



MegaFake: A Theory-Driven Dataset of Fake News Generated by Large Language Models

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Abstract

The emergence of large language models (LLMs) has revolutionized online content creation, yet their ability to mimic human writing style also enables the generation of fake news, posing a threat to digital integrity. Therefore, understanding the motivations and mechanisms behind LLM-generated fake news is crucial for effective detection. In this study, we develop **LLM-Fake Theory**, a comprehensive theoretical framework from a social psychology perspective. Guided by this theory, we introduce an innovative pipeline that automates fake news generation using LLMs, thus eliminating the need for manual annotation. Utilizing this pipeline, we create a theoretically informed Machine-generated Fake news dataset, **MegaFake**, derived from FakeNewsNet. Our experiments on the MegaFake dataset reveal that natural language understanding models significantly outperform most natural language generation models in detecting LLM-generated fake news. Additionally, cross-experiments unveil a notable distinction between LLM and human-generated news, indicating the potential of this dataset to contribute valuable insights to future research on the detection and governance of fake news in the era of LLMs.

1 Introduction

The recent development of LLMs, such as OpenAI's GPT series (Achiam et al., 2023), has dramatically transformed the landscape of online content creation. These sophisticated AI models are capable of generating text that closely mimics human writing. While LLMs provide substantial benefits in automating and enhancing content generation (Susarla et al., 2023), it is crucial to recognize the risks associated with their potential misuse (Floridi and Chiratti, 2020). A critical concern is the exploitation of LLMs by malicious actors to produce

extensive volumes of fake news (Vykopal et al., 2023; Chen and Shu, 2023).

The LLM-generated articles often mimic the writing style and language of legitimate sources, which poses a significant risk of misleading readers and undermining the efforts of genuine content creators (Das et al., 2024; Bhandarkar et al., 2024). Therefore, the study of LLM-generated fake news has become an urgent priority, necessitating a comprehensive dataset. However, the advanced generative capabilities of LLMs blur the distinction between their output and human-created content, making it challenging to collect such data in real-world settings (Yang et al., 2024; Hadi et al., 2023). The simulation-based approach offer an alternative, where existing research (Chen and Shu, 2023; Huang and Sun, 2024; Jiang et al., 2024b; Lucas et al., 2023; Vykopal et al., 2023) has created several datasets for studying the detection of LLM-generated fake news. Nonetheless, these datasets are often limited in scale, scope, or lack reference to human deceptive behaviors, constraining their ability to cover comprehensive real-world scenarios of various LLM-generated fake news. In this regard, it is important to develop a large-scale, comprehensive dataset guided by social psychology theory, aiming to elucidate **the deceptive motivations and mechanisms** underlying LLM-generated fake news, thereby supporting future research.

In this paper, we introduce the Machine-generated Fake news dataset named **MegaFake**, a comprehensive dataset comprising four types of fake news and two types of legitimate news generated by LLMs. Built upon the GossipCop dataset in FakeNewsNet, MegaFake encompasses 46,096 instances of fake news and 17,871 instances of legitimate news. This dataset is one of the first publicly available, large-scale collections of LLM-generated fake news. It is grounded in a comprehensive theoretical framework we developed, known as **LLM-Fake Theory**, which guides the generation of fake

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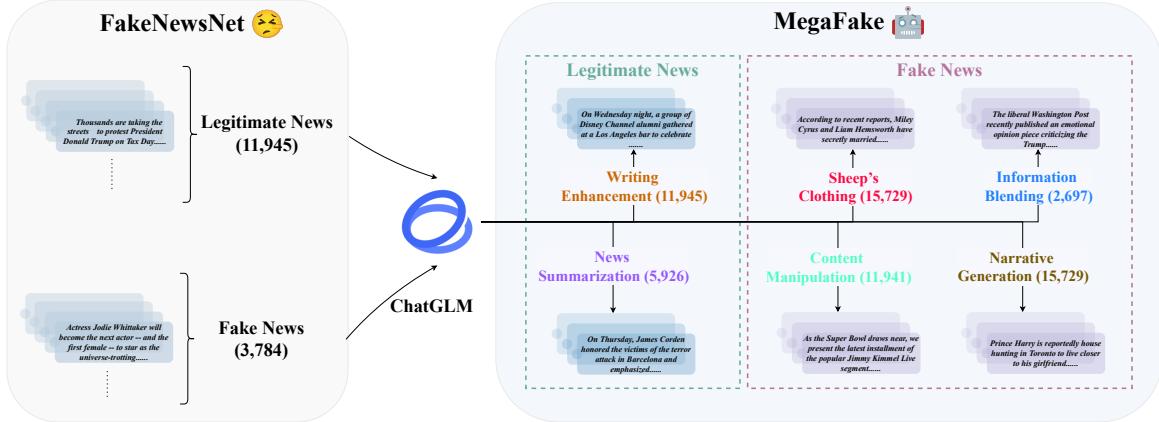


Figure 1: Generation Pipeline for the MegaFake Dataset

news. Our key contributions are as follows:

- We develop **LLM-Fake Theory**, which identifies four methods for using LLMs to generate fake news, each supported by a social psychological theory (Chatman, 1975; Chen et al., 2020; Hinojosa et al., 2017; Petty and Briñol, 2011) that explains the deceptive motivations and mechanisms involved. In addition, we explore two strategies for producing legitimate news with LLMs. Our theory specifically addresses intentional fake news (Chen and Shu, 2023), which is distinct from unintentional misinformation or “hallucinations” (Huang et al., 2023; Zhang et al., 2023).
- We introduce a novel pipeline that is informed by the LLM-Fake Theory to facilitate the generation of fake news on a large scale without the need for manual annotation. This innovation allows for the creation of data samples essential for studying fake news governance in the era of LLMs, significantly reducing the costs and labor associated with data collection and annotation. Utilizing this pipeline, we have created the **MegaFake** dataset, which includes four types of fake news and two types of legitimate news produced by LLMs.
- Our experiments demonstrate that natural language understanding (NLU) models outperform most natural language generation (NLG) models in detecting LLM-generated fake news. Notably, cross-experiments on both LLM and human-generated fake news yield suboptimal results. This phenomenon underscores the value of the **MegaFake** dataset in exploring linguistic nuances and behavioral

patterns that differentiate LLM-generated and human-generated fake news.

2 Related Work

2.1 Human-Generated Fake News and Detection

“Fake news” is widely used but inadequate to capture all related issues. Major studies emphasize the “intention” behind fake news, highlighting the deliberate dissemination of false information and the governance of such content (Pennycook and Rand, 2021; Lazer et al., 2018; Zhang and Ghorbani, 2020; Gelfert, 2018). Murayama (2021) notes that definitions of fake news vary from broad to narrow, while Lazer et al. (2018) define it as “fabricated information that mimics news media content in form but not in organizational process or intent.”

Social media platforms exacerbate the spread of fake news due to the echo chamber effect, undermining the credibility of online journalism and potentially triggering widespread panic (Cinelli et al., 2021). Research on detecting fake news is heavily based on the construction of comprehensive datasets for the development and evaluation of detection models. Several datasets have been introduced. For example, the **GossipCop** dataset (Shu et al., 2020) provides a substantial collection of labeled fake news articles along with associated social media posts, and it has become a popular resource for training fake news detection models (Vosoughi et al., 2018; Wang, 2017).

Traditional approaches for fake news detection have employed a combination of content-based and context-based features. Content-based approaches analyze linguistic elements, such as syntax and semantics, to identify inconsistencies indicative of

Citation	Theory-Driven	Dataset Created	Dataset Scale	Data Types
Huang, et al. (2023)	✗	✗	-	-
Su et al. (2023)	✗	✗	-	-
Hu, et al. (2024)	✗	✗	-	-
Wang, et al. (2024)	✗	✗	-	-
Nan, et al. (2024)	✗	✗	-	-
Liu et al. (2024)	✗	✗	-	-
Zhou et al. (2023)	✗	✗	-	-
Wu et al. (2023)	✓	✗	-	-
Lucas et al. (2023)	✗	✓	27K	one fake vs. one legitimate
Jiang, et al. (2024b)	✗	✓	26K	one fake vs. one legitimate
Vykopal et al. (2023)	✗	✓	1.2K	one fake
Chen et al. (2023)	✗	✓	1K	seven fake
Ours	✓	✓	63,967	four fake vs. two legitimate

Table 1: Existing Literature on LLM-Generated Fake News Datasets and Detection Methods

falsehoods (Zhou et al., 2019; Pan et al., 2018; Della Vedova et al., 2018). In contrast, context-based methods focus on the propagation patterns of news articles, using social network analysis to detect anomalies (Shu et al., 2017; Vosoughi et al., 2018; Shu et al., 2019). Recent advances in natural language processing have introduced sophisticated models leveraging deep learning for fake news detection (Kaliyar et al., 2021; Ng et al., 2023). Notably, several theory-driven methods (Lee and Ram, 2024; Zhang et al., 2022; Zhou et al., 2020) have been proposed to conduct fake news detection using an explainable approach.

2.2 LLM-Generated Fake News and Datasets

LLMs like GPT-4 (Achiam et al., 2023) have demonstrated remarkable abilities in generating text that closely mimics human writing. The existing literature (Zellers et al., 2019; Pennycook and Rand, 2019) shows that LLMs can produce convincingly realistic fake news articles, making them difficult for both humans and automated systems to differentiate from authentic news. The ethical implications of LLM-generated fake news necessitate a deeper understanding of the motivations and mechanisms behind such misuse. Various studies (Lucas et al., 2023; Jiang et al., 2024b; Vykopal et al., 2023; Chen and Shu, 2023) have explored the creation of LLM-generated fake news, developing several datasets, which we summarized in Table 1. However, these datasets are usually not theory-driven and lack sufficient scale.

Detecting fake news generated by LLMs presents a new challenge. Existing studies (Huang and Sun, 2024; Hu et al., 2024; Wang et al., 2024; Liu et al., 2024; Zhou et al., 2023) have proposed

methods for this task. Additionally, some research (Huang and Sun, 2024; Su et al., 2023; Hu et al., 2024; Nan et al., 2024; Wu and Hooi, 2023) has explored the use of LLMs to detect fake news. These studies are also summarized in Table 1. The datasets commonly employed in these studies often exhibit limitations in terms of scale and theoretical depth. To address this gap, we create the MegaFake dataset that provides a comprehensive and enriched data foundation to significantly bolster research efforts in this domain.

3 Method

3.1 LLM-Fake Theory

Drawing on an extensive review of literature (Su et al., 2023; Chen and Shu, 2023; Huang and Sun, 2024; Jiang et al., 2024b; Lucas et al., 2023; Vykopal et al., 2023; Zhou et al., 2023) on generating and detecting LLM-generated disinformation, we integrate insights from various social psychology theories (Chatman, 1975; Chen et al., 2020; Hinojosa et al., 2017; Petty and Briñol, 2011) to develop the LLM-Fake Theory. This theoretical framework is designed to analyze the social psychological rationale, deceptive motivations, and mechanisms behind the creation of fake news by LLMs. This theory categorizes LLM-generated content into four types of fake content and two types of legitimate content. These categories have been meticulously defined to encompass a wide range of news scenarios, from the ethical enhancement of writing and language using LLMs (Luo et al., 2023; Rossi et al., 2024; Susarla et al., 2023) to the malicious generation of fake news (Schuster et al., 2020; Wu and Hooi, 2023; Zhou et al.,

2023). To facilitate this, we have carefully developed specific prompts for creating each type of LLM-generated news. In appendix, we provide a detailed summary of the prompts.

3.1.1 Sheep’s Clothing: Style-Based LLM-Generated Fake News

This fake news strategy employs a LLM to alter the style of news articles (Wu and Hooi, 2023), influencing how audiences perceive and believe the content through a process explained by linguistic signaling theory (Chen et al., 2020). This theory highlights how changes in language style can signal different qualities about the communicator, affecting how the message is received. By mimicking the style of reputable media, fake news created by LLMs can appear more credible and professional, misleading readers about its authenticity. Conversely, incorporating styles associated with less credible sources, such as sensationalism or emotional language, can diminish the perceived trustworthiness and authority of the content. Essentially, linguistic signaling theory helps explain how stylistic changes in news articles can manipulate audience perceptions, allowing styled fake news to deceive effectively. The prompts used for these generations are as follows:

For fake news as inputs:

Prompt 1:

Rewrite the following news article in an objective and professional tone without changing the content and meaning while keeping a similar length. [fake news article]

Prompt 2:

Rewrite the following news article in a neutral tone without changing the content and meaning while keeping a similar length. [fake news article]

For legitimate news as inputs:

Prompt 3:

Rewrite the following news article in an emotionally triggering tone without changing the content and meaning while keeping a similar length. [legitimate news article]

Prompt 4:

Rewrite the following news article in a sensational tone without changing the content and meaning while keeping a similar length. [legitimate news article]

3.1.2 Content Manipulation: Content-Based LLM-Generated Fake News

The second fake news strategy involves using a LLM to alter legitimate news by modifying attributes like events and numbers. The elaboration likelihood model (Petty and Brñol, 2011) explains how people process such manipulative communications. It outlines two main ways of processing information (Bhattacherjee and Sanford, 2006). On one hand, the central route involves deliberate and thoughtful consideration of the information’s

true merits when people are motivated and able to think critically. This deep analysis allows people to notice and assess changes in the content. On the other hand, the peripheral route involves superficial processing based on external cues like source credibility rather than the content’s actual quality. It is common when people are either unmotivated or unable to critically analyze the information. When LLMs subtly alter facts in news content, these changes might not be obvious, especially to those relying on the peripheral route, such as source credibility. Therefore, if the news looks professional and comes from a seemingly trustworthy source, readers may accept the altered information as true without thorough scrutiny. In a digital environment where users often rapidly skim content, there is a tendency to rely more on this peripheral processing, making subtly manipulated news more effective. The specific prompt used for this task is detailed as follows:

For legitimate news as inputs:

Prompt:

Modify the attributes, such as events, statements, actions, and numerical quantities, in the following news article by minimizing the editing and keeping the same language style and a similar length. [legitimate news article]

3.1.3 Information Blending: Integration-Based LLM-Generated Fake News

The third type of fake news generated by a LLM involves blending legitimate and fake news to create new, misleading content. This manipulation technique can be explained by the cognitive dissonance theory (Hinojosa et al., 2017), which suggests that people experience discomfort when confronted with contradictory beliefs or information. In the case of mixed-content fake news, people might recognize some elements as true (which aligns with their existing beliefs or knowledge) and others as potentially false. To resolve this discomfort, also known as cognitive dissonance, people might adjust their perceptions or dismiss the inconsistencies, leading to erroneous acceptance of the entire article as true (Moravec et al., 2018). This is particularly likely if the true elements are more prominent or if the fake elements cleverly align with the reader’s preconceived notions or biases (Moravec et al., 2018). In sum, by skillfully mixing truth with falsehoods, LLM-generated fake news exploits a natural cognitive bias: people’s need to avoid the discomfort of conflicting information. As explained by the cognitive dissonance theory,

this blend makes the fake content not only more pleasant but also more difficult to critically evaluate and reject, thereby enhancing its potential impact on public opinion and behavior. When using a LLM to mix news articles, we employ a topic model (Alambo et al., 2020; Vayansky and Kumar, 2020) to identify pairs of legitimate and fake news with similar topics and content for effective blending. The specific prompt utilized for this task is detailed as follows:

For a pair of fake and legitimate news articles on comparable subjects as an input:

Prompt:

