

PRISMAI: An Environment for AI-generated Text Recognition

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Abstract

We introduce PRISMAI, an environment for the automatic detection of AI-generated text. Our contributions are threefold: Firstly, we release the largest AI-detection dataset to date, comprising 537,588 human-written and AI-generated documents in both English and German across seven domains, including scientific writing, weblogs, parliamentary speeches, legal court cases, classic literature, news articles, and student essays, synthesized using state-of-the-art models. Secondly, we introduce LUMINAR, a CNN-based model for the automatic detection of AI-generated texts. Our experiments show that by leveraging the hidden states of an LLM to derive intermediate likelihoods, our model, despite having a small footprint, can outperform other likelihood-backed baselines significantly while demonstrating strong generalization capabilities in out-of-domain and out-of-language scenarios. Thirdly, we unify existing datasets into a common corpus called AIGT-WORLD and make it accessible through a publicly available web-based corpus explorer, which facilitates searching, reading, visualizing, and interacting with the underlying data. By doing so, we aim to elevate research in this area, expand the field to include non-English texts, propose new models, and unify existing efforts to build toward a common dataset and objective.

1 Introduction

With the advent of the Transformer architecture (Vaswani et al., 2017), Large Language Models (LLMs) have been widely adopted in various aspects of daily life (Veselovsky et al., 2023; Murakami et al., 2023; Jiang et al., 2024), owing to their ability to generate high-quality text (OpenAI et al., 2024; Team et al., 2024a), in some cases even surpassing human writing (Gómez-Rodríguez and Williams, 2023). This has led to a massive influx of AI-generated text on the internet, with recent

studies indicating a 57.3% increase on mainstream websites and an 474% increase on misinformation sites (Hanley and Durumeric, 2023), alongside a rise in plagiarism cases (Bisi et al., 2023; Elali and Rachid, 2023; Pudasaini et al., 2024). This issue was further exacerbated by Lu et al. (2024), who introduced the first fully automated *AI Scientist* — a system composed of AI agents capable of generating entire scientific papers, from idea generation to experimentation and final manuscript writing.

Consequently, concerns have emerged regarding the long-term implications of AI-generated text, not only for information reliability and content originality but also for the broader digital ecosystem (Shen and Zhang, 2024; Wang and Lu, 2025). For instance, Shumailov et al. (2024) have shown that recursively training language models on AI-generated text (AIGT) leads to irreversible degradation in model quality, a phenomenon known as *model collapse*, where later-generation models experience catastrophic forgetting and a decline in linguistic coherence.

To address these issues, research on the automatic detection of AI-generated text has emerged as a crucial field of study. Herein, the collection of datasets (Yu et al., 2023; Su et al., 2023b; Li et al., 2024) and the development of AI-detection models (Wang et al., 2023; Verma et al., 2024) have become the two primary objectives. With PRISMAI, we contribute to this research by, first, releasing the largest AI-detection dataset to date (see Table 1), and second, introducing LUMINAR a novel AI-written text detection model that uses Convolutional Neural Networks on a likelihood-based feature space to detect AI-generated snippets within documents. Thirdly, as part of the PRISMAI framework, we release everything as open-source¹, unify existing datasets into a single corpus called

¹<https://anonymous.4open.science/r/PrismaI-ACL-824C/>

AIQT-WORLD, and provide an interactive corpus explorer via a publicly accessible web portal² that enables users to explore both human-written and AI-generated content through semantic searches and intuitive visualizations (screenshots of the portal are provided by Figure 5 in the appendix).

2 Related Work

We consider two parts of related work. First, we discuss models that have been developed for the automatic detection of various forms of AI-generated text. Second, we examine the most recent datasets collected in connection with these efforts.

2.1 Models

Several approaches focus on the automatic detection of machine-written texts. One of them is based on linguistic analysis, including n -gram frequencies (Badaskar et al., 2008), entropy (Gehrmann et al., 2019), and log-likelihood-based methods, where the latter has led to some of the most prominent models to date: *DetectGPT* (Mitchell et al., 2023), and its successors *DetectLLM* (Su et al., 2023a) and *Fast-DetectGPT* (Bao et al., 2024). *DetectGPT* relies on the *perturbation* of input sequences and its effect on the log-likelihood of predictions, while *Fast-DetectGPT* relies on the sampling of a large number of alternative tokens from the conditional probability distribution produced for each token in an input sequence by an LLM. Therefore, their main limitation is their white-box nature, requiring access to model logits and prediction distributions, which is often unavailable, especially when using APIs or services such as ChatGPT.

A second approach focuses on *watermarking* LLM-generated text, as done by Kirchenbauer et al. (2024) and Lee et al. (2024), the latter primarily addressing the detection of machine-generated code. In this approach, watermarked text can be generated using standard language models without requiring retraining, while the misclassification of human-generated text as machine-generated remains statistically unlikely (Kirchenbauer et al., 2024). Although this research direction is actively explored (Liu et al., 2024; Zhao et al., 2024; Dathathri et al., 2024) and yields promising results, it is not relevant to our scenario, as we focus on detecting AI-generated text in a fully black-box

scenario, where AI-generated content may be deliberately hidden, and only the text is provided.


Since we focus on black-box scenarios where access to the generating LLM or potential watermarks is unavailable, leveraging open-source LLMs for continuation (Yang et al., 2023), rewriting (Mao et al., 2024), or paraphrasing (Quidwai et al., 2023) of texts as part of feature engineering or similarity calculations is a widely adopted approach. Furthermore, labeled as state-of-the-art, *Ghostbuster* (Verma et al., 2024) utilizes a series of weaker language models to obtain token probabilities, which are then used to perform a structured search across model combinations. A linear classifier is subsequently trained to distinguish between AI- and human-written texts. Finally, given the abundance of document-level classification models, Wang et al. (2023) introduced *SeqXGPT* for sentence-level classification. This approach leverages log probabilities from white-box LLMs, which are processed through convolutional and self-attention networks.

2.2 Datasets

Several datasets have been compiled for the detection of AI-generated text (Wu et al., 2025). *HC3* (Guo et al., 2023) and *HC3 Plus* (Su et al., 2023b) are among the first datasets of this kind. They consist of both human-written and AI-generated texts in English and Chinese, making them unique due to the rarity of bilingual data, with a focus on news, translations and Q&A texts. The *CHEAT* dataset (Yu et al., 2023) was created to detect plagiarism in the scientific field. It includes human-written abstracts alongside their ChatGPT-generated summaries, and so-called *fusion* texts, as a mix of human and AI-generated content. One of the largest datasets, *OpenLLMText* (Su et al., 2023a), comprises over 340 000 texts derived from various AI models, with a primary focus on web texts. To detect AI-generated content in academic contexts, such as classroom exercises, Liu et al. (2023) propose *ArguGPT*, a collection of 4 000 argumentative essays generated by seven different GPT models, but with no human-written counterparts. A broader dataset covering a wider range of domains has been introduced by Pu et al. (2022) in the form of *DeepfakeTextDetect*; it includes news articles, stories, scientific texts and more, generated using a variety of models. This dataset is not open-source, as access requires a Google Form submission, which grants the authors the right to withdraw their data at any time and prohibits further distribution.

²*anonymized* - link won't be available during review

Table 1: The datasets unified within AIGT-WORLD and their statistics, including our PRISMAI-dataset. The notation $\langle models \rangle \implies \langle domains \rangle$ indicates that the set of *models* was applied to the given set of *domains* to generate AI counterparts. The *MAGE* dataset uses 27 LLMs, which are variations of the listed base models. The word and sentence counts for the Chinese part of the *HC3-Plus* dataset may not be representative.

<div> AIGT-WORLD</div>						
Dataset	Languages	Label	Documents	Words	Sentences	Size (MB)
SeqXGPT-Bench (Wang et al., 2023)	English	AI	29 904	6 267 328	358 973	36.07
		Human	6 000	1 424 983	81 801	8.04
〈 GPT-2, GPT-J, GPT-NEO, LLaMA, GPT-3.5-turbo 〉 \implies 〈 news, social media posts, web texts, scientific articles, technical documentation 〉						
CHEAT (Yu et al., 2023)	English	AI	30 790	4 490 024	246 586	29.97
		Human	15 395	2 458 466	133 384	15.92
		HU \times AI	4 514	649 925	35 480	4.28
〈 GPT-3.5-turbo 〉 \implies 〈 scholarly literature 〉						
Ghostbuster (Verma et al., 2024)	English	AI	12 000	6 010 131	385 358	38.42
		Human	2 000	1 192 091	86 977	6.76
〈 GPT-3.5-turbo, Claude 〉 \implies 〈 creative writing, news, student essays 〉						
HC3-Plus (Su et al., 2023b)	English Chinese	AI	144 582	8 026 922	540 497	54.31
		Human	178 939	9 643 121	722 092	56.77
〈 GPT-3.5-turbo 〉 \implies 〈 news, translations, question answering 〉						
OpenLLMText (Su et al., 2023a)	English	AI	275 546	92 334 033	5 277 345	546.19
		Human	68 984	38 603 989	2 264 905	229.03
〈 GPT-3.5, PaLM, LLaMA-7B, GPT2-1B 〉 \implies 〈 web texts 〉						
MAGE (Li et al., 2024)	English	AI	281 824	61 590 290	4 532 144	343.97
		Human	150 858	30 093 650	2 325 683	163.52
〈 OpenAI GPT, LLaMA, GLM-130B, FLAN-T5, OPT, BigScience, EleutherAI 〉 \implies 〈 opinion statements, reviews, news, question answering, story generation, reasoning, wikipedia, scientific writing 〉						
PrismaAI	English German	AI	404 066	132 653 218	8 016 429	834.57
		Human	154 978	626 961 931	40 229 029	3 408.67
〈 GPT-4-turbo, GPT-4o-mini, o3-mini, Nemotron, Gemma2-9b, DeepSeek-r1:1.5b & 32b, phi3-3.8b 〉 \implies 〈 scientific writing, weblogs, parliamentary speeches (English & German), news (English & German), legal court cases, classic literature (English & German), student essays 〉						

Recently, Li et al. (2024) proposed *MAGE*, a testbed with the widest variety of domains to date, including opinion statements, story generation, scientific writing and more. The dataset, which consists entirely of English text, uses 27 different LLMs and contains over 400 000 samples, the majority of which are AI-generated. In order to train their model, *Ghostbuster*, Verma et al. (2024) collected three new datasets covering the domains of creative writing, news, and student essays. They used *gpt-3.5-turbo* (Brown et al., 2020) to generate AI counterparts, creating 14 000 texts. While current AI-generated text detection focuses mainly on document-level classification, Wang et al. (2023) synthesized a sentence-level detection dataset. It includes sources such as news articles, social media posts, and technical documentation, and is based on the *SnifferBench* (Li et al., 2023) dataset.

3 Data

While the datasets discussed in Section 2.2 provide a solid foundation, there are still three key gaps. First, the dominance of English texts fails to reflect linguistic diversity. Second, the vast majority of AI-generated text is produced by models that are outdated by today’s standards, including GPT-2, GPT-3.5, and LLaMA (Touvron et al., 2023), raising concerns about their relevance in terms of both performance and text generation. Third, because the focus is primarily on document-level detection, they lack fusion texts, specifically chunk-based AI snippets embedded in human-written content.

To fill these gaps, we introduce the PRISMAI-dataset. It consists of (A): English news articles collected from **CNN-DailyMail** (See et al., 2017) and German news articles from **Spiegel Online**,

(B) English scientific articles harvested by scraping **arXiv** papers and extracting their full PDF content via PyMuPDF, (C) English web-blogs from **blogger.com** (Schler et al., 2006), (D) German parliamentary speeches provided by **Anonymous**³ and English speeches from the **House of Commons** archive (Blumenau, 2021), (E) English legal cases from the **European Court of Human Rights** (Chalkidis et al., 2021), (F) English student essays written by 6th–12th grade students, collected within a kaggle competition (King et al., 2023) and built upon Crossley et al. (2024), and (G) English and German classic literature texts scraped from Project Gutenberg (Gutenberg, n.d.). For generating the AI texts, we employ state-of-the-art models with a focus on publicly accessible and popular LLMs, including **Gemma 2** (9B) (Team et al., 2024b), **Phi-3** (3.8B) (Abdin et al., 2024), **DeepSeek-R1** (1.5B | 32B) (DeepSeek-AI et al., 2025), **Nemotron** (70B) (Nvidia et al., 2024) and OpenAIs **GPT-4-Turbo**, **GPT-4o-Mini** (OpenAI, 2024) and **o3-Mini** (OpenAI, 2025).

