5 rows containing missing values or
## values outside the scale range
## (`geom_line()`).
```



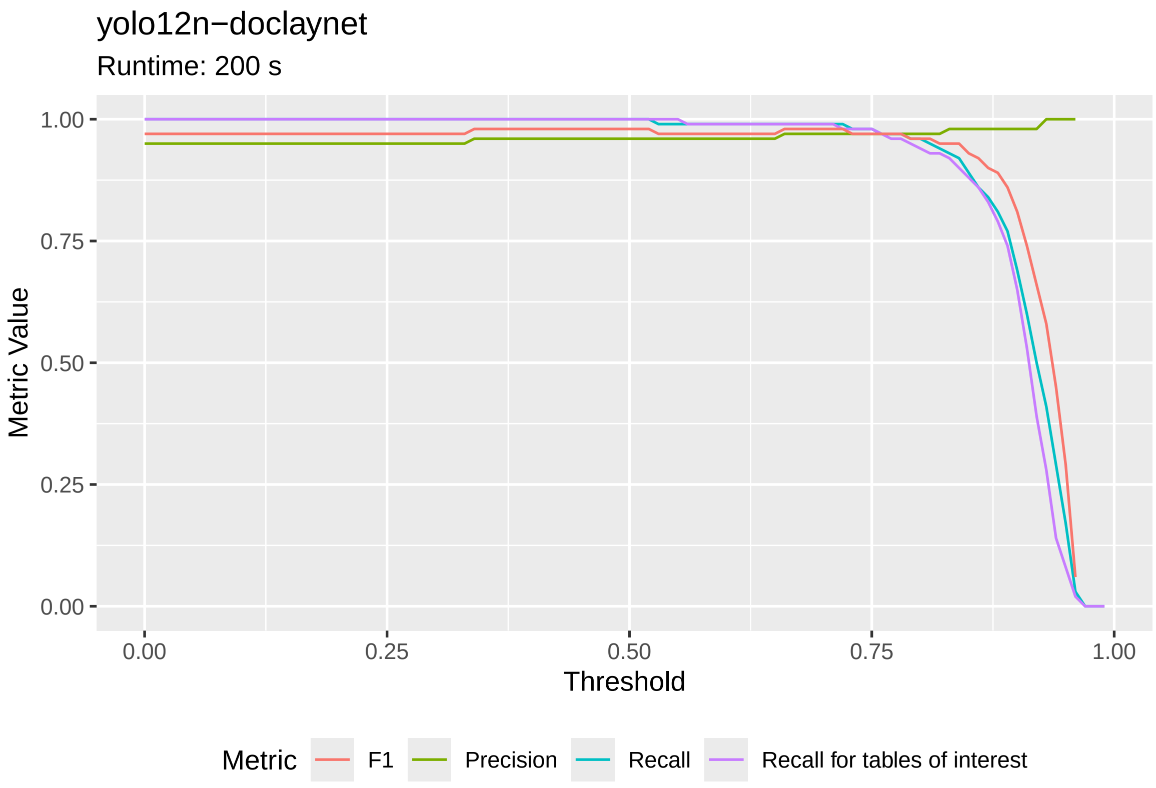


E

You see the plot for: microsoft-table-transformer-detection. (Click to stop automatic rotation.)

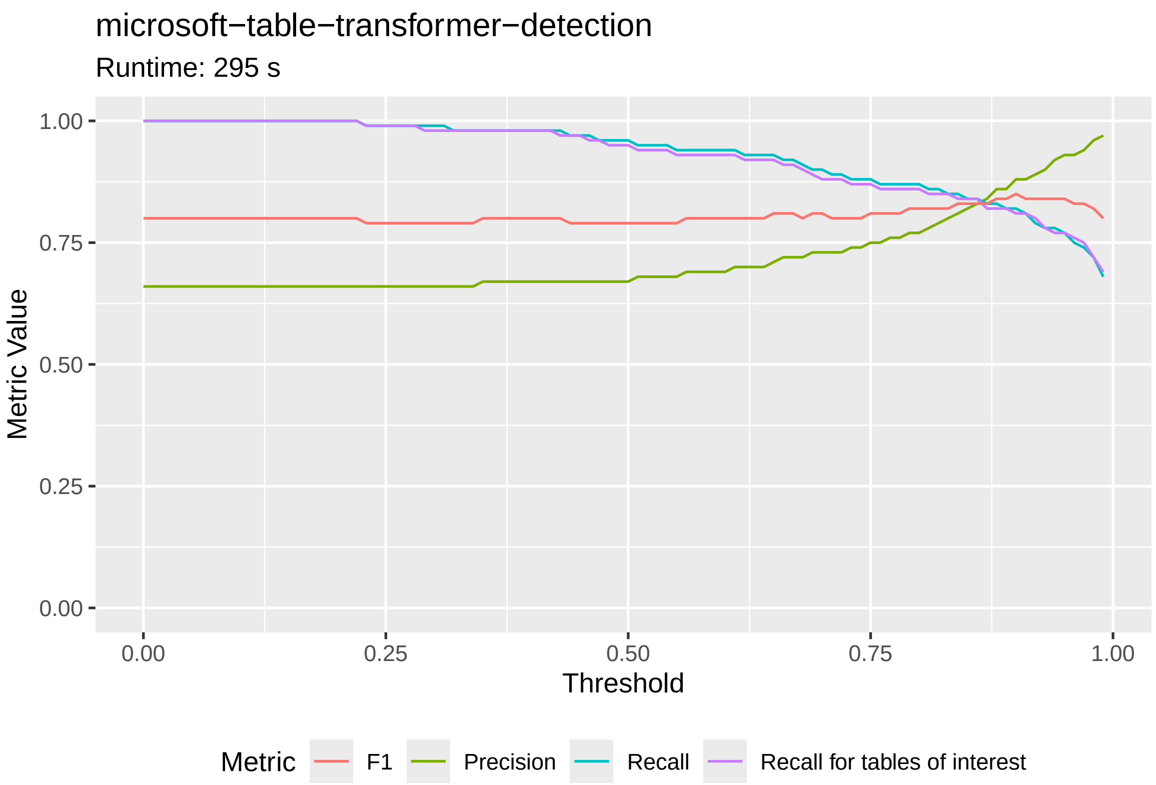


You see the plot for: yolo12l-doclaynet. (Click to stop automatic rotation.)

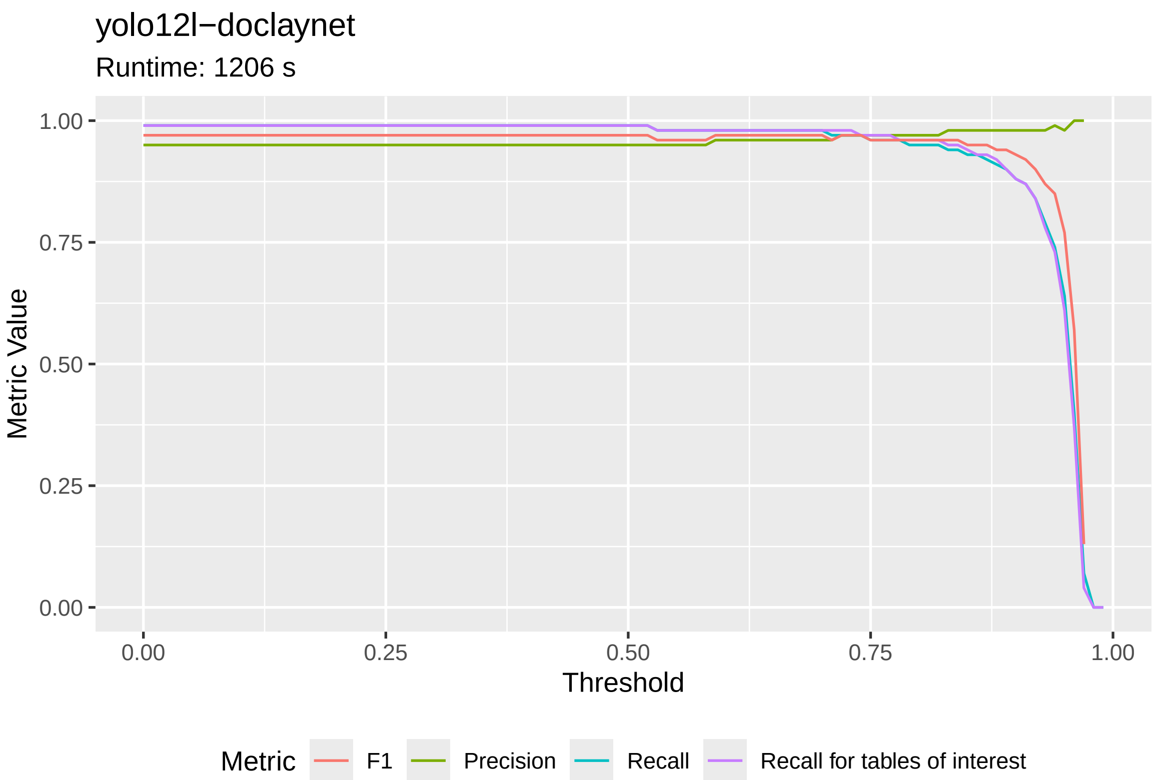


You see the plot for: yolo12n-doclaynet. (Click to stop automatic rotation.)

E

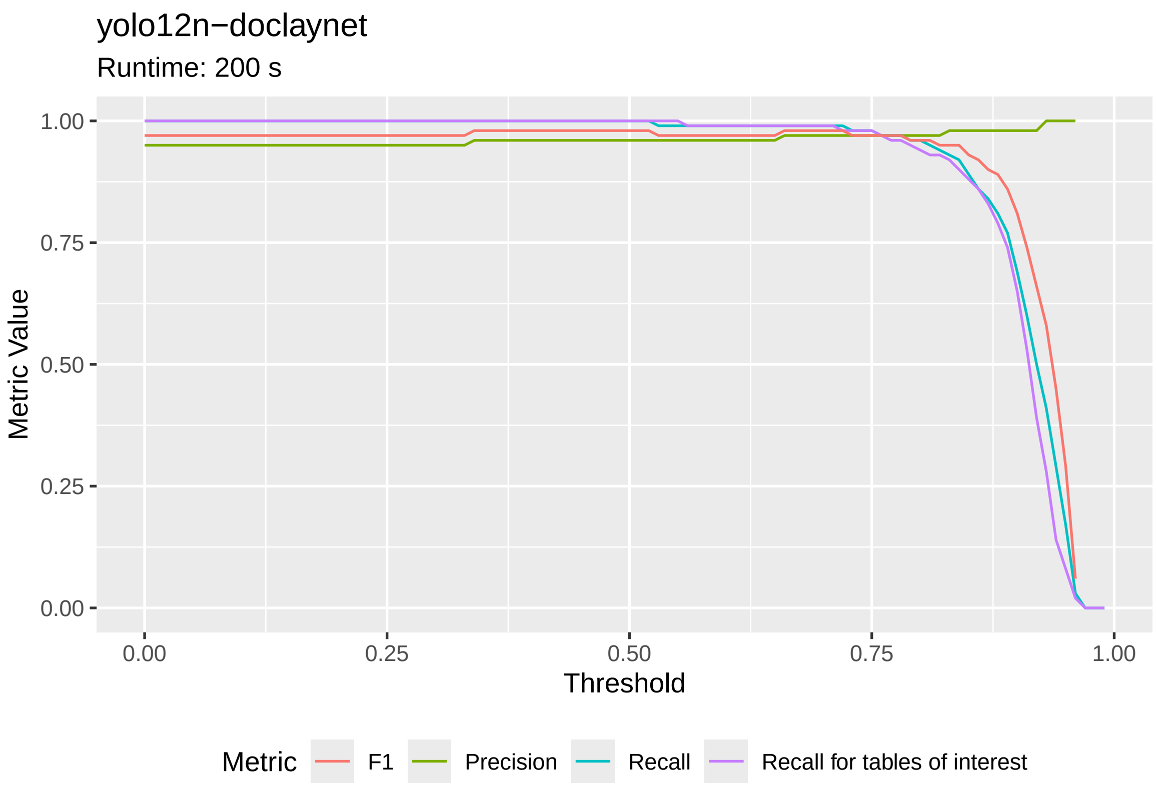


microsoft-table-transformer-detection



yolo12l-doclaynet

E



yolo12n-doclaynet

E.3.3 Large language model process speed

In April 2025 there have been issues with running vLLM within the Python framework. Thus, the first experiments are conducted, using the *transformers* library. When we managed to build a working vLLM based docker image for the experiments, we measured, how long the same task takes with the *transformers* and the vLLM library and how the batched processing competes versus a loop approach. The model family used is Qwen2.5-Instruct. The task is to extract the information from ten real **Aktiva** tables.

Table E.2 shows that the experiments with vLLM run around four to five times faster. Processing the messages in a batched mode is six to seven times faster than using a looped approach. Thus, the change of the experimental setup from a *transformers* powered loop-based approach to a vLLM powered batched processing approach, increased the speed by 2500 %.

This allows us to run the page identification benchmark on whole an nual reports, giving a sound estimate of the false positive rate (see section A.3). Previous experiments were only conducted on a subset of pages, that were selected based on the results of the *simple regex* approach (see section A.1).

E

Table E.2: Comparing time (in seconds) for extract the information from ten Aktiva tables using different libraries and approaches.

Model parameters (in B)	Transformers	vLLM	vLLM batched
0.5	330	65	NA
3.0	628	130	20
7.0	940	217	30

E.4 Prompts

E.4.1 TOC understanding

Base prompt:

```
    messages = [
        {"role": "system", "content": "You are a helpful assistant that can determine
↪   the page range information in a German financial report can be found at based on the
↪   documents table of contents."},
        {"role": "user", "content": f"This is the table of contents:\n\n{toc_string}"},
        {"role": "user", "content": f"On which pages might the win and loss statement
↪   (in German: Gewinn- und Verlustrechnung; GuV) and the balance sheets (German:
↪   Bilanz) be located? Give seperate answers for:\n\n1) the assets (German: Aktiva)
↪   table.\n2) the liabilities (German: Passiva) table.\n3) the win and loss
↪   statement."},
        specific_prompt,
        {"role": "user", "content": f"Answer in JSON format with keys 'GuV', 'Aktiva',
↪   and 'Passiva' and the page range as values."},
    ]
```

First attempt:

```
specific_prompt = {"role": "user", "content": f"The assets and liabilities tables often
↪   are on separate pages. They are often located directly before the win and loss
↪   statement. Rarely the tables for any of the three can span multiple pages."}
```

Given hint that assets and liabilities are part of the balance sheet:

```
specific_prompt = {"role": "user", "content": f"The assets and liabilities are part of
↪   the balance sheet (in German: Bilanz). The assets and liabilities tables often are
↪   on separate pages. They are often located directly before the win and loss
↪   statement. Rarely the tables for any of the three can span multiple pages."}
```

Stating, that liabilities are on next page:

```
specific_prompt = {"role": "user", "content": f"The assets and liabilities are part of
↪   the balance sheet (in German: Bilanz). The liabilities table is often on the page
↪   after the assets table. They are often located directly before the win and loss
↪   statement. Rarely the tables for any of the three can span multiple pages."}
```

TOC extraction from text prompt:

```
    messages = [
        {"role": "system", "content": "[Role] You are a helpful assistant that can
↪   identify table of contents in a German financial report."},
        {"role": "system", "content": f"[Context] These are the text lines of the first
↪   {i} pages:\n\n{start_pages}"},
        {"role": "user", "content": f"[Tasks] 1. Please identify if there is a table of
↪   contents in the text."},
        {"role": "user", "content": f"2. If there is a table of contents, please extract
↪   its text."},
        {"role": "user", "content": f"3. Answer as JSON with the table of contents text
↪   as string in the key 'toc'."},
        {"role": "user", "content": f"If there is no table of contents, return an empty
↪   string."},
    ]
```

E

E.4.2 Classification

binary classification prompt factory

```
messages = [{"role": "system", "content": "[Role and Context]: You are a helpful
↪ assistant that can classify texts extracted from PDFs."}]

if law_context:
    if classification_type == "GuV":
        messages.append({"role": "system", "content": f"You know the laws about how to
↪ structure the 'Gewinn- und Verlustrechnung' (profit and loss statement) table:'
↪ \n\n'''\n{hgb_guv}\n'''."})
    elif classification_type == "Aktiva":
        messages.append({"role": "system", "content": f"You know the laws about how to
↪ structure the 'Aktiva' (assets) table for a 'Bilanz' (balance sheet):'
↪ \n\n'''\n{hgb_aktiva}\n'''."})
    elif classification_type == "Passiva":
        messages.append({"role": "system", "content": f"You know the laws about how to
↪ structure the 'Passiva' (liabilities) table for a 'Bilanz' (balance sheet):'
↪ \n\n'''\n{hgb_passiva}\n'''."})
    else:
        raise ValueError(f"Unknown classification type: {classification_type}. Expected
        ↪ 'GuV', 'Aktiva', or 'Passiva'.")

if random_examples:
    system_messages = self.__get_random_example_message(classification_type, **kwargs)
    for msg in system_messages:
        messages.append({"role": "system", "content": msg})

if rag_examples:
    system_messages = self.__get_rag_example_message(text, classification_type,
↪ **kwargs)
    for msg in system_messages:
        messages.append({"role": "system", "content": msg})

if top_n_rag_examples:
    system_messages = self.__get_top_n_rag_example_message(text, classification_type,
↪ **kwargs)
    for msg in system_messages:
        messages.append({"role": "system", "content": msg})

messages.append({"role": "user", "content": f"[Task]: Decide if the given text contains
↪ {phrase_dict[classification_type]}.\n\n[Rule]: Answer with 'yes' if it does.
↪ Otherwise answer with 'no'.\n\n[Text]: Here is the text to classify:
↪ \n\n'''\n{text}\n'''"})
return messages
```

example for binary classification with 1 random example with Qwen 3

```
<|im_start|>system
/no_think [Role and Context]: You are a helpful assistant that can classify texts
↪ extracted from PDFs.<|im_end|>
<|im_start|>system
You know this example for a \'Gewinn- und Verlustrechnung\' (profit and loss statement)
↪ table and for this example you should answer with "no":

\'\'\'
28
```

```
2023
EUR
2022
EUR
EUR EUR
1. Umsatzerlöse 1.315.073,26 1.507.621,05
2. Sonstige betriebliche Erträge 562.644,72 631.803,96
3. Materialaufwand -388.989,26 -98.471,89
4. Abschreibungen -447.356,00 -460.923,00
5. Sonstige betriebliche Aufwendungen -907.414,53 -2.304.390,53
6. Sonstige Zinsen und ähnliche Erträge 95.260,94 -2.533,45
7. Ergebnis nach Steuern 229.219,13 -726.893,86
8. Sonstige Steuern -857.535,62 -879.289,10
9. Jahresfehlbetrag -628.316,49 -1.606.182,96
Gewinn- und Verlustrechnung
für die Zeit vom 01. Januar bis 31. Dezember 2023
\'\'\'.<|im_end|>
<|im_start|>system
You know this example for a \'Aktiva\' (assets) table and for this example you should answer with "yes":

\'\'\'
BEN Berlin Energie und Netzholding GmbH (vormals: Berlin Energie Rekom 2 GmbH)
Berlin
Bilanz zum 31.12.2021
Aktivseite 31.12.2021 31.12.2020 31.12.2021 31.12.2020
T€ T€ T€ T€
A. Anlagevermögen A. Eigenkapital
imv I. Immaterielle Vermögensgegenstände 0,8 - ek I. Gezeichnetes Kapital 25,0 25,0
bga II. Sachanlagen 73,1 - kr II. Kapitalrücklage 6,9 6,9
III. Finanzanlagen 2.094.146,0 - vv III. Verlustvortrag - 6,9 - 6,9
IV. Jahresüberschuss 1.326,7 -
 2.094.219,9 -
 1.351,7 25,0
B. Umlaufvermögen sor
unf I. Forderungen und sonstige B. Rückstellungen
 Vermögensgegenstände Sonstige Rückstellungen 265,1 6,7
Forderungen gegen verbundene
Unternehmen 423,1 - anzC. Verbindlichkeiten
1. Verbindlichkeiten gegenüber
fll II. Guthaben bei Kreditinstituten 166.662,0 39,2 vll Kreditinstituten 2.180.051,3 -
2. Verbindlichkeiten aus
 167.085,1 39,2 Lieferungen und Leistungen 91,9 1,9
3. Verbindlichkeiten gegenüber
 verbundenen Unternehmen 81.286,7 -
C. Rechnungsabgrenzungsposten 2.471,2 - vvu 4. Verbindlichkeiten gegenüber
 Gesellschaftern 713,9 5,6
5. Sonstige Verbindlichkeiten 15,6 -
 2.262.159,4 7,5
 2.263.776,2 39,2 2.263.776,2 39,2
Passivseite
 21-006917
\'\'\'.<|im_end|>
<|im_start|>system
You know this example for a \'Passiva\' (liabilities) table and for this example you should answer with "no":

