

# When XGBoost Outperforms GPT-4 on Text Classification: A Case Study

**Matyas Bohacek**  
Stanford University  
maty@stanford.edu

**Michal Bravansky**  
University College London  
michal@bravansky.com

## Abstract

Large language models (LLMs) are increasingly used for applications beyond text generation, ranging from text summarization to instruction following. One popular example of exploiting LLMs’ zero- and few-shot capabilities is the task of text classification. This short paper compares two popular LLM-based classification pipelines (GPT-4 and LLAMA 2) to a popular pre-LLM-era classification pipeline on the task of news trustworthiness classification, focusing on performance, training, and deployment requirements. We find that, in this case, the pre-LLM-era ensemble pipeline outperforms the two popular LLM pipelines while being orders of magnitude smaller in parameter size.

## 1 Introduction

Over the past year, large language models (LLMs) have become exceedingly popular with the public. LLM-powered chatbots such as ChatGPT<sup>1</sup> have made LLM use intuitive even for non-technical audiences, which have found creative ways of integrating them into day-to-day tasks (Chan et al., 2023), school work (Kasneji et al., 2023), creative practice (Parra Pennefather, 2023), and more. For many, LLMs have become synonymous with artificial intelligence (Liao and Vaughan, 2023).

One of the many reasons for why the public took notice of LLMs are their emergent capabilities beyond sentence completion (e.g., translation, problem solving, and instruction following) (Wei et al., 2022a; Valmeekam et al., 2023), allowing for many down-stream applications. The abundance of emergent capabilities has also been recognized in the technical communities. In the research domain, LLMs are now being used for code generation (Zhou et al., 2023; Lomshakov et al., 2023), medicine research (Thirunavukarasu et al., 2023),

and drug discovery (Chakraborty et al., 2023). Similarly, many industry solutions that analyze text data now rely on LLM architectures (McElheran et al., 2023).

There are clear benefits of using LLMs beyond the scope of text generation – specifically for classification, tagging, or content detection. For once, LLMs can be used in a few- or a zero-shot fashion, which minimizes or even eliminates the need for training data. Moreover, LLMs have become increasingly accessible and customizable using cloud-based inference and fine-tuning solutions.

On the other hand, the fast adoption of LLMs has, in many ways, exceeded our understanding of their risks and limitations. Initial exploratory work has identified gaps in the robustness of LLMs across diverse tasks and languages (Ahuja et al., 2023; Bang et al., 2023) and patterns of gender, racial, and political biases (Dong et al., 2023; Motoki et al., 2023; Khandelwal et al., 2023). Moreover, LLMs are prone to hallucination: a state in which they construct factually or logically incorrect narratives, possibly leading to user deception (Wang et al., 2023; Zhang et al., 2023; McKenna et al., 2023; Rawte et al., 2023).

In this short paper, we present a case study comparing two LLMs to a pre-LLM-era classification pipeline on the task of news trustworthiness analysis (using the Verifree dataset (Boháček et al., 2023)). We focus on each method’s performance, training, and deployment requirements. This comparison is limited and, on its own, cannot be used to draw broader conclusions about the comparable performance of the examined methods. Nonetheless, it presents a template for easy evaluation of LLMs’ performance compared to previous methods, reflecting aspects beyond pure accuracy. Overall, we believe that this paper can encourage more work evaluating LLMs in comparison to earlier methods, effectively expanding our understanding of the benefits and shortcomings of LLMs.

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<sup>1</sup><https://openai.com/chatgpt>

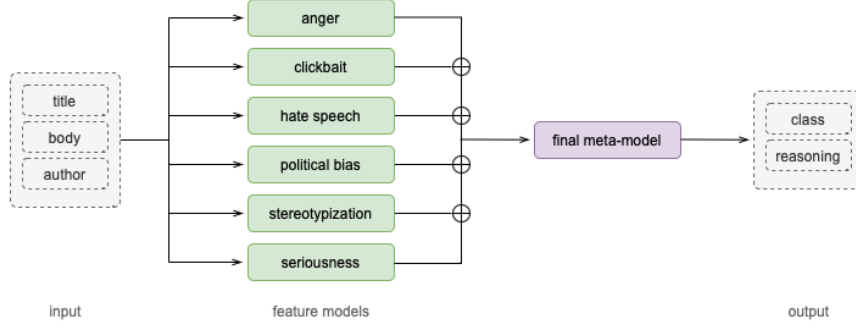


Figure 1: Overview of the modular ensemble pipeline data flow. At the input, a news article is analyzed using each feature model, yielding a feature embedding that is then inserted into the final meta-model. This model outputs a class prediction, along with its reasoning as a list of found features.

