When Locally Deployable Small Models Can Substitute LLMs? An Empirical Study on Active Learning in Real-World Scenarios

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Abstract

Large Language Models (LLMs) excel at diverse benchmarking tasks, yet face many deployment barriers in real-world scenarios, such as data privacy and computing resources. On the other hand, low-resource learning techniques like Active Learning (AL) can reduce the annotation cost for fine-tuning locally deployable small models. Subsequently, when and how those AL-assisted small models with low-resource expert annotations can substitute off-the-shelf generic LLMs in real-world scenarios is critical but being overlooked. This empirical study examines AL-assisted small models versus generic LLMs in **five** real-world tasks with expert annotations. Our AL simulation validates the significance of AL-assisted locally deployable small models as well as the importance of distinct AL sampling strategies in real-world scenarios. We further discuss a promising future paradigm that leverages LLMs to "warm-up" AL-assisted small models.

1 Introduction

Recently, Large Language Models (LLMs) (Brown et al., 2020) have shown great capability in a variety of tasks. However, while several works allow more efficient training and deploying LLMs (Lester et al., 2021), there still exists a barrier to deploying LLMs in many real-world scenarios, such as computational cost (Brown et al., 2020), carbon footprint (Luccioni et al., 2023), and lack of domain knowledge (Xu et al., 2023). Also, in numerous real-world fields such as biomedical and legal, it is not viable to employ generic LLMs that are hosted by third-party companies (Plant et al., 2022). Instead, what consistently shows effectiveness in these domains is smaller, locally deployable models that are trained on expert annotations.

However, human experts are usually hard to access (Rasmussen et al., 2022), expensive to recruit (Wu et al., 2022), and often unwilling to work as a labeler to annotate large-scale and high-quality datasets, especially in many domains that require extensive expertise (e.g., legal, clinical, and education) (Xu et al., 2022; Pappas et al., 2020). To bridge the gap between the scarcity of high-quality data and the huge data demand for model training, the research communities have widely explored low-resource learning techniques, such as transfer learning and meta-learning. Active Learning (AL, Settles (2009)) stands out due to its human-in-the-loop design (Wu et al., 2022). Thus, a crutial question araises: **when and how those AL-assisted small models with low-resource expert annotations can substitute generic LLMs in real-world scenarios?** We hypothesize that AL-assisted small language models with a small number of expert annotations can reliably outperform generic LLMs.

This work presents an empirical study with AL simulations on five datasets from two real-world specialized domains (Biomedicine and Legal). We probe state-of-the-art (SOTA) LLMs (GPT-3.5 and GPT-4 (OpenAI, 2023)) with their best-performing prompting methodologies and compare them with an AL-assisted T5-base model (Raffel et al., 2020) leveraging two different AL strategies.

Our results show that the AL-assisted T5 model with hundreds of human annotations can consistently outperform GPT-3.5 and perform on par with GPT-4. Our results justify our hypothesis that locally deployable small models are irreplaceable in real-world domain-specific scenarios as well as the importance of selecting different AL sampling strategies. To better assist human experts' daily work, we also envision a hybrid paradigm to leverage LLMs to "warm-up" AL models.

2 Empirical Study Design

2.1 Datasets

We thoroughly examine existing expert-annotated datasets for specific real-world domains that re-

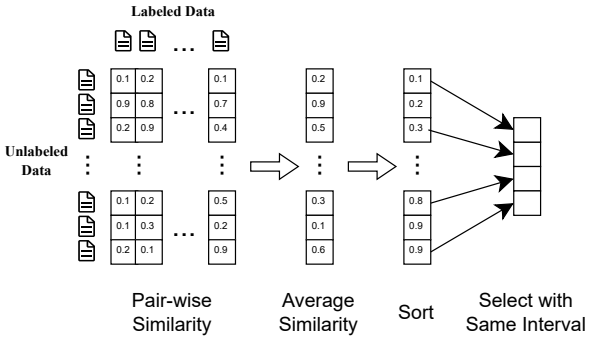


Figure 1: The sampling process of our data diversity-based strategy.

quire extensive expertise and choose BioMRC (Pappas et al., 2020), CUAD (Hendrycks et al., 2021), Unfair_tos (Lippi et al., 2019), ContractNLI (Koreeda and Manning, 2021) and Casehold (Zheng et al., 2021) for our evaluation. The datasets are in legal and biomedical domains and different types of tasks, including Multiple Choice, Classification, and Natural Language Inference (MacCartney and Manning, 2008). The dataset details are in Table 3.