We also address the lack of chunk-based AI snippets that resemble *fusion* texts (Yu et al., 2023). Since AIGT is often embedded in human-written texts, we categorize our dataset into *chunked* and *fulltext*. To generate *chunked* AI texts, we divide human-written texts into segments and replace up to 50% with a contiguous selection of masked chunks. An LLM then reconstructs the missing content based on the surrounding human-authored text. For *fulltext*, we prompt the LLM to extract key information from a human-written text in a structured format. This includes identifying the language, reconstructing contextualized scenarios, determining the topic, and analyzing linguistic style. Based on *few-shot prompting*, we provide an example alongside the desired output. Using the extracted information, we then prompt the LLM in a ghost-writing scenario to generate a new text based on the details provided, including a specified word count (for the details see Appendix ??). Finally, we add the *fulltext* and *chunked* AI-generated variants of all human-written texts to PRISMAI.

4 LUMINAR

We now introduce our model for AI-generated text detection, LUMINAR, a CNN-based text classification model (LeCun et al., 1989) that builds upon the approaches outlined in Section 2. We discuss the

features used to power LUMINAR and its architecture, following by an evaluation of its performance on a subset of PRISMAI.

4.1 Features

Inspired by *DetectLLM* (Su et al., 2023a) and *Fast-DetectGPT* (Bao et al., 2024), we investigate the likelihoods of common LLMs to derive features for LUMINAR. Let $p_\theta(x)$ be the probability of any given token x following a sequence of preceding tokens parametrized by the models’ weights θ (Radford et al., 2019):

$$p_\theta(x) = \prod_{i=1}^n p(x_i | x_1, \dots, x_{i-1})$$

Contemporary LLMs approximate these probabilities by passing encoded inputs, usually consisting of token and position embeddings, through layers of identical *Transformer* blocks TF_θ (Vaswani et al., 2017; cf. Radford et al., 2019; Dubey et al., 2024; Team et al., 2024b) forming hidden states HS between each layer. The output of the last *Transformer* layer is then passed through a *Language Modeling Head* (LM head, LMH), which acts as a projection layer from hidden states to vocabulary space and produces the logits. Given an input encoding method Enc_θ and a tokenized input sequence \mathbf{x} , we can formalize these operations (slightly simplified; omitting model specific operations, activation functions, etc.) as:

$$HS_0 = Enc_\theta(\mathbf{x})$$

$$HS_i = TF_{\theta_i}(HS_{i-1})$$

$$logits = LMH_\theta(HS_H)$$

where there exists a TF_{θ_i} and a HS_i for each $i \in \{1, \dots, H\}$ for an H layer model. Applying $SoftMax(logits)$ yields the likelihood vector L containing value for each token conditioned on its preceding tokens.

Previous work uses pre-trained white-box LLMs to determine the likelihood of a given, potentially permuted token for a given text, and to infer judgments about human authorship. We use the same method but also include **Intermediate Likelihoods** (**IL**), i.e., a set of likelihoods obtained by the intermediate hidden states of an LLM. We discuss IL and a number of features we considered, including the regular *Likelihood* (**L**), the top- k token’s likelihoods in terms of the *top-k Likelihood Likelihood*

³Published at the Jurix 2023 conference

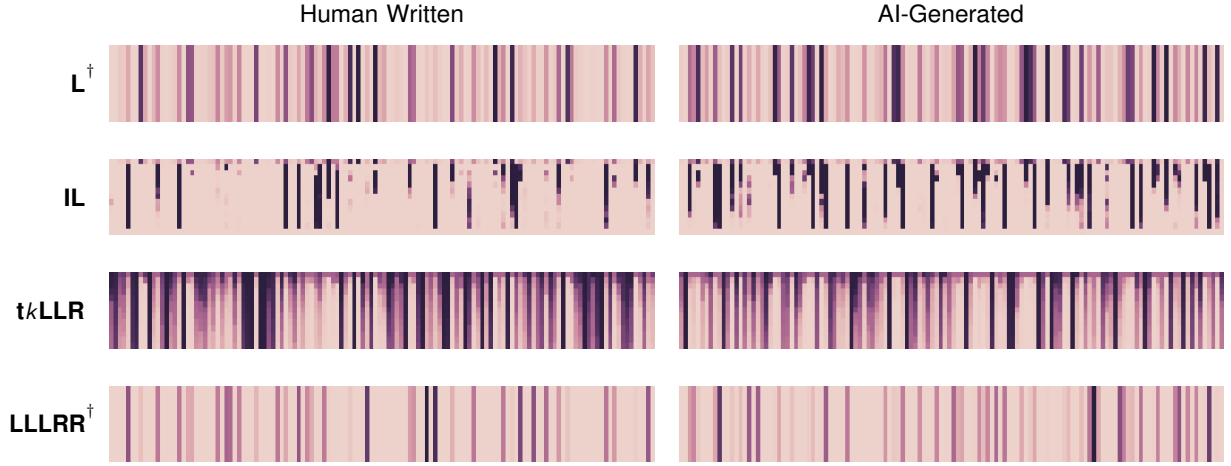


Figure 1: Visualization of four feature types for the first 128 tokens of a *CNN-DailyNews* article and its AI-generated counterpart (created using gpt-4o-mini), utilizing gpt2’s hidden states. Darker shades code higher values. Features from top to bottom: Likelihoods; Intermediate Likelihoods; top- k Likelihood Likelihood Ratio. Log-Likelihood Log-Rank Ratio; †The features are 1D but are shown as 2D for clarity; all other features have 13 dimensions each.

Ratio ($tkLLR$ and its inverse $LtkLR$), and the *Log-Likelihood Log-Rank Ratio* ($LLLRR$, derived from LLR , cf. [Su et al., 2023a](#)).

Intermediate Likelihoods As each *Transformer* layer has the same input/output characteristics we can simply pass each hidden state through the LM head to calculate the intermediate likelihoods L_i :

$$\begin{aligned} logits_i &= LMH_{\theta}(HS_i) \\ L_i &= \text{SoftMax}(logits_i) \end{aligned}$$

Let now $p_i(x_j) = L_{ij}$ be the intermediate likelihood of token x_j for layer i and $p(x_j) = p_H(x_j)$ the “regular” likelihood. Thus our first feature, the *Likelihoods*, are given as vector $\mathbf{L} = (p(x_1) \dots p(x_n))$. Using the likelihoods of the intermediate hidden states, we define our second feature, the *Intermediate Likelihoods*, as a matrix \mathbf{IL} where the rows represent the intermediate likelihood from one layer and the columns represent each token as such that:

$$\mathbf{IL}_{ij} = p_i(x_j)$$

tkLLR Let $\text{top}_k(j)$ be the k -highest likelihood at position j . Thus the *top- k Likelihood Likelihood Ratio* is given as matrix a with values

$$tkLLR_{kj} = \frac{\text{top}_k(j)}{\text{top}_k(j) + p(x_j) + \epsilon}$$

where $k \in \{1, \dots, K\}$ is a variable sized hyperparameter. We may also consider the inverse ratio, $LtkLR$, where $p(x_j)$ is placed in the numerator.

LLLRR By calculating the LLR for each token x_j with likelihood $p(x_j)$ and the corresponding 1-indexed rank $r(x_j)$ separately, we define our *Log-Likelihood Log-Rank Ratio* feature as vector

$$LLLRR_j = -\frac{\log(p(x_j) + \epsilon)}{\log(r(x_j)) + \epsilon}$$

adding a small constant ϵ to avoid $\log(0)$ and $\dot{0}$, respectively. ⁴

Example Figure 1 shows a set of features for two texts from the *CNN-DailyMail* dataset, with the human-written text features’ on the left and the AI-generated text features’ on the right, for the first 128 tokens of each document generated with gpt2, where darker colors code higher values. The first row shows the *Likelihood* features, where we can see a small set of characteristic high-likelihood areas in the first fifth of the features corresponding to the tokenized text

at the christ _ening of Prince George

where the second token ‘the’ has a likelihood of 0.3 while the fourth token ‘_ening’ has a likelihood of 0.7 (_ indicating a continuation token). Below that, we see the *Intermediate Likelihoods*, where the upper row pertains to the likelihood in the last layer and thus matches the *Likelihood* in the first row. We can clearly see the 1.0 likelihood in the lower layers (first vertical dark line) for

⁴While SoftMax likelihoods *should* never be zero, we encountered several cases where numerical instability or loss of precision during data format transitions led to zero likelihoods.

‘the’, but a low likelihood 0.0 for ‘_ening’.⁵ Note that there are only few such patterns in the human-written sample, while the AI-generated sample shows a large number of high-likelihood columns for the lower layers of the model.

The third row shows the *top-k Likelihood Likelihood Ratio*. The likelihood acts as a scaling factor against the top- k tokens, highlighting areas of ambiguity by significantly increasing the top- k likelihood values when the likelihood is small or equal to them.

The fourth row shows the *Log-Likelihood Log-Rank Ratio*, the metric used in perturbation-free *DetectLLM-LLR* approach of Su et al. (2023a). It is the only feature that is not restricted to the unit range $[0, 1]$.

4.2 Document-Level Features

In the general case, we treat AI text detection as a *text classification task*. To this end, we generate text-level features from an input text by first computing the hidden states with a simple forward pass of the tokenized text through an LLM. Then, we compute all *Intermediate Likelihoods* by passing each hidden state through the LM head. This results in a two-dimensional vector $\vec{feat}_D \in \mathbb{R}^{L \times H}$, where L is the length of the tokenized document and H is the number of hidden states (e.g. 13 for gpt2 or 17 for Llama3.2-1B). We experimented with different sampling methods and found that taking the features or randomly selecting strided slices performed the best. To obtain a vector of fixed length from texts of variable size L , we sample k slices of size s from \vec{feat}_D and concatenate them into a single feature vector \vec{feat} . If a text is too short to sample sufficient slices, we fall back on the first $k \cdot s$ features and apply zero padding to the right if necessary.

4.3 Model

The LUMINAR text classification model is backed by a CNN with a linear classifier (see Figure 2). Depending on the operative feature selection method of Section 4.1, we first concatenate the selected feature slices along the sequence length dimension. We experimented with different architectures and found that multiple 1D convolution layers performed best across feature variants. Thus, we pass our two-dimensional features as single vectors with multiple channels into the CNN. The CNN consists

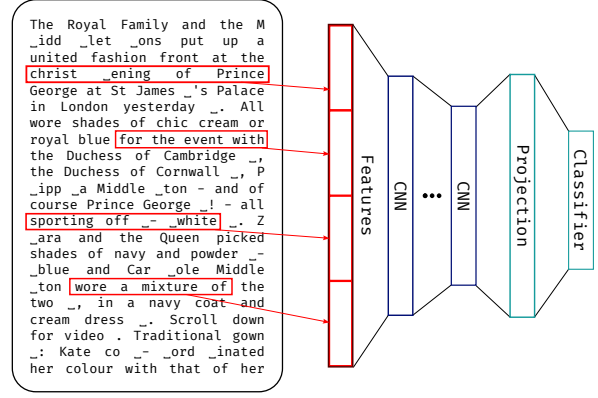


Figure 2: LUMINAR Model Overview.

of multiple layers with LeakyReLU activation functions followed by a linear binary classifier with an optional projection layer.

5 Experiments

During training, we always group human-written documents with their AI-written counterparts before splitting the dataset into training, validation and test sets, so that these paired texts do not appear in different splits. We apply five-fold cross validation with 70 % of the document groups in training, 10 % in validation, and 20 % test splits. We test the performance of our models both *in-domain* and *out-of-domain* (OOD) by training models on one domain or a combination of all domains and testing performance on all domains, and by training a model on all but one domain and testing performance on the held-out domain. We include two German corpora (news and parliamentary speeches, cf. Table 1) in our data to evaluate the cross-lingual performance of the model.

