A Comparison of DeepSeek and Other LLMs

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Abstract

Recently, DeepSeek has been the focus of attention in and beyond the AI community. An interesting problem is how DeepSeek compares to other large language models (LLMs). There are many tasks an LLM can do, and in this paper, we use the task of predicting an outcome using a short text for comparison. We consider two settings, an authorship classification setting and a citation classification setting. In the first one, the goal is to determine whether a short text is written by human or AI. In the second one, the goal is to classify a citation to one of four types using the textual content. For each experiment, we compare DeepSeek with 4 popular LLMs: Claude, Gemini, GPT, and Llama.

We find that, in terms of classification accuracy, DeepSeek outperforms Gemini, GPT, and Llama in most cases, but underperforms Claude. We also find that DeepSeek is comparably slower than others but with a low cost to use, while Claude is much more expensive than all the others. Finally, we find that in terms of similarity, the output of DeepSeek is most similar to those of Gemini and Claude (and among all 5 LLMs, Claude and Gemini have the most similar outputs).

In this paper, we also present a fully-labeled dataset collected by ourselves, and propose a recipe where we can use the LLMs and a recent data set, MADStat, to generate new data sets. The datasets in our paper can be used as benchmarks for future study on LLMs.

Keywords: Citation classification, AI-generated text detection, MADStat, prompt, text analysis, textual content.

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1 Introduction

In the past two weeks, DeepSeek (DS), a recent large language model (LLM) (DeepSeek-AI, 2024), has shaken up the AI industry. Since its latest version was released on January 20, 2025, DS has made the headlines of news and social media, shot to the top of Apple Store's downloads, stunning investors and sinking some tech stocks including Nvidia.

What makes DS so special is that in some benchmark tasks it achieved the same or even better results as the big players in the AI industry (e.g., OpenAI's ChatGPT), but with only a fraction of the training cost. For example,

- In Evstafev (2024), the author showed that over 30 challenging mathematical problems derived from the MATH dataset (Hendrycks and et al., 2021), DeepSeek-R1 achieves superior accuracy on these complex problems, compared with ChatGPT and Gemini, among others.
- In a LinkedIn post on January 28, 2025, Javier Aguirre (a researcher specialized in medicine and AI, South Korea) wrote: "I am quite impressed with Deepseek. Today I had a really tricky and complex (coding) problem. Even chatGPT-o1 was not able to reason enough to solve it. I gave a try to Deepseek and it solved it at once and straight to the point". This was echoed by several other researchers in AI.

See more comparison in DeepSeek-AI (2024); Zuo and et al. (2025); Arrieta and et al. (2025). Of course, a sophisticated LLM has many aspects (e.g., Infrastructure, Architecture, Performances, Costs) and can achieve many tasks. The tasks discussed above are only a small part of what an LLM can deliver. It is desirable to have a more comprehensive and in-depth comparison. Seemingly, such a comparison may take a lot of time and efforts, but some interesting discussions have already appeared on the internet and social media (e.g., Ramadhan (2025)).

We are especially interested in how accurate an LLM is in prediction. Despite that there are a long list of literature on this topic (see, for example, Friedman et al. (2001)), using LLM for prediction still has advantages: while a classical approach may need a reasonable

large training sample, an LLM can work with only a prompt. Along this line, a problem of major interest is how DS compares to other LLMs in terms of prediction accuracy. In this paper, we consider the two classification settings as follows.

- Authorship classification (AC). Determine whether a document is human generated (hum), or AI-generated (AI), or human-generated but with AI-editing (humAI).
- Citation classification (CC). Given an (academic) citation and the small piece of text surrounding it, determine which type the citation is (see below for the 4 types of citations).

For each of the two settings, we compare the classification results of DeepSeek-R1 (DS) with those of 4 representative LLMs: OpenAI's GPT-4o-mini (GPT), Google's Gemini-1.5-flash (Gemini), Meta's Llama-3.1-8b (Llama) and Anthropic's Claude-3.5-sonnet (Claude). We now discuss each of the two settings with more details.