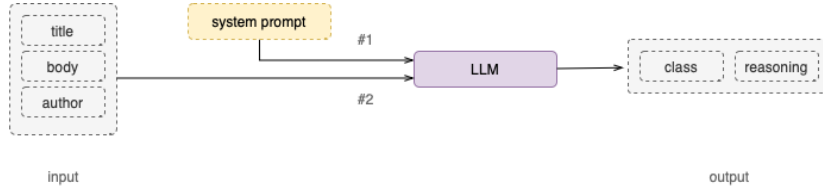


Figure 2: Overview of the LLM pipeline data flow. The LLM is first presented with the system prompt. At the input to the pipeline, a news article is structured as a single body of text and inserted into the LLM. The model first outputs the detected features of the article (i.e., the reasoning) and then proceeds to the final classification.

## 2 Related Works

In this section, we briefly review the existing work about the pre-LLM-era classification pipelines, LLMs, and comparative studies of the two.

### 2.1 Pre-LLM-Era Classification Pipelines

Over the past few years, text classification methods have mostly transitioned from hand-crafted features to deep learning architectures (Gasparetto et al., 2022) such as Electra (Clark et al., 2019), which was the state-of-the-art pre-trained language model on the GLUE benchmark (Wang et al., 2018) before the advent of LLMs. The literature has explored classification in various contexts, finding that achieving the best results requires specific architecture and data adjustments (Riduan et al., 2021; Wang et al., 2021), as there is no universal architecture for complex text classification tasks.

That said, let us consider a niche classification subtopic as an illustration of overarching trends, specifically IT ticket classification (Liu, 2023; Zicari et al., 2022): categorizing user inquiries based on rigid rules and a knowledge base. Recent work (Revina et al., 2021) has found that the best results for this task are obtained through extracting individual features and then utilizing a meta-model for final prediction. We refer to this pipeline approach as the modular ensemble pipeline.

### 2.2 LLM Classification Pipelines

Recent year has seen a boom of new LLM architectures and models (Zhao et al., 2023; Wan et al., 2023) – some of the most popular ones include GPT-4 (OpenAI, 2023), LLAMA 2 70B (Touvron et al., 2023), Claude 2 (Anthropic), and Mistral 7B (Jiang et al., 2023). Originally, LLMs were exploited to generate synthetic data and expand training datasets for conventional classification architectures (Kumar et al., 2020; Li et al., 2023; Golde et al., 2023; Chung et al., 2023). Recently, this approach was replaced by direct LLM inference for classification (Loukas et al., 2023; Chen et al., 2023; Frick, 2023; Sun et al., 2023).

### 2.3 Comparative Studies

Existing comparative studies (Qin et al., 2023; Laskar et al., 2023; Zhong et al., 2023; Wu et al., 2023) evaluate LLMs on conventional NLP tasks (e.g., summarization and question answering). They find that LLMs perform on par with pre-LLM benchmarks on some tasks but mostly score below the state-of-the-art results. However, these studies lack insight into the training and inference considerations of these approaches.

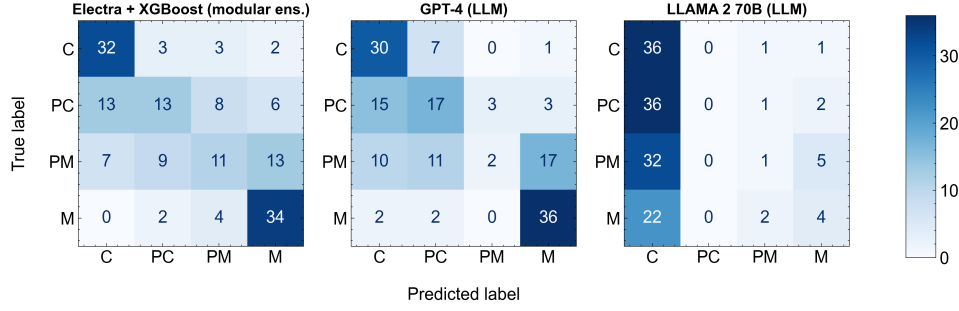


Figure 3: Confusion matrices of the Electra + XGBoost (*modular ensemble*), GPT-4 (*LLM*), and LLAMA 2 70B (*LLM*) pipelines on the testing set of the Verifee dataset. C, PC, PM, and M correspond to credible, partially credible, partially manipulative, and manipulative classes, respectively. Note that for the LLM pipelines, only the best-performing model configuration is shown.