To train the models, we create sized datasets of human texts and individual AI-generated counterparts as well as the combination of multiple agents’ texts. To this end, we consider a subset of 1500 documents for each domain with synthetic texts generated by GPT-4o-Mini. To generate our features, we use GPT-2 and truncate documents that are longer than 1024 tokens to the models maximum context size. We considered using larger LLMs but found the performance of our models with features from GPT-2 (with 124 million parameters) to be sufficient already. Our experiments were conducted using PyTorch (Paszke et al., 2019), Lightning (Falcon and team) and transformers (Wolf et al., 2020). To ensure reproducibility, we run our training in deterministic mode and record all used hyperparameters with the results.

⁵See Section A.2 for the full text of this example.

Table 2: Results for LUMINAR and likelihood-based baselines in the in-domain setting.

Domain	First		Random		LLR		Fast-DetectGPT	
	AUROC	F ₁	AUROC	F ₁	AUROC	F ₁	AUROC	F ₁
Web Blogs	1.000	1.000	0.996	0.968	0.470	0.493	0.369	0.587
Essays	0.971	0.895	0.979	0.895	0.846	0.779	0.925	0.833
CNN	0.995	0.947	0.981	0.912	0.942	0.876	0.972	0.915
ECHR	0.996	0.953	0.991	0.934	0.916	0.851	0.820	0.744
HoC	0.990	0.938	0.973	0.881	0.856	0.829	0.831	0.809
arXiv	0.995	0.977	0.984	0.933	0.965	0.937	0.866	0.847
Gutenberg	0.978	0.910	0.971	0.912	0.859	0.767	0.907	0.874
Bundestag _{de}	0.991	0.963	0.963	0.892	0.846	0.787	0.799	0.748
Spiegel _{de}	0.968	0.936	0.930	0.845	0.868	0.804	0.782	0.701

5.1 Training

The LUMINAR models discussed below were all trained as follows, unless otherwise noted. We train the models for up to 25 epochs using AdamW (Loshchilov and Hutter, 2019) with $\text{lr} = 0.0001$ and a linear learning rate scheduler with a warmup period of one epoch, employing early-stopping conditioned on the validation loss after three consecutive epochs without improvement. In case of **Random** features, we concatenate likelihoods by from four randomly selected slices of size 64 with stride 16, treating the second dimension as input channels. The CNN features five Conv1D layers with $\text{stride}=1$ and (channels, kernel size) of $[(64, 5), (128, 3), (128, 3), (128, 3), (64, 3)]$.

5.2 Results

Table 2 shows the results of our models and selected likelihood-based baselines for each domain individually. F₁-Scores for *DetectLLM*’s LLR and *Fast-DetectGPT* were obtained by calculating metrics for the whole domain dataset and choosing a reasonable threshold by finding the middle point between the means of the distributions for each text class. The scores for our models are the averages of five-fold cross validation using both the *First* and *Random* feature slicing methods as outlined in Section 4.2. We use 0.5 as a fixed threshold to calculate the F₁-Score for our classifiers.

Our classifier outperforms the baselines on all domains, in part with a significant margin. This is especially apparent for the *Blog Authorship* domain, which contains many documents with highly irregular language (see Appendix A.2 for an example). The statistics-based baselines struggle with these irregularities, while our classifier trained on the

Table 3: LUMINAR out-of-domain results.

Domain	First		Random	
	AUROC	F ₁	AUROC	F ₁
Web Blogs	0.296	0.411	0.446	0.474
Essays	0.624	0.699	0.763	0.732
CNN	0.973	0.908	0.973	0.883
ECHR	0.945	0.884	0.940	0.853
HoC	0.967	0.887	0.959	0.853
arXiv	0.993	0.912	0.971	0.857
Gutenberg	0.917	0.846	0.971	0.897
Bundestag _{de}	0.961	0.888	0.795	0.723
Spiegel _{de}	0.506	0.175	0.781	0.663

first 256 tokens’ intermediate likelihoods returns a perfect score. Our model also works very well in a cross-lingual setting, with F₁-scores of 0.963 and 0.936 for the two German subsets, *Bundestag* and *Spiegel Online*, respectively.

Training on randomly sampled feature slices results in consistently worse performance in the in-domain setting. In the out-of-domain setting, that is training on all *but* the test domain, the results are more nuanced: the randomly sampled features yield stronger results for four out of nine domains. Most notably, in the *Spiegel_{de}* domain, the classifier trained on randomly sampled feature slices performs 0.488 points in F₁-score better than the one trained on the first set of features. In addition, the *Web Blogs* and *Essays* domains both fall well below 0.8 F₁-score, too, while the remaining domains retain their performance within ≤ 0.1 points.

On one hand, this highlights the need for diverse training data when training LUMINAR, but it also shows that the model has strong generalization capabilities. To further explore these, we conducted

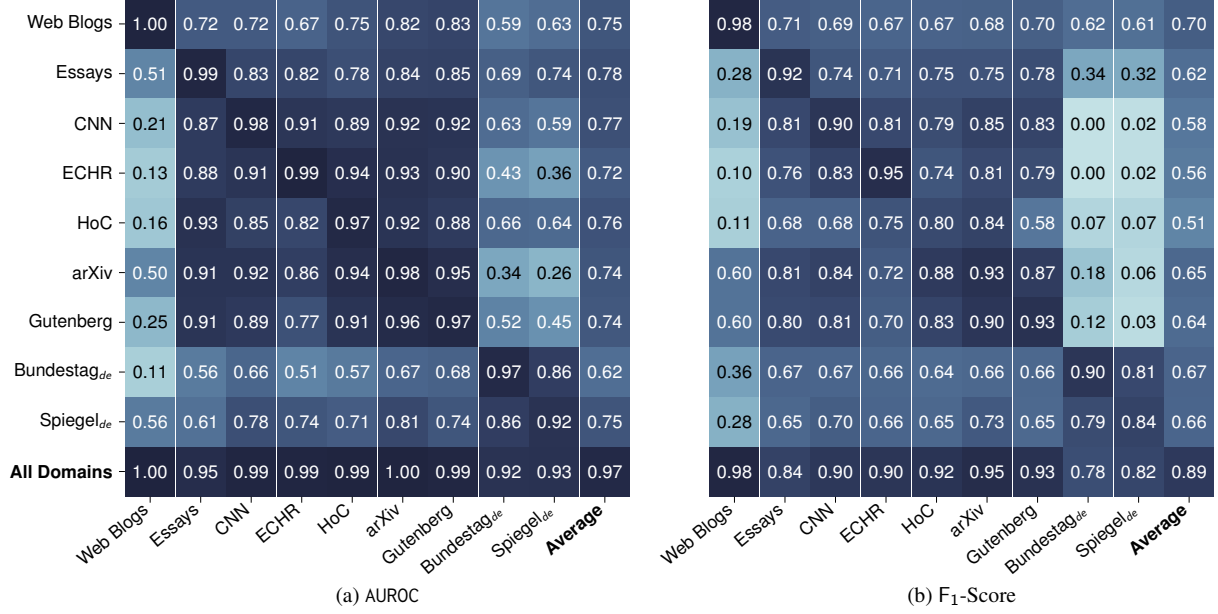


Figure 3: Heatmap of cross-domain evaluation scores of LUMINAR trained on randomly sampled GPT-2 *Intermediate Likelihood* feature slices on human-written texts and texts generated using GPT-4o-Mini. The values shown are for in- and cross-domain settings for each training-test-domain combination, as well as a classifier trained on all domains (last row) and their respective averages (last column), where each row shows the domain which the model was trained on, while the columns pertain to test domain.

cross-domain experiments, training a model on a single as well as all domains and testing it against all domains individually. The heatmap in Figure 3 shows the results of the cross-domain evaluation.

The jointly trained model retains very good AUROC values across all domains while the F₁-score drops significantly, especially for the German domains. Despite being a purely English pre-trained LLM, features from GPT-2 perform very well in the in-domain setting when trained on German texts. We hypothesize that using an LLM pre-trained on multilingual data would help bridge the gap in a multilingual application scenario for LUMINAR.

6 Discussion

Despite being a supervised method, our model with its default configuration is tiny, having only 676k parameters equating to a memory footprint of less than 3MB. Neither training nor inference of the model is computationally intensive and can be done on an average workstation with a consumer-grade GPU. However, for the baseline methods to achieve similar levels of performance, one would have to use much larger LLMs which outweighs the added computational load of training a CNN classifier by multiple levels of magnitude (cf. Table A.5).

When we were investigating related work to draw for a comparison, we noted that multiple

publications only report the AUROC values for their models many times achieving values ≥ 0.99 , while referring to it as a “commonly used metric” for AI-generated text detection research, e.g. Su et al. (2023a) referring to AUROC as a “commonly used to measure zero-shot detector performance, which considers the range of all possible thresholds”. However, for any real-world use case, the AUROC has little value because a high AUROC does not imply high classification performance. As such, we follow Verma et al. (2024) by also calculating the F₁-score in all our experiments.

7 Conclusion

We introduced PRISMAI, an environment for AIGT detection featuring the largest multilingual corpus to date, along with LUMINAR, a CNN-based model for detecting AI-generated text. To advance and expand existing research, we have integrated our new PRISMAI dataset with prior efforts into a unified corpus, AIGT-WORLD, aiming to continuously enhance diversity across domains, models, and languages through a common data pool. Additionally, we introduce a first-of-its-kind corpus explorer for AIGT datasets, allowing users to visually search and interact with data rather than relying solely on programmatic access. Finally, we release everything as open source.

Limitations

Sequence Length

While CNNs do not depend on any particular input size, the *classifier* does. This implies limitations to the input sequence length, as some texts might be much shorter than the average training sample. While our experiments show good generalization for shorter sequences (cf. Table 6 for statistics on the sequence length of our dataset), we can leverage the translation-invariance of the convolution operation to create multiple classifiers backed by the same CNN, trained jointly on different feature sequence lengths, which we will explore in future work.

Calculating Intermediate Likelihoods

Calculating the intermediate likelihoods is no more or less computationally complex than calculating the regular likelihood. However, depending on the size of the model and the number of layers, this can lead to a significant memory overhead (i.e. GPT-2’s LM head makes up 31 % of the models parameters). We address this issue by transferring the hidden states to the CPU before calculating the intermediate likelihoods iteratively on the GPU.

Ethical Considerations

We trained LUMINAR on a diverse range of domains, including two languages, yet this does not encompass all writing styles and topics. As a result, texts resembling those seen during training tend to yield more confident predictions, whereas those from other domains exhibit greater variability. This includes languages as well. We have also seen differences in LUMINAR’s behaviour depending on the length of the texts. In general, the predictions of LUMINAR are not legally binding and should not be considered as definitive or reliable in this context. Particularly in the context of automated plagiarism detection in school or university settings, LUMINAR’s predictions should never be accepted without manual verification. We strongly oppose any unfiltered or fully automated integration of our model into such systems. While we cannot prevent misuse of our model, we still release it as part of the open-source PRISMAI environment for the benefit of research and broader accessibility.