1.1 Authorship classification

In the past two years, AI-generated text content started to spread quickly, influencing the internet, workplace, and daily life. This raises a problem: how to differentiate AI-authored content from human-authored content (Kreps et al., 2022; Danilevsky et al., 2020).

The problem is interesting for at least two reasons. First, the AI-generated content may contain harmful misinformation in areas such as health care, news, and finance (Kreps et al., 2022), and the spread of fake and misleading information may threaten the integrity of online resources. Second, understanding the main differences between human-generated and AI-written content can significantly help improve AI language models (Danilevsky et al., 2020).

We approach the problem by considering two classification settings, AC1 and AC2.

• (AC1). In the first setting, we focus on distinguishing human-generated text and AI-generated text (i.e., hum vs. AI).

• (AC2). In the second setting, we consider the more subtle setting of distinguishing text generated by human and text that are generated by human but with AI editing (i.e., hum vs. humAI).

For experiments, we propose to use the recent MADStat data set (Ji et al., 2022; Ke et al., 2024). MADStat is a large-scale data set on statistical publications, consisting of the bibtex and citation information of 83,331 papers published in 36 journal in statistics and related field, spanning 1975-2015. The data set is available for free download (see Section 2 for the download links).

We propose a general recipe where we use the LLMs and MADStat to generate new data sets for our study. We start by selecting a few authors and collecting all papers authored by thesm in the MADStat. For each paper, the MADStat contains a title and an abstract.

- (hum). We use all the abstracts as the human-generated text.
- (AI). For each paper, we feed in the title to GPT-40-mini and ask it to generate an abstract. We treat these abstracts as the AI-generated text.
- (humAI). For each paper, we also ask GPT-40-mini to edit the abstract. We treat these abstracts as the humAI text.

Seemingly, using this recipe, we can generate many different data sets. These data sets provide a useful platform where we can compare different classification approaches, especially the 5 LLMs.

Remark 1. (The MadStatAI data set). In Section 2.2, we fix 15 authors in the MADStat data set (see Table 2 for the list) and generate a data set containing 582 abstract triplets (each triplet contains three abstracts: hum, AI, and humAI) following the recipe above. For simplicity, we call this data set the MadStatAI.

Once the data set is ready, we apply each of the 5 LLMs above for classification, with the same prompt. See Section 2.1 for details. Note that aside from LLMs, we may apply other algorithms to this problem (Solaiman et al., 2019; Zellers et al., 2019; Gehrmann et al., 2019; Ippolito et al., 2020; Fagni et al., 2021; Adelani et al., 2020; Kashtan and

Kipnis, 2024). However, as our focus in this paper is to compare DeepSeek with other LLMs, we only consider the 5 LLM classifiers mentioned above.

1.2 Citation classification

When a paper is being cited, the citation could be significant or insignificant. Therefore, to evaluate the impact of a paper, we are interested in not only how many times it is being cited, but also how many significant citations it has. The challenge is, while it is comparably easier to count the raw citations of a paper (i.e., by Google Scholar, Web of Science), it is unclear how to count the number of 'significant' citations of a paper.

To address the issue, note that surrounding a citation instance, there is usually a short piece of text. The text contains important information for the citation, and we can use it to predict the type of this citation. This gives rise to the problem of *Citation Classification*, where the goal is to use the short text surrounding a citation to predict the citation type.

Here, we have two challenges. First, it is unclear how many different types academic citations may have and what these types are. Second, we do not have a ready-to-use data set.

To address these challenges, first, after reviewing many literature works and empirical results, we propose to divide all academic citations into four different types:

- "Fundamental ideas (FI)"
- "Technical basis (TB)",
- "Background (BG)",
- "Comparison (CP)".

Below for simplicity, we encode the four types as "1", "2", "3", "4". Note that the first two types are considered as significant, and the other two are considered as comparably less significant. See Section 2.2 for details.