\'\'\'
4
```

```
 Bilanz Elektrizitätsverteilung
Aktiva 31.12.2022
T€
Anlagevermögen
imv Immaterielle Vermögensgegenstände -
bga Sachanlagen -
Finanzanlagen -
 -
Umlaufvermögen
unf Forderungen und sonstige Vermögensgegenstände 329,6
davon Verrechnungsposten gegenüber anderen Aktivitäten 289,9
fll Guthaben bei Kreditinstituten -
 329,6
Rechnungsabgrenzungsposten 17,9
 347,6
Passiva 31.12.2022
T€
Eigenkapital
ek Gezeichnetes Kapital -
kr Kapitalrücklage -
vv Gewinnrücklage/Verlustvortrag -
Jahresüberschuss 0,1
 0,1
Rückstellungen
Sonstige Rückstellungen 258,4
Verbindlichkeiten
anz Verbindlichkeiten gegenüber Kreditinstituten -
vll Verbindlichkeiten aus Lieferungen und Leistungen 89,0
Verbindlichkeiten gegenüber Gesellschaftern -
Sonstige Verbindlichkeiten -
 89,0
 347,6
\'\'\'.<|im_end|>
<|im_start|>system
You know this example for a text that does not suit the categories of interest and for
 ↪  this example you should answer with "no":

\'\'\'
Bericht des
Aufsichtsrates
Sehr geehrte Damen,
sehr geehrte Herren,
mit diesem Bericht informieren wir über unsere Tätigkeit im Geschäftsjahr 2016
und das Ergebnis der Prüfung des Jahresabschlusses. Die uns nach Gesetz, Satzung
und Geschäftsordnung obliegenden Kontroll- und Beratungsaufgaben haben
wir verantwortungsvoll und mit der gebührenden Sorgfalt wahrgenommen. Dabei
haben wir den Vorstand bei der Leitung der GESOBAU beratend begleitet, seine
Tätigkeit überwacht und waren in alle für die Gesellschaft grundlegend bedeutenden
Entscheidungen unmittelbar eingebunden. Der Vorstand ist seinen
 ↪  Informations\x02pflichten uneingeschränkt nachgekommen und hat uns regelmäßig sowohl
 ↪  schrift\x02lich als auch mündlich informiert. Dies geschah zeitnah und umfassend zu
 ↪  allen
Aspekten der Unternehmensplanung, dem Verlauf der Geschäfte, der strategischen
Weiterentwicklung sowie der aktuellen Lage des Unternehmens. Planabweichungen
beim Geschäftsverlauf wurden uns im Einzelnen erläutert und mit schlüssigen
Argumenten begründet. Der Vorstand stimmte die strategische Ausrichtung des
Unternehmens vertrauensvoll mit uns ab. Die für das Unternehmen bedeutenden
Geschäftsvorgänge haben wir auf der Basis der Berichte des Vorstandes ausführlich
erörtert und seinen Beschlussvorschlägen nach gründlicher Prüfung und Beratung
```

```
zugestimmt.
Sitzungen
Im Berichtsjahr fanden vier turnusgemäße und eine außerordentliche Sitzung statt.
Die Sitzungen des Aufsichtsrates sind von einem intensiven und offenen Austausch
geprägt. Ein Mitglied des Aufsichtsrates hat im abgelaufenen Geschäftsjahr an
weniger als der Hälfte der Sitzungen teilgenommen. Aufgrund besonderer
 ↪ Eilbe\x02dürftigkeit erfolgten in Abstimmung mit der Vorsitzenden des Aufsichtsrates
 ↪ vier
Beschlussfassungen im Umlaufverfahren.
Die Mitglieder des Aufsichtsrates bereiten sich auf anstehende Beschlüsse regelmäßig
auch anhand von Unterlagen vor, die der Vorstand vorab zur Verfügung stellt. Dabei
wurden sie von den jeweils zuständigen Ausschüssen unterstützt. Die
 ↪ Aufsichtsrats\x02sitzungen werden zudem von den Arbeitnehmervertretern in Gesprächen
 ↪ mit dem
Vorstand vorbereitet.
Information durch den Vorstand
Über die wichtigsten Indikatoren der Geschäftsentwicklung und bestehende Risiken
unterrichtet der Vorstand den Aufsichtsrat anhand schriftlicher Quartalsberichte.
Zwischen den Sitzungsterminen des Aufsichtsrates und seiner Ausschüsse wurde
die Aufsichtsratsvorsitzende ausführlich unterrichtet. Hierbei wurde die Strategie
des Unternehmens besprochen, wie auch die aktuelle Geschäftsentwicklung und
-lage, das Risikomanagement, Fragen der Compliance sowie wesentliche Einzel\x02themen
 ↪ und bevorstehende bedeutsame Entscheidungen erörtert.
16 Perspektiven Bericht des Aufsichtsrates
\'\'\'.<|im_end|>
<|im_start|>user
[Task]: Decide if the given text contains a \'Aktiva\' (assets) table.

[Rule]: Answer with \'yes\' if it does. Otherwise answer with \'no\'.

[Text]: Here is the text to classify:

\'\'\'
22 Amt für Statistik Berlin-Brandenburg | Geschäftsbericht 2014
Amt für Statistik Berlin-Brandenburg Anstalt des öffentlichen Rechts, Potsdam
Bilanz zum 31. Dezember 2014
A K T I V S E I T E 31.12.2014 Vorjahr
EUR EUR TEUR
A. ANLAGEVERMÖGEN
I. Immaterielle Vermögensgegenstände
1. Entgeltlich erworbene Konzessionen, gewerbliche
Schutzrechte und ähnliche Rechte und Werte
sowie Lizenzen an solchen Rechten und Werten 81.480,00 146
II. Sachanlagen
1. Grundstücke, grundstücksgleiche Rechte und Bauten
einschließlich der Bauten auf fremden Grundstücken 68.386,00 93
2. Andere Anlagen, Betriebs- und Geschäftsausstattung 140.186,00 174
208.572,00 267
III. Finanzanlagen
1. Wertpapiere des Anlagevermögens 2.000.000,00 2.000
2.000.000,00 2.000
2.290.052,00 2.413
B. UMLAUFVERMÖGEN
I. Forderungen und sonstige Vermögensgegenstände
1. Forderungen aus Lieferungen und Leistungen 36.617,86 14
2. Sonstige Vermögensgegenstände 297.982,42 267
334.600,28 281
II. Kassenbestand, Bundesbankguthaben, Guthaben bei
Kreditinstituten und Schecks 5.560.638,85 7.783
```

```
5.895.239,13 8.064
C. RECHNUNGSABGRENZUNGSPOSTEN 216.321,49 213
8.401.612,62 10.690
Bestätigungsvermerk
des Abschlussprüfers
Anhang
\'\'\'<|im_end|>
<|im_start|>assistant
```

multi-class classification prompt factory

```
messages = [
  {"role": "system", "content": "[Role and Context]: You are a helpful assistant that
↪  can classify texts extracted from PDFs."},
]

if law_context:
  messages.append({"role": "system", "content": f"You know the laws about how to
↪  structure the 'Gewinn- und Verlustrechnung' (profit and loss statement) table:'
↪  \n\n'''\n{hgb_guv}\n'''."})
  messages.append({"role": "system", "content": f"You also know the laws about how to
↪  structure the 'Aktiva' (assets) and 'Passiva' (liabilities) table for a 'Bilanz'
↪  (balance sheet):' \n\n'''\n{hgb_bilanz}\n'''."})

if random_examples:
  system_messages = self.__get_random_example_message(**kwargs)
  for msg in system_messages:
      messages.append({"role": "system", "content": msg})

if rag_examples:
  system_messages = self.__get_rag_example_message(text, **kwargs)
  for msg in system_messages:
      messages.append({"role": "system", "content": msg})

if top_n_rag_examples:
  system_messages = self.__get_top_n_rag_example_message(text, **kwargs)
  for msg in system_messages:
      messages.append({"role": "system", "content": msg})

messages.append({"role": "user", "content": f"""
[Task]: Decide of what type the given text is. You can differentiate between four types
↪  of pages: 'Aktiva', 'GuV', 'Passiva' and 'other'.\n\n
[Rules]:\n
  1) If the text contains a 'Gewinn- und Verlustrechnung' (profit and loss statement)
↪  table, answer with 'GuV'.\n\n
  2) If the text contains an 'Aktiva' (assets) table, answer with 'Aktiva'.\n\n
  3) If the text contains a 'Passiva' (liabilities) table, answer with 'Passiva'.\n\n
  4) If the text contains something else, answer with 'other'.\n\n
[Text]: Here is the text to classify: \n\n'''\n{text}\n'''
"""})
```

E

example for multi-class classification with 1 rag example with Qwen 3

```
<|im_start|>system
/no_think [Role and Context]: You are a helpful assistant that can classify texts
↪  extracted from PDFs.<|im_end|>
<|im_start|>system
```

```
You know this example for a \'Gewinn- und Verlustrechnung\' (profit and loss statement)
 ↪  table and for this example you should answer with "GuV":

"""
74
Gewinn- und Verlustrechnung für die Zeit vom 01.01.2014 bis 31.12.2014
Aufwendungen in TEUR Vorjahr
1. Zinsaufwendungen 302.081 314.077
2. Provisionsaufwendungen 714 656
4. Allgemeine Verwaltungsaufwendungen
a) Personalaufwand
 aa) Löhne und Gehälter
 ab) Soziale Abgaben und Aufwendungen
 für Altersversorgung und für Unterstützung
 darunter: für Altersversorgung
b) andere Verwaltungsaufwendungen

39.535
9.009
2.417
48.544
31.161
79.705
39.310
11.020
4.651
50.330
24.983
75.313
5. Abschreibungen und Wertberichtigungen auf immaterielle
Anlagewerte und Sachanlagen 3.647 3.707
6. Sonstige betriebliche Aufwendungen 25.803 26.412
7. Abschreibungen und Wertberichtigungen auf Forderungen und
bestimmte Wertpapiere sowie Zuführungen zu
Rückstellungen im Kreditgeschäft 25.366 14.666
8. Abschreibungen und Wertberichtigungen auf Beteiligungen,
Anteile an verbundenen Unternehmen
und wie Anlagevermögen behandelte Wertpapiere 421 0
9. Aufwendungen aus Verlustübernahme 1.268 0
13. Sonstige Steuern, soweit nicht unter Posten 6 ausgewiesen 65 80
15. Jahresüberschuss 25.863 36.897
Summe der Aufwendungen 464.933 471.808
Jahresüberschuss 25.863 36.897
Gewinnvortrag aus dem Vorjahr 0 0
Bilanzgewinn 25.863 36.897
An unsere Geschäftspartner | Grußwort der Vorsitzenden des Verwaltungsrats | Bericht des
 ↪  Verwaltungsrats
Wohnungsbauförderung | Wirtschaftsförderung | Beteiligungen | Immobilien- und
 ↪  Stadtentwicklung | Personalbericht | Nachhaltigkeit
Lagebericht | Jahresabschluss | Anhang | Bestätigungsvermerk |
 ↪  Corporate-Governance-Bericht | Organigramm
""". (The L2 distance of this example text is: 0.562)<|im_end|>
<|im_start|>system
You know this example for a \'Aktiva\' (assets) table and for this example you should
 ↪  answer with "Aktiva":

"""
52 Gruppenbilanz
Gruppenbilanz zum 31. Dezember 2016
```

```
A K T I V A 31. 12. 2016 31. 12. 2015
€ € €
A. ANLAGEVERMÖGEN
I. Immaterielle Vermögensgegenstände
Entgeltlich erworbene Konzessionen, gewerbliche
Schutzrechte und ähnliche Rechte 122.148,00 185.602,00
II. Sachanlagen
1. Anlageimmobilien 3.423.064.255,69 3.338.758.481,04
2. übrige Grundstücke und Bauten 4.143.376,87 1.087.406,00
3. technische Anlagen und Maschinen 120.700,00 149.667,00
4. andere Anlagen, Betriebs- und Geschäftsausstattung 5.143.477,51 4.555.161,48
5. geleistete Anzahlungen und Anlagen im Bau 1.007.468,36 180.543,58
3.433.479.278,43 3.344.731.259,10
III. Finanzanlagen
1. Anteile an verbundenen Unternehmen 1.026.647,27 1.027.646,27
2. Ausleihungen an verbundene Unternehmen 157.645,00 214.395,00
3. Beteiligungen 284.138,88 40.073,02
4. sonstige Ausleihungen 120.966,91 120.966,91
1.589.398,06 1.403.081,20
3.435.190.824,49 3.346.319.942,30
B. UMLAUFVERMÖGEN
I. Vorräte
1. unfertige Leistungen 48.642.315,18 52.057.422,25
2. andere Vorräte 13.053,63 21.315,99
48.655.368,81 52.078.738,24
II. Forderungen und sonstige Vermögensgegenstände
1. Forderungen aus Lieferungen und Leistungen 32.107.301,91 35.679.035,16
2. Forderungen gegen verbundene Unternehmen 74.457,55 554.130,28
3. Forderungen gegen Unternehmen,
mit denen ein Beteiligungsverhältnis besteht 108.647,73 23.698,71
4. sonstige Vermögensgegenstände 100.560.866,41 100.896.144,88
132.851.273,60 137.153.009,03
III. Wertpapiere
sonstige Wertpapiere 1.700,00 1.700,00
IV. Kassenbestand, Guthaben bei Kreditinstituten 893.140.123,18 689.887.519,98
1.074.648.465,59 879.120.967,25
C. RECHNUNGSABGRENZUNGSPOSTEN 9.245.284,80 9.917.197,12
D. AKTIVER UNTERSCHIEDSBETRAG AUS DER
VERMÖGENSVERRECHNUNG 68.523,69 0,00
4.519.153.098,57 4.235.358.106,67

""". (The L2 distance of this example text is: 0.421)<|im_end|>
<|im_start|>system
You know this example for a \'Passiva\' (liabilities) table and for this example you
↪  should answer with "Passiva":

"""
Anlage 1
BEN Berlin Energie und Netzholding GmbH
Berlin
Bilanz zum 31.12.2023
Aktivseite 31.12.2023 31.12.2022 31.12.2023 31.12.2022
T€ T€ T€ T€
A. Anlagevermögen A. Eigenkapital
imv I. Immaterielle Vermögensgegenstände 58,0 20,2 ek I. Gezeichnetes Kapital 25,0
↪  25,0bga II. Sachanlagen 106,7 70,7 kr II. Kapitalrücklage 6,9 6,9
III. Finanzanlagen 2.194.146,0 2.094.146,0 vv III. Gewinnrücklage/Verlustvortrag
↪  41.023,4 1.319,8
IV. Jahresüberschuss 51.158,5 39.703,6
```

```
 2.194.310,6 2.094.236,9
 92.213,8 41.055,3
B. Umlaufvermögen sor
unf I. Forderungen und sonstige B. Rückstellungen
 Vermögensgegenstände Sonstige Rückstellungen 4.759,3 460,0
1. Forderungen aus Lieferungen und Leistungen 73,1 70,72. Forderungen gegen verbundene
 ↪  C. Verbindlichkeiten Unternehmen 96.998,2 60.960,4 anz 1. Verbindlichkeiten
 ↪  gegenüber 3. Sonstige Vermögensgegenstände 988,6 923,3 Kreditinstituten 2.317.498,9
 ↪  2.148.050,6
fll II. Guthaben bei Kreditinstituten 226.047,2 160.535,8 vll 2. Verbindlichkeiten aus
 Lieferungen und Leistungen 272,0 158,4
 324.107,1 222.490,2 3. Verbindlichkeiten gegenüber
 verbundenen Unternehmen 104.704,9 128.407,54. Verbindlichkeiten gegenüber
C. Rechnungsabgrenzungsposten 1.969,9 2.207,9 vvu Gesellschaftern 695,8 706,1
5. Sonstige Verbindlichkeiten 242,9 97,1
 2.423.414,4 2.277.419,7
 2.520.387,6 2.318.935,0 2.520.387,6 2.318.935,0
Passivseite
3
""". (The L2 distance of this example text is: 0.481)<|im_end|>
<|im_start|>system
You know this example for a text that does not suit the categories of interest and for
 ↪  this example you should answer with "other":

"""
46 Konzernbilanz
Konzernbilanz zum 31. Dezember 2013
A K T I V A 31. 12. 2013 31. 12. 2012
€ € €
A. ANLAGEVERMÖGEN
I. Immaterielle Vermögensgegenstände
Konzessionen, gewerbliche Schutzrechte und ähnliche
Rechte
344.384,00 461.417,00
II. Sachanlagen
1. Grundstücke und Bauten 1.242.921,00 1.272.566,00
2. Technische Anlagen und Maschinen 122.769,00 62.405,00
3. Andere Anlagen, Betriebs- und Geschäftsausstattung 2.339.362,51 1.562.893,45
4. Geleistete Anzahlungen 704,76 33.483,89
3.705.757,27 2.931.348,34
III. Finanzanlagen
1. Anteile an verbundenen Unternehmen 3.201.349,87 3.201.436,42
2. Ausleihungen an verbundene Unternehmen 217.680,00 223.395,00
3. Beteiligungen 42.171.545,24 54.585.174,81
4. Sonstige Ausleihungen 76.015.926,17 99.994.824,65
121.606.501,28 158.004.830,88
125.656.642,55 161.397.596,22
B. UMLAUFVERMÖGEN
I. Vorräte
1. Unfertige Leistungen 12.885.172,94 8.843.369,97
2. Zum Verkauf bestimmte Grundstücke und Gebäude 139.000,00 139.002,00
3. Andere Vorräte 61.319,05 93.039,06
13.085.491,99 9.075.411,03
II. Forderungen und sonstige Vermögensgegenstände
1. Forderungen aus Lieferungen und Leistungen 8.666.340,95 12.099.596,63
2. Forderungen gegen verbundene Unternehmen 1.409.363,51 7.573.168,86
3. Forderungen gegen Unternehmen,
mit denen ein Beteiligungsverhältnis besteht
555.093,06 1.651.573,06
```

```
4. Sonstige Vermögensgegenstände 345.991.815,13 163.003.969,98
356.622.612,65 184.328.308,53
III. Wertpapiere
Sonstige Wertpapiere 52.252.850,00 59.329.212,00
IV. Kassenbestand, Guthaben bei Kreditinstituten 152.594.976,48 248.363.122,67
574.555.931,12 501.096.054,23
C. RECHNUNGSABGRENZUNGSPOSTEN 7.545.702,82 7.957.871,65
707.758.276,49 670.451.522,10
Treuhandvermögen 1.943.915.141,66 1.953.309.522,69
""". (The L2 distance of this example text is: 0.434)<|im_end|>
<|im_start|>user

[Task]: Decide of what type the given text is. You can differentiate between four types
 ↪  of pages: \'Aktiva\', \'GuV\', \'Passiva\' and \'other\'.


[Rules]:

1) If the text contains a \'Gewinn- und Verlustrechnung\' (profit and loss statement)
 ↪  table, answer with \'GuV\'.


2) If the text contains an \'Aktiva\' (assets) table, answer with \'Aktiva\'.


3) If the text contains a \'Passiva\' (liabilities) table, answer with \'Passiva\'.


4) If the text contains something else, answer with \'other\'.


[Text]: Here is the text to classify:

\'\'\'
22 Amt für Statistik Berlin-Brandenburg | Geschäftsbericht 2014
Amt für Statistik Berlin-Brandenburg Anstalt des öffentlichen Rechts, Potsdam
Bilanz zum 31. Dezember 2014
A K T I V S E I T E 31.12.2014 Vorjahr
EUR EUR TEUR
A. ANLAGEVERMÖGEN
I. Immaterielle Vermögensgegenstände
1. Entgeltlich erworbene Konzessionen, gewerbliche
Schutzrechte und ähnliche Rechte und Werte
sowie Lizenzen an solchen Rechten und Werten 81.480,00 146
II. Sachanlagen
1. Grundstücke, grundstücksgleiche Rechte und Bauten
einschließlich der Bauten auf fremden Grundstücken 68.386,00 93
2. Andere Anlagen, Betriebs- und Geschäftsausstattung 140.186,00 174
208.572,00 267
III. Finanzanlagen
1. Wertpapiere des Anlagevermögens 2.000.000,00 2.000
2.000.000,00 2.000
2.290.052,00 2.413
B. UMLAUFVERMÖGEN
I. Forderungen und sonstige Vermögensgegenstände
1. Forderungen aus Lieferungen und Leistungen 36.617,86 14
2. Sonstige Vermögensgegenstände 297.982,42 267
334.600,28 281
II. Kassenbestand, Bundesbankguthaben, Guthaben bei
```

```
Kreditinstituten und Schecks 5.560.638,85 7.783
5.895.239,13 8.064
C. RECHNUNGSABGRENZUNGSPOSTEN 216.321,49 213
8.401.612,62 10.690
Bestätigungsvermerk
des Abschlussprüfers
Anhang
\'\'\'
        <|im_end|>
<|im_start|>assistant
```

E.5 Regular expressions

Here one can find the three regular expressions used for the benchmarks presented in section A.1.