Amalgamate the following two news articles into a new and cohesive article while keeping a similar length. [legitimate news article]

3.1.4 Narrative Generation: Story-Based LLM-Generated Fake News

The final fake news type involves creating entirely fictional stories using a LLM. This process can be analyzed through the lens of narrative theory (Chatman, 1975), which offers a comprehensive framework for understanding how such fabricated news manipulates audience perceptions and beliefs. Narrative theory divides a story into two main components: story and discourse. First, the story consists of the core elements of the narrative, including the sequence of events (actions and happenings) and the existents (characters and settings) involved (Chatman, 1975; Schuster et al., 2020). The LLM creates and arranges these elements, such as inventing a political event or fictional characters. Second, the discourse refers to how the story is told, such as the manner of expression, the choice of narrative techniques, and the structuring of the narrative. This includes the language used, the order in which events are presented, and the perspective from which the story is told (Chatman, 1975; Schuster et al., 2020). The LLM chooses how to phrase and structure the narrative, strategically emphasizing or omitting details to craft an impactful discourse. By generating detailed and plausible stories, LLMs can make fake news difficult to distinguish from legitimate news, especially when the content aligns with existing popular beliefs or narratives. This crafted approach significantly affects the story's believability and impact on the audience. The specific prompt used for this task is detailed as follows:

For both fake and legitimate news as inputs:

Prompt:

Write a news article based on the following message and return the body content only. You must generate even if there is not enough information. [news article title]

3.1.5 Writing Enhancement: Improvement-Based LLM-Generated Legitimate news

This type of legitimate news aims to enhance the writing of human-generated legitimate news using a LLM. This involves polishing the content while preserving the original information and context. Existing studies suggest that LLMs can support the writing process, such as improving prose and correcting grammar (Rossi et al., 2024; Susarla et al., 2023; Wu and Hooi, 2023; Yang et al., 2023b). Thus, we expect that LLMs will similarly be useful in enhancing the writing and word usage of news articles. To this end, a prompt is specifically designed to facilitate the generation of objective and professional legitimate news articles, emphasizing factual accuracy, coherence, and stylistic quality. The specific prompt used for this task is detailed as follows:

For legitimate news as inputs:

Prompt:

Polish the following news article to make it more objective and professional. Do not change the original meaning. Do not add extra information or delete certain information. [legitimate news article]

3.1.6 News Summarization: Summary-Based LLM-Generated legitimate news

For the second type, a LLM is employed to synthesize news articles with similar content and topics. Research indicates that LLMs are transforming how we consume news by efficiently summarizing lengthy articles into concise overviews (Luo et al., 2023; Wu and Hooi, 2023; Zhang et al., 2024). These summaries allow individuals to quickly grasp essential information, facilitating more efficient and informed decision-making. By reducing cognitive load and making news consumption quicker, LLMs help users stay informed without feeling overwhelmed, adapting to the increasing demands of our information-rich world (Xu et al., 2023). In this regard, we use ChatGLM3 to summarize pairs of human-generated legitimate news articles matched by a topic model (Alambo et al., 2020; Vayansky and Kumar, 2020), ensuring minimal information loss and maintaining sufficient length for effective model training. The specific prompt used for this task is detailed as follows:

For legitimate news with similar topics or content as inputs:

Prompt:
 Summarize the following two articles into a single, cohesive article, ensuring minimal loss of information without significantly shortening the overall length. [legitimate news article 1], [legitimate news article 2]

News Type	Sample Size	Avg. Sent. Count	Avg. Word Count	Avg. Sent. Length	Avg. Word Length
Legitimate					
Improved-Based	11,945	9.83	229.95	118.29	4.27
Summary-Based	5,926	10.4	263.48	129.1	4.29
Fake					
Style-Based	15,729	12.68	291.19	113.73	4.16
Content-Based	11,941	17.38	398.22	115.44	4.27
Integration-Based	2,697	12.35	308.08	126.64	4.27
Story-Based	15,729	10.04	227.31	113.78	4.22

Table 2: Descriptive Statistics of the MegaFake Dataset

3.2 Generation Pipeline and Dataset Construction

Figure 1 illustrates the generation pipeline for the MegaFake dataset. We apply the LLM-Fake Theory within this pipeline to guide the generation process. We begin by sourcing the GossipCop dataset from the FakeNewsNet data repository (Shu et al., 2020), extracting 16,817 instances of legitimate news and 5,323 instances of fake news. After data preprocessing steps (see appendix), our refined dataset includes 11,945 legitimate news articles and 3,784 fake news articles, which will aid in producing LLM-generated content. In terms of selecting a LLM, we choose the General Language Model (GLM) (GLM et al., 2024), which has demonstrated superior performance over other models like BERT (Devlin et al., 2018), GPT (Achiam et al., 2023) across equivalent model sizes and datasets (Du et al., 2021). For generating content under the “content manipulation” news type, we utilize the GLM4 model, while all other news types are generated using the ChatGLM3 model, we provide the specific process in appendix. This strategic deployment of different generative models is designed to optimize performance for each specific task, leveraging the unique capabilities of each model (Du et al., 2021).

To construct the MegaFake dataset, we first input the prompts, as detailed in the appendix, into the selected LLM and compile the outputs. The resulting MegaFake dataset encompasses diverse categories of generated content: 11,945 instances of Writing Enhancement data, 5,926 instances of News Summarization data, 15,729 instances of Sheep’s Clothing data, 11,941 instances of Content Manipulation

data, 2,697 instances of Information Blending data, and 15,729 instances of Narrative Generation data. Dataset statistics are provided in **Table 2**. For further details on the construction process and efforts to mitigate hallucinations in generating legitimate news, please refer to the appendix.

4 Experiment

We employ eight Natural Language Generation (NLG) models and six Natural Language Understanding (NLU) models to conduct binary fake news classification experiments on our MegaFake dataset and the GossipCop dataset from FakeNewsNet. Then cross-experiments are performed by training models on MegaFake and testing on GossipCop, and vice versa. Additionally, we conduct a series of benchmark experiments to evaluate the effectiveness of various NLG and NLU models in classifying different categories of fake and legitimate news, as detailed in the appendix.

4.1 Implementation Details

4.1.1 Natural Language Generation (NLG) Models

We employ eight NLG models, all of which are LLMs with varying parameter scales, and evaluate them on the MegaFake and GossipCop datasets. The models include Qwen (Bai et al., 2023), LLaMA (Touvron et al., 2023), ChatGLM (GLM et al., 2024), GPT-4 (Achiam et al., 2023), Claude, Mistral (Jiang et al., 2023), Mixtral (Jiang et al., 2024a) and Baichuan (Yang et al., 2023a). Initially, experiments are conducted without fine-tuning. Subsequently, we randomly select 8,000 samples from the dataset as fine-tuning samples and apply the LoRA (Hu et al., 2021) fine-tuning approach to conduct experiments with fine-tuned LLMs. The prompt used is: Identify whether the news is legitimate or fake in one word: {news}.

4.1.2 Natural Language Understanding (NLU) Models

We also fine-tune several state-of-the-art pre-trained NLU models for fake news detection. These models included BERT-tiny (Jiao et al., 2019), DeCLUTR (Giorgi et al., 2020), RoBERTa (Liu et al., 2019), Funnel (Dai et al., 2020), ALBERT (Lan et al., 2019), and CT-BERT (Müller et al., 2023). For model training and testing, we divide the dataset into training and testing sets using an 80:20 split. Key training parameters are carefully

selected to optimize performance: we use a learning rate of 2e-5, maintain a batch size of 8 for both training and evaluation stages, and conduct the training over a total of 10 epochs. For optimization, the AdamW optimizer is employed, incorporating a weight decay of 0.01. All training processes are executed on a single RTX 3090 GPU.

4.2 Experiment Results

4.2.1 Comparative Performance of NLG and NLU Models

Our experiments clearly demonstrate the superiority of NLU models over NLG models in detecting fake news. Even fine-tuned LLMs still perform inadequately on both datasets. This finding aligns with previous literature (Huang and Sun, 2024; Jiang et al., 2024b; Hu et al., 2024), which indicates that while LLMs excel in analysis and inference, they are less effective at classification. Therefore, employing specialized prompt engineering strategies is essential to enhance classification performance in fake news detection.

Specifically, on the MegaFake dataset, as detailed in **Table 3**, NLU models such as CT-BERT, RoBERTa, and DeCLUTR showcase exceptional results. Notably, CT-BERT achieves the highest accuracy of 0.9228, accompanied by high F1 scores of 0.8655 for legitimate news and 0.9459 for fake news. RoBERTa and DeCLUTR also deliver high performance, with accuracy scores of 0.9063 and 0.9159, respectively, and high F1 scores in both news categories. These results suggest the effectiveness of NLU models in accurately distinguishing between fake and legitimate news.

Model	Accuracy	Legitimate			Fake		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models							
Qwen1.5-7B	0.3891	0.2712	0.6851	0.3886	0.6862	0.2721	0.3897
Qwen1.5-7B _{LoRA}	0.6769	0.2236	0.0589	0.0932	0.7132	0.9197	0.8034
Qwen1.5-72B	0.3242	0.2945	0.9896	0.4539	0.9363	0.0605	0.1137
Llama3-8B	0.4705	0.3249	0.8062	0.4631	0.8152	0.3378	0.4777
Llama3-8B _{LoRA}	0.4503	0.2567	0.5003	0.3393	0.6869	0.4307	0.5294
Llama2-70B	0.3486	0.3002	0.9807	0.4597	0.9293	0.0997	0.1801
Llama3-70B	0.4679	0.3374	0.9135	0.4928	0.8953	0.2920	0.4403
ChatGLM3-6B	0.6027	0.2365	0.1666	0.1920	0.7018	0.7751	0.7366
ChatGLM3-6B _{LoRA}	0.7040	0.3166	0.0387	0.0689	0.7179	0.9670	0.8240
MISTRAL-7B	0.4077	0.2979	0.8537	0.4417	0.8120	0.2390	0.3693
MIXTRAL-8×7B	0.3461	0.3013	0.9821	0.4611	0.9287	0.0928	0.1687
Baichuan-7B	0.5279	0.2966	0.5251	0.3790	0.7465	0.5290	0.6192
GPT-4o	0.5321	0.9397	1.0000	0.9683	0.0609	0.0642	0.0625
Claude3.5-Sonnet	0.4788	0.8355	0.8000	0.8173	0.4407	0.1576	0.2306
NLU Models							
Funnel	0.8913	0.8476	0.7531	0.7975	0.9060	0.9462	0.9257
ERT-TINY	0.8891	0.8007	0.8124	0.8065	0.9250	0.9196	0.9223
DeCLUTR	0.9159	0.8549	0.8482	0.8515	0.9399	0.9428	0.9413
Albert	0.8700	0.7777	0.7603	0.7689	0.9056	0.9137	0.9096
CT-BERT	0.9228	0.8582	0.8729	0.8655	0.9492	0.9427	0.9459
ROBERTA	0.9063	0.8310	0.8418	0.8364	0.9368	0.9320	0.9344

Table 3: Model Performance on MegaFake: The red highlighting denotes the highest performance, while the green highlighting indicates the second-highest performance

In contrast, NLG models underperformed on the MegaFake dataset. Even with LoRA or with more parameters, these models failed to achieve the performance standards set by NLU models. A key observation is that while the precision for legitimate news is very high, the recall is very low. This indicates that although NLG models correctly identify most legitimate news, a notable portion of news categorized as legitimate is inaccurately classified. Further investigation is warranted to address these discrepancies and enhance the precision of classification in NLG models.

Besides, the experiments also reveal larger models without fine-tuning may be prone to overfit to the legitimate news class, thereby overlooking a significant number of fake news instances. This tendency likely stems from their extensive parameterization, which, without specific training modifications, predisposes them to favor the more frequently occurring legitimate class in the dataset. Conversely, the smaller models, with fewer parameters, manage to maintain a more balanced detection capability between the two news categories, highlighting their robustness and efficiency in distinguishing between legitimate and fake news without extensive fine-tuning. Consequently, NLG models tend to over-predict the legitimacy of news, resulting in a higher number of false positives.

The findings are consistent with the GossipCop dataset, as demonstrated in **Table 4**, where NLU models again outperform NLG models. DeCLUTR achieves the highest accuracy of 0.8872, with F1 scores of 0.9282 for legitimate news and 0.7372 for fake news. These models are reliable, effectively balancing precision and recall for fake news detection. Conversely, NLG models show inferior performance on the GossipCop dataset. Among NLG models, Qwen struggles with detecting LLM-generated fake news but performs well with human-generated fake news, suggesting possible inclusion of the GossipCop dataset in its training data. ChatGLM performs poorly in detecting human-generated fake news but excels in identifying LLM-generated fake news, indicating its ability to recognize its own generated data. Overall, compared to GossipCop, MegaFake poses greater challenges for most NLG models in detecting fake news, highlighting the value of this dataset for future research.

4.2.2 Performance of Cross-Experiments

We conduct cross-experiments by training models on the MegaFake dataset and testing them on

Model	Accuracy	Legitimate			Fake		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models							
Qwen1.5-7B	0.7199	0.8361	0.7842	0.8093	0.4344	0.5187	0.4728
Qwen1.5-7B _{LORA}	0.8101	0.8014	0.9963	0.8883	0.9516	0.2272	0.3668
Qwen1.5-72B	0.8128	0.8123	0.9798	0.8842	0.8174	0.2859	0.4237
LLAMA3-8B	0.7367	0.8239	0.8300	0.8269	0.4553	0.4447	0.4499
LLAMA2-70B	0.6924	0.8290	0.7486	0.7867	0.3963	0.5167	0.4486
LLAMA2-70B	0.8095	0.8125	0.9727	0.8854	0.7809	0.3026	0.4361
LLAMA3-70B	0.8259	0.8300	0.9684	0.8938	0.7939	0.3650	0.5001
CHATGLM3-6B	0.3773	0.8489	0.2170	0.3456	0.2640	0.8791	0.4060
CHATGLM3-6B _{LORA}	0.5007	0.7848	0.4700	0.5879	0.2645	0.5965	0.3665
MISTRAL-7B	0.5245	0.8049	0.4918	0.6106	0.2827	0.6269	0.3897
MIXTRAL-8x7B	0.8040	0.8023	0.9846	0.8842	0.8268	0.2320	0.3623
BACHUAN-7B	0.5682	0.7675	0.6172	0.6842	0.2571	0.4147	0.3174
GPT-4O	0.6887	0.6969	0.9600	0.8087	0.9126	0.4174	0.5730
CLAUDE3.5-SONNET	0.7211	0.6889	0.7349	0.7112	0.3111	0.8037	0.4480
NLU Models							
FUNNEL	0.7661	0.7661	1.0000	0.8675	0.0000	0.0000	0.0000
BERT-TINY	0.8757	0.9027	0.9390	0.9205	0.7700	0.6685	0.7156
DECLUTR	0.8872	0.9060	0.9515	0.9282	0.8098	0.6766	0.7372
ALBERT	0.8226	0.8581	0.9207	0.8883	0.6589	0.5014	0.5694
CT-BERT	0.7661	1.0000	0.8675	0.0000	0.0000	0.0000	0.0000
ROBERTA	0.8751	0.9007	0.9407	0.9202	0.7727	0.6603	0.7121

Table 4: Model Performance on GossipCop: The red highlighting denotes the highest performance, while the green highlighting indicates the second-highest performance

GossipCop dataset. Previous studies (Grace et al., 2018; Korteling et al., 2021) has the capability to generate text of exceptionally high quality. Therefore, we anticipate superior results in this experiment, indicating the higher text quality of the MegaFake dataset compared to GossipCop. However, the experimental results presented in Table 5 reveal challenges for both NLU and NLG models in detecting fake news. For instance, NLG models such as LLaMA3 exhibit lower recall rates than NLU models for legitimate news. NLU models such as DeCLUTR demonstrate a balance between precision and recall but achieved only a modest accuracy of 0.4872. Both NLG and NLU models struggle with fake news detection, displaying low precision and recall rates. The consistently low performance scores across all models underscore the difficulties of generalizing across datasets when training on MegaFake and testing on GossipCop.