Second, with substantial efforts, we have *collected from scratch* a new data set by ourselves, which we call the *CitaStat*. In this data set, we downloaded all papers in 4

representative journals in statistics between 1996 and 2020 in PDF format. These papers contain about 360K citation instances. For our study, we selected n = 3000 citation instances. For each citation,

- we write a code to select the small piece of text surrounding the citation in the PDF file and convert it to usable text files.
- we manually label each citation to each of the 4 citation types above.

See Section 2.2 for details. As a result, CitaStat is a fully labeled data set with n = 3000 samples, where each y-variable takes values in $\{1, 2, 3, 4\}$ (see above), and each x-variable is a short text which we call the textual content of the corresponding citation.

We can now use the data set to compare the 5 LLMs above for their performances in citation classification. We consider two experiments.

- (CC1). A 4-class classification experiment where we use the CitaStat without any modification.
- (CC2). A 2-class classification experiment where we merge class "1" and "2" ('FI' and 'TB') to a new class of "S" (significant), and we merge class "3" and "4" ('BG' and 'CP') to a new class of 'I' (incidental).

1.3 Results and contributions

We have applied all 5 LLMs to the four experiments (AC1, AC2, CC1, CC2), and we have the following observations:

• In terms of classification errors, Claude consistently outperforms all other LLM approaches. DeepSeek-R1 underperforms Claude but outperforms Gemini, GPT, and Llama in most of the cases. GPT performs unsatisfactorily for AC1 and AC2, with an error rate similar to that of random guessing, but it performs much better than random guessing for CC1 and CC2. Llama performs unsatisfactorily: its error rates are either comparable to those of random guessing or even larger.

- In terms of computing time, Gemini and GPT are much faster than the other three approaches, and DeepSeek-R1 is the slowest (an older version of DeepSeek, DeepSeek-V3, is faster but does not perform as well as DeepSeek-R1).
- In terms of cost, Claude is much more expensive for a customer than other approaches. For example, for CC1 and CC2 altogether, Claude costs \$12.30, Llama costs \$1.2, and the other three methods (DeepSeek, Gemini and GPT) cost no more than \$0.3.
- In terms of output similarity, DeepSeek is most similar to Gemini and Claude (GPT and Llama are highly similar in AC1 and AC2, but both perform relatively unsatisfactorily).

Table 1 presents the ranks of different approaches in terms of error rates (the method with the lowest error rate is assigned a rank of 1). The average ranks suggest that DeepSeek outperforms Gemini, GPT, and Llama, but underperforms Claude (note that for CC1 and CC2, we have used two versions of DeepSeek, R1 and V3; the results in Table 1 are based on R1. If we use V3, then DeepSeek ties with Gemini in average rank; it still outperforms GPT and Llama). See Section 2 for details.

	Claude	DeepSeek	Gemini	GPT	Llama
Experiment AC1 (hum vs. AI)	1	2	3	5	4
Experiment AC2 (hum vs. humAI)	2	1	3	5	4
Experiment CC1 (4-class)	1	4	2	3	5
Experiment CC2 (2-calss)	1	2	3	4	5
Average Ranking	1.25	2.25	2.75	4.25	4.50

Table 1: The rankings of all 5 LLM approaches in terms of error rates.

Overall, we find that Claude and DeepSeek have the lowest error rates, but Claude is relatively expensive and DeepSeek is relatively slow.

We have made the following contributions. First, as DeepSeek has been the focus of attention in and beyond the AI community, there is a timely need to understand how it compares to other popular LLMs. Using two interesting classification problems, we demonstrate that DeepSeek is competitive in the task of predicting an outcome using a short piece of text. Second, we propose citation classification as an interesting new problem, the understanding of which will help evaluate the impact of academic research. Last but not the least, we provide CitaStat as a new data set which can be used for evaluating academic research. We also propose a general recipe for generating new data sets (with the MadStatAI as an example) for studying AI-generated text. These data sets can be used as benchmarks to compare different algorithms, and to learn the differences between human-generated text and AI-generated text.