2.2 Models

For the experiments with LLM, we utilize two SOTA generic LLMs: GPT-3.5 and GPT-4 (OpenAI, 2023). We probe the best-performing prompting strategy for each dataset with LLMs through extensive experiments on GPT-3.5 (reported in Appendix B) and apply the same settings for GPT-4.

We choose T5 (Raffel et al., 2020) as the backbone for AL because existing works demonstrate that T5 has strong performance for domain-specific fine-tuning (Yao et al., 2022; Mou et al., 2021). We initialize the T5 model with T5-base, a pre-trained weight that is trained on many general-domain downstream tasks.

2.3 Active Learning Strategies

Following the established taxonomies of AL strategies (Schröder and Niekler, 2020), we designed and implemented one **data diversity-based** strategy and one **model uncertainty-based** strategy. The diversity-based approach aims to identify the most representative examples from the unlabeled data space while maximizing the diversity, regardless of the model. On the other hand, the uncertainty-based approach attempts to locate examples that the model is least confident about. We illustrate the details of each strategy below and in Algorithm 1.

Data Diversity-Based Strategy. The process of data diversity-based sampling is illustrated in Figure 1. The objective of the data diversity-based strategy (Schröder et al., 2022) is to identify the most representative and diverse data. During the data pre-processing stage, we utilize Sentence-BERT (Wang et al., 2020) to embed each data content as a vector to prepare for the diversity-based AL sampling. For each iteration of the diversity-based AL sampling strategy, we 1) calculate the average cosine similarity score between each unused training data and all previously used training data, 2) sort the unused data by the average similarity score, and 3) select representative examples with the same interval from the sorted list to ensure diversity. For instance, in order to select 4 examples from 10 unused data, we select the 1st, 4th, 7th and 10th data from the ranked list after Step 2. This strategy design allows us to ensure the diversity and representativeness of selected examples.

Model Uncertainty-based Strategy. Model Uncertainty-Based Strategy (Sener and Savarese, 2018) aspires to identify samples the model is least confident about. Within each iteration, the model operates on the training data, computing the logits and locating the samples holding the minimal average probability on the highest-ranked tokens.

In addition to the aforementioned two types of AL strategies, we also include a random AL sampling baseline. For each iteration in the AL simulations, we follow a common practice of sampling 16 data samples with a specified strategy and then evaluate the model on the test split. Each AL setting was executed 10 times, and we report the mean and standard errors.