### 3 Data

We use the Verifee news trustworthiness dataset (Boháček et al., 2023) with over 10,000 Czech news articles. The authors of this dataset propose the task of news trustworthiness classification, which recognizes the presence of select stylistic, linguistic, and semantic features concerning news credibility (e.g., clickbait, stereotypization, and hate speech). They define 4 classes of credibility: credible, partially credible, partially manipulative, and manipulative.

We choose this dataset because it presents a difficult two-stage classification problem in which the model must provide reasoning for its final prediction. It also comes with a detailed methodology describing the problem at hand, which we saw as a good fit for the system prompt of the LLM pipelines (described in Section 4.2). Notably, since the dataset was created in the pre-LLM era and deemed challenging for the standard architectures at the time, it falls into the category of datasets that were anticipated to significantly benefit from the advent of LLMs.

## 4 Methods

This section describes the two high-level classification pipeline approaches that we compare: the modular ensemble pipeline and the LLM pipeline. As representative examples of these approaches, we specifically evaluate the following models: Electra + XGBoost (*modular ensemble*), GPT-4 (*LLM*), and LLAMA 2 70B (*LLM*).

### 4.1 Modular Ensemble Pipeline

The general idea of the modular ensemble pipeline approach is to create a set of feature models, each

yielding predictions about a single feature in the input, and a meta-model that combines the feature predictions into the final classification. Shown in Figure 1 is an overview of this pipeline adapted to our specific case, comprising 6 feature models and a final meta-model. Each feature model is a language model fine-tuned on a single task, corresponding to the Verifee dataset methodology. To match the language of the dataset, we use the Czech Electra (Kocián et al., 2021) as the fine-tuning baseline. Each feature model is fine-tuned on a task-specific dataset, as listed in Appendix C. The details and configuration of the fine-tuning are described in Appendix A. We open-source the code at <https://github.com/matyasbohacek/xgboost-vs-gpt4>. At input, each feature model is presented with the news article’s title, body, and author.

The final meta-model is an XGBoost classifier (Chen and Guestrin, 2016), which receives the outputs of all the previous feature models as its input. Trained on pairs of the feature model representations and ground-truth classes from the Verifee dataset, this model seeks to predict the final trustworthiness class of the article.

### 4.2 LLM Pipeline

The general idea of the LLM pipeline approach is to leave the entire classification on an LLM, leveraging its emergent capabilities. Any information about the task at hand is conveyed through the system prompt (i.e., natural language).

Shown in Figure 2 is an overview of the LLM pipeline, adapted to our specific case. The system prompt contains the full news assessment methodology of the Verifee dataset and instructions about

Model(s)	Pipe	Lang.	F-1
Electra+XGBoost	mod.	CZ	0.533
GPT-4	LLM	CZ	0.531
GPT-4	LLM	EN	0.425
LLAMA 2 70B	LLM	CZ	0.188
LLAMA 2 70B	LLM	EN	0.256

Table 1: Micro F-1 scores on the testing set of the Veriffee dataset. *Lang.* refers to the language used in the pipeline: CZ (Czech) or EN (English).

the expected output format, following the chain-of-thought practices (Wei et al., 2022b). The system prompt is included in Appendix B.

During inference, the LLM is first presented with the system prompt, followed by the input news article. At the output, the pipeline first provides a list of features in the article, which it then uses for a final trustworthiness classification. The model is used in a zero-shot manner, meaning the pipeline is not trained on the Veriffee dataset.

We specifically use GPT-4 (OpenAI, 2023) and LLAMA 2 70B (Touvron et al., 2023) as the LLM backbones, evaluating 2 configurations for each – one wherein the system prompt is left in its original language (Czech) and one wherein the system prompt is translated to English.

## 5 Results

This section describes the results of our comparison of the example modular ensemble and LLM pipelines.

### 5.1 Quantitative Performance

The F-1 scores obtained on the testing split of the Veriffee dataset are presented in Table 1. The Electra + XGBoost (modular ensemble) with an F-1 score of 0.533 outperformed the LLM pipelines.

The confusion matrix of the predictions on the testing split of the Veriffee dataset is shown in Figure 3. The models perform best on the edge classes (i.e., credible and manipulative) and struggle more with the center classes (i.e., partially credible/manipulative). While worse than the Electra + XGBoost, the GPT-4 pipeline performs better than the LLAMA 2 pipeline, which near uniformly predicts one class.