2 Main results

In this section, we describe our numerical results on the two problems, authorship classification and citation classification, and report the performances of all 5 LLMs.

2.1 Authorship classification

The MADStat (Ji et al., 2022; Ke et al., 2024) contains over 83K abstracts, but it is time-consuming to process all of them.¹ We selected a small subset as follows: First, we restricted to authors who had over 30 papers in MADStat. Second, we randomly drew 15 authors from this pool by sampling without replacement. Each time a new author was selected, we checked if he/she had co-authored papers with previously drawn authors; if so, we deleted this author and drew a new one, until the total number of authors reached 15. Finally, we collected all 15 authors' abstracts in MADStat. This gave rise to a data set with 582 abstracts in total (see Table 2).

For each original human-written abstract, we used GPT-40-mini to get two variants.

• The AI version. We provided the paper title and requested for a new abstract. The prompt is "Write an abstract for a statistical paper with this title: [paper title]."

¹MADStat stands for Multi-Attributed Dataset on Statisticians. MADStat is available for free download at http://zke.fas.harvard.edu/MADStat.html or in the supplementary material of Ji et al. (2022).

Name	#abstracts	Name	#abstracts	Name	#abstracts
Andrew Gelman	40	Anthony Pettitt	60	Damaraju Raghavarao	31
David Nott	35	Frank Proschan	39	Ishwar Basawa	53
Ngai Hang Chan	32	Nicholas I. Fisher	32	Peter X. K. Song	32
Philippe Vieu	31	Piet Groeneboom	30	Richard Simon	45
Sanat K. Sarkar	44	Stephane Girard	33	Yuehua Wu	45

Table 2: The 15 selected authors and their numbers of abstracts in MADStat.

• The humAI version. We provided the original abstract and requested for an edited version. The prompt is "Given the following abstract, make some revisions. Make sure not to change the length too much. [original abstract]."

Both variants are authored by AI, but they look differently. The AI version is usually significantly different from the original abstract, so the 'human versus AI' classification problem is comparably easier. For example, the left panel of Figure 1 is a comparison of the length of the original abstract with that of its AI version. The length of human-written abstracts varies widely, while the length of AI-generated ones is mostly in the range of 100-200 words. The humAI version is much closer to the original abstract, typically only having local word replacements and mild sentence re-structuring. In particular, its length is highly correlated with the original length, which can be seen in the right panel of Figure 1.

As mentioned, we consider two classification problems:

- (AC1). A 2-class classification problem of 'human versus AI',
- (AC2). A 2-class classification problem of 'human versus humAI'.

For each problem, there are $582 \times 2 = 1164$ testing samples, half from each class. We input them into each of the 5 LLMs using the same prompt: "You are a classifier that determines whether text is human-written or AI-edited. Respond with exactly one word: either 'human' for human-written text or 'ChatGPT' for AI-written text. Be as accurate as possible."

Note that comparing with classification approaches (e.g., SVM, Random Forest (Friedman et al., 2001)), an advantage of using an LLM for classification is that, we do not need to provide any training sample. All we need is to input the LLM with a prompt.

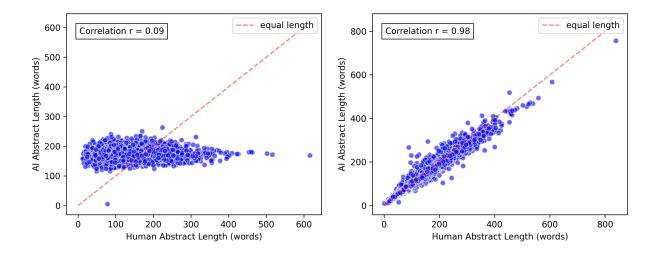


Figure 1: Comparison of the lengths of human-generated and AI-generated abstracts