```
simple_regex_patterns = {
    "Aktiva": [
        r"aktiva",
        r"((20\d{2}).*(20\d{2}))"
    ],
    "Passiva": [
        r"passiva",
        r"((20\d{2}).*(20\d{2}))"
    ],
    "GuV": [
        r"gewinn",
        r"verlust",
        r"rechnung",
        r"((20\d{2}).*(20\d{2}))"
    ]
}
```

```
regex_patterns_5 = {
    "Aktiva": [

        ↪  r"a\s*k\s*t\s*i\s*v\s*a|a\s*k\s*t\s*i\s*v\s*s\s*e\s*i\s*t\s*e|anlageverm.{1,2}gen",
        r"((20\d{2}).*(20\d{2}))|((20\d{2}).*vorjahr)|vorjahr",

        ↪  r"Umlaufverm.{1,2}gen|Anlageverm.{1,2}gen|Rechnungsabgrenzungsposten|Forderungen",
        r"\s([a-zA-Z]|[0-9]{1,2}|[iI]+)[\.\)]\s"
    ],
    "Passiva": [

        ↪  r"p\s*a\s*s\s*s\s*i\s*v\s*a|p\s*a\s*s\s*s\s*i\s*v\s*s\s*e\s*i\s*t\s*e|eigenkapital",
        r"((20\d{2}).*(20\d{2}))|((20\d{2}).*vorjahr)|vorjahr",

        ↪  r"Eigenkapital|R.{1,2}ckstellungen|Verbindlichkeiten|Rechnungsabgrenzungsposten",
        r"\s([a-zA-Z]|[0-9]{1,2}|[iI]+)[\.\)]\s"
    ],
    "GuV": [
        r"gewinn|guv",
        r"verlust|guv",
        r"rechnung|guv",
        r"((20\d{2}).*(20\d{2}))|vorjahr"

        ↪  r"Umsatzerl.{1,2}se|Materialaufwand|Personalaufwand|Abschreibungen|Jahres.{1,2}berschuss|Ja
```

```
        r"\s([a-zA-Z]|[0-9]{1,2}|[iI]+)[\.\)]\s"
    ]
}
```

```
regex_patterns_3 = {
    "Aktiva": [
        
         ↪  r"a\s*k\s*t\s*i\s*v\s*a|a\s*k\s*t\s*i\s*v\s*s\s*e\s*i\s*t\s*e|anlageverm.{1,2}gen",
        r"((20\d{2}).*(20\d{2}))|((20\d{2}).*vorjahr)|vorjahr"
    ],
    "Passiva": [
        
         ↪  r"p\s*a\s*s\s*s\s*i\s*v\s*a|p\s*a\s*s\s*s\s*i\s*v\s*s\s*e\s*i\s*t\s*e|eigenkapital",
        r"((20\d{2}).*(20\d{2}))|((20\d{2}).*vorjahr)|vorjahr"
    ],
    "GuV": [
        r"gewinn|guv",
        r"verlust|guv",
        r"rechnung|guv",
        r"((20\d{2}).*(20\d{2}))|vorjahr"
    ]
}
```

E.6 Annual Comprehensive Financial Report Balance Sheet

E.7 Extraction framework flow chart

E.8 Table extraction with regular expressions

Extract by pdfium for '../../benchmark_truth/synthetic_tables/separate_files/final/aktiva_table__3_columns__span_False__thir
€__enumeration_False__shuffle_True__text_around_True__max_length_50__sum_in_same_row_False__0.pdf':

```
A

ktiva(inMio. €)GeschäftsjahrVorjahr

Anlagevermögen Immaterielle Verm

ögensgegenstände

SelbstgeschaffenegewerblicheSchutzrechteund

ähnlicheRechteundWerte

0,184,77

Geschäfts-oderFirmenwert4,426,78

geleisteteAnzahlungen1,780,65

entgeltlicherworbeneKonzessionen, gewerbliche

SchutzrechteundähnlicheRechteundWertesowie
```

State of California Annual Comprehensive Financial Report

Balance Sheet

Governmental Funds

June 30, 2023

(amounts in thousands)

	General	Federal
ASSETS		
Cash and pooled investments	$ 71,968,861	$ 6,986,275
Investments	—	—
Receivables (net)	46,621,774	2,076,598
Due from other funds	6,933,803	165,231
Due from other governments	4,075,837	37,069,188
Interfund receivables	3,914,413	—
Loans receivable	45,225	384,293
Other assets	6,244	601,252
Total assets	**$ 133,566,157**	**$ 47,282,837**
LIABILITIES		
Accounts payable	$ 14,422,777	$ 24,499,200
Due to other funds	3,911,973	3,865,533
Due to component units	264,995	—
Due to other governments	21,808,112	11,125,464
Interfund payables	2,692,941	—
Benefits payable	—	69,623
Revenues received in advance	25,891	6,675,956
Tax overpayments	21,740,974	—
Deposits	4,231	—
Unclaimed property liability	1,314,797	—
Other liabilities	522,844	46,256,400
Total liabilities	**66,709,535**	**92,492,176**
DEFERRED INFLOWS OF RESOURCES	2,852,934	10,709
Total liabilities and deferred inflows of resources	**69,562,469**	**92,502,885**
FUND BALANCES		
Nonspendable	3,950,919	—
Restricted	24,830,454	1,210,267
Committed	4,210,891	—
Assigned	20,714,283	—
Unassigned	10,297,141	(46,430,315)
Total fund balances (deficit)	**64,003,688**	**(45,220,048)**
Total liabilities, deferred inflows of resources, and fund balances	**$ 133,566,157**	**$ 47,282,837**

42 *The notes to the financial statements are an integral part of this statement.*

E

Figure E.3: Example balance sheet pagefom Californias Annual Comprehensive Financial Report 2023

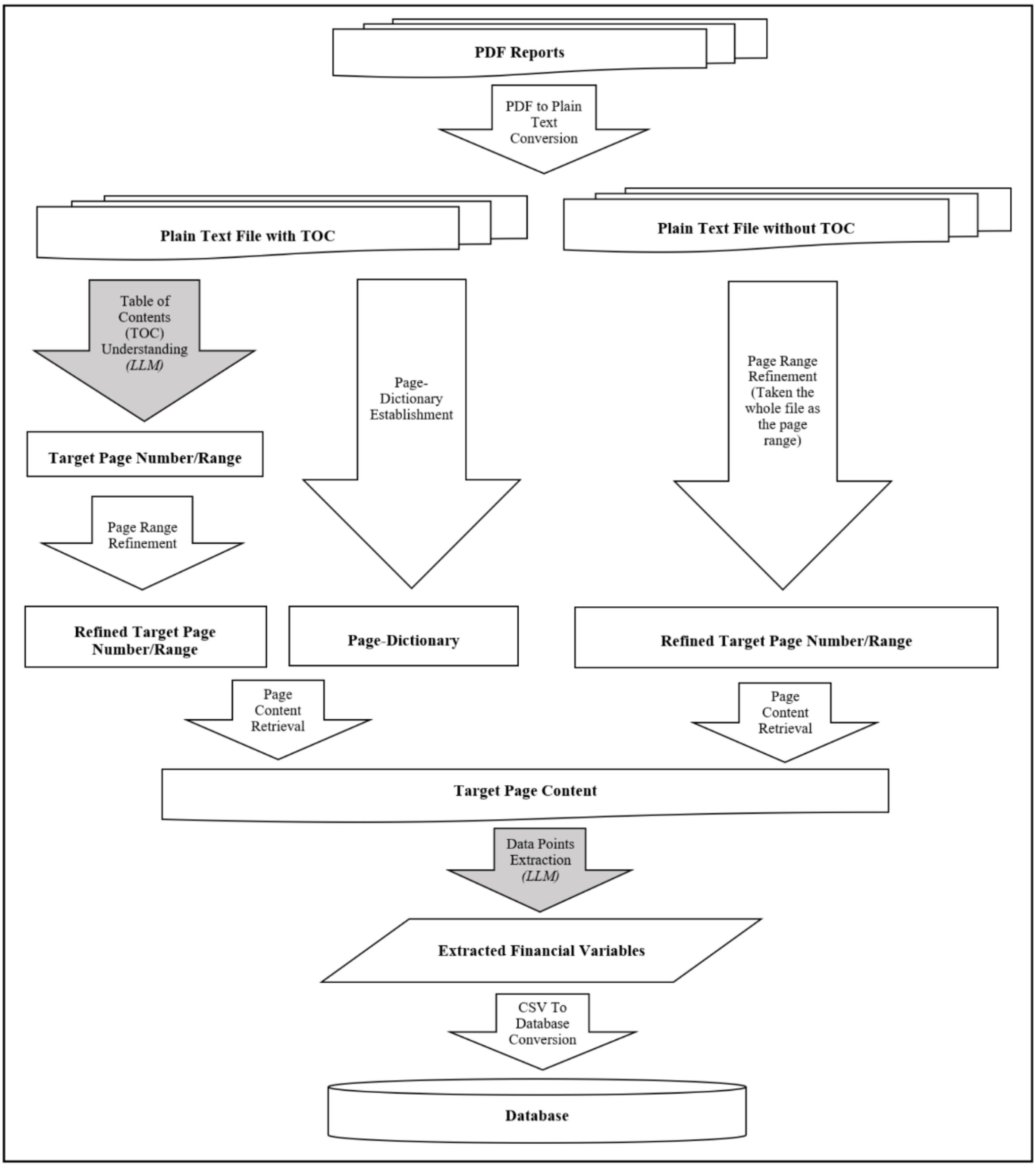


Figure E.4: Flowchart of the extraction framework of Auer et al. (2024)

E

```
LizenzenansolchenRechtenundWerten

4,646,71

11,0218,91

Sachanlagen

Grundstücke, grundstücksgleicheRechteundBauten

einschließlichderBautenauffremdenGrundstücken

2,802,55

TechnischeAnlagenundMaschinen5,205,53

AndereAnlagen, Betriebs-undGeschäftsausstattung1,601,93

geleisteteAnzahlungenundAnlagen imBau3,255,81

12,8615,83

Finanzanlagen

SonstigeFinanzanlagen7,446,51

AnteileanverbundenenUnternehmen0,499,83

AusleihungenanverbundeneUnternehmen0,573,49

Beteiligungen1,059,43

AusleihungenanUnternehmen, mitdenenein

Beteiligungsverhältnisbesteht

6,957,65

WertpapieredesAnlagevermögens2,002,71

SonstigeAusleihungen9,091,52

27,5841,13

51,4675,87

Umlaufvermögen

Vorräte

Roh-, Hilfs-undBetriebsstoffe0,382,98

UnfertigeErzeugnisse, unfertigeLeistungen3,236,19

FertigeErzeugnisseundWaren6,724,98

GeleisteteAnzahlungen4,024,83

14,3418,98
```

```
ForderungenundsonstigeVermögensgegenstände

ForderungenausLieferungenundLeistungen4,328,36

ForderungengegenverbundeneUnternehmen6,082,38

ForderungengegenUnternehmen, mitdenenein

Beteiligungsverhältnisbesteht

7,878,11

SonstigeVermögensgegenstände1,968,30

20,2227,15

Wertpapiere

AnteileanverbundenenUnternehmen2,383,24

SonstigeWertpapiere0,077,65

2,4410,88

Kassenbestand, Bundesbankguthaben, Guthabenbei Kreditinstituten und Schecks

4,144,00

41,1561,01

Rechnungsabgrenzungsposten2,746,78

Aktive latenteSteuern8,464,60

AktiverUnterschiedsbetragausder

Vermögensverrechnung

2,863,35

106,67151,61
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€__enumeration_False__shuffle_True__text_around_True__max_length_50__sum_in_same_row_False__0.pdf':

```
Aktiva (in Mio. €)

Anlagevermögen

Immaterielle Vermögensgegenstände

Selbst geschaffene gewerbliche Schutzrechte und
ähnliche Rechte und Werte

Geschäfts- oder Firmenwert

geleistete Anzahlungen
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entgeltlich erworbene Konzessionen, gewerbliche
Schutzrechte und ähnliche Rechte und Werte sowie
Lizenzen an solchen Rechten und Werten

Sachanlagen

Grundstücke, grundstücksgleiche Rechte und Bauten
einschließlich der Bauten auf fremden Grundstücken

Technische Anlagen und Maschinen

Andere Anlagen, Betriebs- und Geschäftsausstattung

geleistete Anzahlungen und Anlagen im Bau

Finanzanlagen

Sonstige Finanzanlagen

Anteile an verbundenen Unternehmen

Ausleihungen an verbundene Unternehmen

Beteiligungen

Ausleihungen an Unternehmen, mit denen ein
Beteiligungsverhältnis besteht

Wertpapiere des Anlagevermögens

Sonstige Ausleihungen

Umlaufvermögen

Vorräte

Roh-, Hilfs- und Betriebsstoffe

Unfertige Erzeugnisse, unfertige Leistungen

Fertige Erzeugnisse und Waren

Geleistete Anzahlungen

Forderungen und sonstige Vermögensgegenstände

Forderungen aus Lieferungen und Leistungen

Forderungen gegen verbundene Unternehmen

Forderungen gegen Unternehmen, mit denen ein
Beteiligungsverhältnis besteht

Sonstige Vermögensgegenstände

Wertpapiere

Anteile an verbundenen Unternehmen
```