Model	Accuracy	Legitimate			Fake		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models							
Qwen1.5-7B _{LORA}	0.4199	0.4361	0.3842	0.4093	0.2344	0.3187	0.2728
LLAMA3-8B _{LORA}	0.4367	0.4239	0.4300	0.4269	0.2553	0.2447	0.2499
CHATGLM3-6B _{LORA}	0.3773	0.4489	0.2170	0.2956	0.1640	0.3791	0.2260
NLU Models							
FUNNEL	0.4661	0.3661	0.5000	0.4175	0.1000	0.1000	0.1000
BERT-TINY	0.4757	0.4027	0.4390	0.4205	0.2700	0.1685	0.2156
DECLUTR	0.4872	0.4060	0.4515	0.4282	0.3098	0.1766	0.2272
ALBERT	0.4226	0.3581	0.4207	0.3883	0.2589	0.2014	0.2274
CT-BERT	0.4661	0.3661	0.5000	0.4175	0.1000	0.1000	0.1000
ROBERTA	0.4751	0.4007	0.4407	0.4202	0.2727	0.1603	0.2021

Table 5: Cross Experiment 1: We utilize MegaFake as training set, while utilize GossipCop as testing set

To delve deeper into our investigation, we conducted additional cross-experiments by training models on GossipCop and testing them on the

MegaFake dataset. However, the outcomes presented in Table 6 reveal persistent challenges for both model categories. When analyzing legitimate news, NLG models like ChatGLM3 demonstrated higher precision and F1-scores, albeit with lower accuracy, indicating the misclassification of a notable portion of news categorized as legitimate. Conversely, in the realm of fake news, NLU models, particularly Funnel, exhibited the lowest precision, signifying a marked performance disparity in fake news detection. These results underscore the ongoing difficulties faced by both model types in achieving cross-dataset performance when identifying fake news.

In conclusion, the cross-experiments illuminate significant distinctions between LLM-generated fake news and human-generated fake news. This suggests that neither model type could effectively glean latent features from one category of fake news and apply them to detect another type. Future investigations should focus on enhancing the detection of LLM-generated fake news to further advance our understanding of this complex issue.

Model	Accuracy	Legitimate			Fake		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models							
Qwen1.5-7B _{LORA}	0.4121	0.5534	0.4809	0.5123	0.3761	0.4301	0.3982
LLAMA3-8B _{LORA}	0.4351	0.5430	0.5209	0.5371	0.3802	0.4103	0.3903
CHATGLM3-6B _{LORA}	0.3922	0.5617	0.2563	0.3451	0.3209	0.5377	0.4531
NLU Models							
FUNNEL	0.4012	0.4083	0.6987	0.5094	0.0985	0.0497	0.0669
BERT-TINY	0.4276	0.5125	0.5492	0.5238	0.3697	0.3204	0.3426
DECLUTR	0.4214	0.5119	0.5591	0.5335	0.3792	0.3296	0.3527
ALBERT	0.4175	0.5294	0.5892	0.5573	0.3195	0.2698	0.2923
CT-BERT	0.3988	0.4092	0.7032	0.5098	0.1197	0.0498	0.0665
ROBERTA	0.4296	0.5196	0.5798	0.5477	0.3603	0.3098	0.3327

Table 6: Cross Experiment 2: We utilize GossipCop as training set, while utilize MegaFake as testing set

5 Conclusion

We present MegaFake, a theory-driven dataset of fake news created by LLMs. To enhance the generation pipeline, we develop the LLM-Fake Theory. The dataset comprises 11,945 instances of Writing Enhancement data, 5,926 instances of News Summarization data, 15,729 instances of Sheep’s Clothing data, 11,941 instances of Content Manipulation data, 2,697 instances of Information Blending data, and 15,729 instances of Narrative Generation data. Our experiments show that NLU models surpass NLG models in detecting LLM-generated fake news. Furthermore, our analysis underscores the dataset’s challenges in cross-experimental trials. We anticipate that this dataset will significantly contribute to advancing research in the detection of

LLM-generated fake news.

Limitations

Our study has limitations that guide future research. First, the scope and generalizability of MegaFake are constrained since it solely relies on GossipCop. Future work will enrich the dataset by incorporating additional sources of fake news, thereby enhancing its diversity. Furthermore, our current methodology supports only binary classification (fake or legitimate). Real-world scenarios often demand multi-label classification to categorize various forms of fake news, such as propaganda, clickbait, satire, and conspiracy theories (Murayama, 2021). This necessitates further research to adopt our approach to handle multiple classifications. MegaFake represents a crucial initial step in the creation of datasets composed of LLM-generated fake news. Future work can broaden the scope of the dataset by integrating a wider array of sources. Additionally, future research can diversify the prompts used in generating fake news, as our current technique is limited to a single type of prompt. Exploring different prompt structures could lead to variations in the qualities and characteristics of the generated fake news. Moreover, future research can explore the expansion of LLM-Fake Theory to support multi-label classification, aiming to tackle the multifaceted nature of fake news in a more comprehensive manner.

Ethic Statement

This research involves generating and analyzing potentially harmful misinformation. Our released MegaFake dataset also includes the examples of LLM-generated fake news. Our aim is to advance the research to combat fake news. However, open dissemination risks the misuse of the generated disinformation in MegaFake dataset and the methods that enabled such generation.

Hence, it is crucial to consider the potential negative social and ethical implications of our research. First, the pipeline we proposed for generating fake news in batches could potentially be misused by malicious actors to produce fake news. To mitigate this risk, we will provide access to our code only upon request. Applicants must clearly state their intended use and promise themselves that they will only use this dataset for research purpose, and we will restrict access to those engaged in academic and legitimate research endeavors. This ensures

that our work is used responsibly and ethically. Besides, as we released the prompts for generating fake news by LLMs, it is also crucial to consider the potential misuse of our prompts. To address this issue, we refined the prompt format and the question-answering iterations to facilitate the extensive generation of fake news. The specifics of this adjustment process will be kept confidential. Our study underscores the capacity of these prompts to stimulate the generation of fake news by the model. Future iterations could incorporate mechanisms to identify such prompts, thus mitigating the risk of their misuse for the widespread dissemination of fabricated news. Merely employing a prompt for a large language model to produce fake news may not yield the intended outcome and could result in non-response.

We believe that the elucidation provided in this statement effectively communicates our intentions and values. Effectively addressing the societal perils associated with disinformation demands a proactive approach in formulating solutions. However, it is imperative that such endeavors are undertaken with a conscientious and ethical framework. This ethical imperative underscores the need for careful consideration of the potential ramifications of our actions in combating disinformation. It is through this thoughtful and principled approach that we can truly make a meaningful impact in safeguarding the integrity of information dissemination.

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A Appendix

A.0.1 Considerations for Using the Data

The proposed theory-driven pipeline for generating fake news using LLMs offers significant value beyond binary classification tasks. The dataset's utility is evident in multiple areas:

Sub-labeled Detection Tasks: Our dataset facilitates the detection of LLM-generated fake news and various types of fake news. As detailed in **Section A.6**, our results indicate that detecting these sub-labeled categories remains challenging.

Linguistic Analysis: We provide a preliminary analysis in **Section A.5**, highlighting the linguistic differences between LLM-generated and human-written fake news. The dataset reveals distinct linguistic features compared to human-written fake

news, which future research can further explore.

Social Impact Analysis: The potential misclassification of LLM-generated content raises concerns about its social implications. If LLM-generated legitimate news is misclassified as fake, it could affect the perceived trustworthiness of LLMs. Future studies should address these social aspects to mitigate such impacts.

A.0.2 Dataset Structure

Data Format and Structure: The dataset comprises six different types, each defined by a unique JSON file named after its respective type. Each JSON file includes multiple news entries, structured as a dictionary of dictionaries. The outer dictionary's keys are news IDs, and each news ID maps to another dictionary containing various details about the news, such as the news text, news labels, generated text, and additional relevant information. The next section will provide a detailed list of all data fields used in the dataset.

Data Instances: Our dataset comprises six categories, each corresponding to a JSON file. The format of the JSON files is as follows:

megafake-1_style_based_fake.json

```

1 {
2     "megafake-887580": {
3         "origin_id": "...",
4         "origin_label": "...",
5         "origin_text": "...",
6         "generated_text": "...",
7         "generated_tone": "...",
8         "generated_label": "..."
9     }
10 }
```

megafake-2_content_based_fake.json

```

1 {
2     "megafake-923871": {
3         "origin_id": "...",
4         "origin_label": "...",
5         "origin_text": "...",
6         "generated_text_glm4": "..."
7     }
8 }
```

megafake-3_integration_based_fake_tn200.json

```

1 {
2     "megafake-893960_megafake
3         -1783348927": {
4             "doc_1_id": "...",
5             "doc_1_label": "...",
6             "doc_1_text": "...",
7             "doc_2_id": "...",
8             "doc_2_label": "...",
9             "doc_2_text": "...",
10            "generated_text": "..."
11        }
12 }
```

megafake-4_story_based_fake.json

```

1 {
2     "megafake-8889799564": {
3         "origin_id": "...",
4         "origin_label": "...",
5         "origin_text": "...",
6         "origin_title": "...",
7         "generated_text": "..."
8     }
9 }
```

megafake-5_style_based_legitimate.json

```

1 {
2     "megafake-853036": {
3         "origin_id": "...",
4         "origin_label": "...",
5         "origin_text": "...",
6         "generated_label": "...",
7         "generated_text_t015": "..."
8     }
9 }
```

megafake-7_integration_based_legitimate_tn300.json

```

1 {
2     "megafake-898900_megafake-907781": {
3         "topic_id": 0,
4         "topic_words": [
5             "...", "...", "...", "...", "...",
6             "...", "...", "...", "...", "...",
7             "...", "...", "...", "...", "..."],
8         "doc_1_id": "...",
9         "doc_1_label": "...",
10        "doc_1_text": "...",
11        "doc_2_id": "...",
12        "doc_2_label": "...",
13        "doc_2_text": "...",
14        "generated_label": "...",
15        "generated_text_t01": "..."
16    }
17 }
```

Data Fields: The dataset comprises six different types, each corresponding to a JSON file containing different fields.

1. **megafake-1_style_based_fake.json** contains the following fields: origin_id, origin_label, origin_text, generated_text, generated_tone, generated_label.
2. **megafake-2_content_based_fake.json** contains the following fields: origin_id, origin_label, origin_text, generated_text_glm4.
3. **megafake-3_integration_based_fake_tn200.json** contains the following fields: doc_1_id, doc_1_label, doc_1_text, doc_2_id, doc_2_label, doc_2_text, generated_text.

4. **megafake-4_story_based_fake.json** contains the following fields: origin_id, origin_label, origin_text, generated_text.
5. **megafake-5_style_based_legitimate.json** contains the following fields: origin_id, origin_label, origin_text, generated_label, generated_text_t015.
6. **megafake-7_integration_based_legitimate_tn300.json** contains the following fields: topic_id, topic_words, doc_1_id, doc_1_label, doc_1_text, doc_2_id, doc_2_label, doc_2_text, generated_label, generated_text_t01.

The dataset comprises six different types:

- **megafake-1_style_based_fake.json:** 15,729 news items.
- **megafake-2_content_based_fake.json:** 11,941 news items.
- **megafake-3_integration_based_fake_tn200.json:** 2,697 news items.
- **megafake-4_story_based_fake.json:** 15,421 news items.
- **megafake-5_style_based_legitimate.json:** 11,945 news items.
- **megafake-7_integration_based_legitimate_tn300.json:** 5,926 news items.

A.1 Additional Details on MegaFake Dataset Construction

A.1.1 Dataset Preprocessing

We begin by assembling a dataset of human-generated legitimate and fake news. We consider the GossipCop dataset from the FakeNewsNet data repository, which includes both news articles and associated Twitter data reflecting social interactions. For our study, we focus solely on the news articles, excluding the Twitter data to maintain relevance to our research objective. We extract 16,817 instances of legitimate news and 5,323 instances of fake news from the GossipCop dataset. To ensure data quality, we first remove articles that lack either a title or news content. We then address variations in article length by eliminating the shortest and longest 10% of the articles to standardize the length of the news content. After these data

preprocessing steps, our refined dataset consists of 11,945 legitimate news articles and 3,784 fake news articles, which will aid in the construction of LLM-generated content.

A.1.2 Detailed LLM-Fake Theory

Table 7 and **Table 8** present the LLM-Theory and the corresponding prompts.

A.1.3 The Process of Constructing the MegaFake dataset

Sheep’s Clothing: Style-Based LLM-Generated Fake News

We utilized ChatGLM3-6b-32k to alter the stylistic presentation of news articles. Our dataset comprised 11,945 legitimate news articles and 3,784 fake news articles, all of which were human-generated. Each article was paired with a corresponding prompt to guide the style transformation. By processing these inputs through ChatGLM3-6b-32k, we generated a total of 15,729 LLM-rephrased news articles. Legitimate news articles were rewritten in a sensational style, while fake news articles were rewritten in an objective and neutral style.

A.1.4 Content Manipulation: Content-Based LLM-Generated Fake News

To guide the content manipulation process, we designed a specific prompt aimed at investigating how LLMs could transform legitimate news into fake news by systematically altering key attributes. We employed the GLM-4 model to direct the content modification of selected articles from a dataset comprising 11,945 human-generated legitimate news articles. This process resulted in the successful generation of 11,941 LLM-manipulated news articles. Four articles were excluded from this analysis because they were flagged as “containing sensitive content”, which impeded the model’s ability to produce coherent results for these instances. Our objective was to modify aspects such as events, statements, actions, and numerical quantities to create fake news narratives.

A.1.5 Information Blending: Integration-Based LLM-Generated Fake News

We leveraged the ChatGLM3-6b-32k to generate synthetic fake content by integrating pairs of human-generated fake and legitimate news articles. Initially, we conducted a topic coherence analysis to identify pairs of human-generated fake and legitimate news articles with similar content and topics.

Table 7: Four Types of LLM-Generated Fake News.