Table 3 summarizes the performances of 5 LLMs. For 'human vs AI' (AC1), Claude-3.5-sonnet has the best error rate 0.218, and DeepSeek-R1 has the second best one 0.286. The remaining three methods almost always predict 'human-written', which explains why their error rates are close to 0.5. For 'human vs humAI' (AC2), since the problem is harder, the best achievable error rate is much higher than that of 'human vs AI' (AC1). DeepSeek-R1 has the lowest error rate 0.405, and Claude-3.5-sonnet has the second best one 0.435. The error rates of the other three methods are nearly 0.5. In conclusion, Claude-3.5-sonnet and DeepSeek-R1 are the winners in terms of error rate. If we also take the running time into account, Claude-3.5-sonnet has the best overall performance. On the other hand, the cost of Claude-3.5-sonnet is the highest.

Since the 1164 testing abstracts come from 15 authors, we also report the classification error for each author (i.e., the testing documents only include this author's human-written abstracts and the AI-generated variants). Figure 2 shows the boxplots of per-author errors for each of 5 LLMs. Since authors have different writing styles, these plots give more information than Table 3. For 'human vs AI' (AC1), Claude-3.5-sonnet is still the clear winner. For 'human vs humAI' (AC2), DeepSeek-R1 still has the best performance. Furthermore, its advantage over Claude-3.5-sonnet is more visible in these boxplots: Although the overall error rates of two methods are only mildly different, DeepSeek-R1 does have a significantly

Method	human vs. AI			human vs. humAI		
Method	Error	Runtime	Cost	Error	Runtime	Cost
Claude-3.5-sonnet	0.218	7 min	\$ 0.5 USD	0.435	7 min	\$ 0.3 USD
DeepSeek-R1	0.286	$235 \min$	0.05 USD	0.405	183 min	$0.04~\mathrm{USD}$
Gemini-1.5-flash	0.468	6 min	0.1 USD	0.500	6 min	0.09 USD
GPT-40-mini	0.511	$7 \min$	0.1 USD	0.502	8 min	$0.12~\mathrm{USD}$
Llama-3.1-8b	0.511	11 min	\$ 0.2 USD	0.501	12 min	\$ 0.17 USD

Table 3: The classification errors, runtime, and costs of 5 LLMs for authorship classification. (In 'human vs AI' (AC1), if we report four digits after the decimal point, Llama-3.1-8b has a lower error than GPT-40-mini. This is why they have different ranks for AC1 in Table 1.)

better performance for some authors.

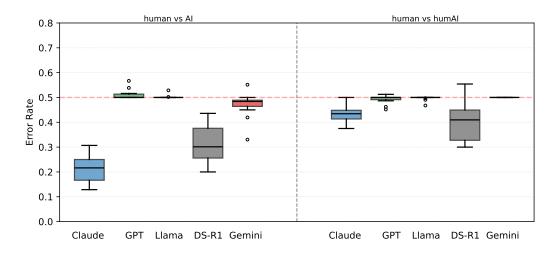


Figure 2: The boxplots of per-author classification errors.

We also investigate the similarity of predictions made by different LLMs. For each pair of LLMs, we calculate the percent of agreement on predicted labels, in both the 'human versus AI' (AC1) setting and 'human versus humAI' (AC2) settings. The results are in Figure 3. For both settings, Gemini-1.5-flash, GPT-40-mini, and Llama-3.1-8b have extremely high agreements with each other. This is because all three models predict 'human-written' for the majority of samples. DeepSeek-R1 and Claude are different from the other three, and they have 64% and 70% agreements with each other in two settings, respectively.