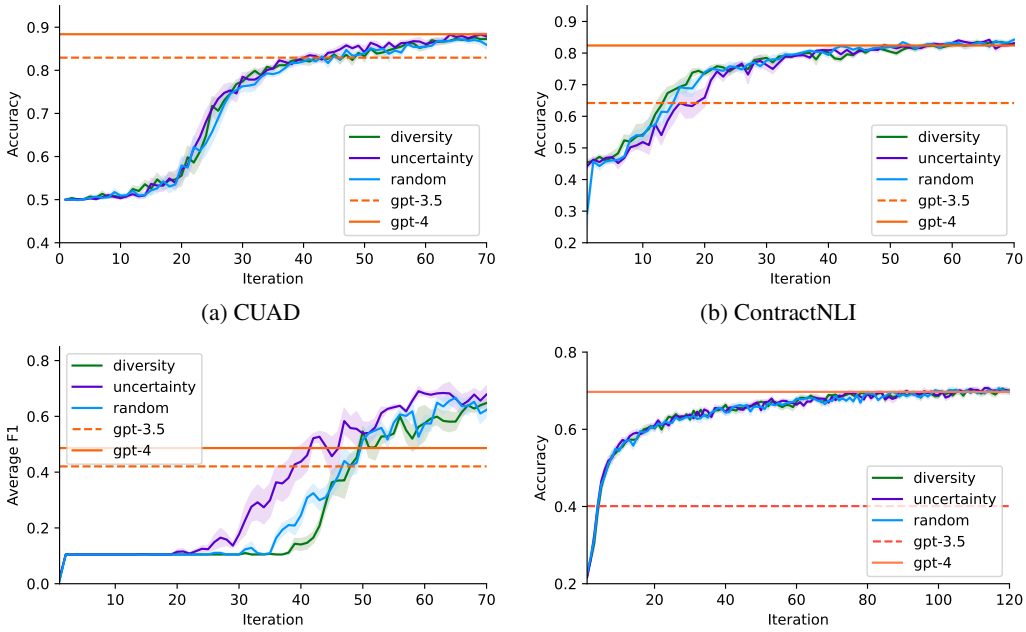
2.4 Evaluation Methods

We utilized the averaged F1 score for each label to evaluate Unfair_TOS to avoid the influence of unbalanced label distribution, which will also be discussed in Section 3.2. We evaluate the other datasets with average prediction accuracy. Detailed task instructions and experiment hyperparameters are shown in Appendix C and D.

3 Study Result

3.1 LLM vs. AL-Assisted Small Models

We plot the results on four legal domain datasets in Figure 2, and the results on BioMRC in Appendix A. The horizontal lines symbolize the best performance of GPT-3.5 and GPT-4, respectively.



(a) CUAD (b) ContractNLI

(c) Unfair_TOS (d) Casehold

Figure 2: AL simulation results. The horizontal line represents two close-domain LLMs' best performance. We report the mean value (line) and standard error (colored shaded area) over 10 trials. Each AL iteration comprises 16 examples. We can observe the T5-base with AL can reliably **outperform GPT-3.5** and reach a saturated performance that is **compatible with or even exceeds GPT-4** on all four datasets.

Unsurprisingly, all AL approaches suffer from the "cold-starting" problem. However, on all four datasets, the T5-base with AL can reliably **outperform GPT-3.5** and eventually reach a saturated performance that is **compatible with or even exceeds GPT-4**, leveraging a total of several hundred data selected. For BioMRC, as shown in Figure 3, the T5-base can also consistently beat GPT-3.5 but is saturated at a slightly lower performance compared to GPT-4. However, we believe GPT-4 might have seen or been trained on most of these datasets because they are publically available text corpora. Regardless, our fine-tuned T5-base achieves compatible performance with GPT-4 despite having hundreds of times fewer parameters and requiring significantly less computational power.

3.2 Further Analysis

Analysis of AL Strategies on Unfair_TOS. We observe the AL models in Unfair_TOS merely output "None" regardless of the input prior to the 20th iteration, but we can also observe clear advantage differences between AL strategies, where the uncertainty-based strategy can lead to better performance and saturate at higher results compared to the other settings.

The Unfair_TOS dataset consists of around 85% of data labeled *None*, and the rest of the data lies in eight other categories. We believe the AL model will be able to achieve a higher averaged F1 score if the AL strategy can select more *Not-None* data for the model to learn from. As a result, we calculate the label ratio for the original dataset and the data sampled by different AL strategies on the Unfair_TOS dataset, which can be found in Table 1. The ratio is calculated by dividing the corresponding data type by the count of all data. We sum the counts of all other eight data types and denote them as *Not-None*. We can observe the model uncertainty-based strategy selects significantly more *Not-None* labeled data than random ($t(14) = -2.46$, $p < 0.05$) and diversity ($t(14) = -2.51$, $p < 0.05$), which justifies the better performance of the uncertainty-based strategy.

Strategy	*Not-None* Ratio	*None* Ratio
Random	0.1247	0.8752
Diversity	0.1255	0.8744
Uncertainty	0.1458	0.8541
Complete dataset	0.1252	0.8747

Table 1: Label distributions of complete dataset and data sampled by different AL strategies in Unfair_TOS. The ratio is calculated by dividing the corresponding data type by all data counts.

Influence of Different Number of Few-Shot Examples. To establish a more solid evaluation, we conducted an additional experiment by evaluating GPT-4's performance when given different amounts of few-shot demonstrations. We used 1, 10, 50, and the maximum amount subject to the model input limit. If GPT-4 can only handle less than 50 examples, we omit the results for the 50 shots and report the max-shot results instead. To ensure reproducibility and control cost, we randomly sample 200 examples from the original test split and set the random seed to 42.

The result is reported in Table 5. We observe that generic LLM's (GPT-4) performance does not always increase when we add more and more data into the prompt, and with 10 shots can generally result in a saturated performance. Also, in three of the five datasets experimented, GPT-4 can only fit fewer than 20 few-shot examples in their context limit, justifying the need for small, fine-tuned models for domain-specific tasks.