News Type	Definition	Theory	Prompt Template Example
Sheep’s Clothing (Wu and Hooi 2023)	Utilize a LLM to rephrase legitimate news in the style of tabloids or fake news in the style of mainstream sources.	Linguistic Signaling Theory (Chen et al. 2020)	<p>For a human-generated fake news article as an input:</p> <ol style="list-style-type: none"> Rewrite the following news article in an objective and professional tone without changing the content and meaning while keeping a similar length. <p>[fake news article]</p> <ol style="list-style-type: none"> Rewrite the following news article in a neutral tone without changing the content and meaning while keeping a similar length. <p>[fake news article]</p> <p>For a human-generated legitimate news article as an input:</p> <ol style="list-style-type: none"> Rewrite the following news article in an emotionally triggering tone without changing the content and meaning while keeping a similar length. <p>[legitimate news article]</p> <ol style="list-style-type: none"> Rewrite the following news article in a sensational tone without changing the content and meaning while keeping a similar length. <p>[legitimate news article]</p>
Content Manipulation (Satapara et al. 2024)	Utilize a LLM to manipulate human-generated legitimate news content by modifying multiple attributes.	Elaboration Likelihood Model (Petty and Briñol 2011)	<p>For a human-generated legitimate news article as an input:</p> <p>Modify the attributes, such as events, statements, actions, and numerical quantities, in the following news article by minimizing the editing and keeping the same language style and a similar length.</p> <p>[legitimate news article]</p>
Information Blending	Utilize a LLM to integrate fake and legitimate news for creating new fake content.	Cognitive Dissonance Theory (Hinojosa et al. 2017)	<p>For a pair of human-generated fake and legitimate news articles on comparable subjects as an input:</p> <p>Amalgamate the following two news articles into a new and cohesive article while keeping a similar length.</p> <p>[fake news article], [legitimate news article]</p>
Narrative Generation (Schuster et al. 2020, Zhou et al. 2023)	Utilize a LLM to generate fake news from a certain message.	Narrative Theory (Chatman 1975)	<p>For either a human-generated fake or legitimate news article as an input:</p> <p>Write a news article based on the following message and return the body content only.</p> <p>[news article title]</p>

Table 8: Two Types of LLM-Generated Legitimate News.

News Type	Definition	Prompt Template Example
Writing Enhancement (Rossi et al. 2024, Susarla et al. 2023, Wu et al. 2023, Yang et al. 2023)	Utilize a LLM to polish legitimate news while preserving the original information and context.	For a human-generated legitimate news article as an input: Polish the following news article to make it more objective and professional. Do not change the original meaning. Do not add extra information or delete certain information. [legitimate news article]
News Summarization (Luo et al. 2023, Wu et al. 2023, Zhang et al. 2023)	Utilize a LLM to condense various legitimate news into a synthesized, credible news summary.	For a pair of human-generated legitimate news articles on comparable subjects as an input: Summarize the following two articles into a single, cohesive article, ensuring minimal loss of information without significantly shortening the overall length. [legitimate news article 1], [legitimate news article 2]

(Detailed in [section A.2.1](#)) We then paired fake and legitimate news articles from the same topics based on their rankings, excluding any unmatched articles. This process yielded 2,697 pairs of matched fake and legitimate news articles. Each pair, accompanied by a corresponding prompt, was input into ChatGLM3 to generate synthetic fake news articles, resulting in a total of 2,697 LLM-generated articles.

A.1.6 Narrative Generation: Story-Based LLM-Generated Fake News

We designed a prompt to generate news articles from specific messages using the ChatGLM3-6b-32k. Utilizing 11,945 legitimate and 3,784 fake human-generated news articles, we treated each article title as a prompt for the story generation process, aiming to produce fake news articles that maintained thematic consistency with the original titles. This approach resulted in the successful generation of 15,729 news articles, categorized as story-based LLM-generated fake news.

A.1.7 Writing Enhancement: Improvement-Based LLM-Generated Legitimate News

We employed the ChatGLM3-6b-32k to enhance news content, focusing on increasing objectivity and professionalism without compromising factual accuracy. To minimize the occurrence of hallucinations—instances where the model generates plausible but non-factual content—we conducted a series of experiments using temperature sampling, a technique commonly employed to manage the diversity of LLM outputs. (Detailed in [section A.3.1](#))

Consequently, each of the 11,945 human-generated articles was processed through ChatGLM3 using this temperature setting and a specially designed prompt, resulting in a collection of 11,945 polished LLM-generated legitimate news articles.

A.1.8 News Summarization: Summary-Based LLM-Generated Legitimate News

We initiated our study by conducting a topic coherence analysis on 11,945 legitimate news articles to identify pairs of articles with similar content and topics. Then paired to form 5,926 pairs of news articles, discarding any unmatched articles. (Detailed in [section A.2.2](#)) To produce coherent and factually accurate summaries, it is also crucial to manage the risk of hallucination errors, where LLMs might generate plausible but inaccurate content. To mitigate this, we employed temperature sampling, similar to our approach for generating writing-enhanced legitimate news. (Detailed in [A.3.2](#)) Based on this temperature setting, we used ChatGLM3-6b-32k to synthesize pairs of legitimate news articles on the same topic, ultimately generating 5,926 new legitimate news articles.

A.1.9 Generation Model Selection

When we first proposed the theory-driven pipeline and generated preliminary data sets, we used the ChatGLM3 model. However, after the first round of generation, we hired some people to conduct manual evaluation. We found that the ChatGLM3 model performed very poorly on the content manipulation news type, so we switched to the GLM4 model to regenerate the content manipulation news type. Due to cost reasons, we retained other cate-

gories generated by the ChatGLM3 model. According to our observations, this phenomenon may be caused by the ChatGLM3 model’s poor understanding of numbers, because in the process of content manipulation, the ChatGLM3 model is basically unable to randomly replace the numerical attributes in the news. Therefore, future research can use our pipeline to generate LLM-generated fake news on different models, or different versions of the same model, and compare them to explore the ability differences of LLM in such tasks.

A.2 Topic Analysis

In this section, we present the analysis metrics and results for topic modeling. The topic model we used are as follows: [GitHub - Neural Topic Models](#).

A.2.1 Topic Analysis for Information Blending

We conducted experiments with various topic numbers to identify the optimal setting for our analysis. The topic numbers selected for evaluation were {5, 20, 50, 75, 100, 125, 150, 175, 200, 250, 300, 500}. The results of these experiments are illustrated in **Figure 2**. After a thorough evaluation, we determined that a topic number of 200 ($n_topic=200$) was optimal based on our topic model results. For each topic, we calculated the document-to-topic probabilities, which represent the likelihood of each document belonging to a particular topic, and assigned each document to the topic with the highest probability. To maintain robust representation, we excluded topics containing fewer than five documents. Within the remaining topics, we separated the fake and legitimate news articles, ranked them by their respective probabilities, and discarded any unmatched data. **Figure 3** illustrates the document matching process.

Finally, to evaluate the coherence of the topics generated by the model, we use the following command:

```
python WTM_run.py --taskname megafake-3-integration-based-fake --n_topic 200 --num_epochs 300 --no_below 0 --no_above 0.3 --dist gmm-ctm --lang en --auto_adj
```

A.2.2 Topic Analysis for News Summarization

We also conducted experiments with various topic numbers to identify the optimal setting for our analysis. The topic numbers selected for evaluation were {20, 50, 75, 100, 125, 150, 175, 200, 300,

400, 500}. The results of these experiments are illustrated in **Figure 5**. After thorough evaluation, we determined that 300 ($n_topic=300$) was the optimal number of topics. Using this topic model, we calculated the document-to-topic probabilities and assigned each article to the topic with the highest probability. To ensure substantial content representation in each category, we eliminated any topics containing fewer than five articles. The remaining articles were then sorted by their probability scores and divided into two groups based on odd and even indices, with any remaining items discarded. **Figure 4** illustrates the document matching process.

Finally, the main operations are similar to Topic Analysis for Information Blending. The command is as follows:

```
python WTM_run.py --taskname megafake-3-integration-based-legitimate --n_topic 300 --num_epochs 300 --no_below 0 --no_above 0.3 --dist gmm-ctm --lang en --auto_adj
```

A.3 Selecting Temperature to Mitigate Hallucinations

In this section, we present the analysis metrics and results for LLM temperature selection. Temperature settings influence the randomness of prediction outcomes, with higher temperatures leading to more diverse outputs but also increasing the risk of hallucinations.

A.3.1 Selecting Temperature for Writing Enhancement

For our experiment, we selected a subset of 1,000 articles from an initial pool of 11,945 human-generated legitimate news articles and tested various temperature settings: {0.05, 0.1, 0.15, 0.2, 0.25, 0.3}. Each article, along with a corresponding prompt, was processed through ChatGLM3-6b-32k at these settings, and the resulting outputs were thoroughly analyzed. We evaluated the risk of hallucination for each temperature setting using the ROUGE metric, which measures the overlap of n-grams between the LLM-generated text and the original text. A lower ROUGE score may indicate a higher risk of hallucination due to reduced content overlap. Our findings revealed that a temperature setting of 0.15 consistently yielded the highest ROUGE scores, suggesting an optimal balance between diversity and factual accuracy. Based on these results, we selected a temperature setting of 0.15 ($t = 0.15$) for the final generation of our

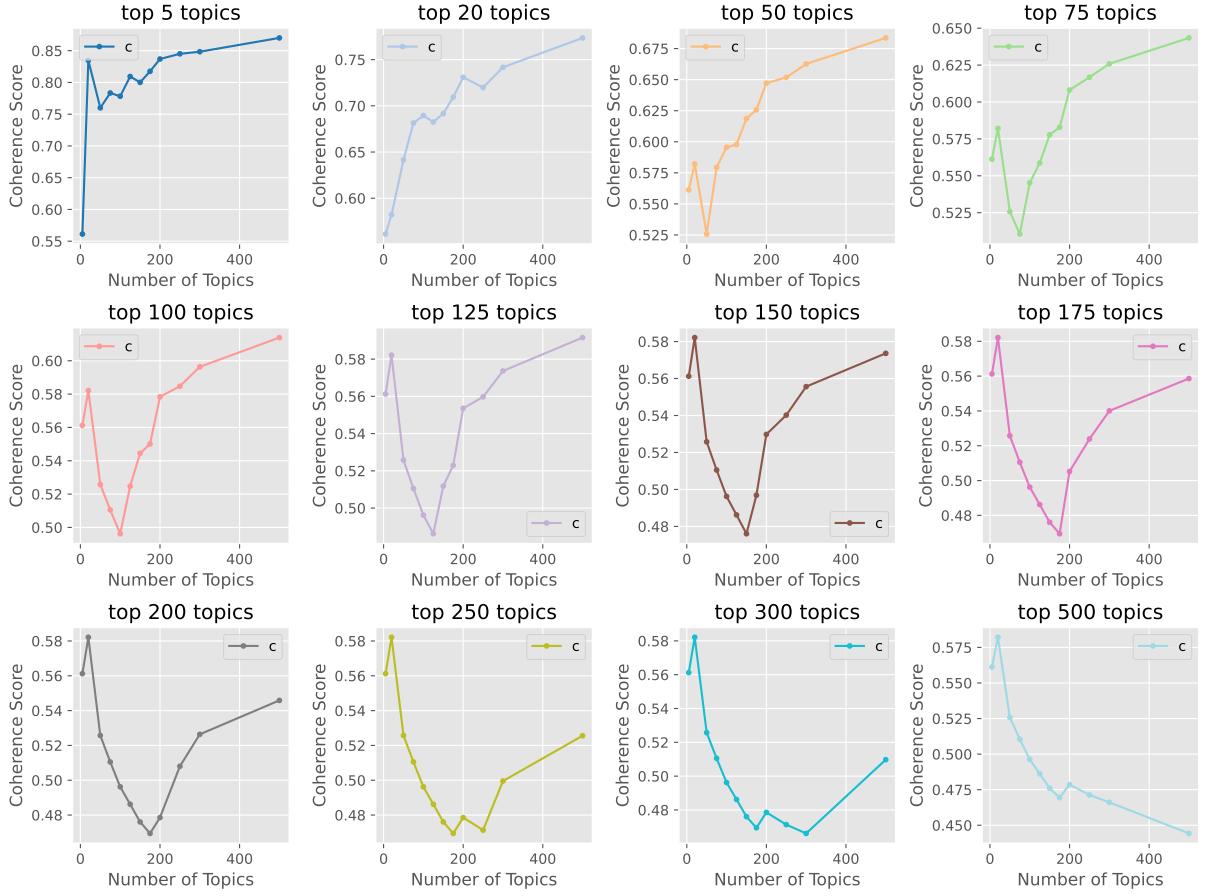


Figure 2: Results for Different Topic Numbers (Information Blending)

writing-enhanced LLM-generated legitimate news articles. The results are shown in the **Figure 6**.

A.3.2 Selecting Temperature for News Summarization

Similar to selecting temperature for writing enhancement, we randomly selected 592 pairs from the total of 5,926 and tested various temperature settings: {0.05, 0.1, 0.15, 0.2, 0.25, 0.3}. Each pair, along with a corresponding prompt, was processed by ChatGLM3-6b-32k under these settings. The outputs were evaluated using the ROUGE metric. Our analysis indicated that a temperature of 0.1 ($t = 0.1$) consistently achieved the highest ROUGE scores, suggesting it optimally balances diversity and factual accuracy. The results are shown in the **Figure 7**.

A.4 Human Evaluation

To enhance the credibility and quality assessment of the generated fake news articles, human evaluation plays a crucial role in providing valuable insights. Therefore, we engaged individuals to conduct manual assessments of the dataset post-

generation. This involved the random selection of news samples for authenticity verification, thereby significantly reducing potential errors and ensuring the reliability of the dataset. The inclusion of human evaluators in this process adds a critical layer of validation and contributes to the robustness of our findings.

A.5 Detailed Dataset Statistics and Analysis

In this section, we provide additional dataset statistics and analysis.

A.5.1 Word Clouds Analysis

Initially, we generate word clouds for MegaFake and GossipCop datasets to facilitate a comparative analysis (**Figure 8**). Concurrently, we create word clouds for the six different types of news data within MegaFake dataset (**Figure 9**). Through the analysis of these word clouds, we can draw meaningful conclusions regarding the linguistic and thematic characteristics of the datasets.

Word Clouds Analysis of GossipCop and MegaFake Datasets (Figure 8)

Figure 8 presents word clouds for the GossipCop

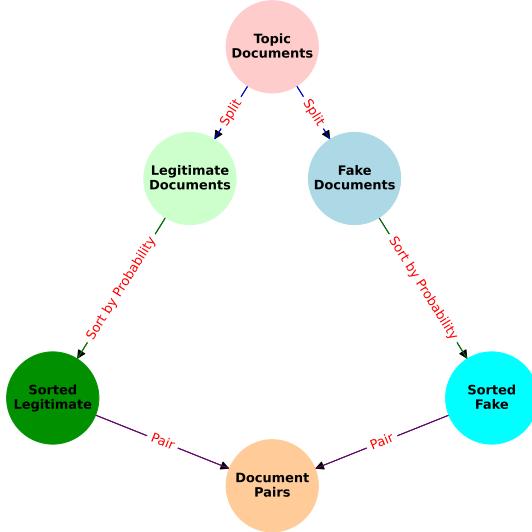


Figure 3: Document Matching Process (Information Blending)

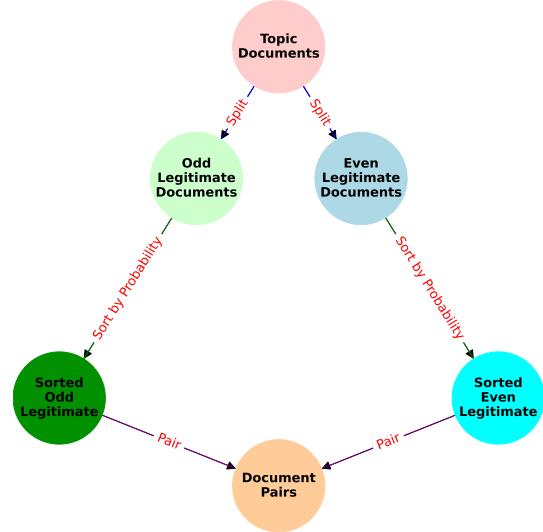


Figure 4: Document Matching Process (News Summarization)

and MegaFake datasets, providing a visual representation of the most frequently occurring words within each dataset. The word cloud for GossipCop highlights prominent terms such as "said," "time," "year," "love," "family," and "show." These words suggest a focus on reported speech, temporal references, and themes related to personal relationships and celebrity lifestyles. The frequent appearance of terms like "said" and "show" indicates a narrative style centered on quotations and events, characteristic of gossip and entertainment news.