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Sonstige Wertpapiere

Kassenbestand, Bundesbankguthaben, Guthaben bei
Kreditinstituten und Schecks

Rechnungsabgrenzungsposten

Aktive latente Steuern

Aktiver Unterschiedsbetrag aus der
Vermögensverrechnung

Geschäftsjahr

Vorjahr

0,18

4,42

1,78

4,64

11,02

2,80

5,20

1,60

3,25

12,86

7,44

0,49

0,57

1,05

6,95

2,00

9,09

27,58

51,46

0,38

3,23
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E

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6,72

4,02

14,34

4,32

6,08

7,87

1,96

20,22

2,38

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2,44

4,14

41,15

2,74

8,46

2,86

4,77

6,78

0,65

6,71

18,91

2,55

5,53

1,93

5,81

15,83

6,51

9,83

3,49

9,43
```

E

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7,65

2,71

1,52

41,13

75,87

2,98

6,19

4,98

4,83

18,98

8,36

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151,61
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E

Extract by PdfReader for '../Geschaeftsberichte/IBB/ibb_geschaeftsbericht_2006.pdf', p. 67:

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'\x18\x18
Jahresbilanz zum 31. Dezember 2006
a ktivseite in te U r
31.12.2006 31.12.2005
1. Barreserve
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b)

Guthaben

bei

Zentralnotenbanken
darunter:

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der

Deutschen

Bundesbank:
TEUR

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(31.12.2005

:

TEUR

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3. Forderungen an
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     a)

täglich

fällig
     b)

andere

Forderungen
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Grundpfandrechte

gesichert:
TEUR

9.496.661

(31.12.2005
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TEUR

10.660.277)
Kommunalkredite:

TEUR

3.532.796

(31.12.2005

:

TEUR

2.338.961)
5. Schuldverschreibungen und andere festverzinsliche Wertpapiere
     a)

    Geldmarktpapiere

         ab)

von

anderen

Emittenten
     b)

    Anleihen

und

Schuldverschreibungen

         ba)

von

öffentlichen

Emittenten

         darunter:

beleihbar

bei

der

Deutschen

Bundesbank
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E

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         bb)

von

anderen

Emittenten

         darunter:

beleihbar

bei

der

Deutschen

Bundesbank
     c)

    eigene

Schuldverschreibungen
         Nennbetrag
7. Beteiligungen