3.3 Discussion

We can observe all AL strategies suffer from well-known "cold-start" issues (Chen et al., 2022; Jin et al., 2022), where the model performs poorly at the early iterations due to potentially under-fitting issues as a result of the lack of enough labeled data. On the other hand, LLMs, specifically GPT-4 in our case, yield reasonably good performance despite eventually being surpassed by AL models fine-tuned on domain-specific datasets.

We envision a promising future paradigm in real-world domain-specific tasks of incorporating LLMs and AL fine-tuned smaller models in parallel. At first, the LLM's prediction will be presented to the human expert, and the collected annotation will be used to train the AL model. When the AL model begins to outperform LLM, the system will "switch" to present the AL model's prediction. Thus, the LLM's prediction can help overcome the "cold-starting" problem of AL, and the calibration ability (Zhu et al., 2023) can also be used to help identify the hard-to-answer or the wrong predicted examples in the sampling process to be annotated. And, the system can still benefit from AL's continually improving and up-to-date performance. The "switch" mechanism to efficiently and continually evaluate the AL model against the LLM will be a crucial component of such a paradigm, which will be investigated in our future work.

4 Related Works

Active Learning. Active Learning allows the model to iteratively sample a few annotations to be finetuned on (Shen et al., 2017; Ash et al., 2019; Teso and Kersting, 2019; Kasai et al., 2019; Zhang et al., 2022; Xiao et al., 2023). Thus, the key element of AL lies in the sampling strategy (Yao et al., 2023; Sharma et al., 2015). Many AL surveys categorize AL sampling strategies into three high-level underlying concepts – data diversity-based, model uncertainty-based, and hybrid strategies (Settles, 2009; Olsson, 2009; Fu et al., 2013; Schröder and Niekler, 2020; Ren et al., 2021).

Large Language Models LLMs (Brown et al., 2020; OpenAI, 2023; Touvron et al., 2023a,b) can learn task-solving from the context of few-shot examples and generate high-quality content without fine-tuning (Wei et al., 2021; Chung et al., 2022). Several recent works claim that LLMs can outperform human annotators for text classification (Gilardi et al., 2023), task evaluations (Chiang and Lee, 2023; Liu et al., 2023; Törnberg, 2023), and even in specialized domains (Nori et al., 2023). LLMAAA (Zhang et al., 2023) utilizes LLM as a weak annotator to train a small model with AL.

5 Conclusion

While LLMs such as GPT-4 have been endorsed to outperform smaller models in many benchmarking datasets, whether they can substitute smaller models, especially in real-world tasks and domains requiring extensive domain expertise, is important and debatable. In this work, we present an empirical study evaluating the performance between SOTA generic LLMs (GPT-3.5 and GPT-4) and a much smaller language model (T5-base) fine-tuned with different Active Learning strategies on five specialized datasets representing real-world domain-specific tasks.

Our evaluation demonstrates that smaller AL-assisted models trained with expert annotation can consistently achieve or exceed best-performing LLMs with only a few hundred expert-annotated data, justifying that human experts remain indispensable in domain-specific tasks. Derived from our results, we posit a future paradigm that utilizes LLMs to overcome the "cold-start" issue of AL models as a "warm-up" strategy and eventually switch back to small models fine-tuned on domain-specific data once the latter outperforms LLMs.

6 Limitations

This work primarily presents an empirical study of generic LLMs versus AL-assisted small language models fine-tuned on experts-annotated domain-specific data. Our experiment of AL-assisted models solely utilizes a T5-base model, where the performance of other models, such as BART (Lewis et al., 2019) and even LLMs that can be efficiently fine-tuned with Parameter-Efficient Fine-Tuning techniques (Mangrulkar et al., 2022; Hu et al., 2021; Lester et al., 2021), remains to be explored. This work only benchmarks two SOTA generic LLMs (GPT-3.5 and GPT-4). We are aware other LLMs exist that we do not include in this work, such as Mistral-7B (Jiang et al., 2023), Llama-2 (Touvron et al., 2023b), etc.