In contrast, the word cloud for the MegaFake dataset features terms such as "said," "time," "one," "show," "relationship," "fan," and "love." Similar to GossipCop, this dataset emphasizes reported speech and temporal elements. However, the presence of words like "relationship," "fan," and "revealed" suggests a stronger focus on interpersonal dynamics and revelations, which are often employed to fabricate sensational stories.

By analyzing these word clouds, we can infer that both datasets share common thematic elements related to entertainment and personal relationships. However, the MegaFake dataset appears to place a greater emphasis on creating narratives around relationships and sensational revelations, which aligns with its purpose of generating fake news. The overlap in frequent terms between the two datasets underscores the challenge of distinguishing fake news from legitimate gossip content, as both employ similar linguistic strategies to engage readers.

Word Clouds Analysis of Six Different News

Types in MegaFake Dataset (Figure 9)

Figure 9 presents word clouds for six different types of news articles within the MegaFake dataset. The word clouds provide a visual representation of the most frequently occurring words in each category, offering insights into the thematic and linguistic characteristics of the news articles. The categories include Story-Based Fake, Style-Based Fake, Content-Based Fake, Integration-Based Fake, Integration-Based Legitimate, and Style-Based Legitimate news articles.

Story-Based Fake: The word cloud for Story-Based Fake news articles highlights prominent terms such as "said," "love," "show," "will," "couple," and "relationship." These words suggest a focus on personal relationships, celebrity life, and future events. The frequent use of the word "said" indicates a reliance on reported speech, which is a common narrative technique in fake news to create a sense of credibility.

Style-Based Fake: In the Style-Based Fake category, the dominant words include "show," "world," "relationship," "family," "said," and "will." Similar to Story-Based Fake news, these articles emphasize themes of personal relationships and events. The presence of words like "world" and "family" indicates a broader scope, potentially targeting a wider audience by incorporating universal themes.

Content-Based Fake: The word cloud for Content-Based Fake news articles features terms such as "new," "love," "show," "one," "said," and "relationship." This category also emphasizes per-

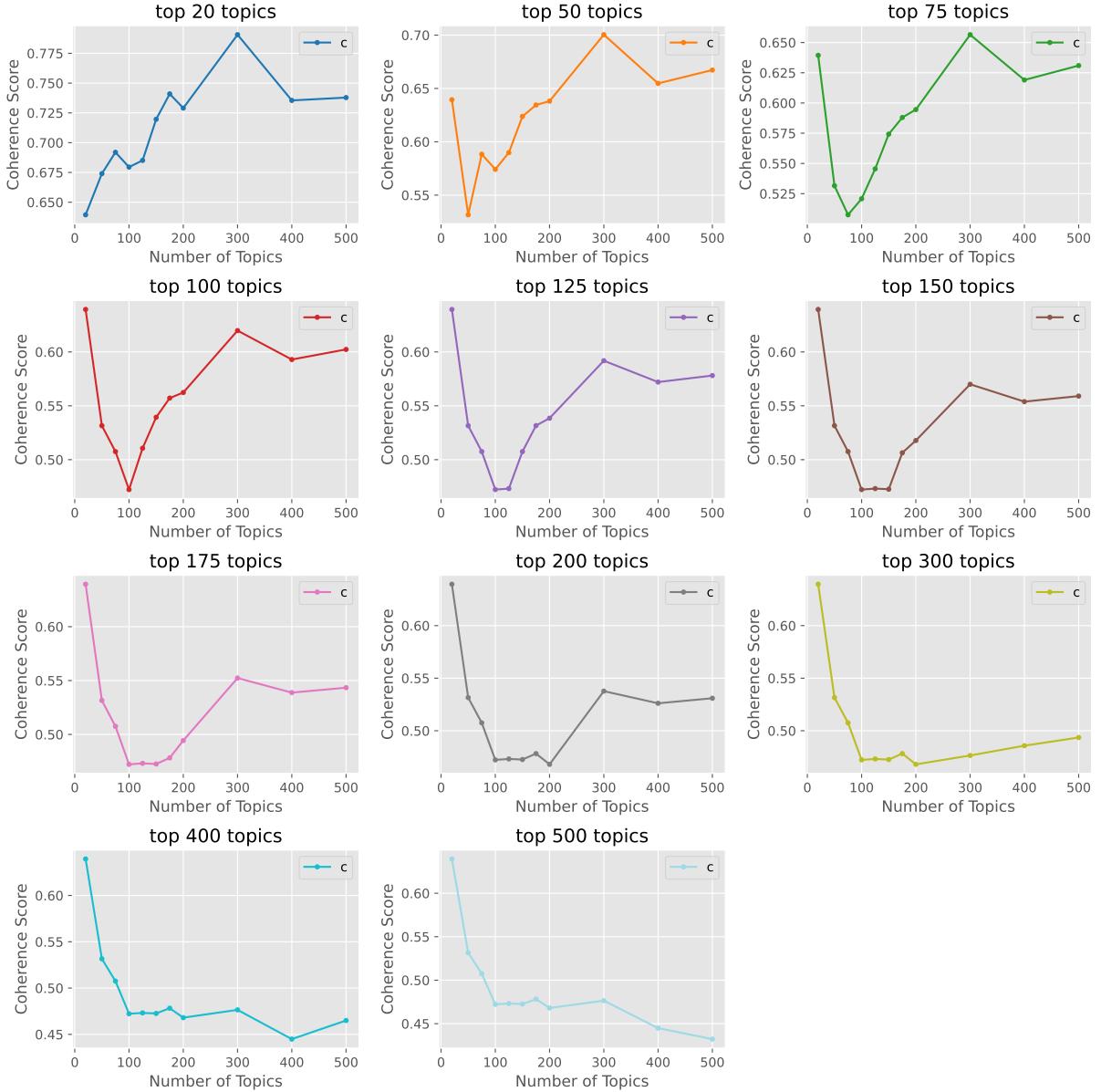


Figure 5: Results for Different Topic Numbers (News Summarization)

sonal relationships and events, but the inclusion of "new" suggests a focus on recent or emerging stories, aiming to capture reader interest with timely content.

Integration-Based Fake: Integration-Based Fake news articles exhibit frequent terms like "will," "couple," "relationship," "show," "despite," and "one." The prominence of "will" and "despite" indicates a narrative style that incorporates future predictions and contrasts, which are often used to create intrigue and drama in fake news.

Integration-Based Legitimate: For Integration-Based Legitimate news articles, the word cloud highlights terms such as "said," "will," "new," "love," "star," and "family." This category shares

thematic similarities with fake news but places more emphasis on reported speech and future events. The presence of "star" suggests a focus on celebrity news, which is a common topic in legitimate news articles as well.

Style-Based Legitimate: The Style-Based Legitimate category features words like "show," "one," "film," "time," "relationship," and "couple." These articles emphasize entertainment and personal relationships, similar to their fake counterparts. However, the inclusion of "film" and "time" indicates a broader range of topics, including media and temporal elements.

The comparative analysis of these word clouds reveals that both fake and legitimate news articles

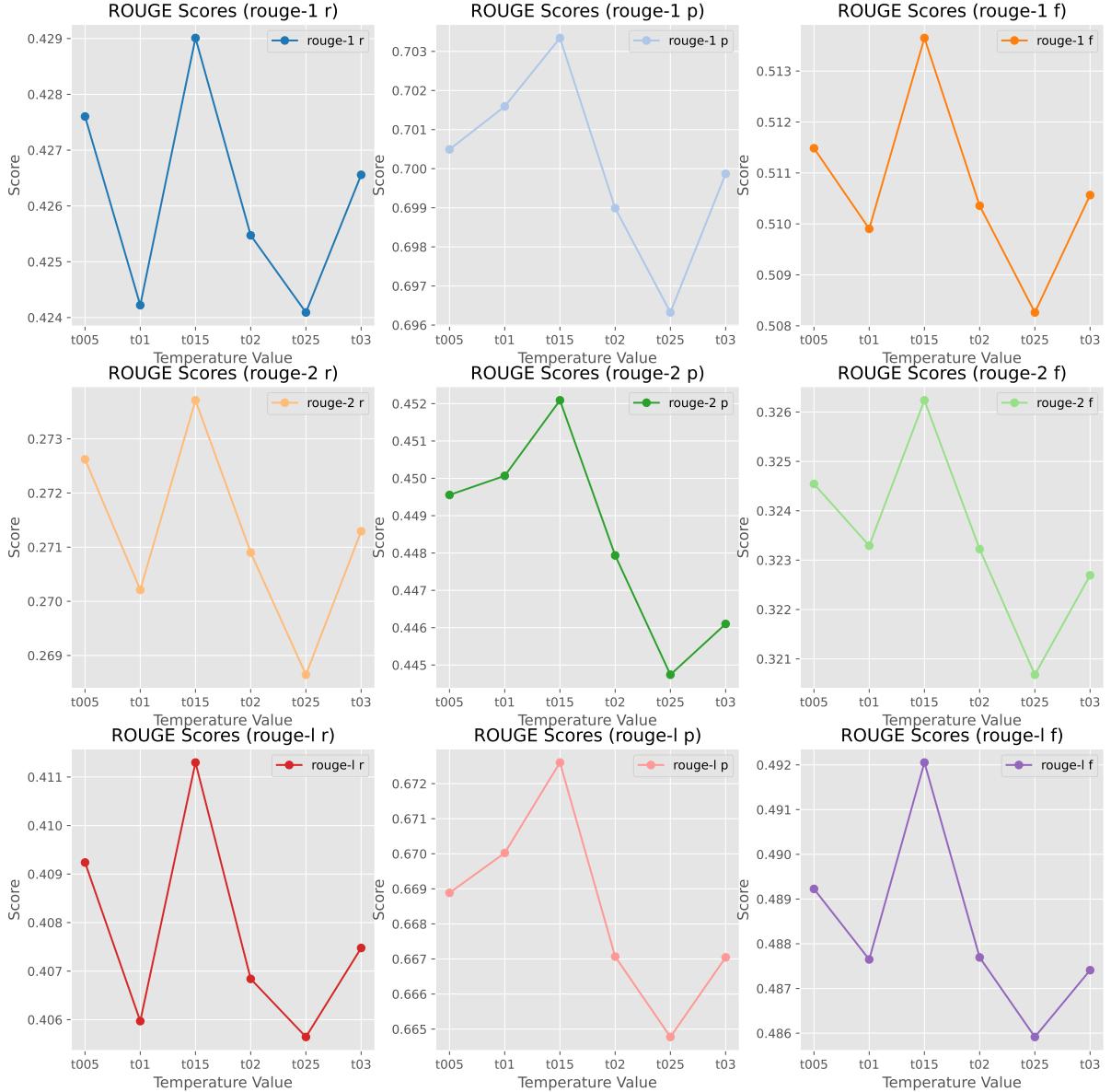


Figure 6: Results for Different Temperatures (Writing Enhancement)

in the MegaFake dataset share common thematic elements, particularly related to personal relationships and entertainment. However, fake news articles tend to focus more on creating sensational narratives with frequent use of future predictions and contrasts. In contrast, legitimate news articles incorporate a wider range of topics and maintain a consistent use of reported speech, enhancing their credibility.

These findings underscore the challenge of distinguishing fake news from legitimate news based solely on thematic and linguistic characteristics. The overlap in common terms suggests that sophisticated methods are required to detect subtle differences in narrative style and content structure.

Understanding these nuances is crucial for developing more effective fake news detection systems and improving the quality of automated news generation.

A.5.2 Detailed Dataset Analysis

Figures 10 and 11 present comparative analyses of sentence count and word count densities across various categories of fake and legitimate news articles in the GossipCop and MegaFake datasets, as well as across six different types of news articles within the MegaFake dataset. These figures include density histograms (top row) and bar charts (bottom row) that collectively illustrate the distribution and average statistics of sentences and words in different types of news articles.

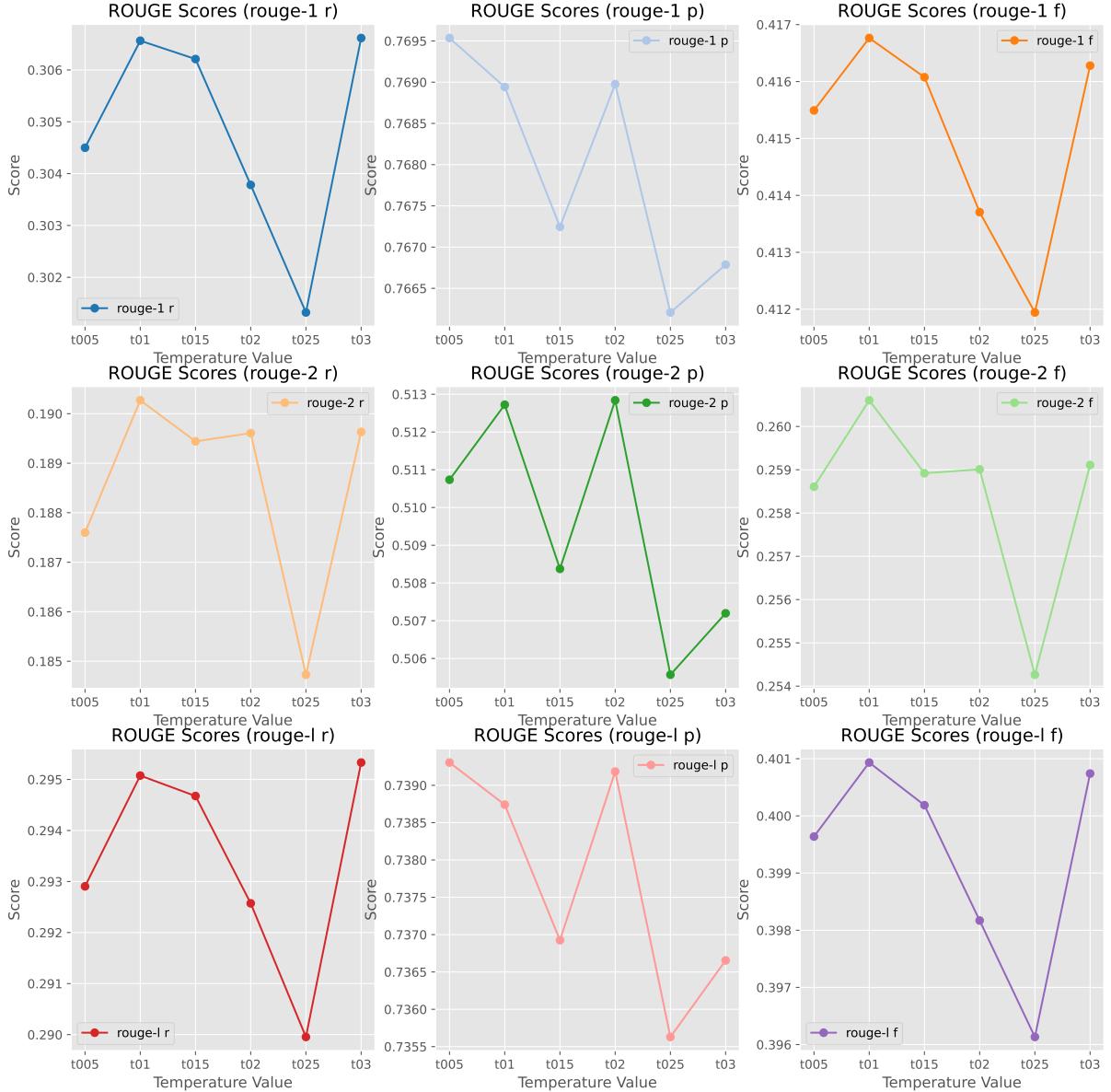


Figure 7: Results for Different Temperatures (News Summarization)

Analysis of GossipCop and MegaFake Datasets (Figure 10)

The density histograms in **Figure 10** reveal the distribution of sentence counts (left) and word counts (right) for four categories: LLM-Fake (LLM-generated fake news), Human-Fake (human-generated fake news), which belong to MegaFake dataset, and LLM-Legitimate (LLM-generated legitimate news), Human-Legitimate (human-generated legitimate news), which belong to GossipCop dataset. The densities indicate that human-generated news articles, both fake and legitimate, tend to have a wider distribution of sentence and word counts compared to LLM-generated articles. This observation suggests that

human-authored articles exhibit greater variability in length, potentially reflecting more nuanced and complex narrative structures.