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Kreditinstituten

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Kreditinstituten

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Treuhandkredite
11. Immaterielle
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12. Sachanlagen
15. Sonstige
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ermögensgegenstände
16.
r
echnungsabgrenzungsposten
Summe der
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ktiva
19.823


132.272
1.562.290
24.138
126.223
126.223
3.115.852
2.976.213
718
718
101.246
19.823
1.694.562
14.758.008
3.266.931
11.440
178.004
101.246
10.038
46.863
141.626
17.804
20.246.345
28.873
2.195.434
205.129
1.990.305
14.728.310
1.682.660
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E

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49.152
49.152
1.585.752
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47.756
47.722
11.440
178.004
103.297
103.297
17.705
50.334
141.791
11.957
19.149.805
Jahresabschluss  | Jahresbilanz'
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E

Appendix F

Tables

F.1 Classification

F.2 Table extraction

F.2.1 Hybrid approach

Table F.1: Comparing the actual number of provided examples depending on the classification type, example selection strategy and chosen parameter n_examples.

approach	classification	n_example	target	other	sum
n_random_examples	binary	1	1	1	4
n_random_examples	binary	3	3	1	6
n_random_examples	binary	5	5	2	11
n_random_examples	multi	1	1	1	4
n_random_examples	multi	3	3	3	12
n_random_examples	multi	5	5	5	20
n_rag_examples	binary	1	1	1	4
n_rag_examples	binary	3	3	1	6
n_rag_examples	binary	5	5	2	11
n_rag_examples	multi	1	1	1	4
n_rag_examples	multi	3	3	3	12
n_rag_examples	multi	5	5	5	20
top_n_rag_examples	binary	1	NA	NA	1
top_n_rag_examples	binary	3	NA	NA	3
top_n_rag_examples	binary	5	NA	NA	5
top_n_rag_examples	binary	7	NA	NA	7
top_n_rag_examples	binary	9	NA	NA	9
top_n_rag_examples	binary	11	NA	NA	11
top_n_rag_examples	binary	13	NA	NA	13
top_n_rag_examples	multi	1	NA	NA	1
top_n_rag_examples	multi	3	NA	NA	3
top_n_rag_examples	multi	5	NA	NA	5
top_n_rag_examples	multi	7	NA	NA	7
top_n_rag_examples	multi	9	NA	NA	9
top_n_rag_examples	multi	11	NA	NA	11
top_n_rag_examples	multi	13	NA	NA	13

Table F.2: Comparing extraction performance for real Aktiva extraction task with synthetic and real examples for incontext learning with a zero shot approach averaged over all methods

model	median_real	median_synth	median_zero_shot	delta_rate_real_synth	delta_