References

- Marah Abdin, Jyoti Aneja, Hany Awadalla, Ahmed Awadallah, Ammar Ahmad Awan, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Jianmin Bao, Harkirat Behl, Alon Benhaim, Misha Bilenko, Johan Bjorck, Sébastien Bubeck, Martin Cai, Qin Cai, Vishrav Chaudhary, Dong Chen, Dongdong Chen, Weizhu Chen, Yen-Chun Chen, Yi-Ling Chen, Hao Cheng, Parul Chopra, Xiyang Dai, Matthew Dixon, Ronen Eldan, Victor Fragoso, Jianfeng Gao, Mei Gao, Min Gao, Amit Garg, Allie Del Giorno, Abhishek Goswami, Suriya Gunasekar, Emman Haider, Junheng Hao, Russell J. Hewett, Wenxiang Hu, Jamie Huynh, Dan Iter, Sam Ade Jacobs, Mojan Javaheripi, Xin Jin, Nikos Karampatziakis, Piero Kauffmann, Mahoud Khademi, Dongwoo Kim, Young Jin Kim, Lev Kurilenko, James R. Lee, Yin Tat Lee, Yuanzhi Li, Yunsheng Li, Chen Liang, Lars Liden, Xihui Lin, Zeqi Lin, Ce Liu, Liyuan Liu, Mengchen Liu, Weishung Liu, Xiaodong Liu, Chong Luo, Piyush Madan, Ali Mahmoudzadeh, David Majercak, Matt Mazzola, Caio César Teodoro Mendes, Arindam Mitra, Hardik Modi, Anh Nguyen, Brandon Norick, Barun Patra, Daniel Perez-Becker, Thomas Portet, Reid Pryzant, Heyang Qin, Marko Radmilac, Liliang Ren, Gustavo de Rosa, Corby Rosset, Sambudha Roy, Olatunji Ruwase, Olli Saarikivi, Amin Saied, Adil Salim, Michael Santacrose, Shital Shah, Ning Shang, Hiteshi Sharma, Yelong Shen, Swadheen Shukla, Xia Song, Masahiro Tanaka, Andrea Tupini, Praneetha Vaddamanu, Chunyu Wang, Guanhua Wang, Lijuan Wang, Shuohang Wang, Xin Wang, Yu Wang, Rachel Ward, Wen Wen, Philipp Witte, Haiping Wu, Xiaoxia Wu, Michael Wyatt, Bin Xiao, Can Xu, Jiahang Xu, Weijian Xu, Jilong Xue, Sonali Yadav, Fan Yang, Jianwei Yang, Yifan Yang, Ziyi Yang, Donghan Yu, Lu Yuan, Chenruidong Zhang, Cyril Zhang, Jianwen Zhang, Li Lyna Zhang, Yi Zhang, Yue Zhang, Yunan Zhang, and Xiren Zhou. 2024. [Phi-3 technical report: A highly capable language model locally on your phone](#). *Preprint*, arXiv:2404.14219.
- Sameer Badaskar, Sachin Agarwal, and Shilpa Arora. 2008. [Identifying real or fake articles: Towards better language modeling](#). In *Proceedings of the Third International Joint Conference on Natural Language Processing: Volume-II*.
- Guangsheng Bao, Yanbin Zhao, Zhiyang Teng, Linyi Yang, and Yue Zhang. 2024. [Fast-detectgpt: Efficient zero-shot detection of machine-generated text via conditional probability curvature](#). *Preprint*, arXiv:2310.05130.
- Théophile Bisi, Anthony Risser, Philippe Clavert, Henri Migaud, and Julien Dartus. 2023. [What is the rate of text generated by artificial intelligence over a year of publication in orthopedics & traumatology: Surgery & research? analysis of 425 articles before versus after the launch of chatgpt in november 2022](#). *Orthopaedics & Traumatology: Surgery & Research*, 109(8):103694.
- Jack Blumenau. 2021. [Measuring political debate:](#)

784	Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, and	Taehyun Lee, Seokhee Hong, Jaewoo Ahn, Ilgee Hong,	836
785	et al. 2024. The llama 3 herd of models . <i>CoRR</i> ,	Hwaran Lee, Sangdoo Yun, Jamin Shin, and Gunhee	837
786	abs/2407.21783.	Kim. 2024. Who wrote this code? watermarking for	838
		code generation . <i>Preprint</i> , arXiv:2305.15060.	839
787	Faisal R. Elali and Leena N. Rachid. 2023. Ai-generated	Linyang Li, Pengyu Wang, Ke Ren, Tianxiang Sun, and	840
788	research paper fabrication and plagiarism in the sci-	Xipeng Qiu. 2023. Origin tracing and detecting of	841
789	entific community . <i>Patterns</i> , 4(3):100706.	llms . <i>Preprint</i> , arXiv:2304.14072.	842
790	William Falcon and The PyTorch Lightning team. Py-	Yafu Li, Qintong Li, Leyang Cui, Wei Bi, Zhilin Wang,	843
791	torch lightning .	Longyue Wang, Linyi Yang, Shuming Shi, and Yue	844
792	Sebastian Gehrmann, Hendrik Strobelt, and Alexander	Zhang. 2024. MAGE: Machine-generated text de-	845
793	Rush. 2019. GLTR: Statistical detection and visual-	tection in the wild . In <i>Proceedings of the 62nd An-</i>	846
794	ization of generated text . In <i>Proceedings of the 57th</i>	<i>Annual Meeting of the Association for Computational</i>	847
795	<i>Annual Meeting of the Association for Computational</i>	<i>Linguistics (Volume 1: Long Papers)</i> , pages 36–53,	848
796	<i>Linguistics: System Demonstrations</i> , pages 111–116,	Bangkok, Thailand. Association for Computational	849
797	Florence, Italy. Association for Computational Lin-	Linguistics.	850
798	guistics.		
799	Carlos Gómez-Rodríguez and Paul Williams. 2023. A	Aiwei Liu, Leyi Pan, Xuming Hu, Shiao Meng, and	851
800	confederacy of models: a comprehensive evaluation	Lijie Wen. 2024. A semantic invariant robust	852
801	of LLMs on creative writing . In <i>Findings of the</i>	watermark for large language models . <i>Preprint</i> ,	853
802	<i>Association for Computational Linguistics: EMNLP</i>	arXiv:2310.06356.	854
803	2023, pages 14504–14528, Singapore. Association	Yikang Liu, Ziyin Zhang, Wanyang Zhang, Shisen Yue,	855
804	for Computational Linguistics.	Xiaojing Zhao, Xinyuan Cheng, Yiwen Zhang, and	856
		Hai Hu. 2023. Argugpt: evaluating, understanding	857
805	Biyang Guo, Xin Zhang, Ziyuan Wang, Minqi Jiang, Jin-	and identifying argumentative essays generated by	858
806	ran Nie, Yuxuan Ding, Jianwei Yue, and Yupeng Wu.	gpt models . <i>Preprint</i> , arXiv:2304.07666.	859
807	2023. How close is chatgpt to human experts? com-	Ilya Loshchilov and Frank Hutter. 2019. De-	860
808	parison corpus, evaluation, and detection . <i>Preprint</i> ,	coupled weight decay regularization . <i>Preprint</i> ,	861
809	arXiv:2301.07597.	arXiv:1711.05101.	862
810	Project Gutenberg. n.d. Project gutenberg . Retrieved	Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foer-	863
811	February 21, 2016, from https://www.gutenberg.org .	ster, Jeff Clune, and David Ha. 2024. The ai scientist:	864
812		Towards fully automated open-ended scientific dis-	865
		covery . <i>Preprint</i> , arXiv:2408.06292.	866
813	Hans W. A. Hanley and Zakir Durumeric. 2023.	Chengzhi Mao, Carl Vondrick, Hao Wang, and Jun-	867
814	Machine-made media: Monitoring the mobilization	feng Yang. 2024. Raider: generative ai detection via	868
815	of machine-generated articles on misinformation and	rewriting . <i>Preprint</i> , arXiv:2401.12970.	869
816	mainstream news websites . In <i>International Confer-</i>		
817	<i>ence on Web and Social Media</i> .	Eric Mitchell, Yoonho Lee, Alexander Khazatsky,	870
818	Juyong Jiang, Fan Wang, Jiasi Shen, Sungju Kim,	Christopher D Manning, and Chelsea Finn. 2023.	871
819	and Sunghun Kim. 2024. A survey on large	DetectGPT: Zero-shot machine-generated text de-	872
820	language models for code generation . <i>Preprint</i> ,	tection using probability curvature . In <i>Proceedings of</i>	873
821	arXiv:2406.00515.	<i>the 40th International Conference on Machine Learn-</i>	874
822	Jules King, Perpetual Baffour, Scott Crossley, Ryan	<i>ing</i> , volume 202 of <i>Proceedings of Machine Learning</i>	875
823	Holbrook, and Maggie Demkin. 2023. Llm -	<i>Research</i> , pages 24950–24962. PMLR.	876
824	detect ai generated text . https://kaggle.com/	Soichiro Murakami, Sho Hoshino, and Peinan Zhang.	877
825	competitions/llm-detect-ai-generated-text .	2023. Natural language generation for advertising:	878
826	Kaggle .	A survey . <i>Preprint</i> , arXiv:2306.12719.	879
827	John Kirchenbauer, Jonas Geiping, Yuxin Wen,	Nvidia, :, Bo Adler, Niket Agarwal, Ashwath Aithal,	880
828	Jonathan Katz, Ian Miers, and Tom Goldstein. 2024.	Dong H. Anh, Pallab Bhattacharya, Annika Brun-	881
829	A watermark for large language models . <i>Preprint</i> ,	dyn, Jared Casper, Bryan Catanzaro, Sharon Clay,	882
830	arXiv:2301.10226.	Jonathan Cohen, Sirshak Das, Ayush Dattagupta,	883
831	Yann LeCun, Bernhard Boser, John S Denker, Donnie	Olivier Delalleau, Leon Derczynski, Yi Dong, Daniel	884
832	Henderson, Richard E Howard, Wayne Hubbard, and	Egert, Ellie Evans, Aleksander Ficek, Denys Frid-	885
833	Lawrence D Jackel. 1989. Backpropagation applied	man, Shaona Ghosh, Boris Ginsburg, Igor Gitman,	886
834	to handwritten zip code recognition . <i>Neural compu-</i>	Tomasz Grzegorzec, Robert Hero, Jining Huang,	887
835	tation , 1(4):541–551.	Vibhu Jawa, Joseph Jennings, Aastha Jhunjhunwala,	888
		John Kamalu, Sadaf Khan, Oleksii Kuchaiev, Patrick	889
		LeGresley, Hui Li, Jiwei Liu, Zihan Liu, Eileen Long,	890

891	Ameya Sunil Mahabaleshwarkar, Somshubra Majumdar, James Maki, Miguel Martinez, Maer Rodrigues de Melo, Ivan Moshkov, Deepak Narayanan, Sean Narenthiran, Jesus Navarro, Phong Nguyen, Osvald Nitski, Vahid Noroozi, Guruprasad Nutheti, Christopher Parisien, Jupinder Parmar, Mostofa Patwary, Krzysztof Pawelec, Wei Ping, Shrimai Prabhumoye, Rajarshi Roy, Trisha Saar, Vasanth Rao Naik Sabavat, Sanjeev Satheesh, Jane Polak Scowcroft, Jason Sewall, Pavel Shamis, Gerald Shen, Mohammad Shoebybi, Dave Sizer, Misha Smelyanskiy, Felipe Soares, Makesh Narsimhan Sreedhar, Dan Su, Sandeep Subramanian, Shengyang Sun, Shubham Toshniwal, Hao Wang, Zhilin Wang, Jiaxuan You, Jiaqi Zeng, Jimmy Zhang, Jing Zhang, Vivienne Zhang, Yian Zhang, and Chen Zhu. 2024. Nemotron-4 340b technical report . <i>Preprint</i> , arXiv:2406.11704.	
908	OpenAI. 2024. Gpt-4o mini: advancing cost-efficient intelligence .	
910	OpenAI. 2025. Openai o3-mini .	
911	OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fullford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li,	
	Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O’Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolaus Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. Gpt-4 technical report . <i>Preprint</i> , arXiv:2303.08774.	952 953 954 955 956 957 958 959 960 961 962 963 964 965 966 967 968 969 970 971 972 973 974 975 976 977 978 979 980 981 982 983 984 985 986 987 988 989 990 991 992 993 994 995 996 997 998
	Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. Pytorch: An imperative style, high-performance deep learning library . <i>Preprint</i> , arXiv:1912.01703.	999 1000 1001 1002 1003 1004 1005 1006 1007
	Jiameng Pu, Zain Sarwar, Sifat Muhammad Abdullah, Abdullah Rehman, Yoonjin Kim, Parantapa Bhat-tacharya, Mobin Javed, and Bimal Viswanath. 2022. Deepfake text detection: Limitations and opportunities . <i>Preprint</i> , arXiv:2210.09421.	1008 1009 1010 1011 1012
	Shushanta Pudasaini, Luis Miralles-Pechuán, David Lil-	1013