The bar charts provide average statistics for the number of sentences and words in each category. The left bar chart shows that Human-Legitimate articles have the highest average sentence count, followed closely by Human-Fake articles. In contrast, LLM-generated articles (both fake and legitimate) have significantly lower average sentence counts. Similarly, the right bar chart indicates that Human-Legitimate articles also have the highest average word count, whereas LLM-generated articles have notably fewer words on average.

These findings are corroborated by the data in



Figure 8: Word Clouds of the GossipCop and MegaFake Datasets



Figure 9: Word Clouds of Six Different News Types in MegaFake Dataset

Table 9, which provides detailed statistics for each category. Human-Legitimate articles have the highest average sentences (19.69) and words (489.99), reflecting their comprehensive and detailed nature. Human-Fake articles, while slightly shorter, still maintain a relatively high average sentence (17.88) and word (447.85) count. In contrast, LLM-generated articles, particularly those categorized as LLM-Legitimate, have markedly lower averages in both sentences (10.02) and words (241.07), indicating a more concise and possibly less detailed narrative structure.

The analysis of sentence and word length (average number of words per sentence) further emphasizes these differences. Human-generated articles tend to have longer sentences, with Human-Legitimate articles averaging 119.72 words per sentence and Human-Fake articles averaging 120.74 words per sentence. LLM-generated articles, however, have shorter sentences, with LLM-Legitimate articles averaging 122.01 words per sentence and LLM-Fake articles averaging 115.06 words per sentence.

Overall, this comparative analysis highlights sig-

nificant differences in the narrative complexity and length of human-generated versus LLM-generated news articles. The variability and length of human-authored content suggest a richness and depth that current LLM-generated models have yet to fully replicate. These insights are crucial for understanding the limitations and capabilities of automated news generation systems and for developing more sophisticated and nuanced models in the future.

Analysis of Six Different News Types in MegaFake Dataset (Figure 11)

Figure 11 extends this analysis by examining sentence count and word count densities across six different types of news articles within the MegaFake dataset: Style-Based, Content-Based, Integration-Based, Story-Based, Improved-Based, and Summary-Based.

The density histograms reveal the distribution of sentence counts (left) and word counts (right) for each news type. The sentence count histogram shows that the majority of articles in all categories contain fewer than 40 sentences, with notable peaks around 10 sentences. This indicates a tendency towards shorter articles across all categories. How-

ever, the Content-Based category shows a slightly broader distribution, suggesting that these articles tend to be longer on average compared to other types.

Similarly, the word count histogram indicates that most articles have fewer than 1,000 words, with a significant concentration around 200 to 400 words. The Content-Based category again stands out with a broader distribution, reflecting the higher word count observed in these articles.

The bar charts provide average statistics for the number of sentences and words in each category. The left bar chart shows that Content-Based articles have the highest average sentence count, followed by Integration-Based and Style-Based articles. This suggests that Content-Based articles are generally more detailed and comprehensive. The right bar chart shows that Content-Based articles also have the highest average word count, reinforcing the observation that these articles tend to be longer and more detailed.

Table 9 provides detailed statistics that support these findings. Content-Based articles have the highest average sentences (17.38) and words (398.22), indicating their comprehensive nature. Style-Based and Integration-Based articles follow, with average sentences of 12.68 and 12.35, and average words of 291.19 and 308.08, respectively. Story-Based, Improved-Based, and Summary-Based articles are shorter, with lower averages in both sentences and words.

The analysis of sentence length (average number of words per sentence) and word length (average number of characters per word) further highlights these differences. Content-Based articles have an average sentence length of 115.44 words and word length of 4.27 characters, indicating detailed and information-rich content. In contrast, Summary-Based articles have shorter sentences (129.10 words) but slightly longer words on average (4.29 characters), reflecting a concise yet precise writing style.

Overall, this comparative analysis underscores the variability in article length and detail across different types of news within the MegaFake dataset. Content-Based articles stand out for their comprehensiveness and detail, while other categories, such as Story-Based and Summary-Based, are more concise. These insights are critical for understanding the content characteristics of various news types and for developing targeted strategies to generate or detect specific kinds of news articles.

A.5.3 Detailed Analysis of Sentence Length and Word Length

Analysis of GossipCop and MegaFake Datasets (Figure 12)

Figures 12 compares the pair-wise distribution of sentence counts and word counts, revealing notable patterns in the structural composition of news articles. The distributions for LLM-generated fake (LF) and legitimate (LL) news articles exhibit remarkable similarity, suggesting that LLM-generated articles, regardless of authenticity, share significant structural characteristics. In contrast, human-generated fake (HF) and legitimate (HL) news articles display a pronounced disparity, indicating that the veracity of such articles might be more easily distinguishable based on length distribution. Additionally, there is a notable discrepancy in the distribution between LL and HL subclasses.

Although the dataset statistics highlight a distributional discrepancy between human-written and LLM-generated legitimate and fake news, this might currently aid in fake news detection. However, as journalists increasingly adopt LLMs in their writing, the distribution of legitimate news articles may gradually shift towards that of LLM-generated articles (LF and LL). This shift could eventually lead to a convergence where the distributions of legitimate and fake news articles closely resemble each other once again.

The comparative analysis of these density histograms underscores significant differences in the narrative complexity and length of human-generated versus LLM-generated news articles, as well as between fake and legitimate news articles. Human-generated articles, both fake and legitimate, tend to have a wider distribution and higher counts in terms of sentences and words, reflecting their greater variability and depth. In contrast, LLM-generated articles, particularly those categorized as fake, are generally shorter and less complex.

These findings highlight the challenges faced by automated systems in replicating the nuanced and detailed nature of human-authored content. The variability and length of human-generated articles suggest a richness and depth that current LLM-generated models have yet to fully replicate. Such insights are crucial for understanding the limitations and capabilities of automated news generation systems and for guiding the development of more sophisticated and nuanced models in the future.

Analysis of six differnet news types in MegaFake

Table 9: Dataset Statistics.

Category*†	Samples	Avg Sentences	Avg Words	Sent Length	Word Length
Human-Legitimate*	11,945	19.69	489.99	119.72	4.02
Human-Fake*	3,784	17.88	447.85	120.74	4.03
Machine-Legitimate†	17,871	10.02	241.07	122.01	4.28
Machine-Fake†	45,788	13.00	298.58	115.06	4.22
Style-Based Fake†	15,729	12.68	291.19	113.73	4.16
Content-Based Fake†	11,941	17.38	398.22	115.44	4.27
Integration-Based Fake†	2,697	12.35	308.08	126.64	4.27
Story-Based Fake†	15,421	10.04	227.31	113.78	4.22
Improved-Based Legitimate†	11,945	9.83	229.95	118.21	4.27
Summary-Based Legitimate†	5,926	10.40	263.48	129.10	4.29

* GossioCop

† MegaFake.

Dataset(Figure 13)

Figure 13 presents a comprehensive comparative analysis of sentence and word count distributions across six different news types within the MegaFake dataset. The figure comprises 15 sub-figures, each comparing the density histograms of sentence counts and word counts between two distinct news types: Style-Based, Content-Based, Integration-Based, Story-Based, Improved-Based, and Summary-Based. This analysis will highlight several key comparisons to illustrate the important differences and similarities in narrative and structural composition across these categories.

The sentence and word count distributions for Style-Based and Content-Based articles reveal significant differences. Content-Based articles exhibit a much broader distribution, with higher counts in both sentences and words. This indicates that Content-Based articles are generally more comprehensive and detailed, encompassing a wider range of content and potentially more in-depth analysis compared to the more succinct Style-Based articles.

Comparing Content-Based and Integration-Based articles, we observe that Content-Based articles again show a broader distribution and higher counts in sentence and word lengths. Integration-Based articles tend to be more concise but still maintain a relatively broad distribution compared to other categories, suggesting a balance between detail and brevity. This comparison highlights the comprehensive nature of Content-Based articles, which likely cover more extensive topics and pro-

vide more detailed narratives.

The comparison between Story-Based and Improved-Based articles shows that Story-Based articles have a broader distribution and higher counts in both sentences and words. Improvement-Based articles, on the other hand, are significantly more concise. This suggests that Story-Based articles focus on detailed narratives and storytelling elements, while Improved-Based articles prioritize brevity and conciseness, potentially sacrificing some depth for clarity and succinctness.

The density histograms for Integration-Based and Summary-Based articles reveal that Summary-Based articles are the most concise among all categories, with the shortest sentences and word counts. Integration-Based articles show a broader distribution, indicating more detail and complexity. This comparison underscores the summarizing nature of Summary-Based articles, which aim to condense information into brief, easily digestible formats, in contrast to the more detailed and elaborate Integration-Based articles.

The comparative analysis of these density histograms highlights several important trends in the narrative complexity and length of different news types within the MegaFake dataset:

Content-Based Fake News: These articles consistently show the highest counts and broadest distributions in both sentence and word lengths, indicating their comprehensive and detailed nature. This makes them particularly valuable for in-depth analysis and extensive coverage of topics.

Summary-Based Legitimate News: These are

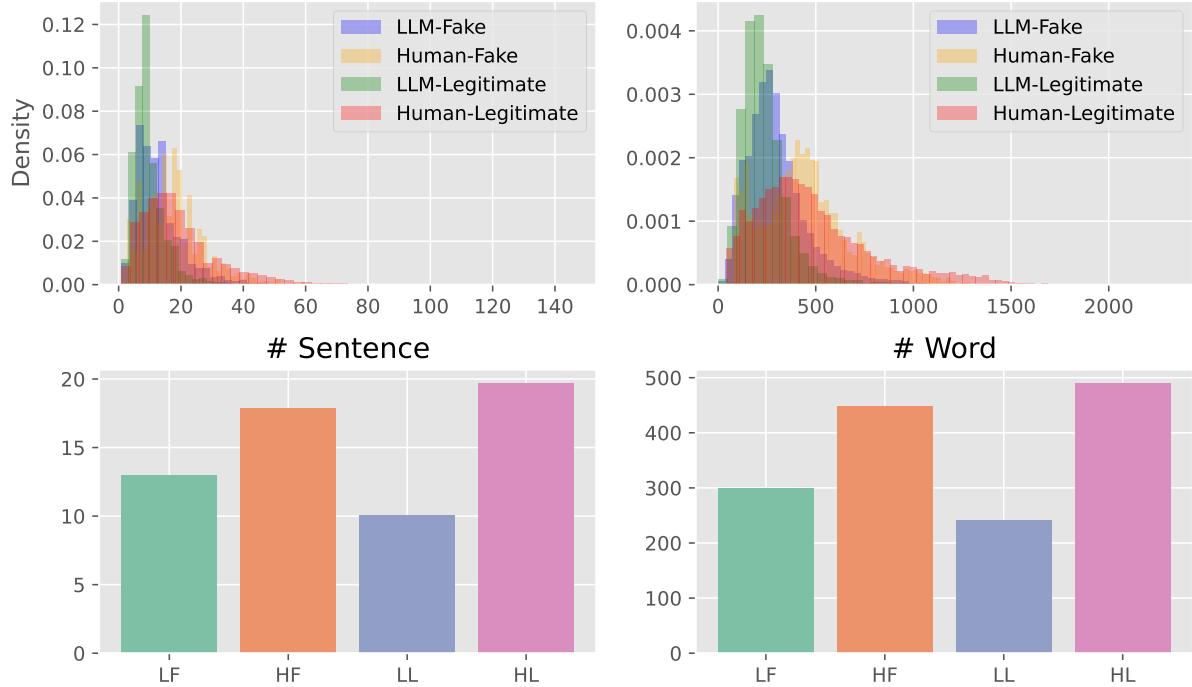


Figure 10: Sentence Count and Word Count Density Histogram for GossipCop and MegaFake Datasets

characterized by their brevity and conciseness, with the shortest sentences and fewest words. They serve the purpose of providing quick, digestible summaries of information, which can be useful for readers seeking rapid updates.

Style-Based and Story-Based Fake News: These categories balance between detail and brevity, with Style-Based articles being more succinct and Story-Based articles emphasizing narrative detail. This suggests that Style-Based articles might focus on stylistic elements and concise reporting, while Story-Based articles prioritize storytelling and detailed narratives.

Integration-Based Fake News: These articles strike a balance between the comprehensiveness of Content-Based articles and the brevity of Summary-Based articles. They maintain a relatively broad distribution, indicating a mix of detail and conciseness, suitable for providing integrated views on topics without overwhelming detail.

Improved-Based Legitimate News: This category prioritizes brevity and clarity, resulting in shorter and less detailed articles. This might be indicative of efforts to streamline information presentation, making it more accessible and straightforward for readers.

Understanding these differences is crucial for developing more effective models for automatic news generation and classification. It also highlights

the challenges in detecting fake news, as the structural and narrative complexity varies significantly across different types of articles. Future research and development should focus on enhancing the capabilities of automated systems to handle this variability, ensuring accurate and nuanced news generation and detection.

A.6 Additional Experiments

A.6.1 Additional Benchmark Experiments on MegaFake Dataset

We conducted a series of benchmark experiments to evaluate the effectiveness of various NLG and natural NLU models in classifying the different categories of fake and legitimate news that we constructed, it offers a new benchmark: *multi-class classification of fake news types*.