Qwen3-235B-A22B-Instruct-2507-FP8	**0.983**	**0.966**	**0.897**	0.5	
Llama-4-Scout-17B-16E-Instruct	0.931	0.897	0.448	0.33	
Mistral-Large-Instruct-2411	0.966	0.897	0.776	0.67	
Llama-3.1-8B-Instruct	0.828	0.759	0.552	0.286	
Qwen3-8B	0.931	0.759	0.336	**0.714**	
Ministral-8B-Instruct-2410	0.862	0.741	0.552	0.467	
gemma-3-27b-it	0.862	0.672	0.207	0.579	
gemma-3-12b-it	0.793	0.5	0.543	0.586	

Appendix G

Figures

NA predicting

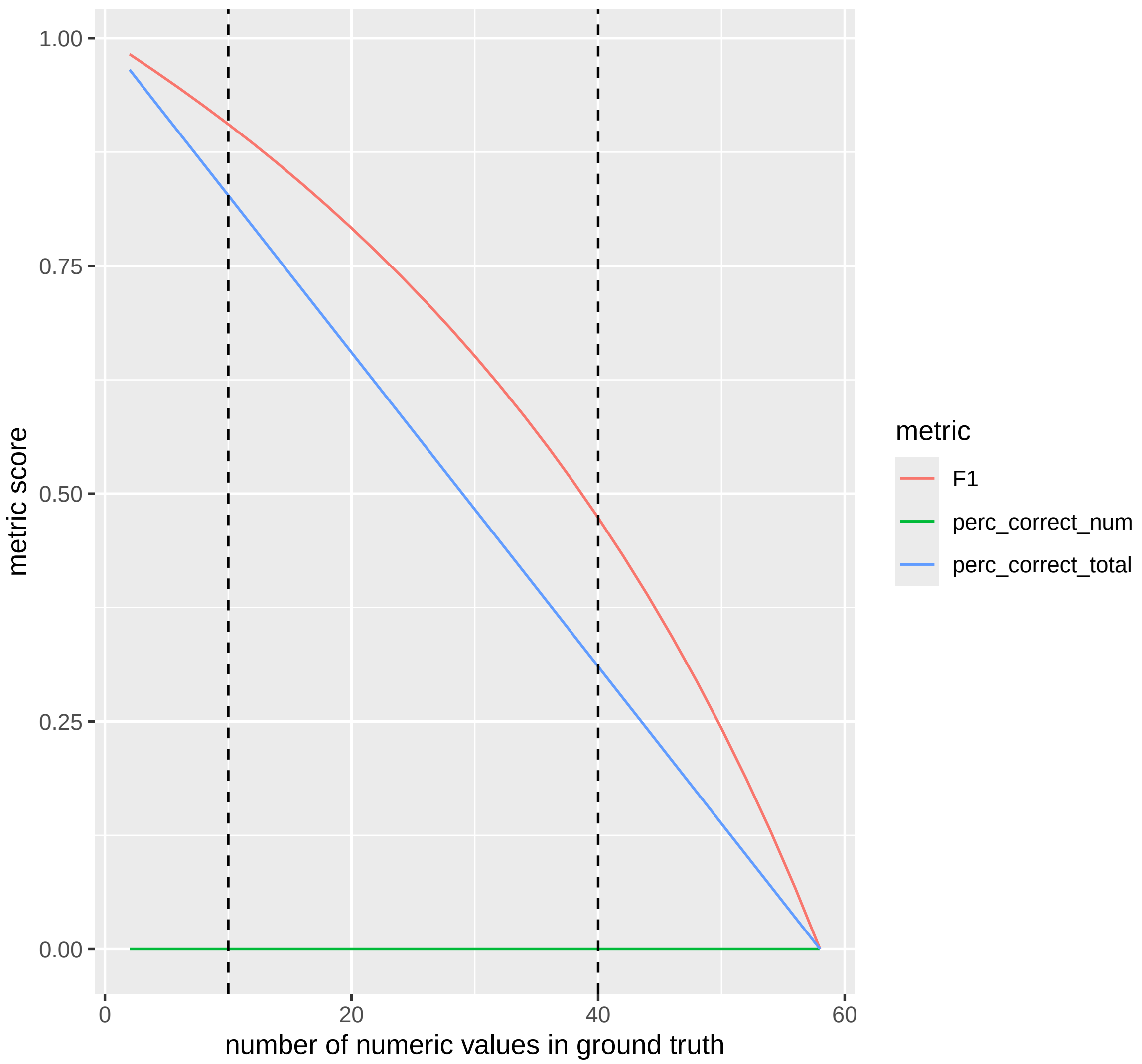


Figure G.1: Displaying the performance metrics a LLMs response would have, if all predictions are 'null'. The area between the two dashed lines shows the number of numeric values found in the real Aktiva tables.

G.1 Page identification

G.1.1 Regex baseline

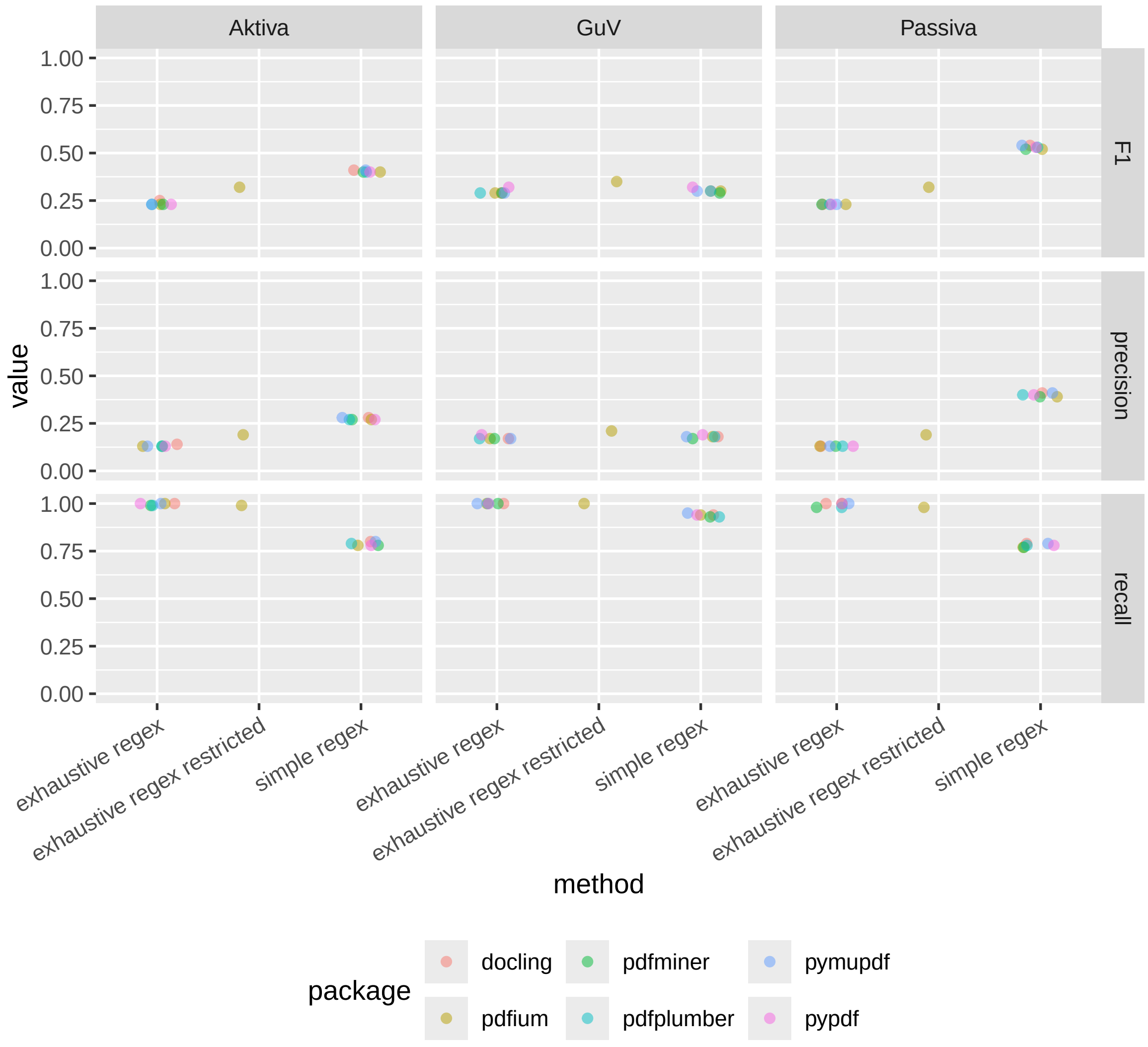


Figure G.2: Comparing page identification metrics for different regular expressions for each classification task by type of the target table.

G.1.2 TOC understanding

G.1.3 Classification

G.1.3.1 Binary

Binary classification F1 score over runtime limited to 60 minutes

Binary classification F1 score over runtime unlimited

G.1.3.2 Multi-class classification

Multi-class classification micro minorites F1 score over runtime limited to 60 minutes

Multi-class classification micro minorites F1 score over runtime

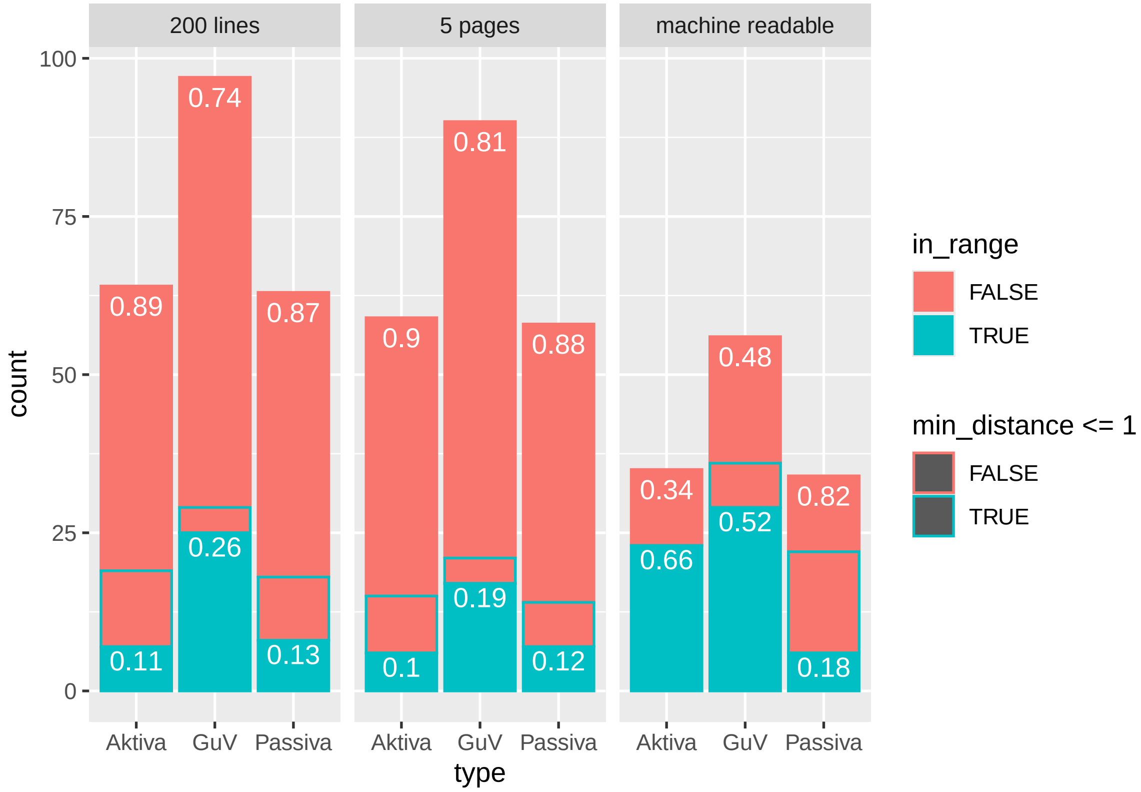


Figure G.3: Comparing number of fount TOC and amount of correct and incorrect predicted page ranges

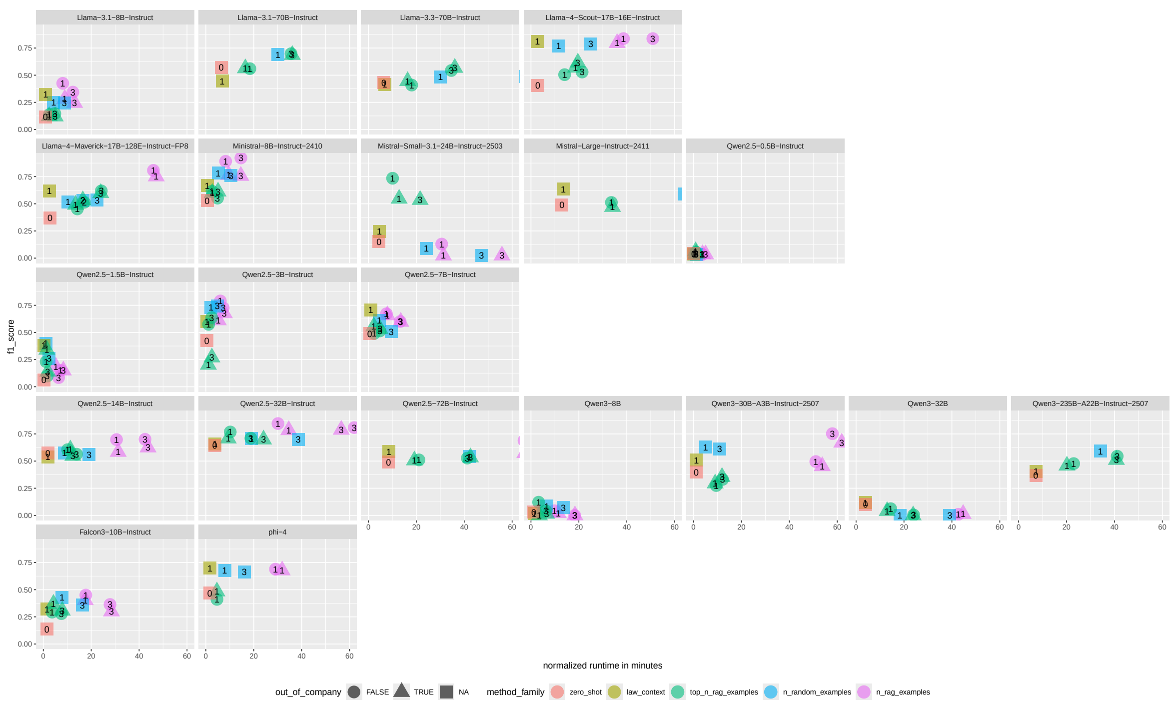


Figure G.4: Comparing F1 score over normalized runtime for binary classification task. The normalized runtime is given in minutes of processing on a single B200. The time to load the model into the VRAM is excluded. Focussing on small models showing only 60 minutes of runtime.

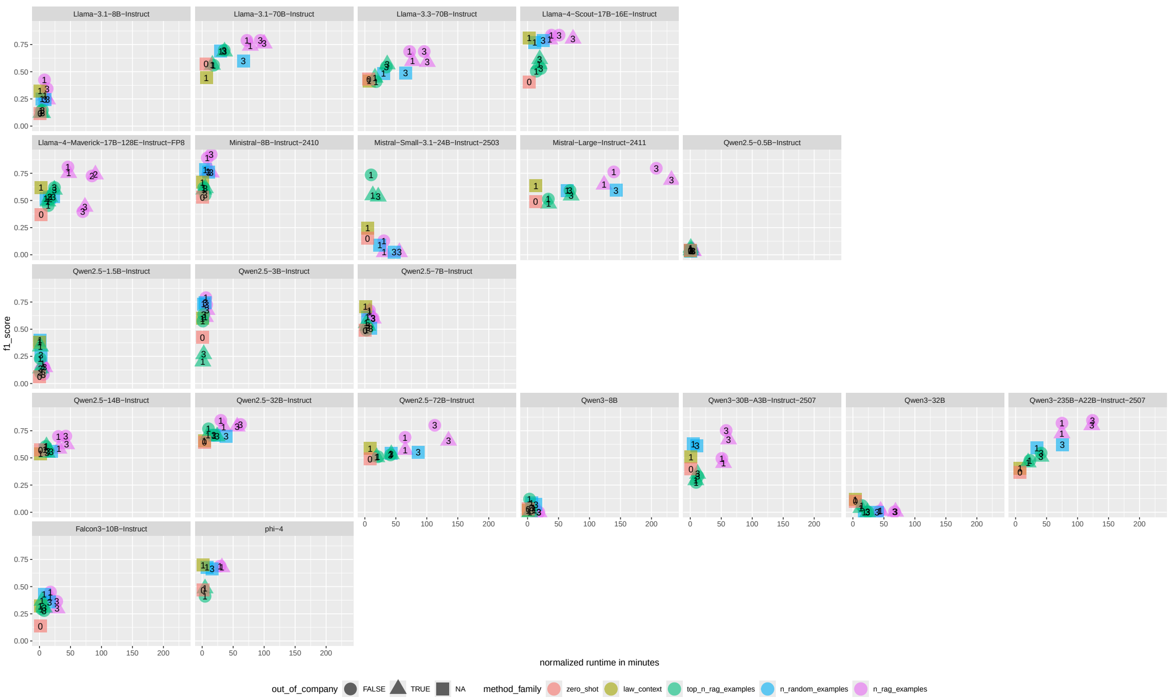


Figure G.5: Comparing F1 score over normalized runtime for binary classification task. The normalized runtime is given in minutes of processing on a single B200. The time to load the model into the VRAM is excluded.

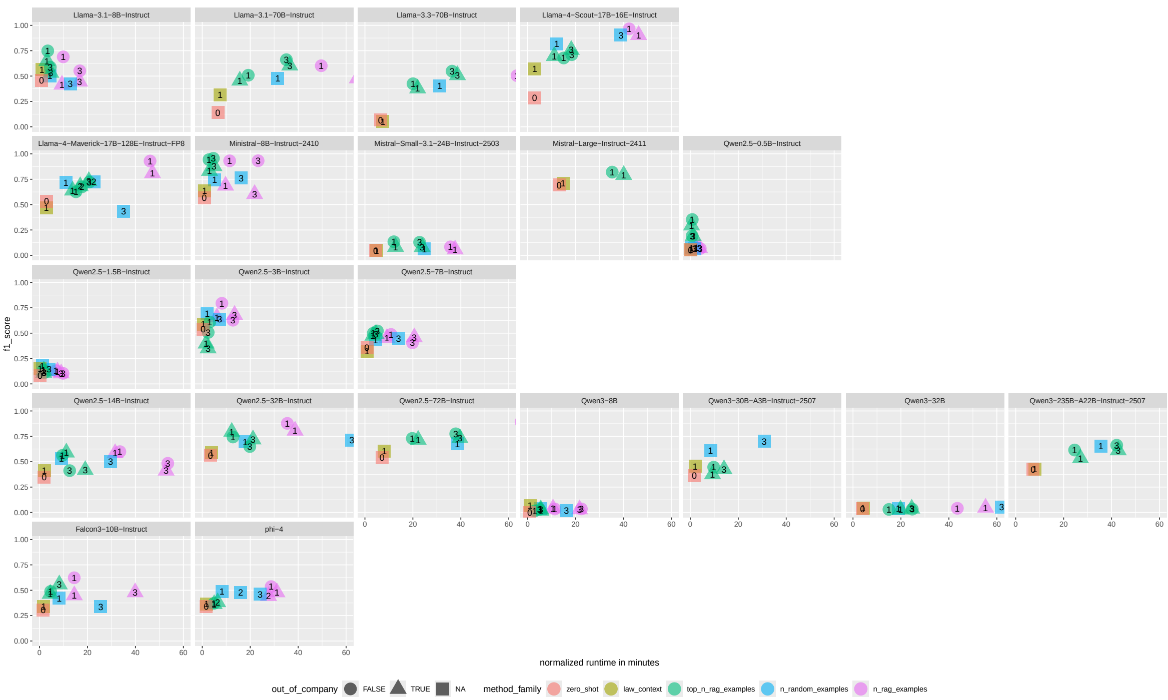


Figure G.6: Comparing F1 score over normalized runtime for multi-class classification task. The normalized runtime is given in minutes of processing on a single B200. The time to load the model into the VRAM is excluded. Focussing on small models showing only 60 minutes of runtime.

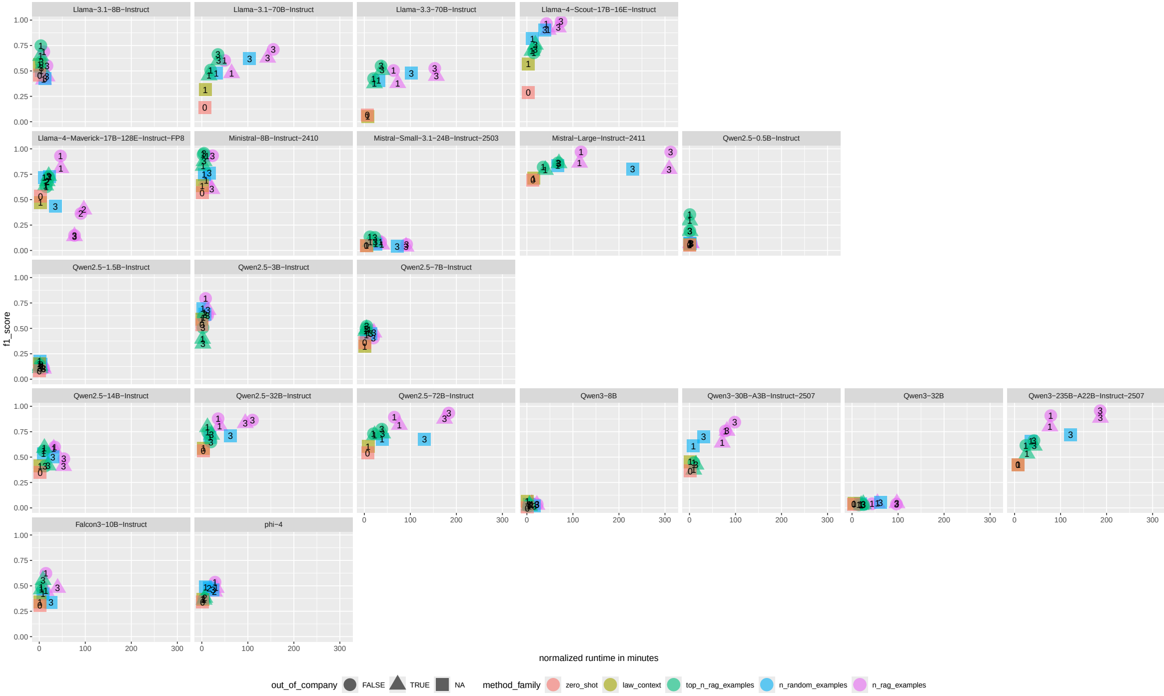


Figure G.7: Comparing F1 score over normalized runtime for multi-class classification task. The normalized runtime is given in minutes of processing on a single B200. The time to load the model into the VRAM is excluded.