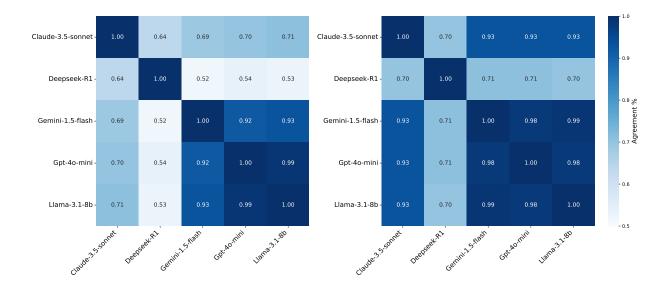


Figure 3: The prediction agreement among 5 LLMs in detecting AI from human texts. Left: 'human versus AI' (AC1). Right: 'human versus humAI' (AC2). Take the cell on the first row and second column (left panel) for example: for 70% of the samples, the predicted outcomes by DeepSeek-R1 and Claude-3.5-sonnet are exactly the same.

2.2 Citation classification

The MADStat only contains meta-information and abstracts, rather than full papers. We created a new data set, CitaStat, by downloading full papers and extracting the text surrounding citations. Specifically, we restricted to those papers published during 1996-2020 in 4 representative journals in statistics: Annals of Statistics, Biometrika, Journal of the American Statistical Association, and Journal of the Royal Statistical Society Series B. We wrote code to acquire PDFs from journal websites, convert PDFs to plain text files, and then extracted the sentence (using SpaCy, a well-known python package for sentence parsing) containing each citation (we call it a 'citation instance'). There are over 367K citation instances in total. We randomly selected n=3000 of them and manually labeled them using one of the following four categories:

• 'Fundamental Idea (FI)' (previous work that directly inspired or provided important ideas for the current paper). Example: "The proposed class of discrete transforma-

tion survival models is originally motivated from the continuous generalized odds-rate model by Dabrowska and Doskum (1988a) with time-invarying covariate and Zeng and Lin (2006) for..."

- 'Technical Basis (TB)' (important tools, methods, data sets, and other resources).

 Example: "We solve this system numerically via the Euler method (Protter and Talay 1997; Jacod 2004) with a time-step of one day..."
- 'Background (BG)' (background, motivations, related studies, and examples to support/illustrate points). Example: "Estimation of current and future cancer mortality broken down by geographic area (state) and tumor has been discussed in a number of recent articles, including those by Tiwari et al. (2004) ..."
- 'Comparison (CP)' (comparison of methods or theoretical results). Example: "Another way of determining the number of neuron pairs is to follow Medeiros and Veiga (2000b) and Medeiros et al. (2002) and use a sequence of..."

These definitions were inspired by existing studies on citation types (Moravcsik and Murugesan, 1975; Teufel et al., 2006; Dong and Schäfer, 2011). Occasionally, two categories may overlap. For example, a reference is cited as providing a fundamental idea, and a comparison with it is also stated in the same sentence. In this case, we label it as 'Fundamental Idea (FI)', to highlight that this is more important than a general comparison. There were 20 citation instances for which manual labeling gave 'not sure'. We removed them and obtained n = 2980 labeled samples (see Table 4).

	Background	Comparison	Fundamental Idea	Technical Basis	Total
Count	1721	316	169	774	2980
Fraction	57.8%	10.6%	5.7%	26%	-

Table 4: The distribution of four classes in CitaStat.

With this CitaStat data set, we consider two problems as mentioned:

- (CC1). The 4-class classification problem: Given the textual content of a citation (i.e., the text surrounding the citation), we aim to classify it to one of the four classes.
- (CC2). The 2-class classification problem: We re-combine the four categories into two, where 'Fundamental Idea' and 'Technical Basis' are considered as 'Significant (S)', and Background and Comparison are considered as 'Incidental (I)'.² Given the textual content of a citation, we aim to predict whether it is a 'Significant (S)' citation.

For each of the 5 LLMs, we used prompts to get classification decisions. Unlike the previous authorship classification problem, the class definitions in this problem are not common knowledge and need to be included in the prompt. In the 2-class problem, we use the prompt as in Figure 4. It provides definitions, examples, and how the four classes are re-combined into two, aiming to convey to the LLM as much information as possible. The prompt for the 4-class problem is similar, except that the description of grouping 4 classes into 2 is removed and the requirement for output format is modified (see Figure 4).