### 5.2 Training Requirements

The example modular ensemble pipeline approach, Electra + XGBoost, involves a multi-stage training

Model(s)	Pipe	Params.	Size
Electra+XGBoost	Mod.	$78 \times 10^6$	0.9
LLAMA 2 70B	LLM	$70 \times 10^9$	140
GPT-4	LLM	$1.8 \times 10^{12}$	3370

Table 2: Model size comparison. *Params.* refers to the absolute number of parameters. *Size* refers to the size of the model in virtual memory in GB, estimated for a single-batch input (16-bit precision, 512 tokens), using [https://github.com/RahulSchand/gpu\\_poor/](https://github.com/RahulSchand/gpu_poor/).

process. First, 6 separate Electra models are fine-tuned for binary classification tasks. Next, these models analyze the news articles in the training split of the Veriffee dataset and build up their feature representations, which are then fed into the XGBoost (meta-model classifier). The XGBoost model is trained to classify the news article into one of the four credibility classes based on the aggregated insights from the feature representations. On the other hand, the example LLM pipeline approaches, GPT-4 and LLAMA 2, are used out of the box and require no additional fine-tuning.

### 5.3 Deployment Requirements

Model statistics about deployment requirements are presented in Table 2. The example modular ensemble pipeline approach, Electra + XGBoost, can be executed on consumer-grade hardware, requiring 0.9 GB of virtual memory. In contrast, the LLM pipelines are 3 and 6 orders of magnitude larger in parameter size and require cloud-level GPU resources. LLAMA 2 requires about 140 GB of virtual memory, while GPT-4 requires 3370 GB.

## 6 Conclusion

We find that LLM classification pipelines may not necessarily be better than the pre-LLM-era classification pipelines on all classification tasks. In the case study of news trustworthiness assessment, deemed particularly challenging in the pre-LLM era, we identify an example use case in which an ensemble pipeline outperforms two popular LLM pipelines. While the LLM pipelines come with lesser training requirements, they pose orders of magnitude higher computational deployment costs.

While there are many exciting use cases of LLMs that can push NLP and other disciplines, further, we argue that critical work on the robustness of LLM-based methods is lacking. To that end, this narrow case study paper can serve as a template for similar task- and dataset-specific studies, together



solidifying our understanding of where LLMs stand compared to their architecture predecessors.

## Limitations

While we strive to make the comparison in this paper as fair and representative as possible, our analysis, of course, has limitations. Notably, we only compare the pipelines on a single classification task in two languages. The pipelines may exhibit different performance on different tasks and languages. Therefore, this dataset should not be seen as representative of all classification tasks – task-specific datasets must be used for each task to make judgments about LLM and pre-LLM-era pipelines on that particular task. We call for similar studies following this template in different tasks to offer a broader picture of where LLM classification pipelines stand compared to pre-LLM-era classification pipelines across tasks, languages, and datasets.

In terms of the architectures, it must be stated that the LLMs described in this paper operate in the domain of few- and zero-shot classification, whereas the ensemble pipeline is supervised. Moreover, one could argue that the performance of both of the examined pipeline approaches could be further improved using techniques such as hyperparameter optimization for the modular ensemble pipeline or LLM fine-tuning for the LLM pipeline. While likely true, we believe that evaluating both pipelines in a default setting without these additional techniques maintains a fair comparison of these methods as they would be used. Moreover, a more detailed comparison goes beyond the scope of this short paper.

An additional limitation we would like to point out is the number of parameters of the GPT-4 model, which we obtained from <https://www.semianalysis.com/p/gpt-4-architecture-infrastructure>. Albeit speculative, the estimate we refer to is supported by external evidence and several independent sources. Still, we must reiterate that this is not a precise number but rather a rough estimate.

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## A Modular Ensemble Pipeline: Training Details

The feature models in the modular ensemble pipeline (of the Electra architecture) are implemented using the Hugging Face 3 (Wolf et al., 2019) and PyTorch (Paszke et al., 2019) libraries. Namely, we use the ElectraForSequenceClassification<sup>2</sup> pipeline and train it using the default hyperparameters. If any of the feature-specific datasets is not already available in the same language as the Verifee news trustworthiness dataset, we translate it using DeepL<sup>3</sup>. The final-meta model (of the XGBoost architecture) is implemented using the DMLC XGBoost (Chen and Guestrin, 2016) library and also trained with the default hyperparameters.

## B LLM Pipeline System Prompt

We use the following system prompt for the LLM pipelines, which is derived from the news assessment methodology of the Verifee dataset (Boháček et al., 2023). In the actual prompting, the model is asked to first list out the features found in the article. Then, it is asked to provide the final trustworthiness class prediction. Moreover, examples of the features outlined below were provided.