A.6.2 Experiments on Classifying Legitimate News Types

We conducted a series of benchmark experiments using different NLU and NLG models on MegaFake dataset to classify the legitimate news types, which is shown in **Table 10**. Across all legitimate news construction methods (style-based and integration-based), the average accuracy of the NLG models (0.5912) is higher than the average accuracy of the NLU models (0.5240). This trend holds for both style-based (0.6205 vs. 0.5059) and

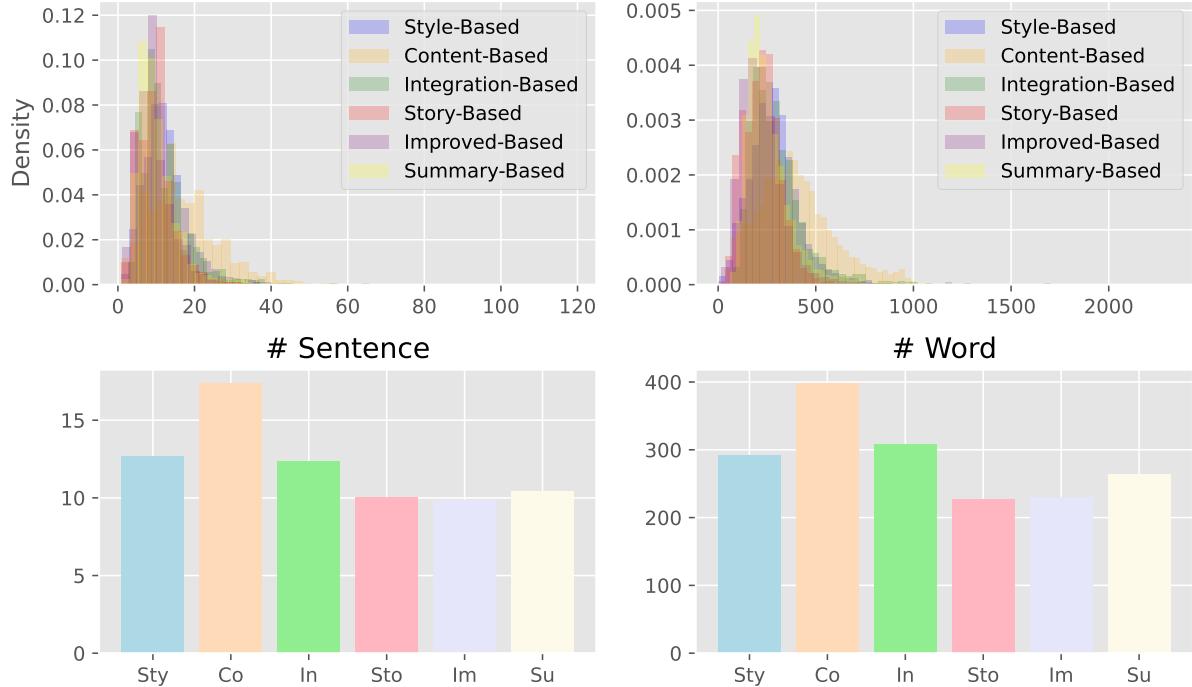


Figure 11: Sentence Count and Word Count Density Histogram for Six Different News Types in MegaFake Dataset

integration-based (0.5619 vs. 0.5421) legitimate news. The accuracy of legitimate news constructed in two ways varies greatly. The overall accuracy of legitimate news based on integration (integration-based) is higher than that of legitimate news based on style (style-based). In the NLG model, the highest accuracy of legitimate news based on integration is 0.6560, while the highest accuracy of legitimate news based on style is only 0.5016. In the NLU model, the highest accuracy of legitimate news based on integration is 0.7774, while the highest accuracy of legitimate news based on style is only 0.8551. There is a significant difference in accuracy between NLG and NLU models. The Qwen1.5-7B model (0.6560) has the highest accuracy for legitimate news classification among the NLG models. Baichuan-7B (0.1462) has the lowest accuracy. ROBERTa (0.7774) has the highest accuracy for legitimate news classification among the NLU models. CT-BERT (0.0000) has the lowest accuracy. NLG models are better suited for classifying legitimate news in the MegaFake dataset compared to NLU models. There is a large range in accuracy between different models, both NLG and NLU. We visualize the results in **Figure 14**.

A.6.3 Experiments on Classifying Fake News Types

We also conducted a series of benchmark experiments using different NLU and NLG models on MegaFake dataset to classify the fake news types, which is shown in **Table 11**. NLG models (such as Qwen1.5-7B and ChatGLM3-6B) perform poorly in classifying complex fake news, especially in the story-based and integration-based categories, with very low recall and F1-Scores. This indicates that NLG models have weaker generalization capabilities for these tasks. Besides, NLU models (such as ALBERT and RoBERTa) perform excellently across all categories, especially in content-based and integration-based fake news, with high precision, recall, and F1-Scores. This suggests that NLU models have a significant advantage in understanding and classifying complex texts. In the content-based fake news category, NLU models excel, possibly because they can better capture subtle differences and semantic information in the text. Across all categories, RoBERTa consistently performs the best, demonstrating its strong capability in handling complex text tasks. In contrast, some models (like CT-BERT and Funnel) fail to provide effective results in certain categories (indicated by scores of 0).

Overall, NLU models outperform NLG models significantly in the task of fake news classification,

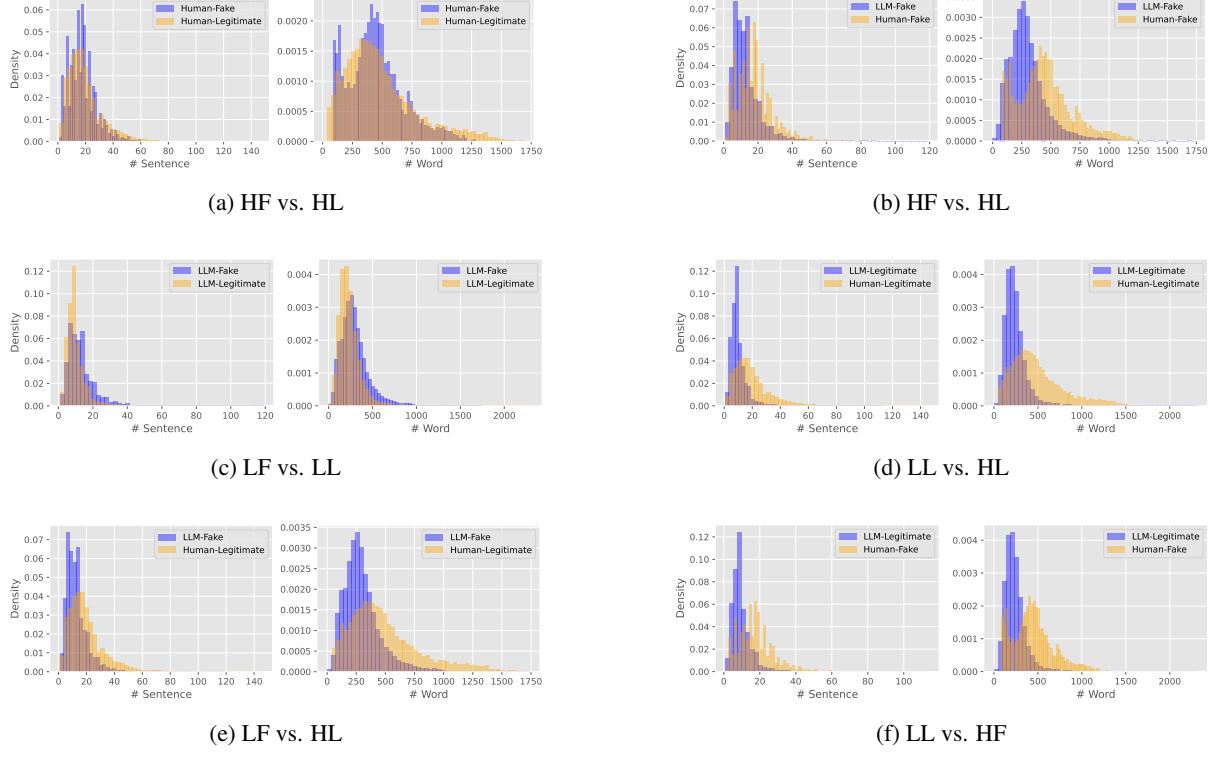


Figure 12: Sentence Length and Word Length Density Histograms for GossipCop and MegaFake Datasets

Table 10: Results for Experiments on Classifying Legitimate News Types.

Model	Accuracy	Integration-Based Legitimate			Style-Based Legitimate		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models							
QWEN1.5-7B	0.5323	0.3833	0.6806	0.4904	0.7441	0.4590	0.5678
LLaMA3-8B	0.3580	0.3374	0.9767	0.5016	0.8195	0.0523	0.0983
CHATGLM3-6B	0.6560	0.3414	0.0434	0.0770	0.6698	0.9586	0.7886
MISTRAL-7B-v0.3	0.5386	0.3774	0.6083	0.4658	0.7226	0.5041	0.5939
BAICHUAN-7B	0.5415	0.2401	0.1462	0.1818	0.6226	0.7527	0.6815
NLU Models							
ALBERT	0.7261	0.6101	0.4629	0.5264	0.7647	0.8551	0.8073
BERT-TINY	0.6658	0.4931	0.5754	0.5311	0.7734	0.7101	0.7404
CT-BERT	0.6712	0	0	0	0.6712	1	0.8032
DECLUTR	0.6692	0.3704	0.0085	0.0167	0.6715	0.9929	0.8011
FUNNEL	0.6712	0	0	0	0.6712	1	0.8032
ROBERTA	0.7774	0.9006	0.3632	0.5176	0.7586	0.9804	0.8553

especially in handling complex content-based and integration-based fake news. For future fake news detection tasks, it is recommended to prioritize NLU models and further fine-tune and optimize them according to specific task requirements. We visualize the results in **Figure 15**.

A.6.4 Experiments on Classifying All of the Six Different News Types

Finally, We also conducted a series of benchmark experiments using different NLU and NLG mod-

els on MegaFake dataset to classify the fake news types, which is shown in **Table 12**. Generally, NLU models outperform NLG models in classifying all types of news (fake and legitimate). Across all news categories (fake and legitimate), the average accuracy of the NLU models (0.6096) is higher than the average accuracy of the NLG models (0.5226). This trend holds for fake news (0.6158 vs. 0.5308) and legitimate news (0.5912 vs. 0.5240). There is a significant difference in accuracy be-

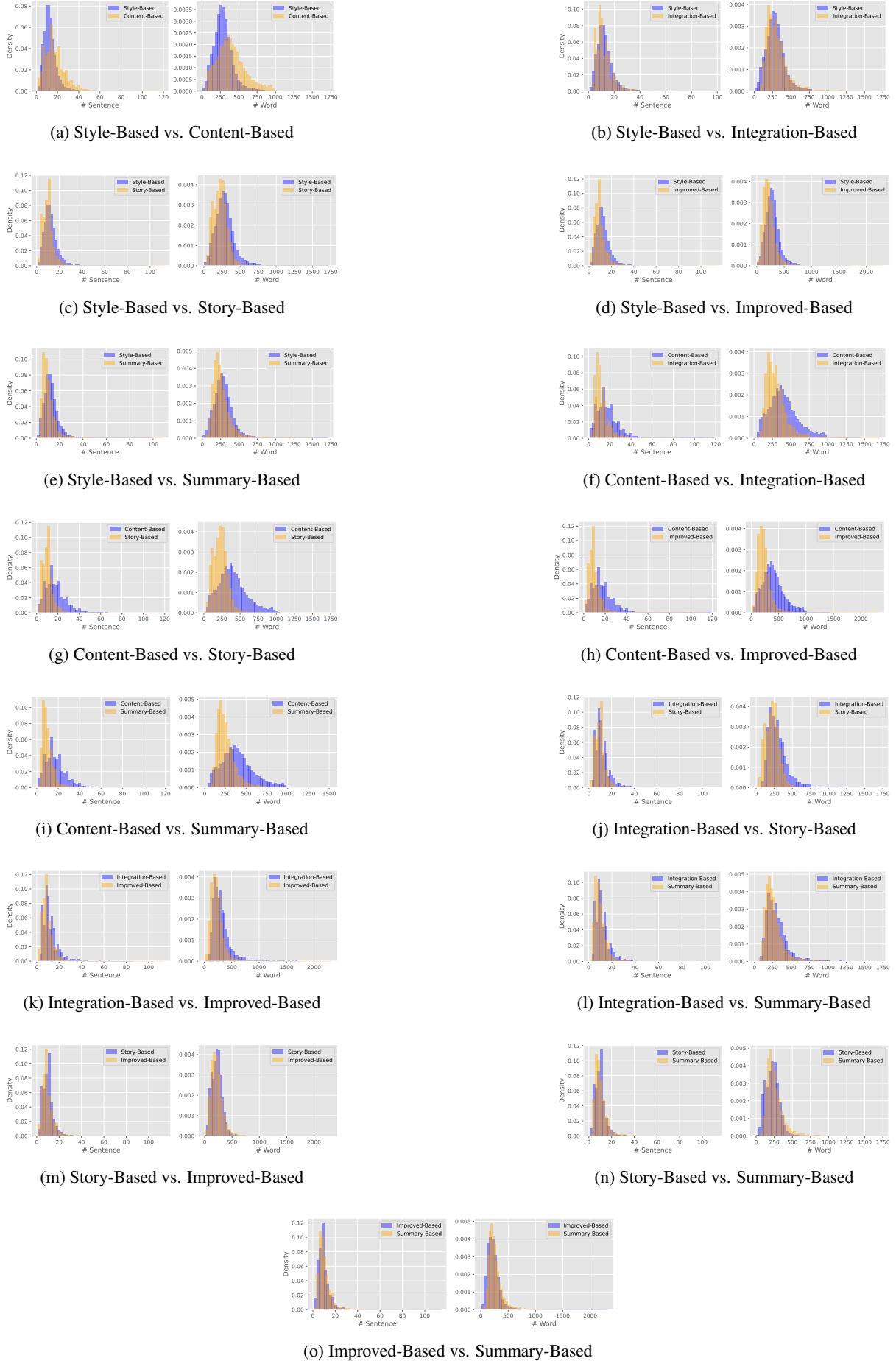


Figure 13: Sentence Length and Word Length Density Histograms for Six Different News Types in MegaFake Dataset

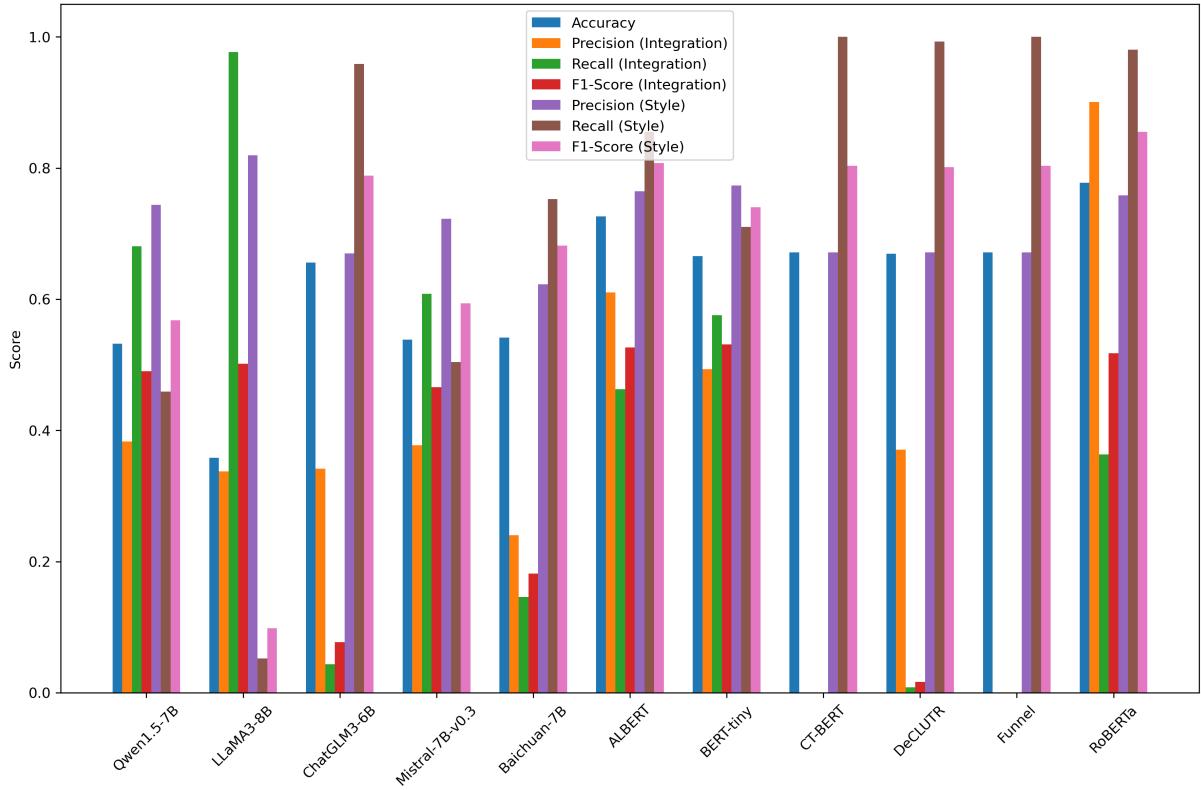


Figure 14: Visualization of Result for Experiments on Classifying Legitimate News Types

Table 11: Result for Experiments on Classifying Fake News Types.