We examined the performances of all 5 LLMs. Since the runtime of DeepSeek-R1 is much longer than other methods, we only implemented it on 149 randomly selected samples (which included 5% of all samples and maintained the same class fractions as the full data set) to evaluate its classification error rate. Meanwhile, we ran DeepSeek-V3, an earlier-released version of DeepSeek-R1, in all samples. The results are reported in Table 5.

For the 4-class problem, Claude-3.5-sonnet has the lowest error rate at 0.327, followed closely by Gemini-1.5-flash at 0.347. DeepSeek-R1 outperforms DeepSeek-V3 but underperforms other methods except Llama-3.1-8b. For the 2-class problem, Claude-3.5-sonnet still achieves the best performance with an error rate of 0.261. DeepSeek-R1 is the second best, with an error rate of 0.275. Gemini-1.5-flash is worse than DeepSeek-R1 but slightly better than DeepSeek-V3. In summary, Claude-3.5-sonnet is the winner in terms of error rate.

²As mentioned, when a citation potentially belongs to two categories (e.g., 'Fundamental Idea' and 'Comparison'), we always manually label it to the more 'significant' one (e.g., 'Fundamental Idea'). This prevents mis-interpreting important comparisons as 'incidental' citations in the manual labeling.

The content in the text comes from a paragraph in an academic paper A that includes citations. Please classify the citation [Reference Key] appearing in the following text into one of the categories:

- Background (citations that include descriptions of the research background, summaries of previous or recent studies and methods in a general way, and examples to support and illustrate points. For example, [Example 1],
- Comparison (citations that compare methods or results with those of this paper. For example, [Example 2],
- Fundamental idea (citations about the previous work that inspired or provided ideas for this paper. For Example, [Example 3],
- Technical basis (citations of important tools, methods, data, and other resources used in this paper. For example, [Example 4].

Furthermore, we consider Background or Comparison as Incidental, and Fundamental idea or Technical basis as Important.

Text: [Citation text]

Please reply only with one of the following: Important or Incidental.

Figure 4: The prompt for 2-class citation classification, where [Reference Key] is the phrase in the text representing this reference, and [Example 1] is an example text from Background (other categories are similar). The prompt for 4-class classification is similar, except that the sentence "Furthermore, we consider ..." is removed and the last sentence is changed to "Please reply only with one of the following: Background, Comparison, Fundamental idea, or Technical basis."

Regarding the runtime, GPT-40-mini and Gemini-1.5-flash are the fastest (especially, GPT-40-mini only spent 15 minutes). DeepSeek-V3 and Llama-3.1-8b are relatively slow, requiring a few hours. Regarding the cost, DeepSeek-V3 is the cheapest one, and Claude-3.5-sonnet is significantly most expensive than the other methods.

Additionally, in the 4-class setting, we divided all samples into three groups according to the average prediction error by 5 LLMs (this is an average of 5 binary values; we

Model	Error (4-class)	Error (2-class)	Runtime	Cost
Claude-3.5-sonnet	0.327	0.261	1-2 h	\$ 12.30 USD
DeepSeek-V3	0.432	0.332	3-4 h	Ψ 0.60 RMB
DeepSeek-R1 \dagger	0.403	0.275	-	-
Gemini-1.5-flash	0.347	0.313	$25 \min$	\$ 0.12 USD
GPT-40-mini	0.363	0.371	$15 \min$	0.30 USD
Llama-3.1-8b	0.576	0.457	4-5 h	\$ 1.20 USD

Table 5: The error rate, runtime and cost of 6 LLMs for citation classification. (†The error rates of DeepSeek-R1 were evaluated on only 5% randomly selected samples. It took about 3-4 hours to run DeepSeek-R1 in this small sample.)

exclude DeepSeek-R1 here, as we don't have the results on all samples). The lowest 30%, middle 40%, and highest 30% are called the Easy, Medium, and Difficult case, respectively. Table 6 shows the per-group error rates of all 5 LLMs. In the Easy case, the error rates of all methods except Llama-3.1-8b are less than 0.01. In the Difficult case, all methods perform poorly, with GPT-4o-mini attaining the lowest error rate at 0.832 and DeepSeek-V3 attaining the highest at 0.956. In the Medium case, Claude-3.5-sonnet performs well with an error rate of 0.177, followed by Gemini-1.5-flash with a similar error rate 0.211. Llama-3.1-8b shows a notably higher error rate of 0.732.