1014	lis, and Marisa Llorens Salvador. 2024. Survey on plagiarism detection in large language models: The impact of chatgpt and gemini on academic integrity . Preprint, arXiv:2407.13105.	1070
1015		1071
1016		1072
1017		1073
1018	Ali Quidwai, Chunhui Li, and Parijat Dube. 2023. Beyond black box AI generated plagiarism detection: From sentence to document level . In <i>Proceedings of the 18th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2023)</i> , pages 727–735, Toronto, Canada. Association for Computational Linguistics.	1074
1019		1075
1020		1076
1021		1077
1022		1078
1023		1079
1024		1080
1025	Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners . <i>OpenAI Blog</i> , 1(8):9.	1081
1026		1082
1027		1083
1028		1084
1029	Jonathan Schler, Moshe Koppel, Shlomo Engelson Argamon, and James W. Pennebaker. 2006. Effects of age and gender on blogging . In <i>AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs</i> .	1085
1030		1086
1031		1087
1032		1088
1033		1089
1034	Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks . In <i>Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)</i> , pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.	1090
1035		1091
1036		1092
1037		1093
1038		1094
1039		1095
1040		1096
1041	Yang Shen and Xiuwu Zhang. 2024. The impact of artificial intelligence on employment: the role of virtual agglomeration . <i>Palgrave Communications</i> , 11(1):1–14.	1097
1042		1098
1043		1099
1044		1100
1045	Ilia Shumailov, Zakhar Shumaylov, Yiren Zhao, Nicolas Papernot, Ross Anderson, and Yarin Gal. 2024. AI models collapse when trained on recursively generated data . <i>Nature</i> , 631(8022):755–759.	1101
1046		1102
1047		1103
1048		1104
1049	Jinyan Su, Terry Zhuo, Di Wang, and Preslav Nakov. 2023a. DetectLLM: Leveraging log rank information for zero-shot detection of machine-generated text . In <i>Findings of the Association for Computational Linguistics: EMNLP 2023</i> , pages 12395–12412, Singapore. Association for Computational Linguistics.	1105
1050		1106
1051		1107
1052		1108
1053		1109
1054		1110
1055	Zhenpeng Su, Xing Wu, Wei Zhou, Guangyuan Ma, and Song Hu. 2023b. Hc3 plus: A semantic-invariant human chatgpt comparison corpus . <i>ArXiv</i> , abs/2309.02731.	1111
1056		1112
1057		1113
1058		1114
1059	Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M. Dai, Anja Hauth, Katie Millican, David Silver, Melvin Johnson, Ioannis Antonoglou, Julian Schrittwieser, Amelia Glaese, Jilin Chen, Emily Pitler, Timothy Lillicrap, Angeliki Lazaridou, Orhan Firat, James Molloy, Michael Isard, Paul R. Barham, Tom Hennigan, Benjamin Lee, Fabio Viola, Malcolm Reynolds, Yuanzhong Xu, Ryan Doherty, Eli Collins, Clemens Meyer, Eliza Rutherford, Erica Moreira, Kareem Ayoub, Megha	1115
1060		1116
1061		1117
1062		1118
1063		1119
1064		1120
1065		1121
1066		1122
1067		1123
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1444	Madeleine Elish, Steve Li, Aakash Kaku, Jigar Gupta,	
1445	Ice Pasupat, Da-Cheng Juan, Milan Someswar, Tejvi	
1446	M., Xinyun Chen, Aida Amini, Alex Fabrikant, Eric	
1447	Chu, Xuanyi Dong, Amruta Muthal, Senaka Buth-	
1448	pitiya, Sarthak Jauhari, Nan Hua, Urvashi Khan-	
1449	delwal, Ayal Hitron, Jie Ren, Larissa Rinaldi, Sha-	
1450	har Drath, Avigail Dabush, Nan-Jiang Jiang, Har-	
1451	shal Godhia, Uli Sachs, Anthony Chen, Yicheng	
	Fan, Hagai Taitelbaum, Hila Noga, Zhuyun Dai,	1452
	James Wang, Chen Liang, Jenny Hamer, Chun-Sung	1453
	Ferng, Chenel Elkind, Aviel Atias, Paulina Lee, Vít	1454
	Listík, Mathias Carlen, Jan van de Kerkhof, Marcin	1455
	Pikus, Krunoslav Zaher, Paul Müller, Sasha Zykova,	1456
	Richard Stefanec, Vitaly Gatsko, Christoph Hirn-	1457
	schall, Ashwin Sethi, Xingyu Federico Xu, Chetan	1458
	Ahuja, Beth Tsai, Anca Stefanoiu, Bo Feng, Kes-	1459
	hav Dhandhanian, Manish Katyal, Akshay Gupta,	1460
	Atharva Parulekar, Divya Pitta, Jing Zhao, Vivaan	1461
	Bhatia, Yashodha Bhavnani, Omar Alhadlaq, Xiaolin	1462
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	gava Urala, Chaitanya Krishna Lanka, Derik Clive,	1465
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	Ianna Li, Kalind Thakkar, Kuanysh Omarov, Kushal	1467
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	Swetha Sankar, Vineet Shah, Lakshmi Ramachan-	1471
	dru, Xiangkai Zeng, Ben Bariach, Laura Wei-	1472
	dinger, Tu Vu, Alek Andreev, Antoine He, Kevin	1473
	Hui, Sheleem Kashem, Amar Subramanya, Sissie	1474
	Hsiao, Demis Hassabis, Koray Kavukcuoglu, Adam	1475
	Sadovsky, Quoc Le, Trevor Strohman, Yonghui Wu,	1476
	Slav Petrov, Jeffrey Dean, and Oriol Vinyals. 2024a.	1477
	Gemini: A family of highly capable multimodal mod-	1478
	els. Preprint, arXiv:2312.11805.	1479
	Gemma Team, Morgane Riviere, Shreya Pathak,	1480
	Pier Giuseppe Sessa, Cassidy Hardin, Surya Bhupati-	1481
	raju, Léonard Hussenot, Thomas Mesnard, Bobak	1482
	Shahriari, Alexandre Ramé, Johan Ferret, Peter	1483
	Liu, Pouya Tafti, Abe Friesen, Michelle Casbon,	1484
	Sabela Ramos, Ravin Kumar, Charline Le Lan,	1485
	Sammy Jerome, Anton Tsitsulin, Nino Vieillard,	1486
	Piotr Stanczyk, Sertan Girgin, Nikola Momchev,	1487
	Matt Hoffman, Shantanu Thakoor, Jean-Bastien Grill,	1488
	Behnam Neyshabur, Olivier Bachem, Alanna Wal-	1489
	ton, Aliaksei Severyn, Alicia Parrish, Aliya Ah-	1490
	mad, Allen Hutchison, Alvin Abdagic, Amanda	1491
	Carl, Amy Shen, Andy Brock, Andy Coenen, An-	1492
	thony Laforge, Antonia Paterson, Ben Bastian, Bilal	1493
	Piot, Bo Wu, Brandon Royal, Charlie Chen, Chintu	1494
	Kumar, Chris Perry, Chris Welty, Christopher A.	1495
	Choquette-Choo, Danila Sinopalnikov, David Wein-	1496
	berger, Dimple Vijaykumar, Dominika Rogozińska,	1497
	Dustin Herbison, Elisa Bandy, Emma Wang, Eric	1498
	Noland, Erica Moreira, Evan Senter, Evgenii Elty-	1499
	shv, Francesco Visin, Gabriel Rasskin, Gary Wei,	1500
	Glenn Cameron, Gus Martins, Hadi Hashemi, Hanna	1501
	Klimczak-Plucińska, Harleen Batra, Harsh Dhand,	1502
	Ivan Nardini, Jacinda Mein, Jack Zhou, James Svens-	1503
	son, Jeff Stanway, Jetha Chan, Jin Peng Zhou, Joana	1504
	Carrasqueira, Joana Iljazi, Jocelyn Becker, Joe Fer-	1505
	nandez, Joost van Amersfoort, Josh Gordon, Josh	1506
	Lipschultz, Josh Newlan, Ju yeong Ji, Kareem Mo-	1507
	hamed, Kartikeya Badola, Kat Black, Katie Mil-	1508
	lican, Keelin McDonell, Kelvin Nguyen, Kiranbir	1509
	Sodhia, Kish Greene, Lars Lowe Sjoesund, Lau-	1510
	ren Usui, Laurent Sifre, Lena Heuermann, Leti-	1511
	cia Lago, Lilly McNealus, Livio Baldini Soares,	1512
	Logan Kilpatrick, Lucas Dixon, Luciano Martins,	1513
	Machel Reid, Manvinder Singh, Mark Iverson, Mar-	1514