*You are a perfect AI system capable of evaluating article trustworthiness. Consider only the information presented within the article and make assumptions based on the methodology.*

*Output in this JSON format: {"explanation": list of criteria found in the article, "label": One of the trustworthiness labels}}*

*Base your evaluation solely on this methodology:*

### 1. Trustworthiness Classification:

#### 1.1 Trustworthy:

**Positive Criteria (5+ required):** Citations from relevant authorities, Representation of all interested parties' views, Facts presented within context, Grammatically correct, neutral language, Identifiable author, Undistorted data

**Negative Criteria (1 or fewer allowed):** Missing citations, Unrepresented opposing views, Facts without context, Grammatical errors or overly expressive language, Anonymous author, Distorted data

**Forbidden Criteria:** Clickbait, Hate speech, Unjustified attack on an opinion opponent, Manipulation of reader, Conspiracy theories, Emotional appeals, Logical fallacies, Tabloid language

#### 1.2 Partially Trustworthy:

**Positive Criteria:** Grammatically correct and neutral language, Undistorted data

**Negative Criteria (2-5 allowed):** Missing citations, Unrepresented opposing views, Facts without context, Grammatical errors or overly expressive language, Anonymous author, Distorted data, Clickbait, Emotional appeals, Tabloid language

**Forbidden Criteria:** - Hate speech - Unjustified attack on an opinion opponent - Manipulation of reader - Conspiracy theories - Logical fallacies

#### 1.3 Misleading:

**Positive Criteria:** None required

**Negative Criteria (6-7 allowed):** Missing citations, Unrepresented opposing views, Facts without context, Grammatical errors or overly expressive language, Anonymous author, Distorted data, Clickbait, Emotional appeals, Tabloid language, Logical fallacies, Unjustified attack on an opinion opponent

**Forbidden Criteria:** Hate speech, Manipulation of reader, Conspiracy theories

#### 1.4 Manipulative:

**Positive Criteria:** None required

**Negative Criteria (8+ allowed or any of the 3 forbidden criteria):** Missing citations, Unrepresented opposing views, Facts without context, Grammatical errors or overly expressive language, Anonymous author, Distorted data, Clickbait, Emotional appeals, Tabloid language, Logical fallacies, Unjustified attack on an opinion opponent, Hate speech, Manipulation of reader, Conspiracy theories

**Forbidden Criteria:** None

### 2. Handling Unclassifiable Articles and Errors:

*If an article's length or structure makes it unclassifiable or lacks sufficient content for analysis, label it as unclassifiable.*

<sup>2</sup>[https://huggingface.co/transformers/v3.0.2/model\\_doc/electra.html?highlight=electra#transformers.ElectraForSequenceClassification](https://huggingface.co/transformers/v3.0.2/model_doc/electra.html?highlight=electra#transformers.ElectraForSequenceClassification)

<sup>3</sup><https://www.deepl.com/translator>

## C Modular Ensemble Pipeline: Datasets

Feature	Dataset	Description
Anger	GoEmotions (Demszky et al., 2020)	This dataset comprises 10,000 comments scraped from the internet, annotated for the emotions they convey. While the dataset recognizes 28 emotion classes, we only use the anger class versus a balanced sample of the remaining classes (including ‘neutral’) to model this as a binary classification task.
Clickbait	Kaggle Clickbait Dataset (Anand, 2020)	This dataset contains 32,000 headlines from 10 diverse news sources, classified as either clickbait or non-clickbait.
Hate speech	HateXplain (Mathew et al., 2020)	This dataset comprises 20,148 social media posts classified into 3 categories of hate speech (hate, offensive, and normal), with additional annotations about the target community and rationales.
Political bias	German News Bias Dataset (Aksenov et al., 2021)	This dataset contains 47,362 news articles from 15 news sources, classified into 5 categories of political bias.
Stereotypization	StereoSet (Nadeem et al., 2020)	This dataset comprises sentences with common gender-, profession-, race-, and religion-based stereotypes, as well as counterparts without stereotypes.
Seriousness	Kaggle News Category Dataset (Misra, 2022)	This dataset contains 210,000 news headlines classified into 42 news categories. We use only a subset of these categories (namely, ‘style and beauty,’ ‘comedy,’ ‘entertainment,’ ‘wellness,’ and ‘home & living’), which we group under the umbrella category of tabloid news, and the rest, modeling this as a binary classification task.

Table 3: Overview of the datasets used for fine-tuning of the respective feature models. Each dataset is used for a single classification task.