	Claude-3.5-sonnet	DeepSeek-V3	Gemini-1.5-flash	GPT-4o-mini	Llama-3.1-8b
Easy	.001	.007	.004	.010	.063
Medium	.177	.358	.211	.277	.732
Difficult	.851	.956	.870	.832	.881

Table 6: The per-group error rates for 5 LLMs in citation classification.

Finally, we investigate the similarity of predictions made by different LLMs. For DeepSeek-R1, since we only implemented it on 5% of samples, we excluded it in the comparison. For each pair of the remaining 5 LLMs, we calculated the percent of agreement on predicted labels, in both the 4-class and 2-class settings. The results are given in Figure 5.

In the 4-class citation classification setting (CC1), except for Llama-3.1-8b, the percent

of agreement between any other two LLMs is above 70%. Especially, Claude-3.5-sonnet and Gemini-1.5-flash have the highest level of agreement at 77%. Llama-3.1-8b has relatively low agreements with other models. In the 2-class setting, there is a high level of agreement among the 3 LLMs: Claude-3.5-sonnet, DeepSeek-V3, and Gemini-1.5-flash; especially, the agreement between the last two is 83%. Still, Llama-3.1-8b has relatively low agreements with other models. In summary, Gemini-1.5-flash and Claude-3.5-sonnet have a consistently high agreement. For DeepSeek-V3, it has the highest agreement with Gemini-1.5-flash, and its level of agreement with GPT-40-mini is only in the medium rage.



Figure 5: The prediction agreement among 5 LLMs in citation classification.

In summary, DeepSeek underperforms Claude, but consistently outperforms Gemini, GPT, and Llama. Also, DeepSeek is computationally slower than others, and Claude is much more expensive than others. Given that DeepSeek is a new LLM where the training cost is only a fraction of that of other LLMs, we expect that in the near future, DeepSeek will grow substantially and may become the most appealing LLM approach for our study.

3 Discussion

Since the release of its latest version on January 20, 2025, DeepSeek has been the focus of the attention in and beyond the AI community. It is desirable to investigate how it compares to other popular LLMs. In this paper, we compare DeepSeek with 4 other popular LLMs (Claude, Gemini, GPT, Llama) with the task of predicting an outcome using a short piece of text. We consider two settings, an authorship classification setting and a citation classification setting. In these settings, we find that in terms of the prediction accuracy, DeepSeek outperforms Gemini, GPT, and Llama in most cases, but consistently underperforms Claude.

Our work can be extended in several directions. First, it is desirable to compare these LLMs with many other tasks (e.g., natural language processing, computer vision, etc.). For example, we may use the ImageNet data set (Deng and et al., 2009) to compare these LLMs and see which AI is more accurate in classification. Second, for both classification problems we considered in this paper, it is of interest to further improve the performance of the LLM by combining tools in statistics and machine learning. Take the authorship classification for example. We can first use statistical tools to suggest a list of words that are discriminative between AI-generated text and human-generated text. We then construct a new prompt by combining these words with the prompt used earlier in our paper. With the new prompt, we expect that the performance of an LLM can be much improved. See our forthcoming manuscripts (Gao et al., 2024; Jin et al., 2025) for example. Last but not the least, the datasets we generated can be used not only as a platform to compare different approaches, but also as useful data to tackle many interesting problems. For example, the MadStatAI data set can be used to identify the patterns of AI generated documents, and the CitaStat data set can be used to tackle problems such as author ranking or estimating the research interest of an author (see for example Ji et al. (2022) and Ke et al. (2024)).

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