1515	tin Görner, Mat Velloso, Mateo Wirth, Matt Davi-	Pengyu Wang, Linyang Li, Ke Ren, Botian Jiang, Dong	1575
1516	dow, Matt Miller, Matthew Rahtz, Matthew Watson,	Zhang, and Xipeng Qiu. 2023. SeqXGPT: Sentence-	1576
1517	Meg Risdal, Mehran Kazemi, Michael Moynihan,	level AI-generated text detection. In <i>Proceedings of</i>	1577
1518	Ming Zhang, Minsuk Kahng, Minwoo Park, Mofi	the 2023 Conference on Empirical Methods in Natu-	1578
1519	Rahman, Mohit Khatwani, Natalie Dao, Nenshad	ral Language Processing, pages 1144–1156, Singa-	1579
1520	Bardoliwalla, Nesh Devanathan, Neta Dumai, Nilay	pore. Association for Computational Linguistics.	1580
1521	Chauhan, Oscar Wahltinez, Pankil Botarda, Parker	Thomas Wolf, Lysandre Debut, Victor Sanh, Julien	1581
1522	Barnes, Paul Barham, Paul Michel, Pengchong	Chaumond, Clement Delangue, Anthony Moi, Pier-	1582
1523	Jin, Petko Georgiev, Phil Culliton, Pradeep Kup-	ric Cistac, Tim Rault, Remi Louf, Morgan Funtow-	1583
1524	pala, Ramona Comanescu, Ramona Merhej, Reena	icz, Joe Davison, Sam Shleifer, Patrick von Platen,	1584
1525	Jana, Reza Ardeshtir Rokni, Rishabh Agarwal, Ryan	Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu,	1585
1526	Mullins, Samaneh Saadat, Sara Mc Carthy, Sarah	Teven Le Scao, Sylvain Gugger, Mariama Drame,	1586
1527	Cogan, Sarah Perrin, Sébastien M. R. Arnold, Se-	Quentin Lhoest, and Alexander Rush. 2020. Trans-	1587
1528	bastian Krause, Shengyang Dai, Shruti Garg, Shruti	formers: State-of-the-art natural language processing.	1588
1529	Sheth, Sue Ronstrom, Susan Chan, Timothy Jor-	In <i>Proceedings of the 2020 Conference on Empirical</i>	1589
1530	dan, Ting Yu, Tom Eccles, Tom Hennigan, Tomas	<i>Methods in Natural Language Processing: System</i>	1590
1531	Kocisky, Tulsee Doshi, Vihan Jain, Vikas Yadav,	<i>Demonstrations</i> , pages 38–45, Online. Association	1591
1532	Vilobh Meshram, Vishal Dharmadhikari, Warren	for Computational Linguistics.	1592
1533	Barkley, Wei Wei, Wenming Ye, Woohyun Han,	Junchao Wu, Shu Yang, Runzhe Zhan, Yulin Yuan,	1593
1534	Woosuk Kwon, Xiang Xu, Zhe Shen, Zhitao Gong,	Lidia Sam Chao, and Derek Fai Wong. 2025. A	1594
1535	Zichuan Wei, Victor Cotruta, Phoebe Kirk, Anand	survey on llm-generated text detection: Necessity,	1595
1536	Rao, Minh Giang, Ludovic Peran, Tris Warkentin,	methods, and future directions. <i>Computational Lin-</i>	1596
1537	Eli Collins, Joelle Barral, Zoubin Ghahramani, Raia	guistics, pages 1–65.	1597
1538	Hadsell, D. Sculley, Jeanine Banks, Anca Dragan,	Xianjun Yang, Wei Cheng, Yue Wu, Linda Petzold,	1598
1539	Slav Petrov, Oriol Vinyals, Jeff Dean, Demis Hass-	William Yang Wang, and Haifeng Chen. 2023.	1599
1540	abis, Koray Kavukcuoglu, Clement Farabet, Elena	Dna-gpt: Divergent n-gram analysis for training-	1600
1541	Buchatskaya, Sebastian Borgeaud, Noah Fiedel, Ar-	free detection of gpt-generated text. <i>Preprint</i> ,	1601
1542	mand Joulin, Kathleen Kenealy, Robert Dadashi,	arXiv:2305.17359.	1602
1543	and Alek Andreev. 2024b. Gemma 2: Improving	Peipeng Yu, Jiahao Chen, Xuan Feng, and Zhihua Xia.	1603
1544	open language models at a practical size . <i>Preprint</i> ,	2023. Cheat: A large-scale dataset for detecting	1604
1545	arXiv:2408.00118.	chatgpt-written abstracts . <i>ArXiv</i> , abs/2304.12008.	1605
1546	Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier	Xuandong Zhao, Sam Gunn, Miranda Christ, Jaiden	1606
1547	Martinet, Marie-Anne Lachaux, Timothée Lacroix,	Fairoze, Andres Fabrega, Nicholas Carlini, Sanjam	1607
1548	Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal	Garg, Sanghyun Hong, Milad Nasr, Florian Tramèr,	1608
1549	Azhar, Aurelien Rodriguez, Armand Joulin, Edouard	Somesh Jha, Lei Li, Yu-Xiang Wang, and Dawn Song.	1609
1550	Grave, and Guillaume Lample. 2023. Llama: Open	2024. Sok: Watermarking for ai-generated content .	1610
1551	and efficient foundation language models . <i>Preprint</i> ,	<i>Preprint</i> , arXiv:2411.18479.	1611
1552	arXiv:2302.13971.	A Appendix	1612
1553	Ashish Vaswani, Noam M. Shazeer, Niki Parmar, Jakob	A.1 Dataset Creation Details	1613
1554	Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz	For the creation of AI-generated counterparts, we	1614
1555	Kaiser, and Illia Polosukhin. 2017. Attention is all	distinguish between two types: <i>chunked</i> and <i>full-</i>	1615
1556	you need . In <i>Neural Information Processing Systems</i> .	<i>text</i> .	1616
1557	Vivek Verma, Eve Fleisig, Nicholas Tomlin, and Dan	<i>Fulltext</i> -based AI documents are generated by	1617
1558	Klein. 2024. Ghostbuster: Detecting text ghostwrit-	firstly, prompting the LLM to extract a set of char-	1618
1559	ten by large language models . In <i>Proceedings of</i>	acteristics from the original human text. The ex-	1619
1560	the 2024 Conference of the North American Chap-	tracted information is then used to prompt the LLM	1620
1561	ter of the Association for Computational Linguistics:	in a ghostwriting scenario, generating a rewritten	1621
1562	<i>Human Language Technologies (Volume 1: Long</i>	text based on the provided details. The correspond-	1622
1563	<i>Papers</i>), pages 1702–1717, Mexico City, Mexico. As-	ing prompts are as follows:	1623
1564	sociation for Computational Linguistics.		
1565	Veniamin Veselovsky, Manoel Horta Ribeiro, and	Ghostwriting Prompt	
1566	Robert West. 2023. Artificial artificial artificial in-	As a ghostwriter, your job is to write texts according to	
1567	telligence: Crowd workers widely use large lan-	the requirements provided by users. Below, you will find	
1568	guage models for text production tasks . <i>Preprint</i> ,	descriptions provided by users that outline a text for you to	
1569	arXiv:2306.07899.	write. This outline includes:	
1570	Kuang-Hsien Wang and Wen-Cheng Lu. 2025. Ai-	- The language in which the text needs to be written	1624
1571	induced job impact: Complementary or substitution?		
1572	empirical insights and sustainable technology consid-		
1573	erations . <i>Sustainable Technology and Entrepreneur-</i>		
1574	<i>ship</i> , 4(1):100085.		

- The topic of the text
 - The linguistic style to use
 - Additional context
 - The required length of the text
- It is of utmost importance that you adhere to these requirements. Follow these key steps:
1. Carefully read the given requirements.
 2. Internalize the requirements.
 3. Write the text in the specified language.
 4. Follow all outlined requirements meticulously.
 5. Proofread your text and ensure it matches the requirements, especially the linguistic style and length.
 6. Adjust the text if needed.
- Only output the final text.

Information Extraction Prompt

As a linguistic annotator, your task is to extract parameters from the texts provided by users. These parameters are used to reconstruct a prompt that approximately generates the given text. Please adhere to the following key points:

1. Extract the language of the text (English or German).
2. Gather contextualized outer information, such as potential circumstances, possible authors, and background details.
3. Identify the topic and extract relevant subjects.
4. Analyze and describe the linguistic style such that another AI agent can understand it.

Please take into consideration the following example:

<example> <example-input> "Deception and Betrayal: Inside the Final Days of the Assad Regime. As rebels advanced toward the Syrian capital of Damascus on Dec. 7, the staff in the hilltop Presidential Palace prepared for a speech they hoped would lead to a peaceful end to the 13-year civil war. Aides to President Bashar al-Assad were brainstorming messaging ideas. A film crew had set up cameras and lights nearby. Syria's state-run television station was ready to broadcast the finished product: an address by Mr. al-Assad announcing a plan to share power with members of the political opposition, according to three people who were involved in the preparation." </example-input> <example-output> - Language: English - Context: Written for a news article by a journalist; written in a passive and neutral tone. - Topic: The current situation involving President Bashar al-Assad and the rebels' advance on Damascus; describes the circumstances of al-Assad's governance. - Style: Passive and neutral voice, well-written in advanced English. Uses dramatic pauses with paragraphs and short sentences to add excitement. </example-output> </example>

Always output in English.

Chunked-based AI documents are generated using domain-specific prompts that instruct the LLM to reconstruct missing text within a given scenario. For parliamentary speeches, the LLM assumes the role of a speaker; for court case texts, it acts as a judge, and so on. The corresponding prompts are as follows for each domain:

Domain: arXiv

You are a scientist in the Research Department at a university, and you and your colleagues are preparing a paper for publication on arXiv. You are responsible for submitting the paper, but just before uploading it, you realize that a crucial section has been accidentally deleted! Unfortunately, it's too late to contact the colleague who wrote that part, so it's your responsibility to rewrite the missing section. Below, you will find the beginning and end of the paper.

Your task is to reconstruct the missing part while adhering to the following guidelines:

1. Ensure that readers cannot tell this section was written by someone else.
 2. Analyze the beginning and end of the paper carefully: - What topic is being discussed? Stay focused on this topic. - What is the goal of the research? Remain true to the original intent. - What is the core message of the paper? Continue and reinforce this message. - What linguistic and rhetorical features are present? Use the same style and tone. - Identify any necessary LaTeX formulas or figures to support your statements. - Fill in the gap seamlessly so that it appears as if it was always part of the paper.
 3. The missing section is approximately [LENGTH] words/symbols long; ensure your reconstruction matches this length. After writing, count the words/symbols and make adjustments as needed to maintain conciseness and fidelity to the original.
- Please provide only the newly formulated missing section of the paper.

Domain: Weblogs

You are a blogger who writes about your daily life. Unfortunately, you've accidentally deleted a portion of your latest blog post. Your task is to rewrite the missing section from memory as accurately and creatively as possible, making it feel like it was never missing.

Below, you will find the beginning and end of the article. Your task is to reconstruct the missing part, adhering to the following guidelines:

1. Ensure that the readers do not realize that you are improvising.
 2. Carefully analyze the beginning and end of the article to understand: - What language the article was written in so you can continue in the same. - The topic being covered and ensure you do not deviate from it. - The context of the article. - The core message of the article and continue with it. - The linguistic and rhetorical features used in the article and stick to them. - How to fill the gap seamlessly so it appears as though it was never missing.
 3. The missing section should be approximately [LENGTH] words. Ensure that the reconstructed part matches this length. Once written, verify the word count and adjust as necessary to maintain precision and coherence.
- Please include only the newly formulated missing part of the article.

Domain: German Parliament (Bundestag)

Sie sind ein Abgeordneter oder eine Abgeordnete des deutschen Bundestags und halten eine Rede in der Bundestags-Sitzung am [DATE]. Während Ihres vorbereiteten und niedergeschriebenen Vortrags stellen Sie plötzlich fest, dass Teile Ihrer Rede fehlen!

Im Folgenden finden Sie den Start und das Ende Ihrer Rede. Ihre Aufgabe ist es, den fehlenden Teil unter Berücksichtigung der unten stehenden Richtlinien zu rekonstruieren:

- Die Zuhörer dürfen nicht bemerken, dass Sie improvisieren.
- Analysieren Sie sorgfältig den Beginn und das Ende Ihrer Rede: * Welches Thema wird behandelt? Schweifen Sie nicht davon ab! * Was ist Ihre Haltung dazu? Bleiben Sie sich treu! * Was ist die Kernbotschaft Ihrer Rede? Führen Sie diese fort! * Welche sprachlichen und rhetorischen Merkmale werden in der Rede verwendet? Halten Sie sich an diese! * Wie können Sie die Lücke so füllen, dass niemand merkt, dass sie je existiert hat?
- Sie erinnern sich, dass der fehlende Abschnitt ungefähr [LENGTH] Wörter lang war; halten Sie sich unbedingt an diese Original-Länge. Wenn Sie Ihren Text geschrieben haben, zählen Sie diesen nochmal und kürzen Sie diesen

zur Not - er muss auf den Punkt geschrieben und wie im verlorenen Original sein!
Geben Sie nur den neu formulierten fehlenden Teil der Rede an.

Domain: German Spiegel Online News

Sie sind Journalist beim Verlag "DER SPIEGEL" und schreiben einen Artikel am [DATE]. Kurz bevor Sie den Artikel veröffentlichen wollen, stellen Sie fest, dass ein Teil des Artikels fehlt—die Veröffentlichungssoftware hat ihn gelöscht!

Im Folgenden finden Sie den Anfang und das Ende Ihres Artikels. Ihre Aufgabe ist es, den fehlenden Mittelteil zu rekonstruieren, wobei Sie die untenstehenden Richtlinien beachten sollen:

- Die Leser und Leserinnen dürfen nicht merken, dass Sie nachgeschrieben haben. - Analysieren Sie sorgfältig den Beginn und das Ende Ihres Artikels: * Welches Thema wird behandelt? Schweifen Sie nicht davon ab! * Was ist Ihre Haltung dazu? Bleiben Sie sich treu! * Was ist die Kernbotschaft Ihres Artikels? Führen Sie diese fort! * Welche sprachlichen und rhetorischen Merkmale werden im Artikel verwendet? Halten Sie sich an diese! * Wie können Sie die Lücke so füllen, dass niemand merkt, dass sie je existiert hat?

Geben Sie nur den neu formulierten fehlenden Teil der Rede an.

Domain: CNN News

You are a journalist at CNN News who writes an article. Shortly before you want to publish the article, you realize that part of it is missing—the publishing software has deleted it!

Below you will find the beginning and end of your article. Your task is to reconstruct the missing middle section, following the guidelines below:

- Readers must not realize that you have rewritten it. - Carefully analyze the beginning and end of your article: * What topic is covered? Do not digress from it! * What is your stance on it? Stay true to yourself! * What is the core message of your article? Continue this! * What linguistic and rhetorical features are used in the article? Stick to these! * How can you fill the gap so that no one realizes it ever existed? - You remember that the missing paragraph was about [LENGTH] words long; be sure to stick to this original length. When you have written your text, count it again and shorten it if necessary - it must be written to the point and as in the lost original!

Only include the newly formulated missing part of the speech.

Domain: Euro Court Cases

You are a Judicial Assistant to the court tasked with collecting and listing facts for a case from [DATE]. These facts are to be read out loud by the judge. Just before handing over the list, you realize that some facts were deleted. You need to rewrite the missing facts from memory in such a way that no one realizes they were ever missing.