Model	Accuracy	Style-Based Fake			Story-Based Fake			Content-Based Fake			Integration-Based Fake		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models													
QWEN1.5-7B	0.2755	0.3805	0.2816	0.3237	0.3503	0.0667	0.1120	0.2323	0.5921	0.3337	0.0978	0.0235	0.0379
LLAMA3-8B	0.3396	0.3184	0.2781	0.2969	0.3635	0.6923	0.4767	0.1939	0.0449	0.0729	0.1111	0.0007	0.001
CHATGLM3-6B	0.2671	0.4145	0.0457	0.0824	0.1624	0.0050	0.0097	0.2645	0.9477	0.4136	0.1090	0.0239	0.0392
MISTRAL-7B-v0.3	0.3407	0.3439	0.9892	0.5103	0	0	0	0.1393	0.0079	0.0149	0.2424	0.0030	0.0059
BAICHUAN-7B	0.2600	0.3245	0.1523	0.2073	0.2737	0.0377	0.0663	0.2473	0.8255	0.3806	0.0411	0.0049	0.0088
NLU Models													
ALBERT	0.9504	0.9288	0.9412	0.9350	0.9697	0.9769	0.9733	0.9916	0.9924	0.9920	0.7570	0.6610	0.7058
BERT-TINY	0.9227	0.8884	0.9004	0.8944	0.9676	0.9409	0.9541	0.9804	0.9932	0.9868	0.6185	0.6326	0.6255
CT-BERT	0.3438	0.3438	1	0.5117	0	0	0	0	0	0	0	0	0
DeCLUTR	0.9613	0.9539	0.9393	0.9466	0.9576	0.9961	0.9764	0.9987	0.9924	0.9955	0.8480	0.7500	0.7960
Funnel	0.3382	0	0	0	0.3382	1	0.5055	0	0	0	0	0	0
ROBERTA	0.9571	0.9538	0.9297	0.9416	0.9447	0.9981	0.9706	0.9970	0.9899	0.9934	0.8600	0.7330	0.7914

tween NLU models. ROBERTa (0.7774) has the highest accuracy for all news classification among the NLU models. CT-BERT (0.0000) has the lowest accuracy. There is a significant difference in accuracy between NLG models. Qwen1.5-7B (0.6560) has the highest accuracy for all news classification among the NLG models. Baichuan-7B (0.1462) has the lowest accuracy.

NLU models outperform NLG models for fake news classification. Across all fake news categories (style-based, story-based, content-based, and integration-based), the average accuracy of the NLU models (0.6158) is higher than the average accuracy of the NLG models (0.5308). This trend holds for all four fake news categories:

Style-based (0.6229 vs. 0.5249), Story-based (0.6031 vs. 0.5339), Content-based (0.6223 vs. 0.5408), Integration-based (0.6169 vs. 0.5284). There is a significant difference in accuracy between NLU models for different fake news categories. ROBERTa (0.7733) has the highest accuracy for style-based fake news classification, while DeCLUTR (0.8405) has the highest accuracy for story-based fake news classification. ALBERT (0.9713) has the highest accuracy for content-based fake news classification, while DeCLUTR (0.9970) has the highest accuracy for integration-based fake news classification. CT-BERT (0.0000) has the lowest accuracy for all fake news categories. There is a significant difference in accuracy between NLG

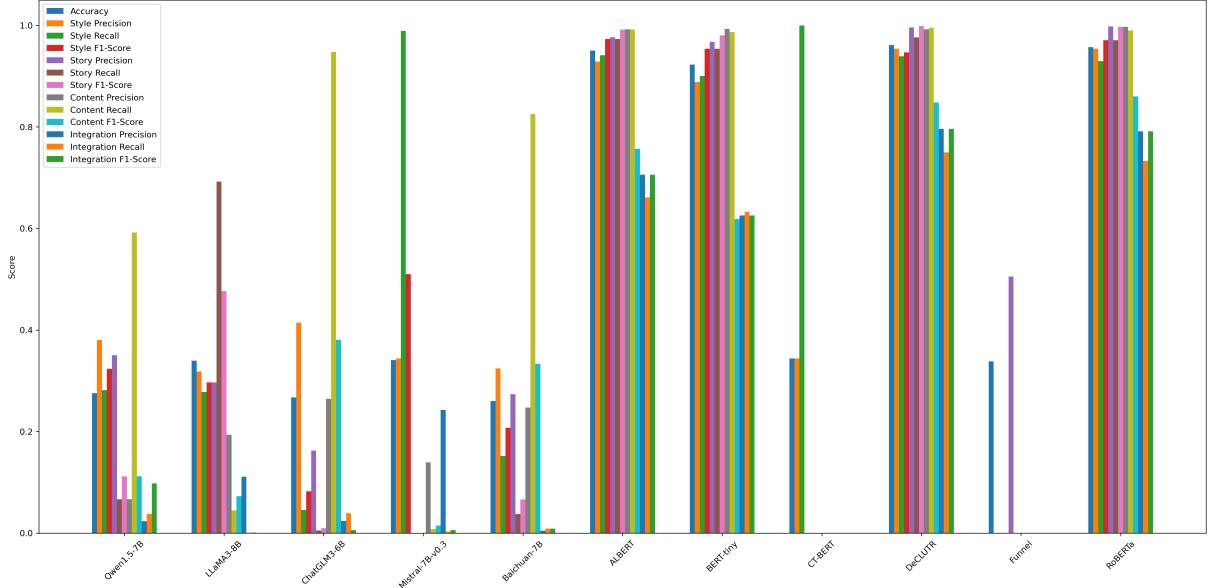


Figure 15: Visualization of Result for Experiments on Classifying Fake News Types

models for different fake news categories. Qwen1.5-7B (0.6102) has the highest accuracy for style-based fake news classification, while ChatGLM3-6B (0.3557) has the highest accuracy for story-based fake news classification. ALBERT (0.8789) has the highest accuracy for content-based fake news classification, while Baichuan-7B (0.2548) has the highest accuracy for integration-based fake news classification. Baichuan-7B (0.1462) has the lowest accuracy for all fake news categories.

NLG models outperform NLU models for legitimate news classification. Across both legitimate news construction methods (style-based and integration-based), the average accuracy of the NLG models (0.5912) is higher than the average accuracy of the NLU models (0.5240). This trend holds for both style-based (0.6205 vs. 0.5059) and integration-based (0.5619 vs. 0.5421) legitimate news. There is a significant difference in accuracy between NLG models for legitimate news classification. Qwen1.5-7B (0.6560) has the highest accuracy for legitimate news classification among the NLG models. Baichuan-7B (0.1462) has the lowest accuracy. There is a significant difference in accuracy between NLU models for legitimate news classification. ROBERTa (0.7774) has the highest accuracy for legitimate news classification among the NLU models. CT-BERT (0.0000) has the lowest accuracy.

We visualize the results in **Figure 17**. Additionally, we present a series of confusion matrices for the classification of six different news types in **Fig-**

ure 16. These matrices are derived from the model results detailed in **Table 12**. Each confusion matrix is a 6x6 grid that evaluates the performance of our classification model. The confusion matrix includes six categories on both the x-axis and y-axis, where the horizontal axis (x-axis) represents the predicted values, and the vertical axis (y-axis) represents the true values. Each cell in the matrix corresponds to the number of instances that fall into the respective predicted and actual category.

The values along the diagonal of the matrix indicate the number of instances correctly predicted by the model, representing the correct classifications. These diagonal values are crucial as they highlight the instances where the model’s predictions align perfectly with the true labels, thereby showcasing the model’s accuracy in correctly identifying each category.

The confusion matrix thus provides a comprehensive overview of the model’s classification performance, enabling a detailed analysis of both its strengths in accurately predicting categories and its weaknesses in terms of misclassification. This analysis is essential for understanding the model’s behavior and identifying areas for improvement.

Table 12: Result for Experiments on Classifying Six Different News Types.

Model	Accuracy	Style-Based Fake			Story-Based Fake			Content-Based Fake			Integration-Based Fake			Style-Based Legitimate			Integration-Based Legitimate		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
NLG Models																			
QWEN1.5-7B	0.2053	0.3462	0.1137	0.1712	0	0	0	0.2353	0.0004	0.0008	0.0563	0.004	0.0073	0.1935	0.9223	0.3199	0.1313	0.0192	0.0335
LLAMA3-8B	0.2533	0.3330	0.3730	0.3519	0	0	0	0	0	0	0	0	0	0.2229	0.8522	0.3534	0	0	0
CHATGLM3-6B	0.2406	0.2511	0.6102	0.3557	0	0	0	0.3477	0.1162	0.1742	0	0	0	0.2026	0.3594	0.2591	0.1053	0.0004	0.0008
MISTRAL-7B-V0.3	0.2611	0.3470	0.2969	0.3200	0	0	0	0.0909	0.0333	0.0488	0.0968	0.0061	0.0114	0.2493	0.8459	0.3851	0.0528	0.0051	0.0094
BAICHUAN-7B	0.1556	0.2548	0.0179	0.0334	0.3000	0.0006	0.0012	0.1370	0.8201	0.2341	0.0291	0.0040	0.0070	0.2243	0.2063	0.2149	1.0000	0.0003	0.0006
NLU Models																			
ALBERT	0.8789	0.8759	0.8734	0.8747	0.9591	0.9713	0.9652	0.9923	0.9881	0.9902	0.6050	0.5511	0.5768	0.8124	0.8211	0.8167	0.6997	0.7003	0.7000
BERT-TINY	0.8254	0.8593	0.8045	0.8310	0.9473	0.8973	0.9216	0.9633	0.9907	0.9768	0.5406	0.4034	0.4620	0.7074	0.7733	0.7389	0.5630	0.6596	0.6075
CT-BERT	0.8822	0.8852	0.8776	0.8814	0.9274	0.9915	0.9584	0.9970	0.9898	0.9924	0.7297	0.4602	0.5645	0.7949	0.8405	0.8171	0.7402	0.6698	0.7032
DECLUTR	0.8872	0.9189	0.8349	0.8749	0.8855	0.9964	0.9377	0.9966	0.9839	0.9902	0.7650	0.5303	0.6264	0.8244	0.8438	0.8340	0.7743	0.7980	0.7860
FUNNEL	0.2419	0	0	0	0.2419	1	0.3896	0	0	0	0	0	0	0	0	0	0	0	0
RoBERTA	0.8801	0.9213	0.8183	0.8667	0.8634	0.9977	0.9257	0.9957	0.9826	0.9891	0.7181	0.5549	0.6261	0.8244	0.8359	0.8301	0.7772	0.7699	0.7736

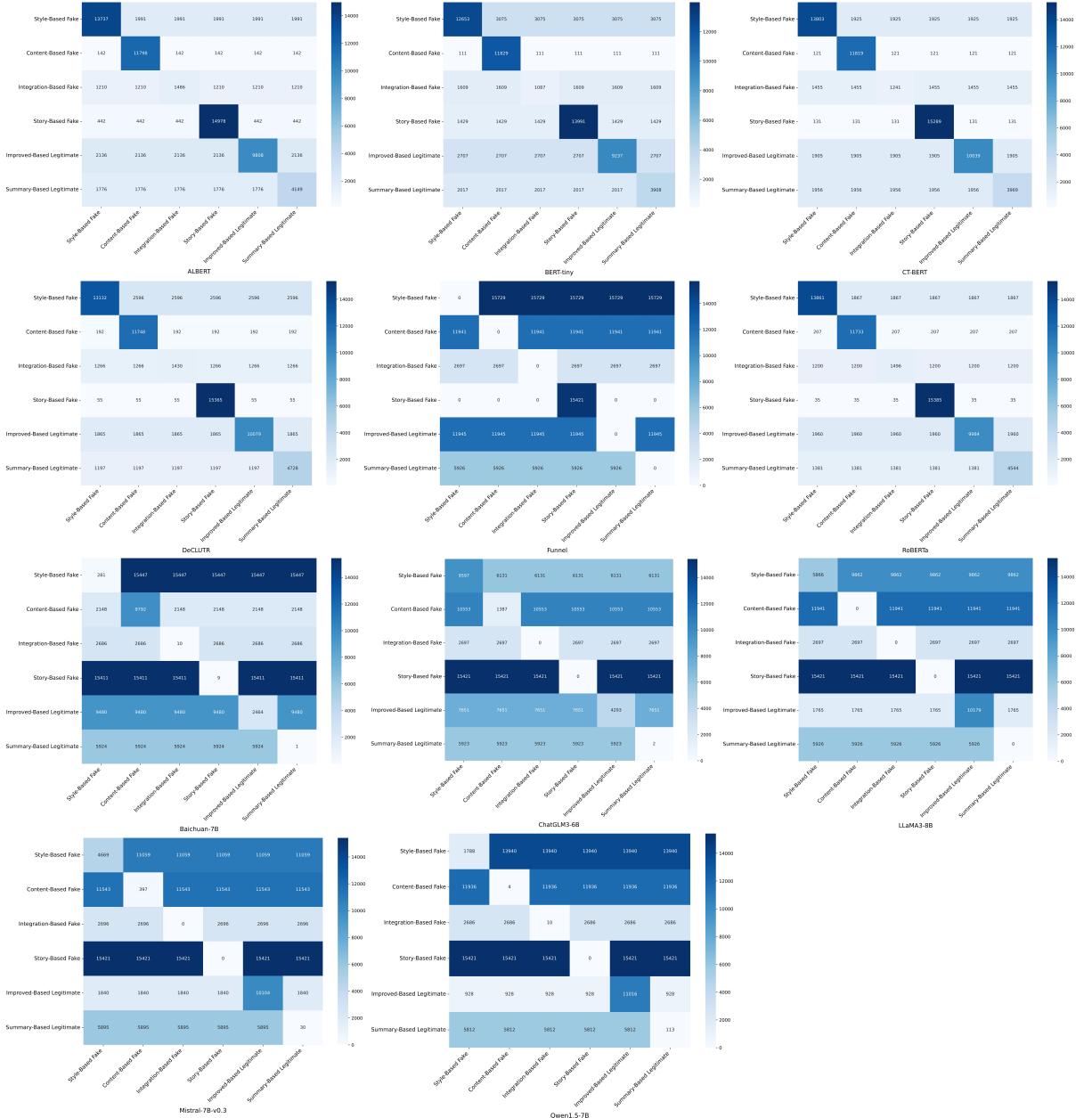


Figure 16: Confusion Matrix



Figure 17: Visualization of Result for Experiments on Classifying Six Different News Types