G.2 Table extraction

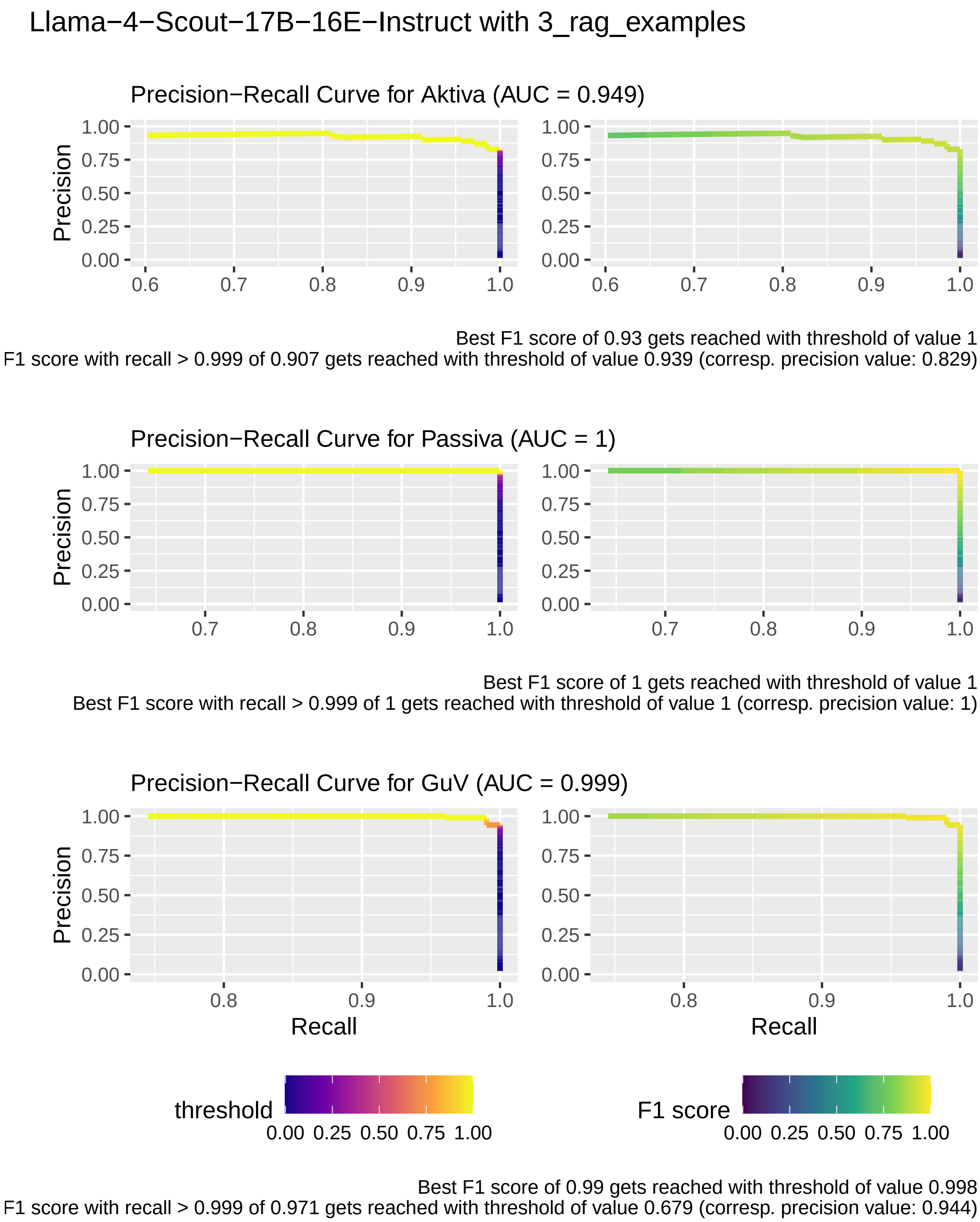


Figure G.8: Showing the precsion-recall-curve for Llama-4-Scout-17B-16E-Instruct.

G.2.1 Regex approach

G.2.1.1 Real tables

G.2.1.2 Synthetic tables

G.2.2 Real tables

G.2.2.1 Examples from same company

G.2.2.2 OpenAI models

G.2.2.3 Hypotheses

G.2.3 Synthetic tables

G.2.3.1 Confidence

G.2.4 Hybrid approach

real_table_extraction_llm_synth_context_shap_plot

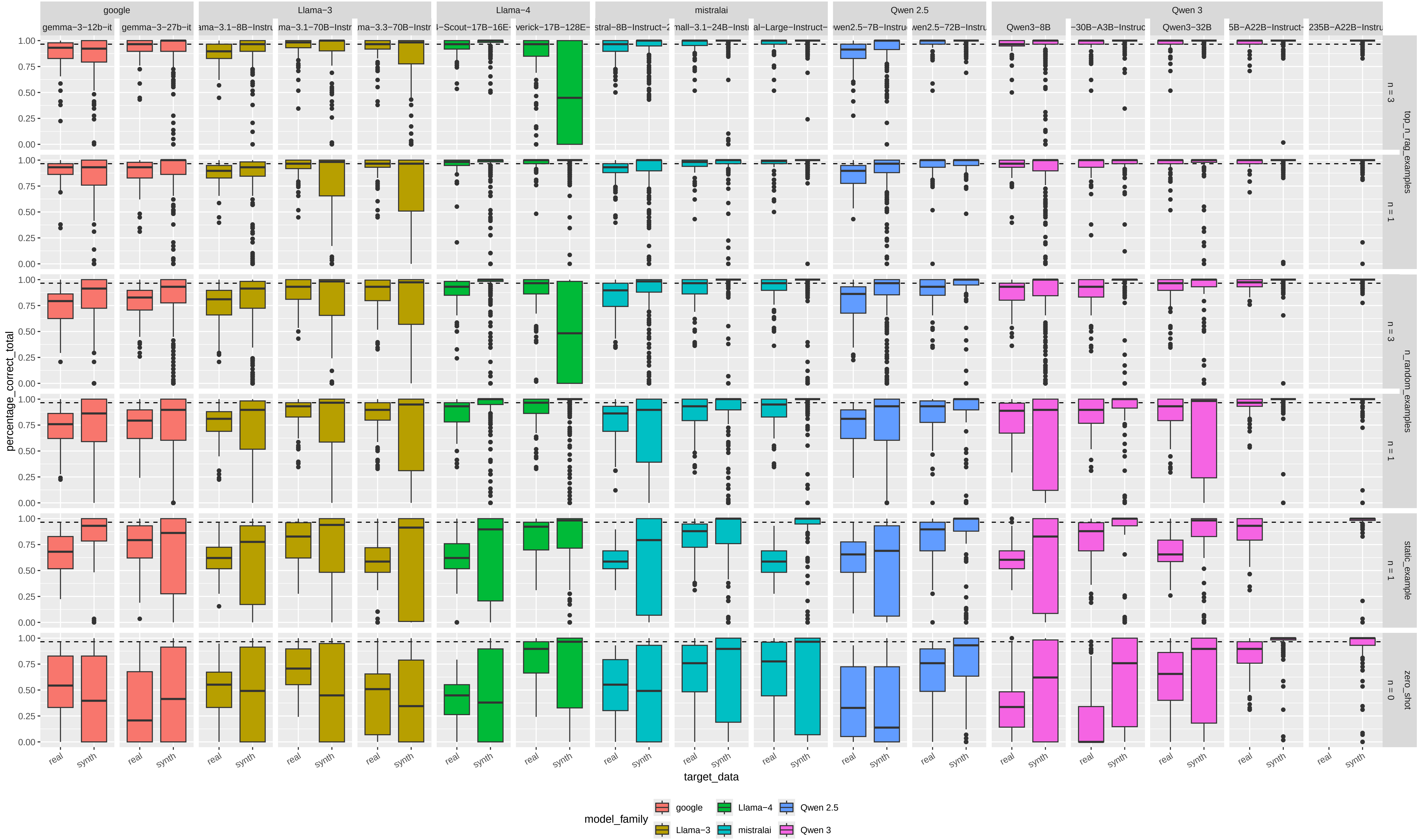


Figure G.9: Comparing the table extraction performance among real and synthetic Aktiva tables

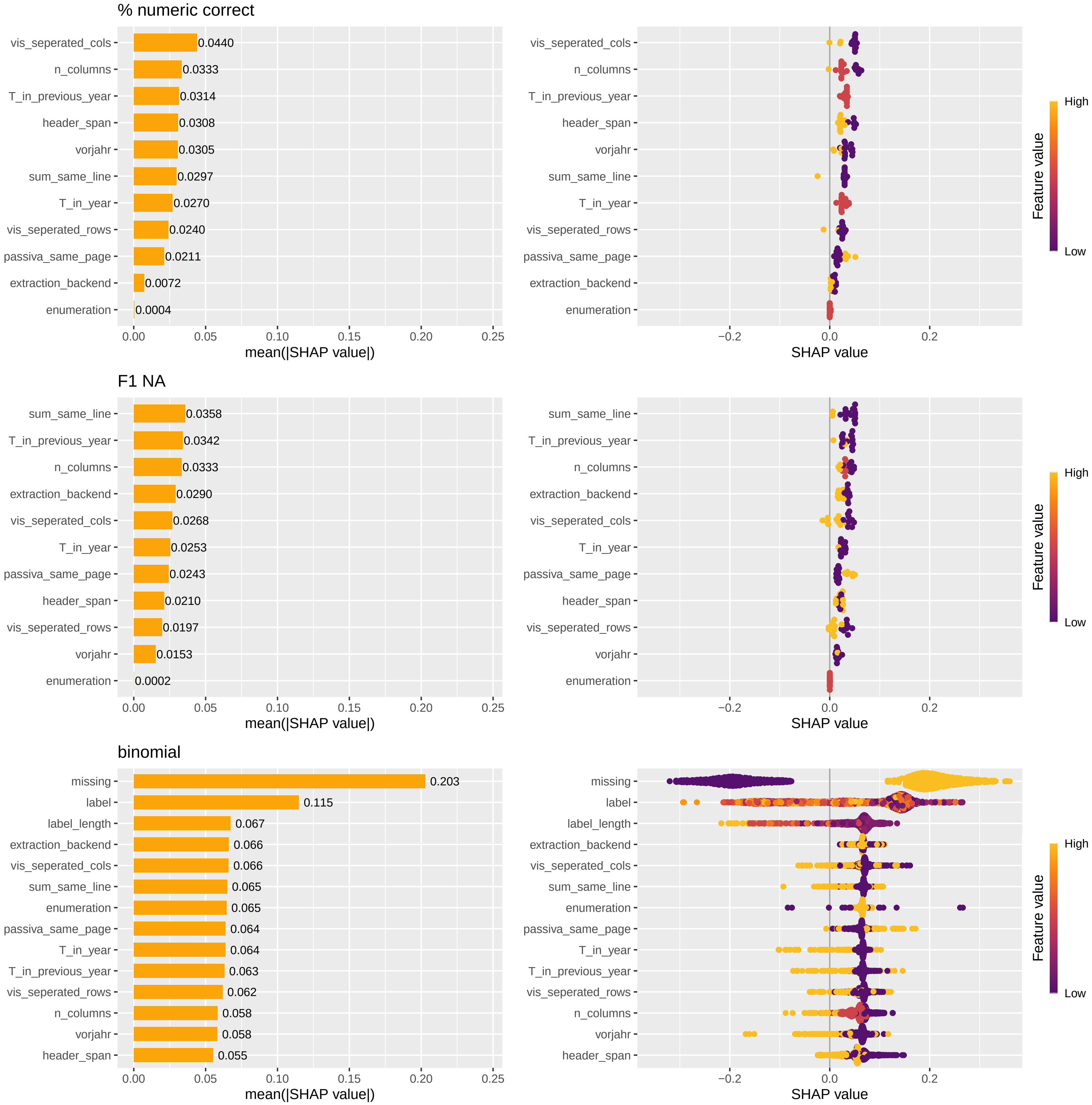


Figure G.10: Mean absolute SHAP values and beeswarm plots for real table extraction with regular expression approach

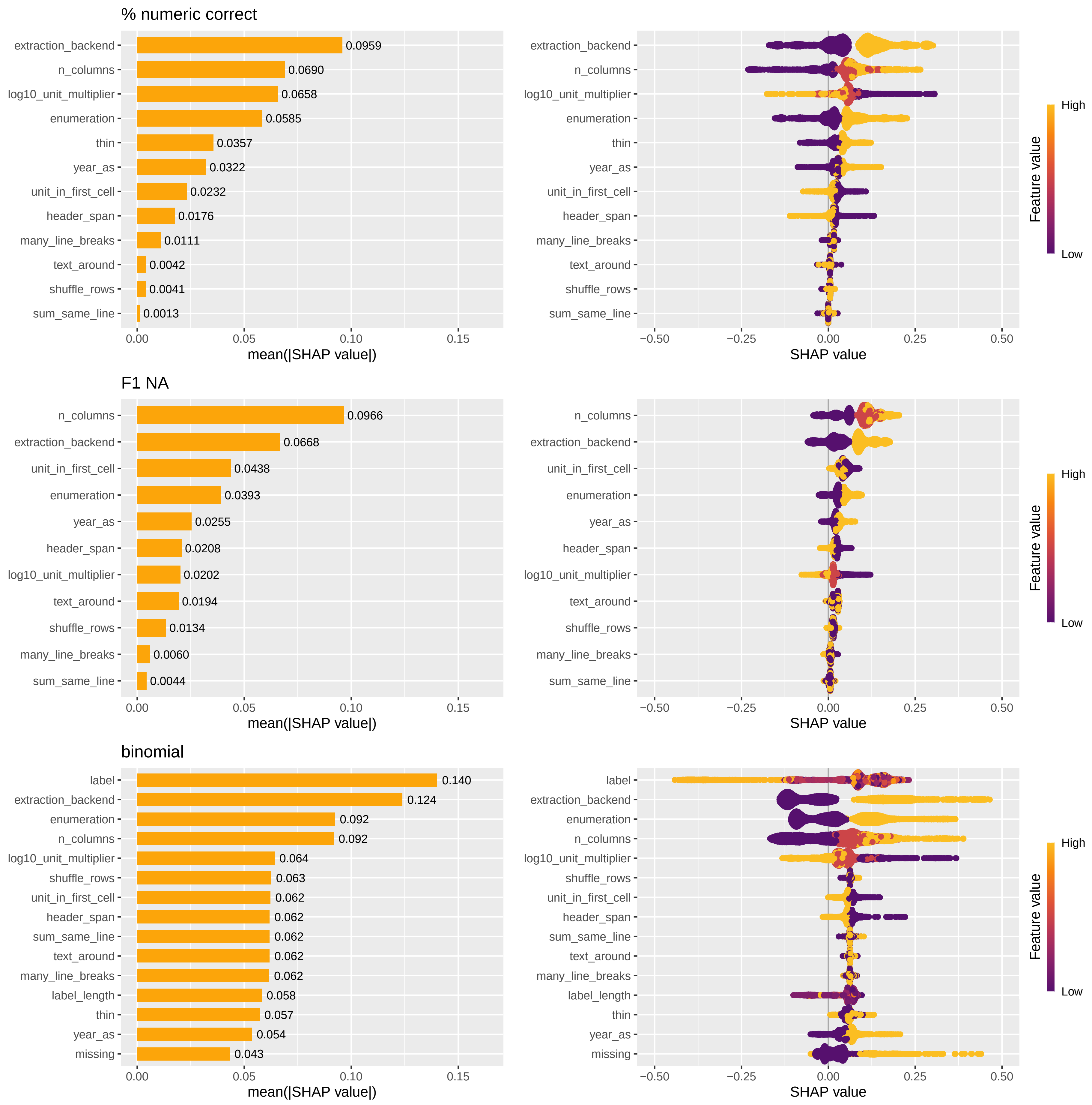


Figure G.11: Mean absolute SHAP values and beeswarm plots for synth table extraction with regular expression approach

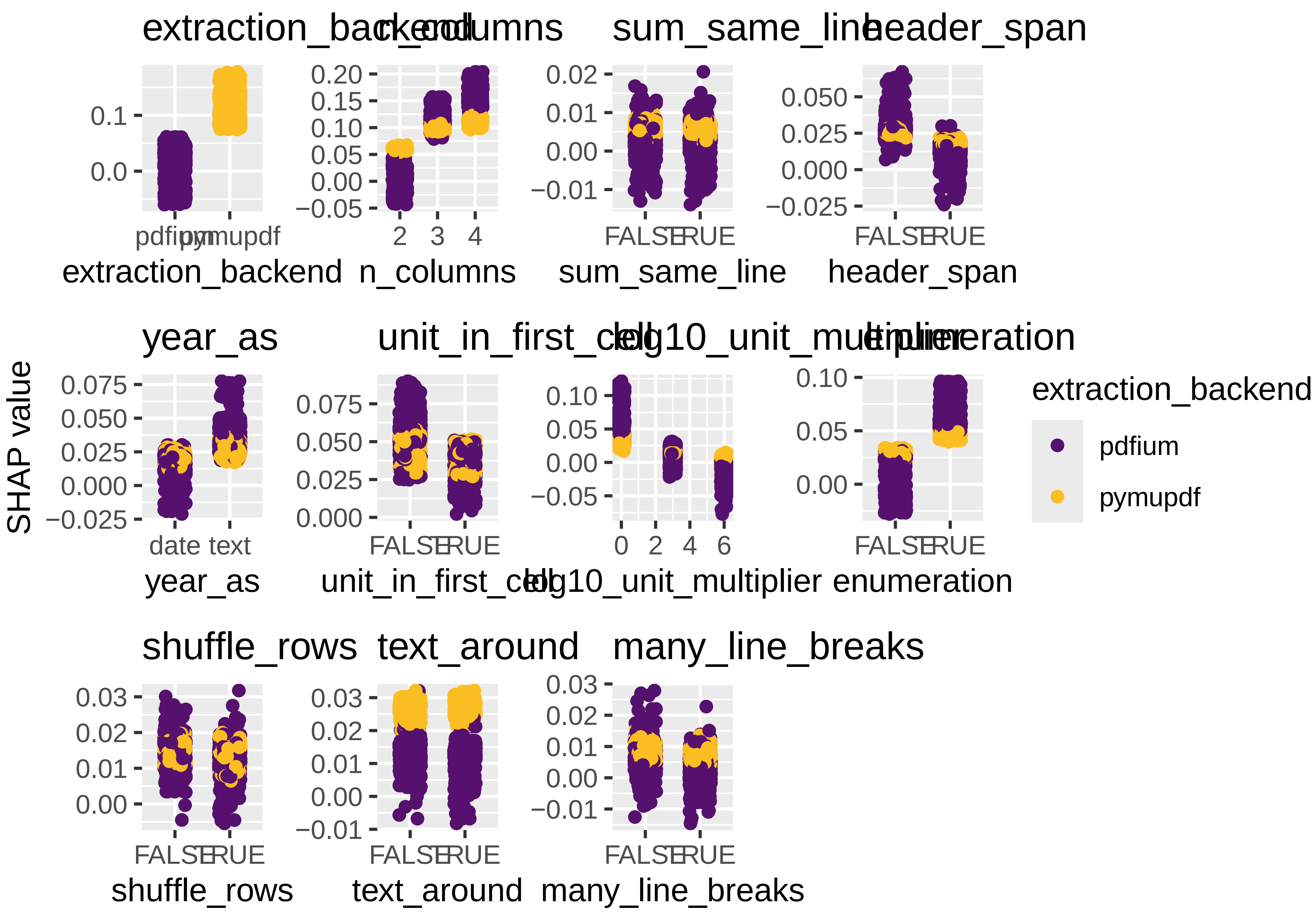


Figure G.12: Showing the interactions of the extraction backend pdfium with the table characteristics for F1 score.

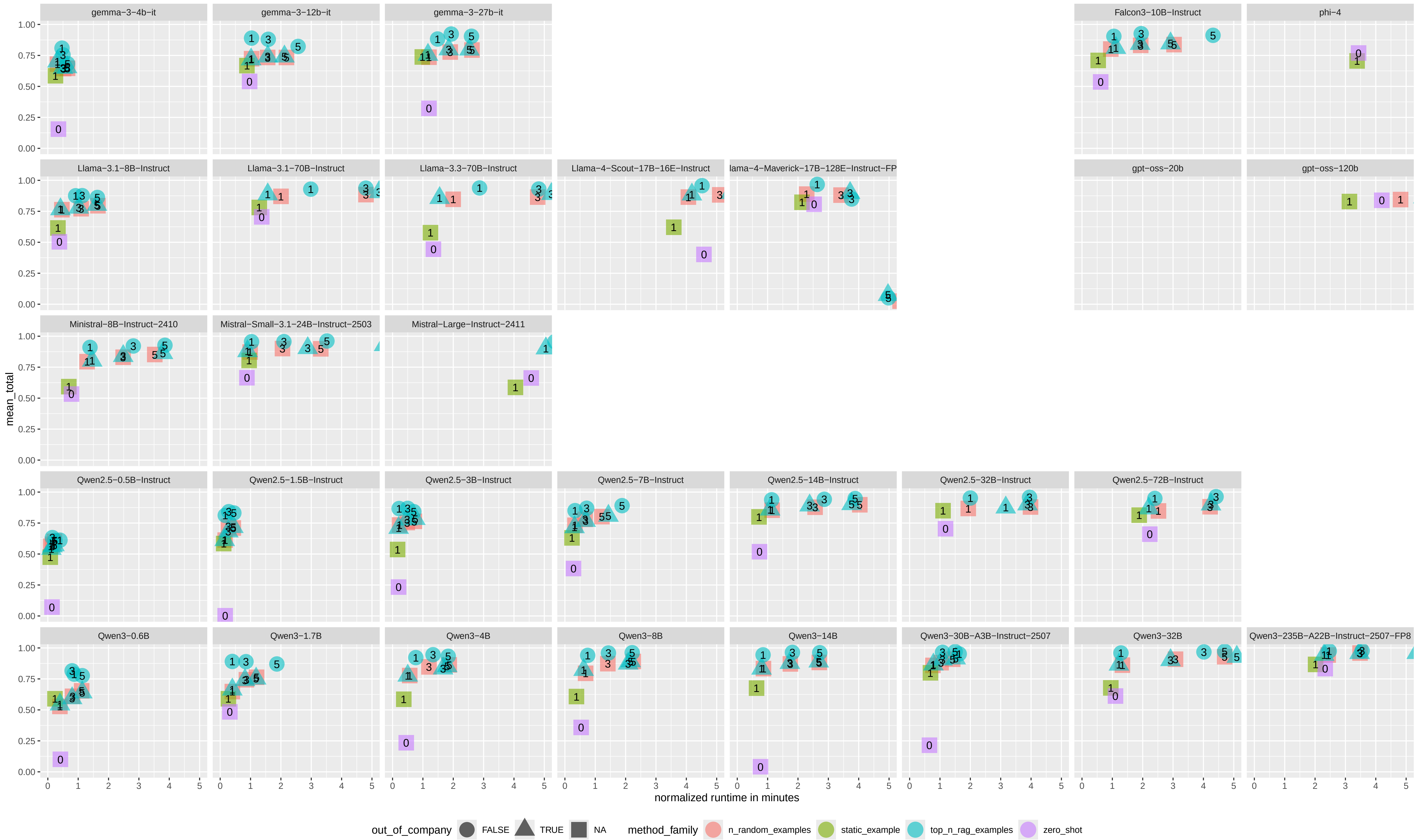


Figure G.13: Comparing percentage of correct predictions total over the normalized runtime. The normalized runtime is given in minutes of processing on a single B200. The time to load the model into the VRAM is excluded. Focussing on small models showing only 5 minutes of runtime.

Figure G.14: Comparing percentage of correct predictions total over the normalized runtime. The normalized runtime is given in minutes of processing on a single B200. The time to load the model into the VRAM is excluded. Showing the full runtime range.

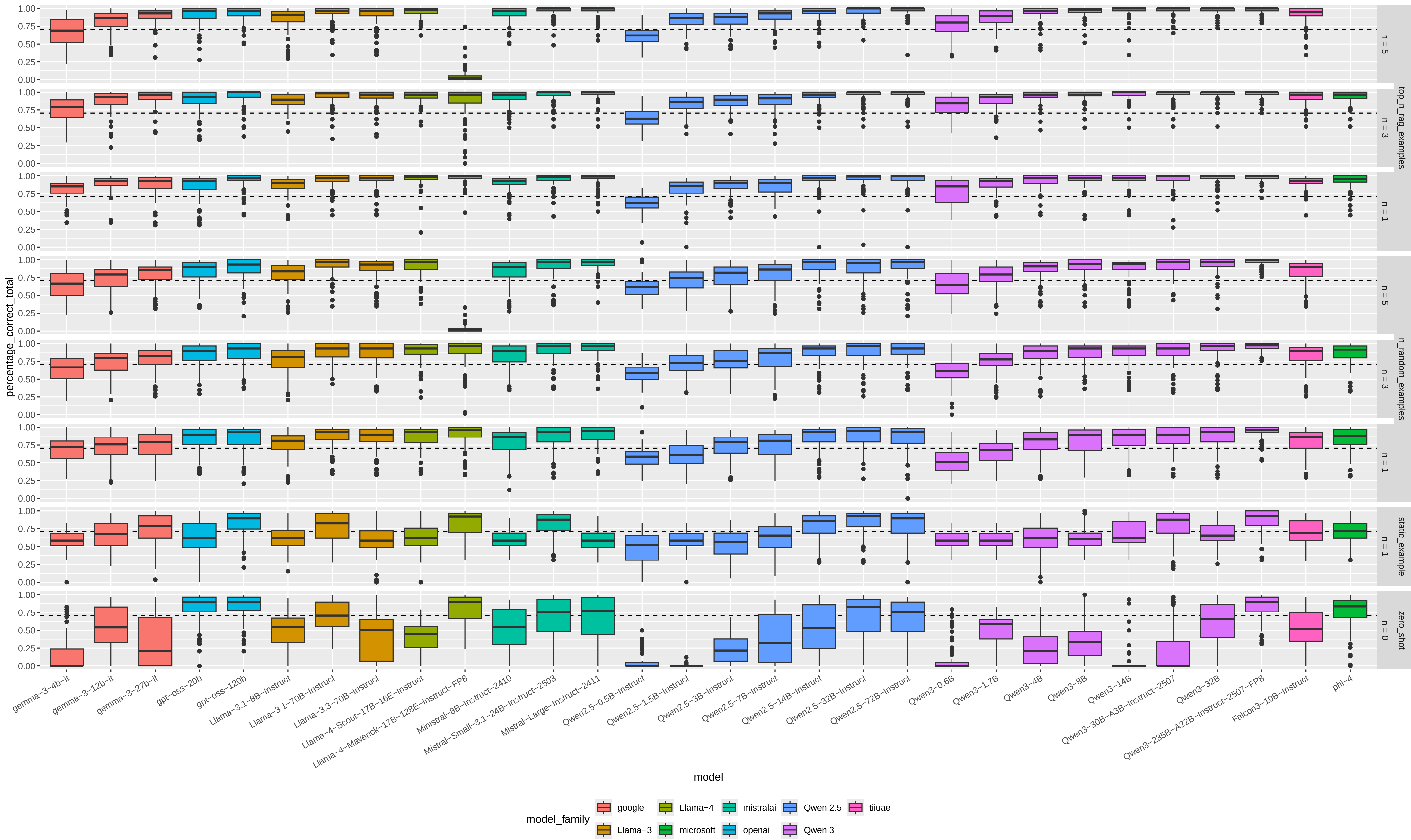


Figure G.15: Percentage of correct extracted or as missing categorized values for table extraction task on real Aktiva tables

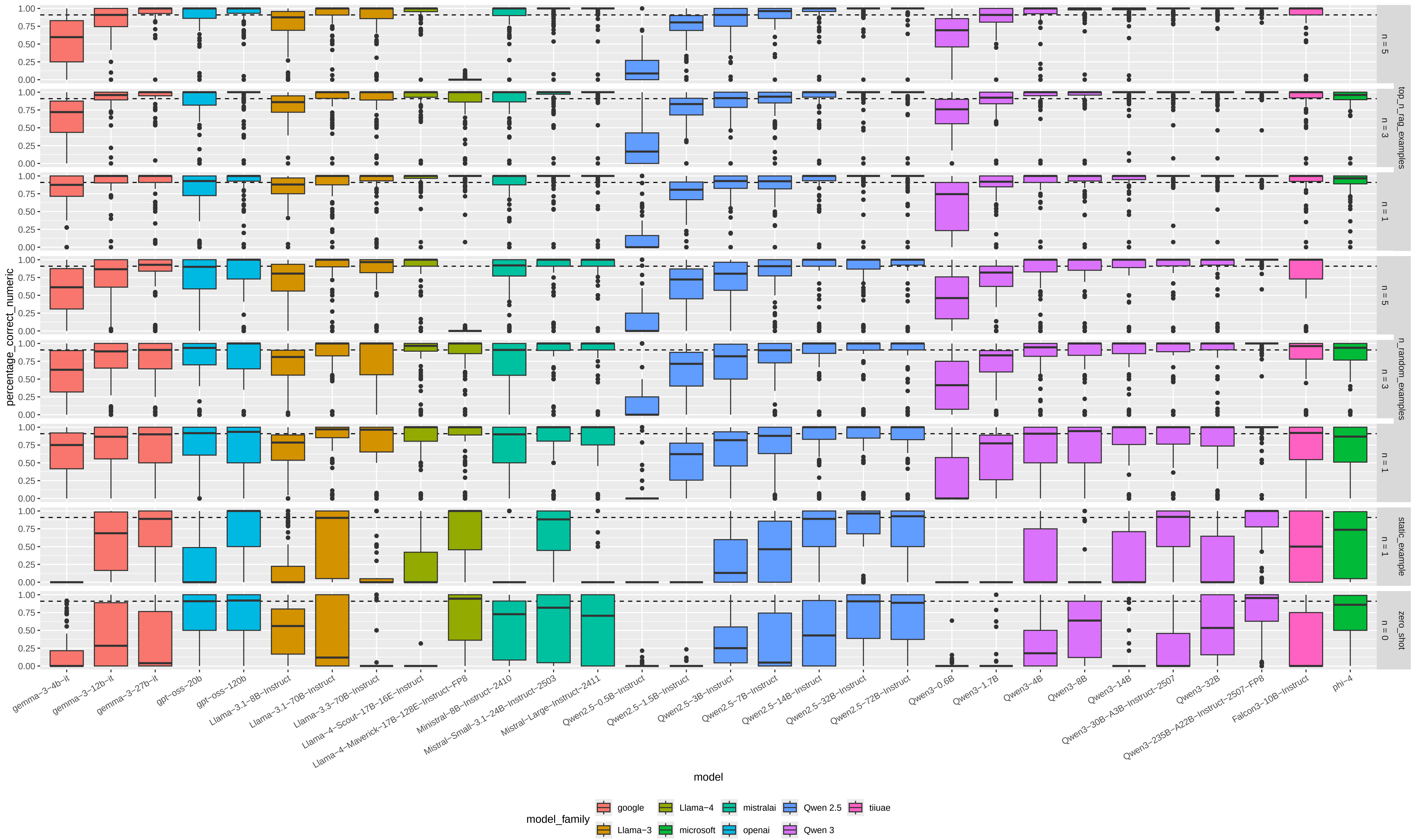


Figure G.16: Percentage of correct extracted numeric values for table extraction task on real Aktiva tables

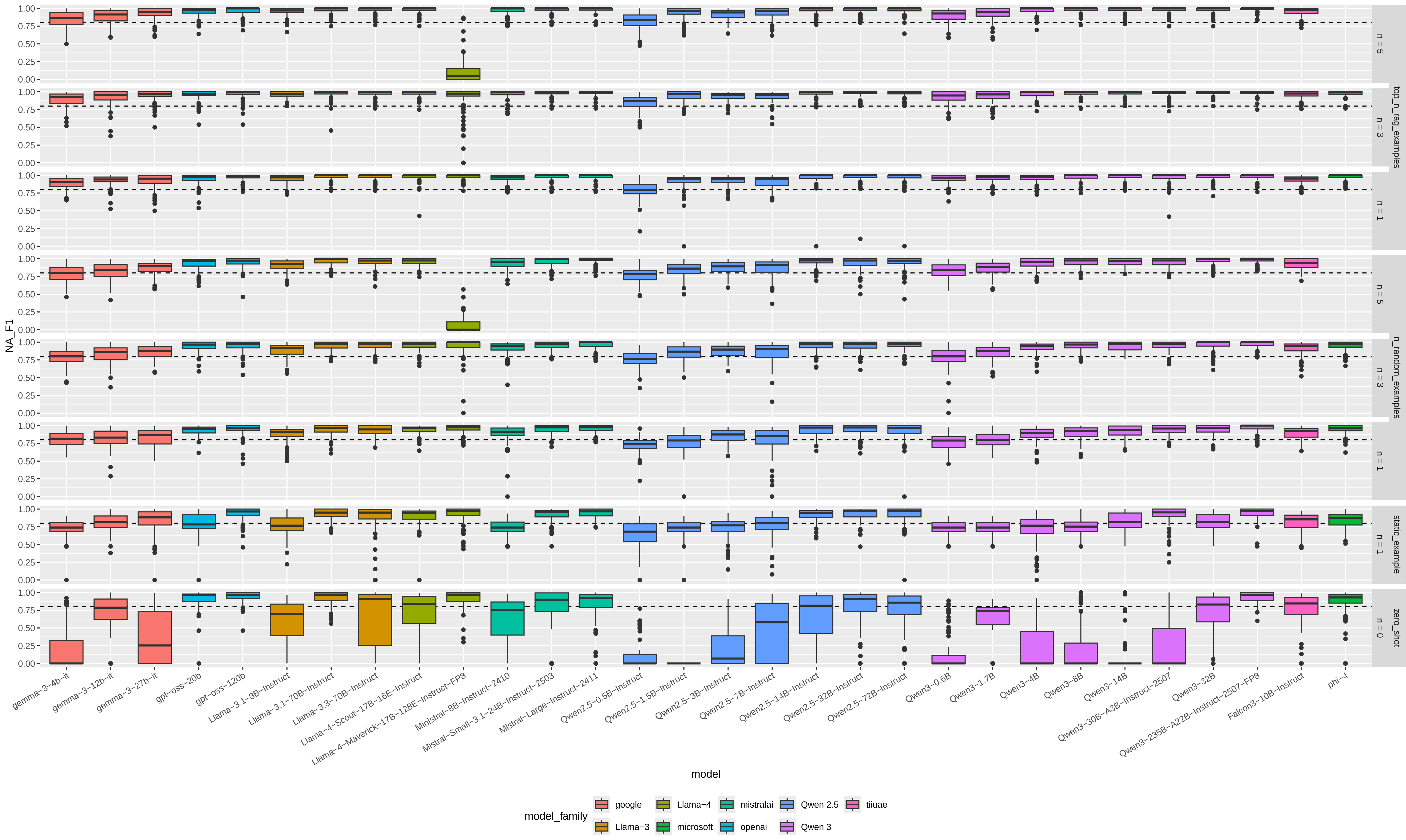


Figure G.17: F1 score for the missing classification if a value is missing for table extraction task on real Aktiva tables

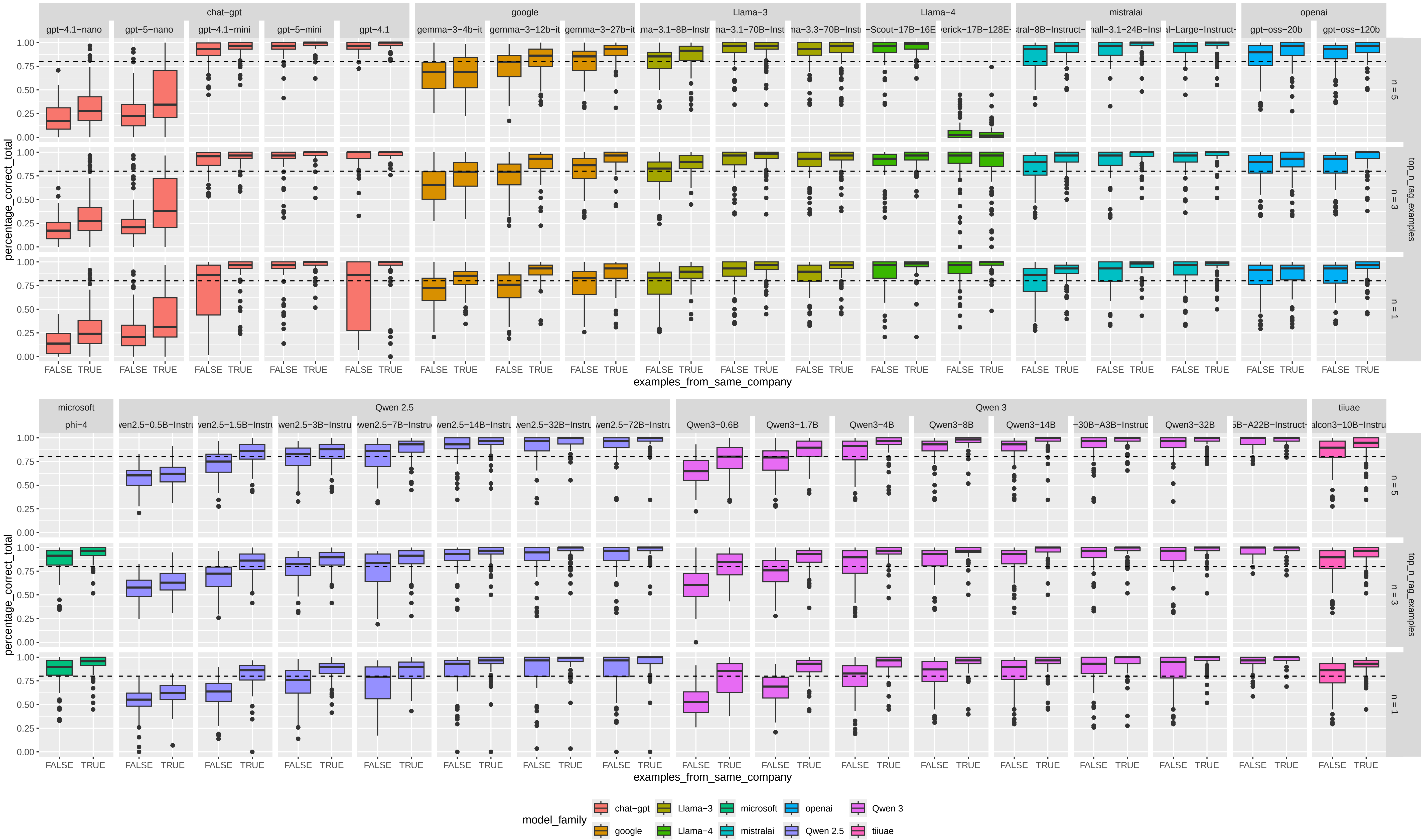


Figure G.18: Comparing the overall extraction performance depending on the condition if examples from the same company can be used.

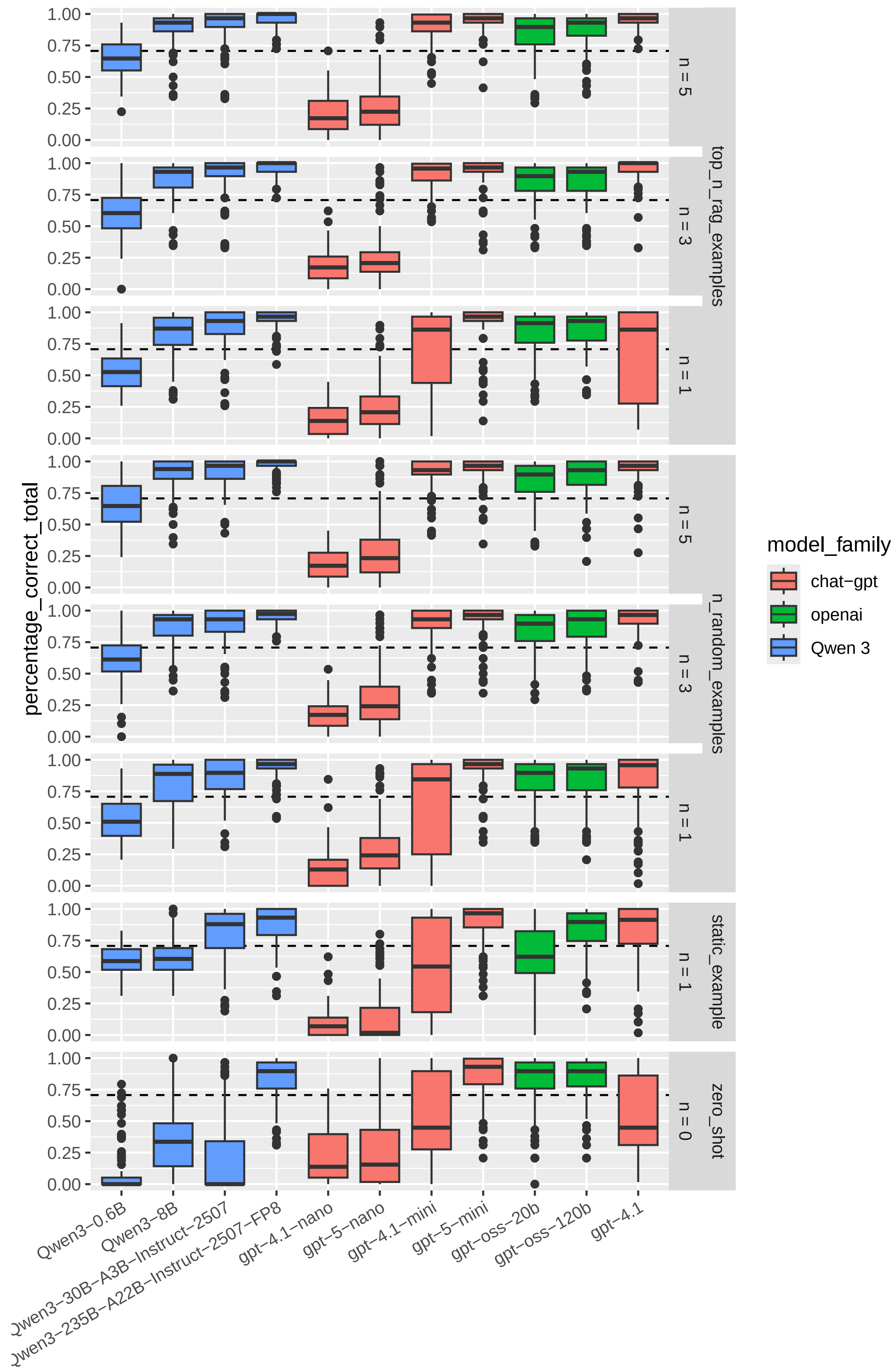


Figure G.19: Comparing the percentage of correct predictions overall for OpenAi's LLMs with some Qwen 3 models

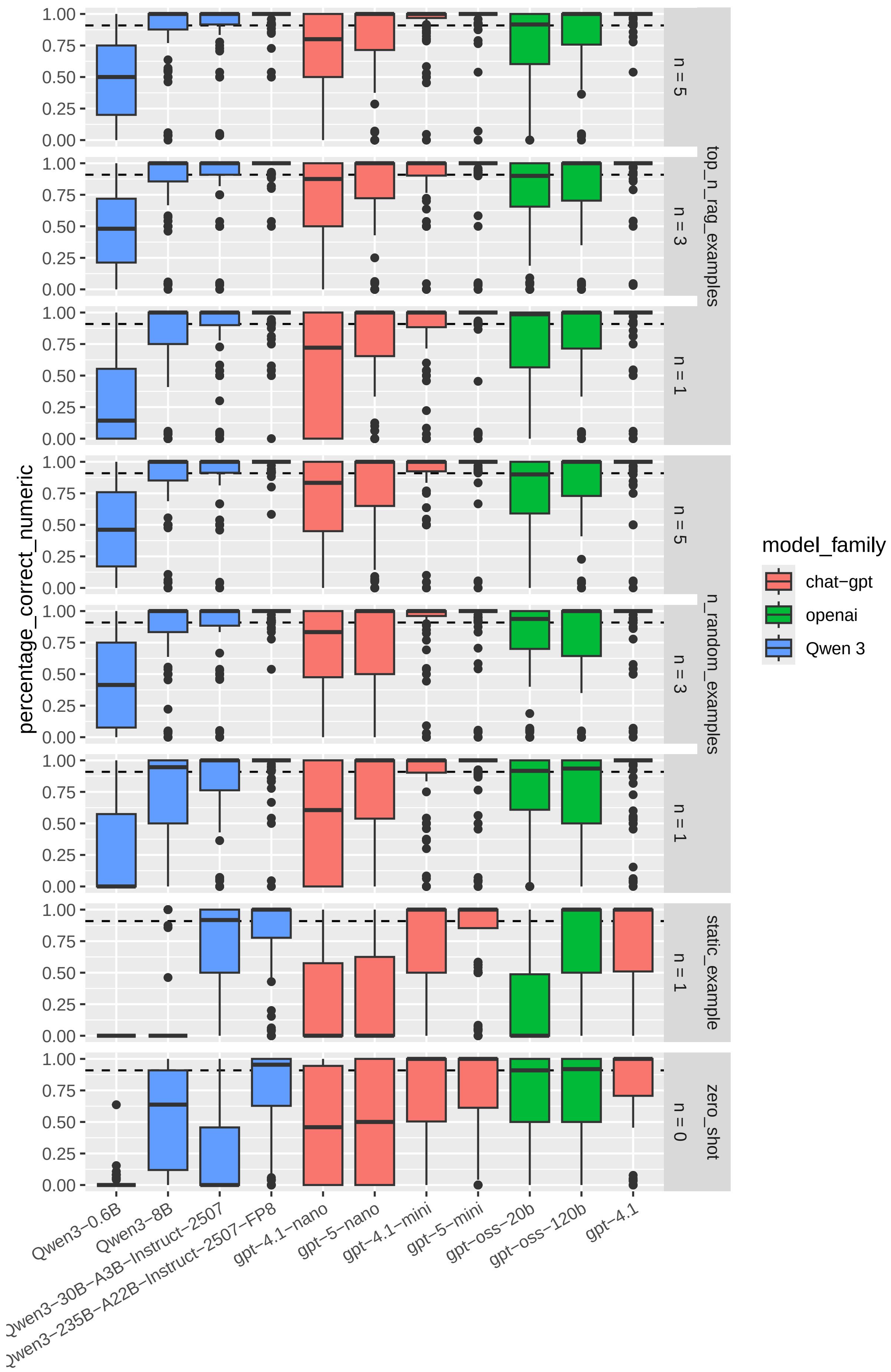