Below is the beginning and end of your facts. Your task is to reconstruct the missing part, adhering to the guidelines provided:

1. Ensure the audience does not realize you are improvising. 2. Carefully analyze the beginning and end of the facts: - Identify the topic being covered and do not deviate from it. - Maintain the same attitude and tone as in the original facts. - Continue the core message present in the facts. - Use the same linguistic and rhetorical features as in the rest of the facts. - Seamlessly fill the gap so it appears the facts was

unbroken. 3. The missing section should be approximately [LENGTH] words. Ensure the reconstructed part matches this length. Once written, verify the word count and adjust as necessary to maintain precision and coherence. Please include only the newly formulated missing part of the speech.

Domain: Classic Literature (Gutenberg)

You are a publisher of classical books and stories. You are currently in the final stages of publishing such a book, but just before clicking the "publish" button, you notice that some sections of the book have accidentally been deleted. As a former writer, you decide to recreate the missing sections from memory so that no one notices they were ever missing. Below, you will find the beginning and end of the story. Your task is to reconstruct the missing part, adhering to the following guidelines:

1. Ensure that the readers do not realize that you are improvising. 2. Carefully analyze the beginning and end of the story to understand: - What language the story was written in so you can continue in the same. - The topic being covered and ensure you do not deviate from it. - The context of the story. - The core message of the story and continue with it. - The linguistic and rhetorical features used in the story and stick to them. - How to fill the gap seamlessly so it appears as though it was never missing. 3. The missing section should be approximately [LENGTH] words. Ensure that the reconstructed part matches this length. Once written, verify the word count and adjust as necessary to maintain precision and coherence.

Please include only the newly formulated missing part of the story.

Domain: House of Commons

You are a Member of Parliament at the House Of Commons and are giving a speech at the plenary meeting in [DATE]. During your prepared and written speech, you suddenly realize that parts of your speech are missing!

Below you will find the start and end of your speech. Your task is to reconstruct the missing part, taking into account the guidelines below:

- The audience must not realize that you are improvising. - Carefully analyze the beginning and end of your speech: * What topic is being covered? Do not digress from it! * What is your attitude towards it? Stay true to yourself! * What is the core message of your speech? Continue this! * What linguistic and rhetorical features are used in the speech? Stick to them! * How can you fill the gap so that no one realizes it ever existed? - You remember that the missing section was about [LENGTH] words long; be sure to stick to this original length. When you have written your text, count it again and shorten it if necessary - it must be written to the point and as in the lost original!

Only include the newly formulated missing part of the speech.

Domain: Student Essays

You are a student currently taking a test, and you need to write an essay on a topic of your choosing. You haven't prepared for the test, but you notice that your seat neighbor is doing well and decide to copy their essay while the teacher is not looking.

After a while, your neighbor finishes and hands in their test, but you haven't copied the entire essay yet! Below, you'll find the beginning and end of the essay you have copied so far. Your task is to fill in the missing middle part of the essay. To do that, adhere to the following list.

- Carefully analyze the beginning and end of your essay: *

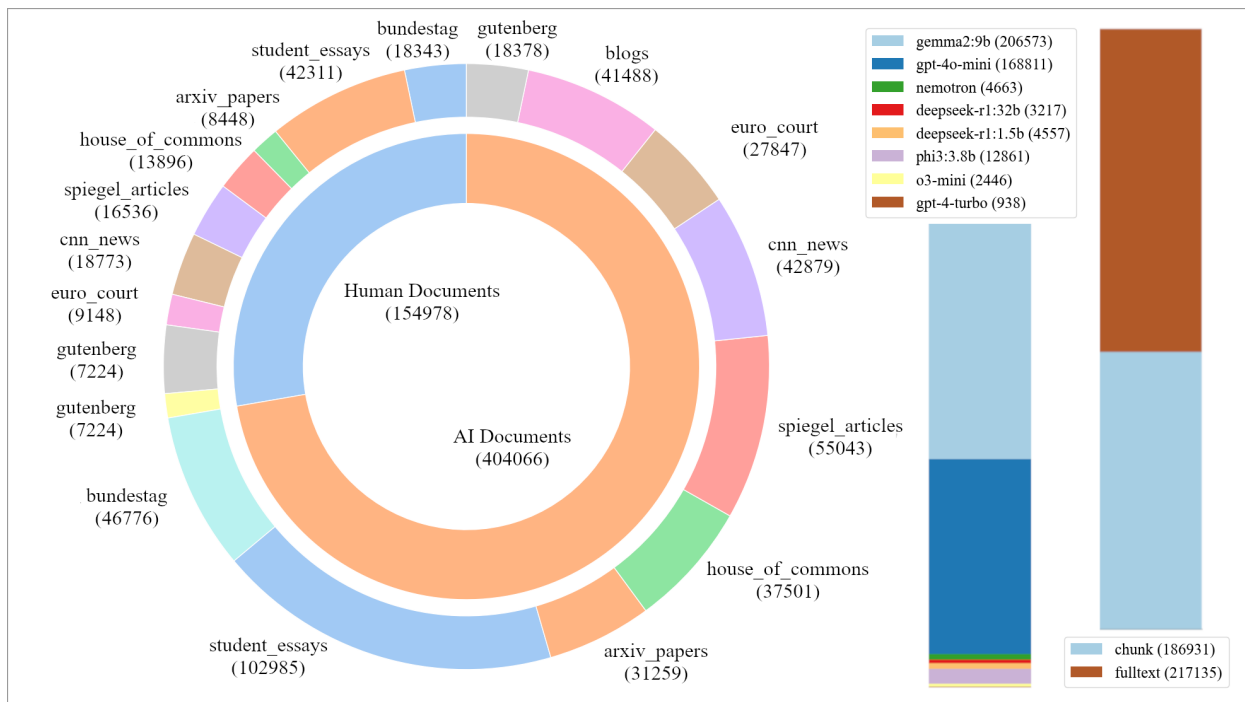


Figure 4: On the left, illustrating the distribution of AI-generated and human-written text in the PRISMAI-dataset (inner layer) alongside domain-specific counts (outer layer). On the right, showcasing the distribution of texts generated by the different AI agents within the PRISMAI-dataset and their distribution by type.

What topic is being covered? Do not digress from it! * What is your attitude towards it? Stay true to yourself! * What is the core message of your essay? Continue this! * What linguistic and rhetorical features are used in the essay so far? Stick to them! * How can you fill the gap so that no one realizes it ever existed? - You remember that the missing section was about [LENGTH] words long; be sure to stick to this original length. When you have written your text, count it again and shorten it if necessary - it must be written to the point and as in the lost original! Only include the newly formulated missing part of the speech.

The detailed distribution of domains, agents, and types within the PRISMAI dataset is presented in Figure 4.

A.2 Dataset Examples

The following presents dataset examples from each domain, with the original human-written snippet on top and its AI-generated counterpart below.

arXiv

The latter is the (local) supersymmetric extension of Weyl gravity and it should be regarded as the gauge theory of the superconformal algebra. It was pioneered in [2, 3] and its quantum structure was explored initially in [4]. The fourth order equations of motion of Weyl gravity make the appearance of ghost-like states (of helicity $\pm 2, \pm 1$) [5] together with ordinary massless graviton, [...]

In this paper, we explore the massless spectrum of N-extended conformal supergravity, emphasizing its profound implications for the theoretical framework of gravitational theories. By employing a systematic approach to the supersymmetry algebra and its representations, we elucidate the structure of the massless states arising from conformal supergravity. [...]

Weblogs

T_T ... 2 dae is such a f**kin dae... TT GUY ...HE ... HE ... HE was AVOIDIN mi again ... He did it b4... hurtin my feelins ... my heart ... But ... i don understand Y he mus do tt ... i did nth ... Y ... yyyyyyyyy... sorri 2 dae a bit mentally unstable ... bear wif moi 4 awhile ...I LUV HIM SO I WOULD NVR GIV HIM UP... until ... til... 1 dae my heart dies ... Mmm hmm ... Luv U so i will nvr hate u ... wo zhen de hen ai ni ... SARANGHAEYO ...

TT he doesnt even txt back anymore. Like how can u just stop talking like that?? HE said he liked me tho!!! DAE ever feel so rlly confused and hurt??? Mus do tt rn but idk wat to post. He's always doing this, pulling away then coming back and saying stuff... He hurts me, makes me feel crazy! SARANGHAEYO? What does that even mean anymore?? Im not stupid i know u don't mean it HE. Why do u keep saying these things?? HE just wants to play games!! Like im a joke or somethin!!! [...]

German Parliament (Bundestag)

Herr Präsident! Meine sehr verehrten Damen und Herren! Werter Herr Kollege Trittin, wir gehören dem Deutschen Bundestag ja eine vergleichbare Zeit an. Ich muss sagen: Ihre Reden waren auch schon mal realitätsbezogener. Wir

haben seit vielen Jahren ein gemeinsames Bemühen, [...]

Meine sehr verehrten Damen und Herren, Heute stehen wir vor einer der größten Herausforderungen unserer Zeit: der Sicherstellung einer zuverlässigen Energieversorgung bei gleichzeitiger Einhaltung unserer ambitionierten Klimaziele im Rahmen der Energiewende. Kritik an unseren Entscheidungen ist leicht zu äußern, [...]

German Spiegel Online News

Der FC Barcelona hat in der Primera División gegen Betis Sevilla gewonnen und damit einen Fehlstart abgewendet. Auffälligster Spieler beim 5:2 (1:1)-Erfolg war Neuzugang Antoine Griezmann, der für Barcelona zwei Tore erzielte (41. Minute/50.). Zudem trafen Carles Perez Sayol (56.), Jordi Alba (60.) und Arturo Vidal (77.) für die Katalanen. Für Betis waren Nabil Fekir (15.) und Loren Morón (79.) erfolgreich.[...]

FC Barcelona Bezwingt Betis Sevilla in packendem La-Liga-Duell. In einem atemberaubenden La-Liga-Spiel sicherte sich FC Barcelona einen hart umkämpften Sieg gegen den unergiebigsten Gegner Betis Sevilla. Das Highlight des Abends war ohne Zweifel der fulminante Einstand von Antoine Griezmann, der binnen 45 Minuten doppelt traf und somit die Grundlage für den 3:2-Erfolg legte. [...]

CNN News

The Royal Family and the Middletons put up a united fashion front at the christening of Prince George at St James's Palace in London yesterday. All wore shades of chic cream or royal blue for the event with the Duchess of Cambridge, the Duchess of Cornwall, Pippa Middleton - and of course Prince George! - all sporting off-white. Zara and the Queen picked shades of navy and powder-blue and Carole Middleton wore a mixture of the two, in a navy coat and cream dress. Scroll down for video . Traditional gown: Kate co-ordinated her colour with that of her son, who was [...]

On a sun-drenched afternoon in July, the grandeur of St. James's Palace was illuminated not just by the bright rays of summer but also by the presence of the British Royal Family and the Middleton clan, all gathered to celebrate the christening of the adorable Prince George. The event, which marked a significant milestone in the young prince's life, was as much about the ceremonial blessings as it was about the dazzling array of fashion choices on display.

As the royal family arrived, a hush fell over the crowd, quickly followed by a flurry of excitement. The atmosphere was electric, filled with the kind of anticipation [...]

Euro Court Cases

5. The applicant was born in 1976 and is currently detained in Kassel, Germany.

6. On 7 December 2007 the applicant was arrested on suspicion of uttering threats and domestic violence. On 8 December 2007 the Žary District Court ordered his detention on remand.

7. On 22 December 2007 he was admitted to a psychiatric hospital and diagnosed with paranoid schizophrenia. He was discharged from the hospital on 2 January 2008. [...]

The defendant, Mr. Edward Thompson, was brought before the Honorable Judge Amelia Harding on this, the 17th day of August, 2023, for a hearing concerning his continued detention under involuntary commitment procedures. Present in the courtroom were the defense attorney, Ms. Sarah Evans, and the prosecuting attorney, Mr. Michael Davis. Dr. Helen Ramirez, a forensic psychiatrist who conducted an evaluation of Mr. Thompson, was also sworn in as a witness. [...]