Figure G.20: Comparing the percentage of correct numeric predictions for OpenAi's LLMs with some Qwen 3 models

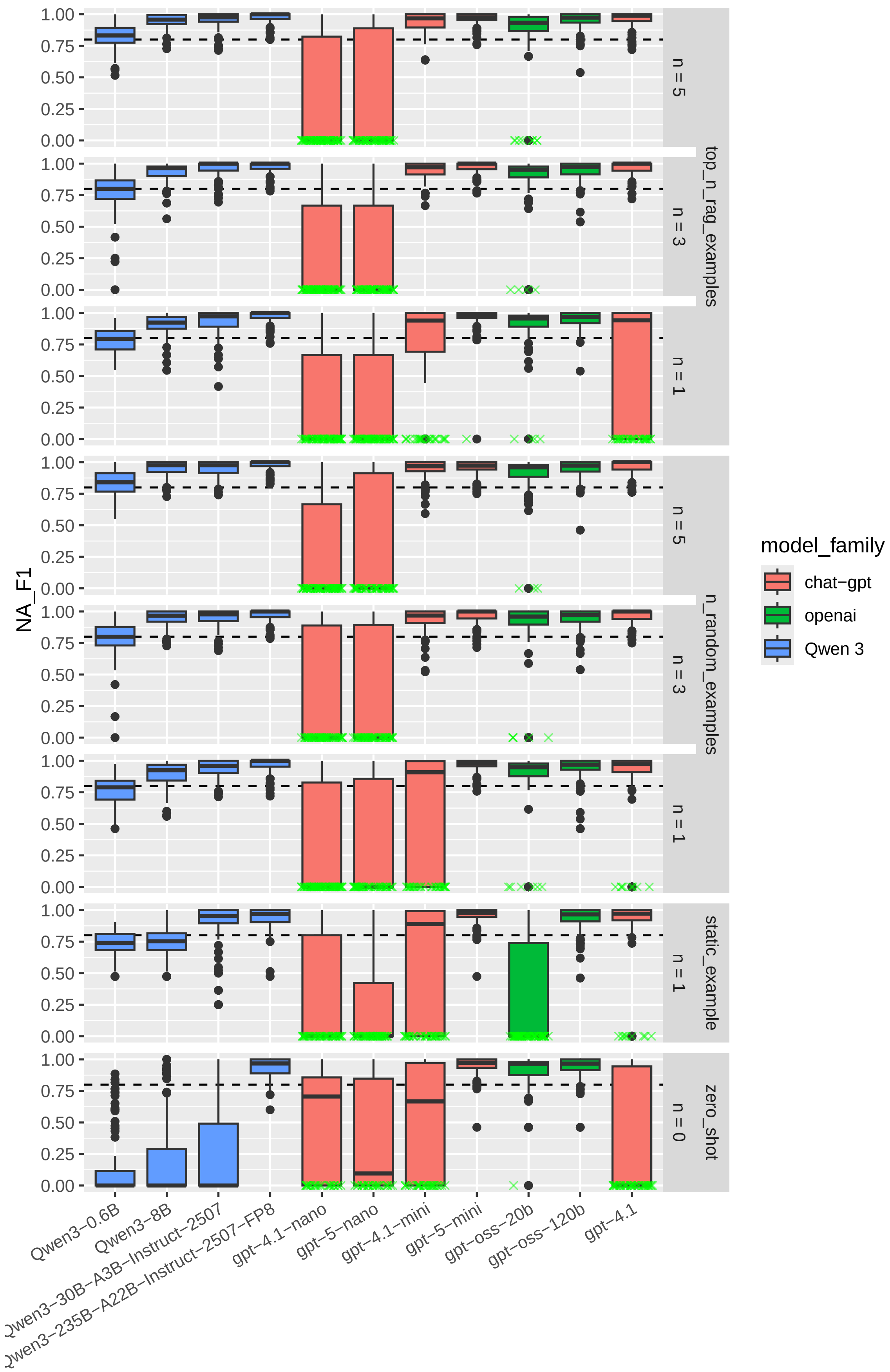


Figure G.21: Comparing the F1 score for predicting the missingness of a value for OpenAi's LLMs with some Qwen 3 models. The green crosses indicate results where a model has predicted only numeric values even though there have been missing values.

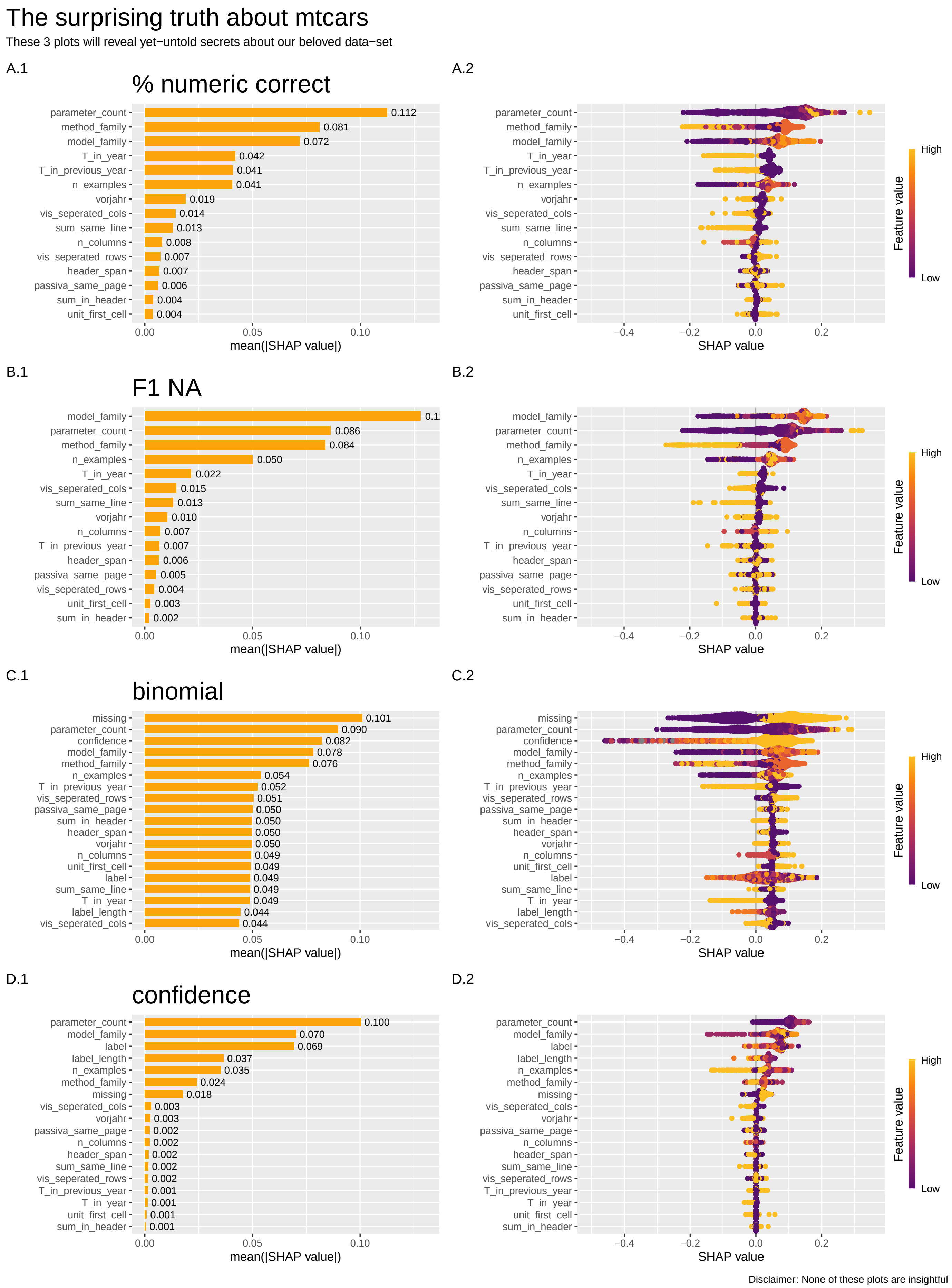


Figure G.22: Mean absolute SHAP values and beeswarm plots for real table extraction with LLMs

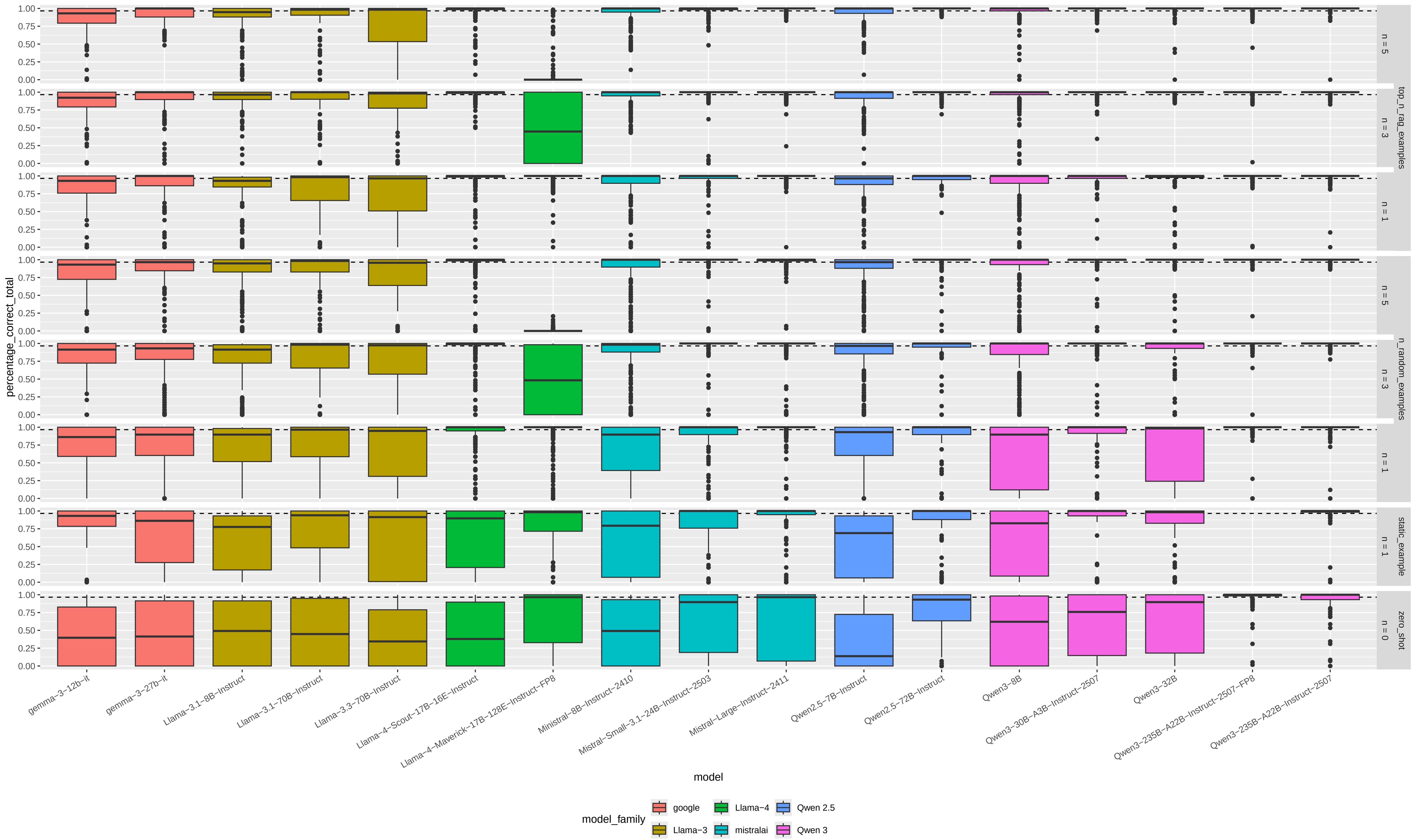


Figure G.23: Percentage of correct extracted or as missing categorized values for table extraction task on synthetic Aktiva tables

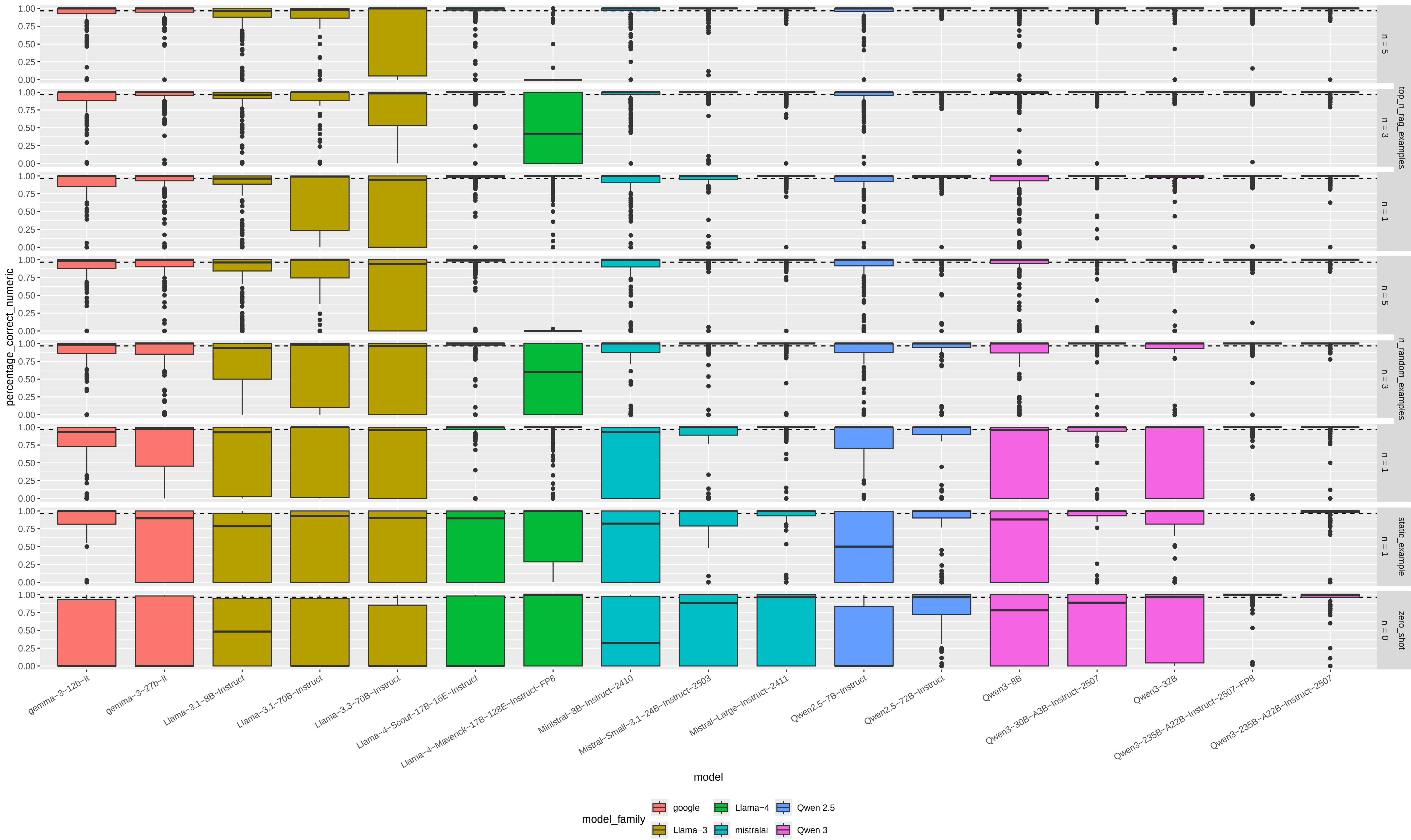


Figure G.24: Percentage of correct extracted numeric values for table extraction task on synthetic Aktiva tables

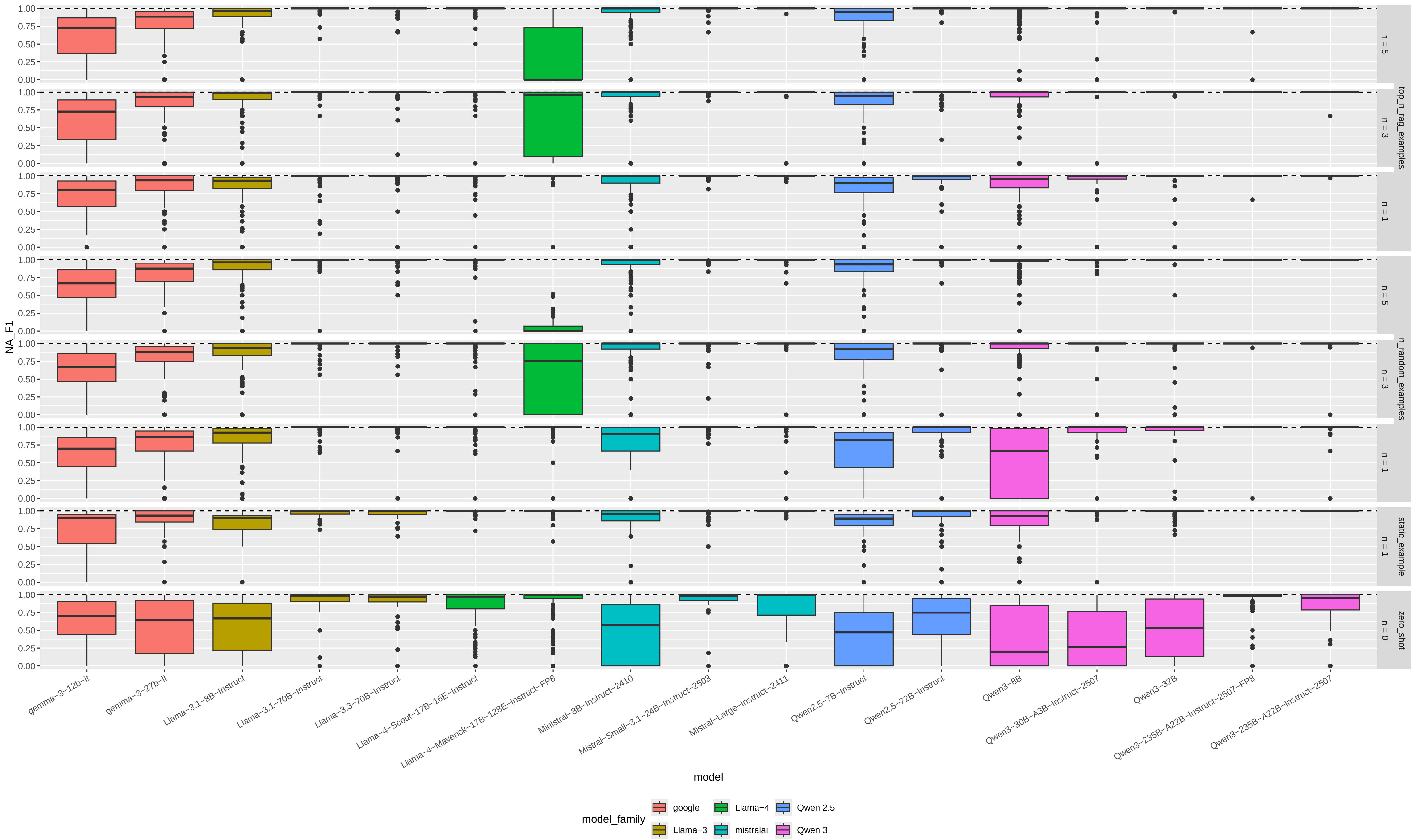


Figure G.25: F1 score for the missing classification if a value is missing for table extraction task on synthetic Aktiva tables

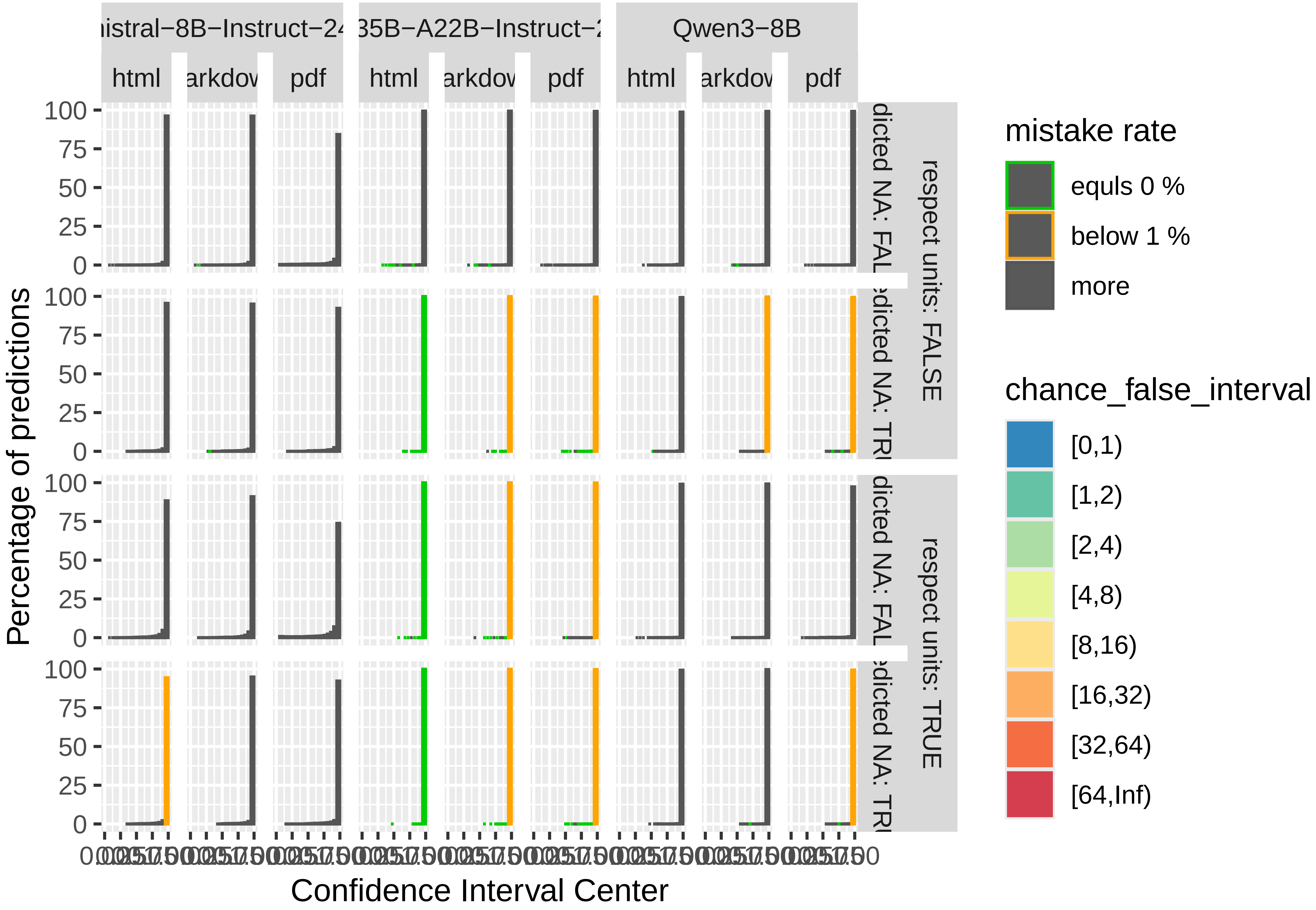
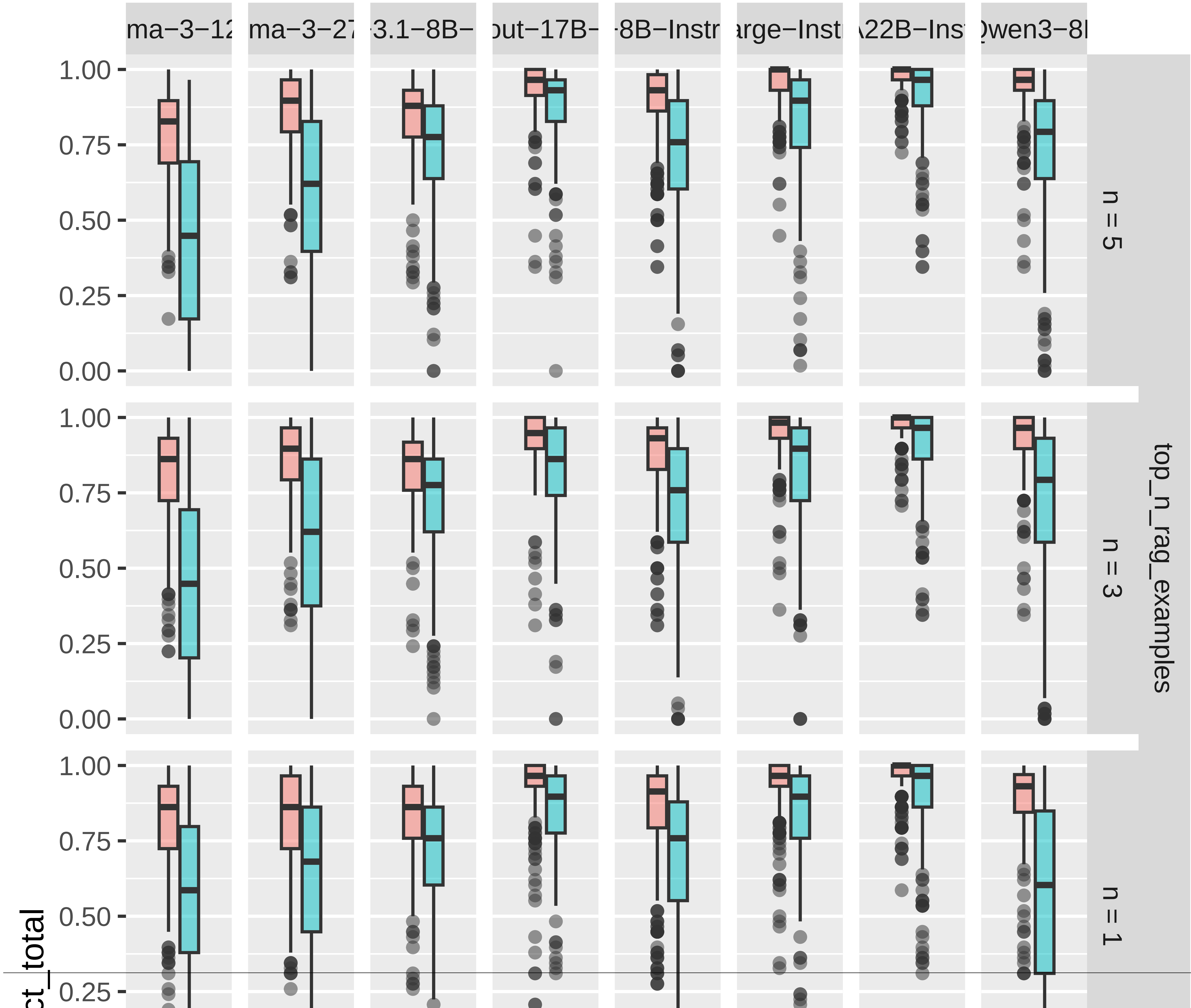


Figure G.26: Estimating the relative frequency to find a wrong extraction result over different confidence intervals for predictions for the synthetic table extraction task. Additionally grouped by input format.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ma−3−27
3.1−8B−
out−17B−
8B−Instr
arge−Inst
22B−Ins
Qwen3−8
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0.50
0.25
0.00
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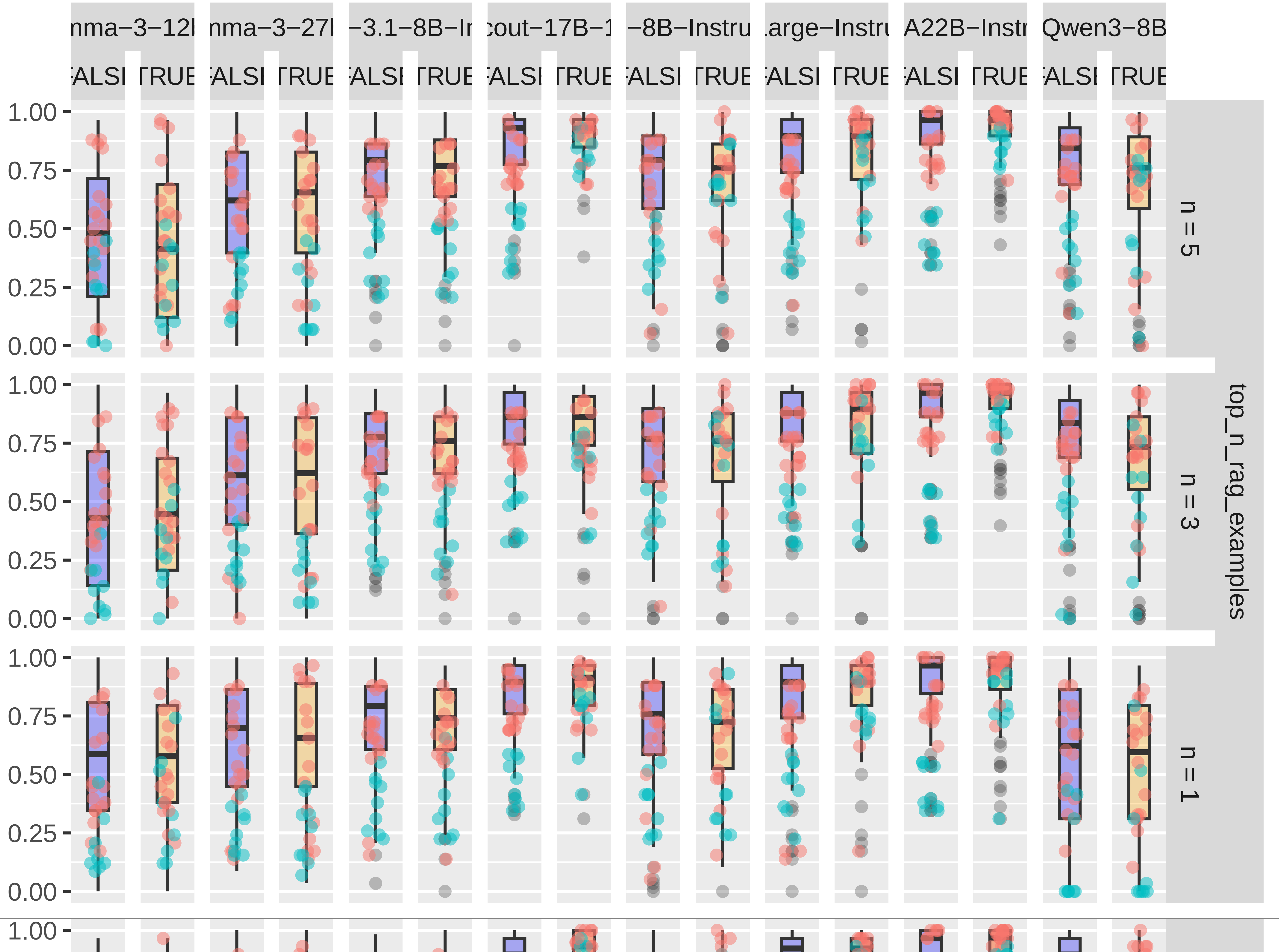
top_n_rag_examples
ct_total



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nma−3−27I
−3.1−8B−Ir
cout−17B−1
−8B−Instru
.arge−Instru
A22B−Instr
Qwen3−8B
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0.50
0.25
0.00
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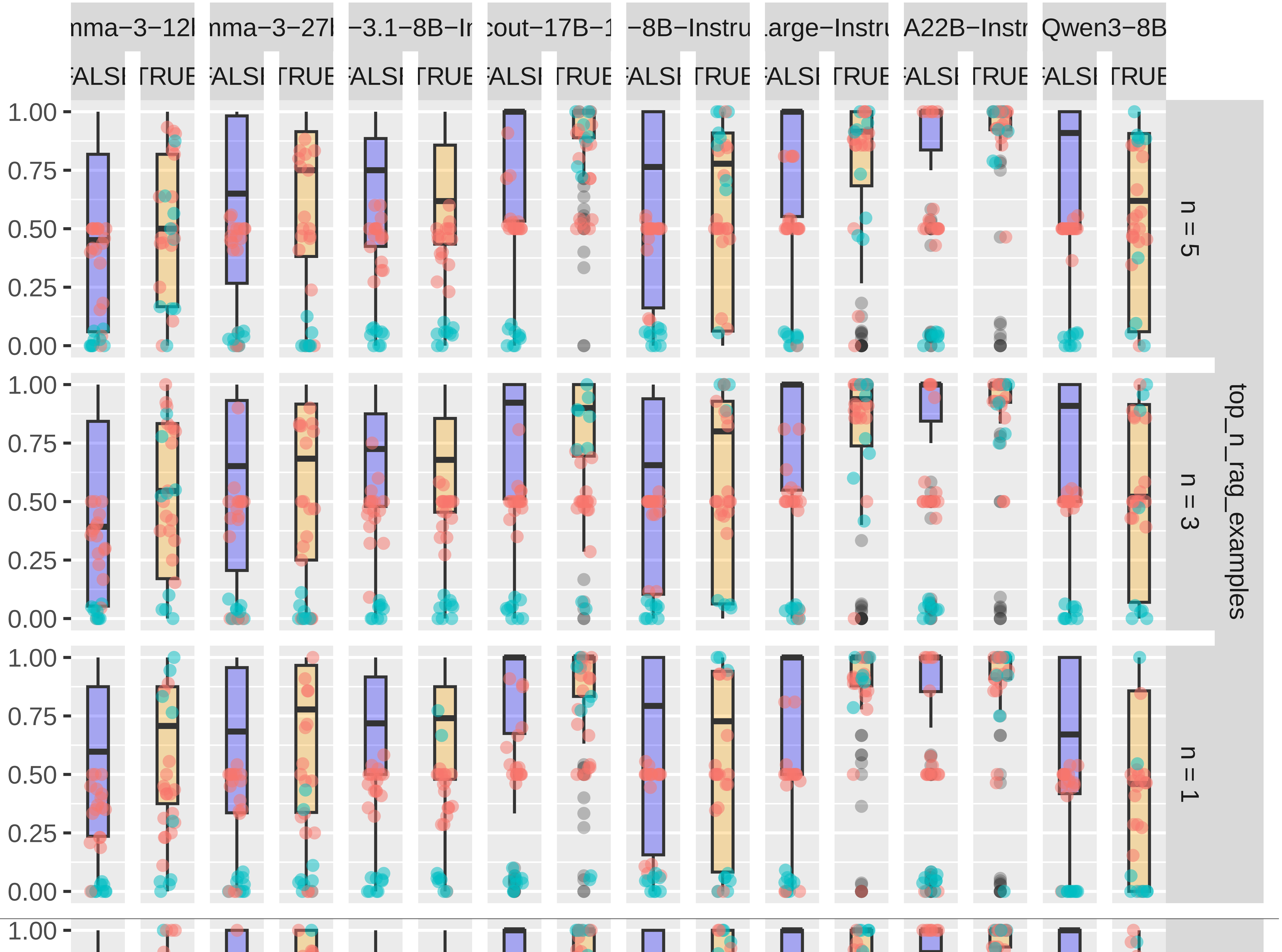
n = 3
n = 1
top_n_rag_examples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nma−3−27l
−3.1−8B−Ir
cout−17B−1
−8B−Instru
.arge−Instru
A22B−Instr
Qwen3−8B
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0.00
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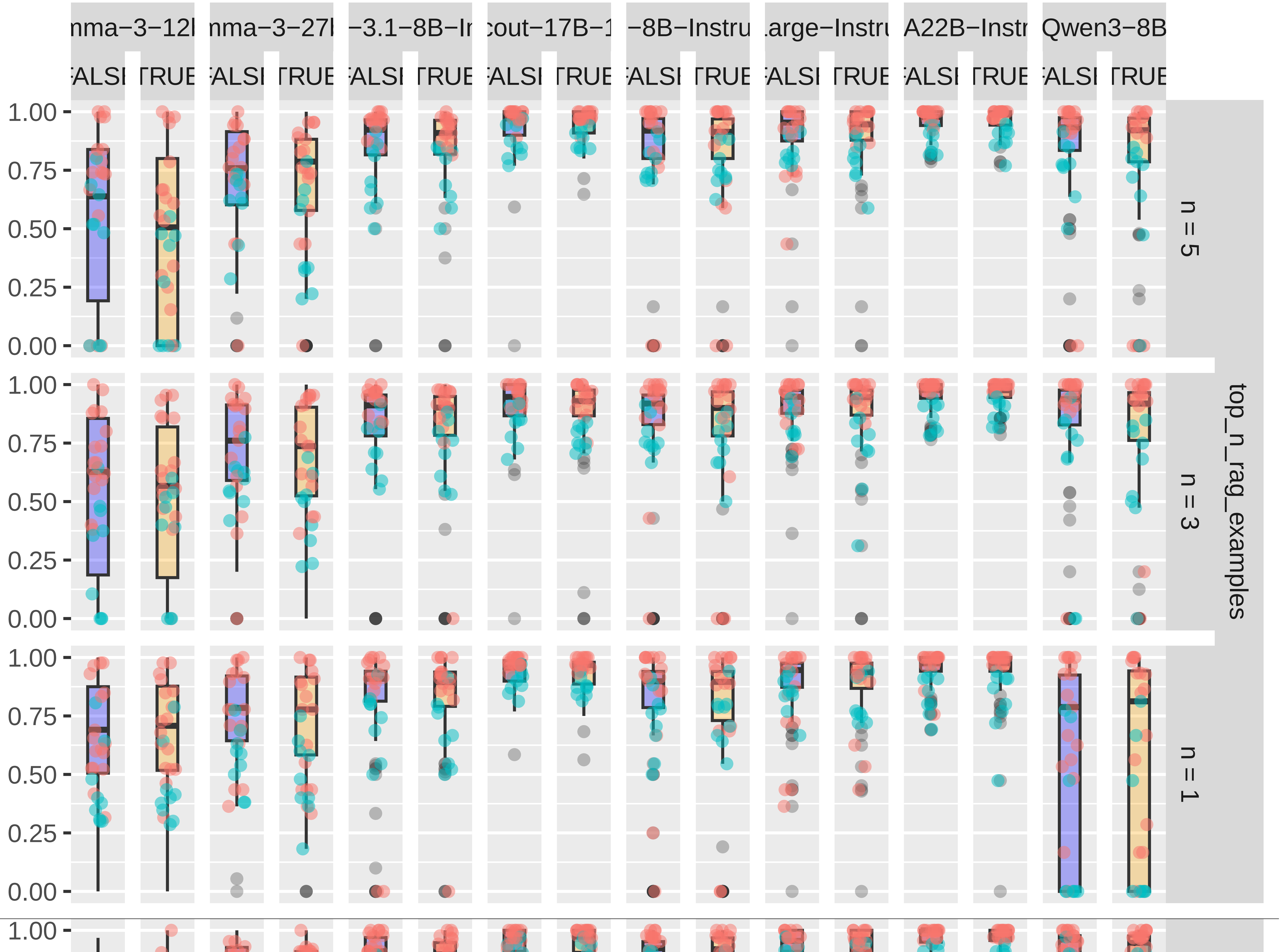
n = 3
n = 1
top_n_rag_examples


nma−3−12l
nma−3−27l
−3.1−8B−Ir
cout−17B−1
−8B−Instru
.arge−Instru
A22B−Instr
Qwen3−8B
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TRUE
1.00
0.75
0.50
0.25
0.00
n = 5
n = 3
n = 1
top_n_rag_examples

Appendix H

Layout testing

12sdgsdgj

Landscape Landscape

Hello