Classic Literature (Gutenberg)

It was five o'clock on a raw, gusty February afternoon. All that day and all the night before it had been snowing hard. New York lay buried beneath over two feet of its cold white mantle, and with the gathering dusk a fierce hurricane set in, proclaiming the approach of the terrible blizzard which had been predicted. On this afternoon, which was destined to be so memorable, [...]

The gas lamp cast long, dancing shadows across Lester Armstrong's neat, tidy study. It was a space of order and predictability, his sanctuary from the chaos that seemed to perpetually follow his cousin, Clinton Kendale.

Lester sat hunched over his ledger, the scratch of his quill a soothing counterpoint to the distant rumble of carriages on the cobblestone street below. He sighed, running a hand through his neatly parted hair [...]

House of Commons

What plans he has to reduce the incidence of antisocial behaviour in British cities. The Government have taken a series of initiatives to tackle antisocial behaviour. The Crime and Disorder Act 1998 introduced crime and disorder partnerships, antisocial behaviour orders, important changes to the youth justice system and other measures and new offences, including those of racial harassment and violence. More than 140 antisocial behaviour orders have now been made by the courts. [...]

I rise today to address the pressing issue of antisocial behaviour plaguing our cities, a matter of grave concern to communities across the nation. The Conservative party has consistently pledged to restore order and ensure the safety of our citizens, yet despite numerous initiatives and billions poured into tackling this problem, the reality on the ground paints a disheartening picture. [...]

Student Essays

The Face On Mars - Have you ever seen something crazy on something, maybe a face or something that you seen before? Have you thought about how that face or something else has gotten there? Well, for a start it definitley wasn't aliens! Just like the face on mars, people believe that the face was created by aliens! But that isn't true, the face on mars is just and only a natural landform that some how was created on earth. [...]

Is the "Face on Mars" Really a Face? Okay, so there's this picture, right? A picture taken by a spaceship way out in space, on Mars! And guess what? It kind of looks like a face staring back at us. Like, two eyes, a nose, and even a mouth! People started going crazy saying it was proof that aliens lived on Mars. But hold on! I think this whole "Face

on Mars” thing is just people’s imaginations running wild.
First of all, look at the picture closely. [...]

A.3 Implementation Details

Our experiments were conducted using PyTorch (Paszke et al., 2019), Lightning (Falcon and team) and transformers (Wolf et al., 2020). To ensure reproducibility, we run our training in deterministic mode and record all used hyper-parameters with the results. After calculating likelihoods and ranks, we stored them alongside their corresponding documents in a document database. At training time, we fetch the required features to the local machine and cache them there for future reuse. To stem the significant workload of calculating features for thousands of documents – including very long ones – with a variety of LLMs, we implement a bucketing approach that tokenizes a batch of documents and sorts the `input_ids` by length before creating mini-batches that are passed into the model in order to minimize the processing of padding tokens. We also implemented two distinct methods to process large documents with small models where the documents’ length exceeds the maximum input size of the model by either: (a) processing overlapping strided windows on the `input_ids` or by (b) leveraging *natural* text segmentation such as sentences and (where available) document structure elements (i.e. paragraph breaks) to create *rolling chunk window* where each chunk is, for example, filled with the current paragraph and as many previous paragraphs as will fit the models input size.⁶

A.4 Ablation

We run extensive ablation experiments on our model. Table 4 shows an overview of the major experiments.

⁶Results regarding this are not included in this paper due to size constraints but will be included in future work.

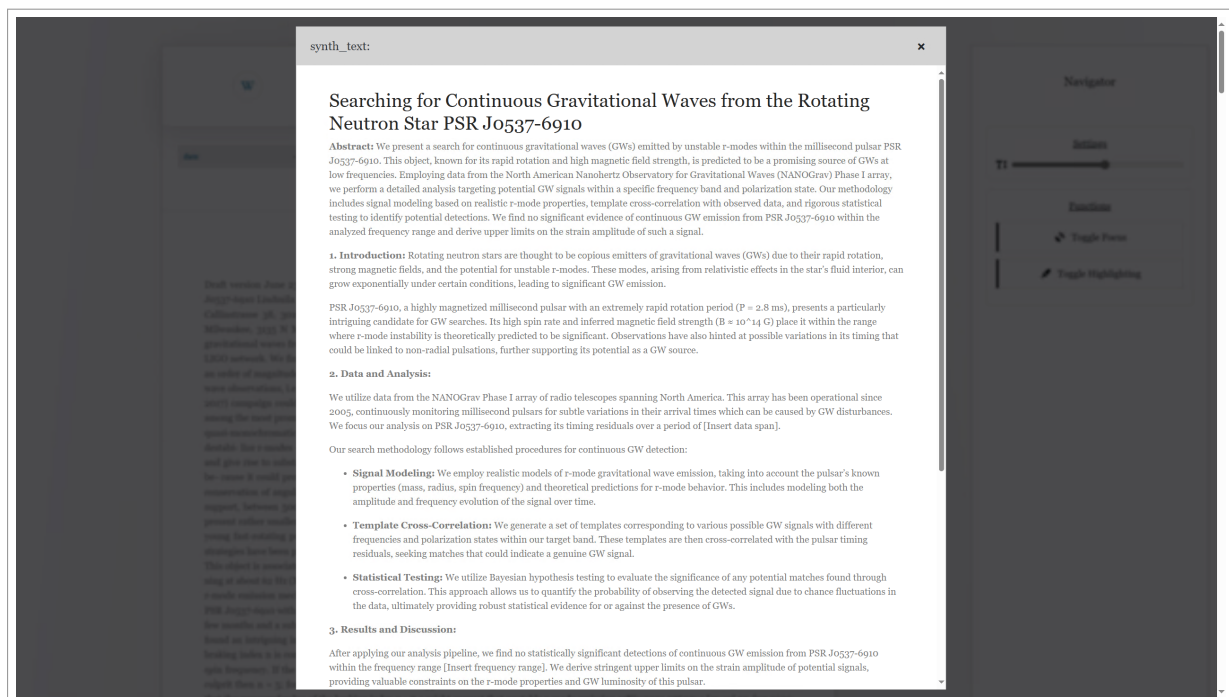
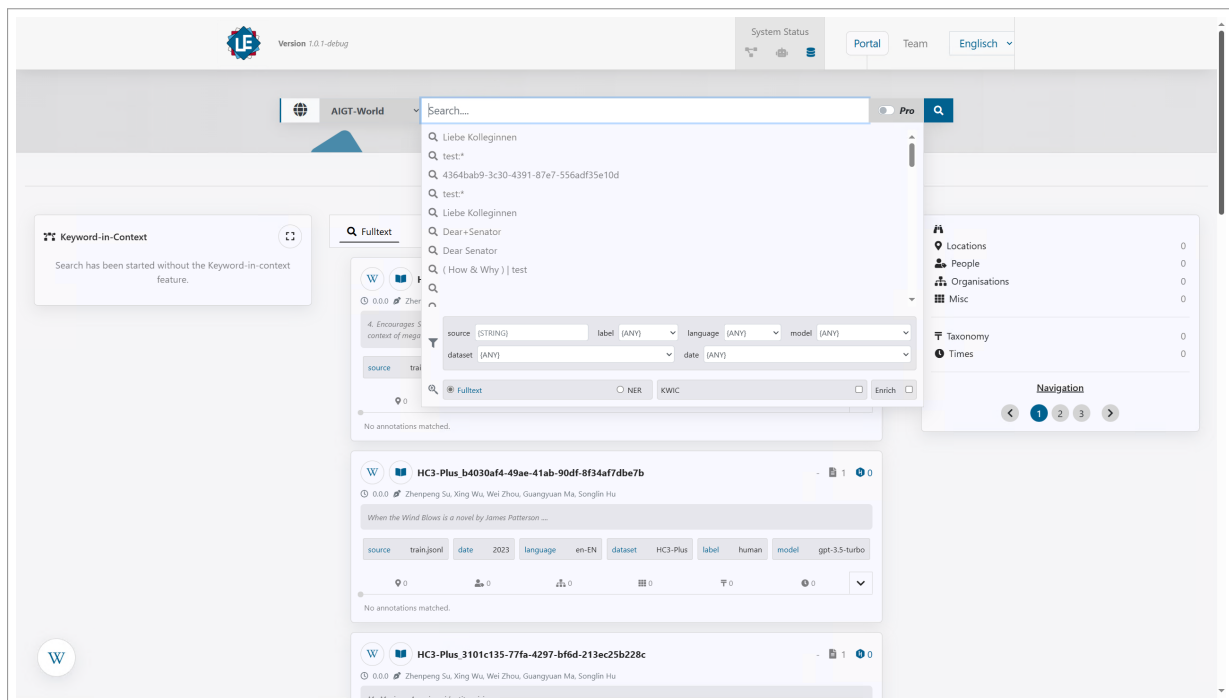


Figure 5: Screenshots illustrating the corpus explorer web portal for the PRISMAI and AIGT-WORLD datasets. The top section highlights the search functionality, enabling filtering by dataset, model, and label across all included datasets. The bottom section presents the reader view, currently showcasing an AI-generated rewrite of an arXiv paper, allowing users to access and read both AI- and human-written documents in the corpus.

Table 4: All ablation experiments.

Method	Δ AUROC	Δ F ₁
Likelihood	−0.033	−0.043
tkLLR	−0.164	−0.159
LtkLLR	−0.021	−0.023
LLRR	−0.027	−0.039
Number of IL Layers (max. 13)		
n = 11	−0.000	−0.009
n = 9	−0.001	−0.001
n = 7	−0.010	−0.022
n = 5	−0.019	−0.022
n = 3	−0.024	−0.039
n = 2	−0.026	−0.044
2D Convolution	−0.003	−0.005
No Convolution	−0.115	−0.134
No Projection	−0.000	0.010
Conv(16, 32, 16)	−0.032	−0.045
Conv(32, 64, 32)	−0.016	−0.019
Conv(32, 64, 64, 64, 32)	−0.008	−0.009
First(64)	−0.038	−0.052
First(128)	−0.017	−0.021
First(512)	0.007	0.019
Random(256)	−0.003	−0.012
Rand. Multiple(256, 2, 16)	−0.012	−0.032
Rand. Multiple(256, 4, 16, sorted)	−0.020	−0.045
Rand. Multiple(256, 4, 16)	−0.022	−0.037
Rand. Multiple(256, 4, 64)	−0.008	−0.024
Rand. Multiple(256, 8, 16)	−0.017	−0.042
Shift Unit Interval	0.003	0.007

Domain	LLR		Fast-DetectGPT	
	AUROC	F ₁	AUROC	F ₁
Blog Authorship	0.804	0.678	0.886	0.766
Essays	0.980	0.931	0.963	0.892
CNN News	0.976	0.935	0.950	0.873
Euro Court Cases	0.836	0.753	0.612	0.558
House of Commons	0.840	0.827	0.894	0.822
ArXiv Papers	0.831	0.803	0.878	0.811
Spiegel _{de}	0.975	0.930	0.972	0.902

Table 5: Baseline results using Llama3.2-1B.

Dataset	GPT-2			Llama 3.2		
	5 %	50 %	95 %	5 %	50 %	95 %
Web Blogs	15	65	600	16	66	593
Essays	213	439	890	212	436	884
CNN	309	749	1 597	309	748	1 588
ECHR	258	984	5 046	280	1 019	5 140
HoC	89	818	18 497	91	822	18 700
arXiv	1 009	11 338	34 941	966	11 158	34 433
Gutenberg	784	39 006	222 774	778	37 531	202 753
Spiegel _{de}	334	912	2 603	250	682	1 934
Bundestag _{de}	234	1 342	2 483	170	946	1 747
CHEAT	106	176	298	105	173	291
Ghostbuster	280	632	997	281	631	998
HC3-Plus	12	52	383	11	41	257
MAGE	36	141	951	37	142	952
OpenLLMText	120	392	1 024	120	390	1 031
SeqXGPT	72	270	504	73	270	499

Table 6: The distribution of number of tokens for each model across the considered datasets given by their 5 %, 50 % (median), and 95 % percentiles rounded down to the next integer.