We only implemented and evaluated two fundamental types (data diversity-based and uncertainty-based) of Active Learning strategies in our work, and we are aware there exist other families of AL strategies that could extend our study, e.g., hybrid or ensemble approaches (Krogh and Vedelsby, 1994; Qian et al., 2020). Nevertheless, our empirical study with two fundamental Active Learning strategies justifies our primary statement that human experts are still needed in real-world domain-specific data annotation tasks.

Our evaluation comprises five datasets from two specialized real-world domains (legal and biomedical). We identify there are other domains and publically available domain-specific datasets, and we leave the analysis of the generalizability of our observations from this work to other domains and tasks as future work. In addition, we primarily engage in model comparisons through automated metrics. However, these may not necessarily provide an accurate representation of a model's performance. Also, an error analysis on which type of questions LLMs may excel or fail is also meaningful for future work. Therefore, human evaluation of these datasets, including human agreement and error analysis, might be needed for a more comprehensive assessment.

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A Empirical Study Result on BioMRC

For BioMRC, as shown in Figure 3, the T5-base with AL can quickly **outperform GPT-3.5** and eventually reach a saturated performance that is slightly lower than GPT-4. We posit that GPT-4 may have performed exceptionally well due to its exposure or training on BioMRC, given its source's public accessibility. Nevertheless, our refined T5-base model demonstrates comparable performance to GPT-4. Remarkably, this is achieved despite the T5-base model's comparative parameter deficiency - in the hundreds of times less - and a significantly lower demand for computational resources.

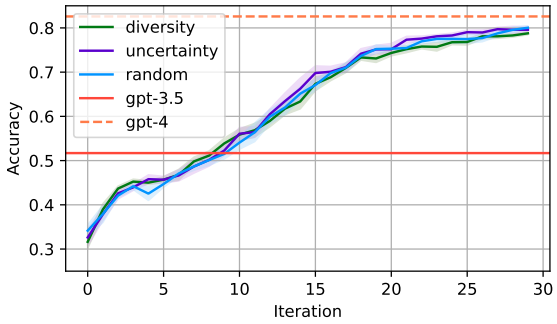

Figure 3: Result on BioMRC

B LLM Prompting Experiments

The LLM prompting experiments can be found in Table 2. To obtain the SOTA performance, we experiment with GPT-3.5 under zero-shot and few-shot (1,3, 10 shots) to find the best-performing setting (bolded) for each dataset and execute GPT-4 with the same settings.

C Hyperparameters and Settings

We report the experiment hyperparameters in Table 4. All our experiments are executed on one of two resources: 1) four NVIDIA V100 32G graphic cards and 2) eight NVIDIA V100 32G graphic cards. For GPT-3.5 and GPT-4, we used GPT-3.5-0613 and GPT-4-0613 respectively.

For model uncertainty-based strategies, we calculate the model probability on a randomly sampled subset of the training data to reduce the time complexity of the model uncertainty-based data sampling process. Compared to the naive approach's $O(n^2)$ time complexity, our implementation remains to have a time complexity of $O(n)$, which is the same as that of non-AL's (where n is the number of training data).

Algorithm 1 Active Learning Sampling Process

function SELECT($D_t, D_p, N, strategy$)
  D_t: unlabeled data in the training split
  D_p: previously selected data
  N: number of data needed
  $strategy$: Active Learning strategy
  if $strategy =$ `"similarity"` **then**
    $S \leftarrow \left(\frac{\sum_{d_p \in D_p} \cos(d_i, d_p)}{|D_p|}\right)_{1 \le i \le |D_t|}$
    $id \leftarrow \text{argsort}(S)$
    $step \leftarrow \frac{|D_t|}{N}$
    $result \leftarrow (id_i)_{i \equiv 0 (\text{mod } step), 1 \le i \le |D_t|}$
    return $result, id - result$
  end if
  if $strategy =$ `"uncertainty"` **then**
    $S \leftarrow (\text{Uncertainty}(d_i))_{1 \le i \le |D_t|}$
    $id \leftarrow \text{argsort}(S)$
    return $id_{<N}, id_{\ge N}$
  end if
end function

Dataset	Learning Rate	Training Epoch
BioMRC	1e-4	20
Unfair_TOS	1.5e-4	12
ContactNLI	1.5e-4	20
Casehold	4e-5	28
CUAD	6e-5	18

Table 4: Hyperparameters for each dataset.

D Prompts Used for Each Dataset

Text in [[double brackets]] denotes input data.

D.1 BioMRC (Pappas et al., 2020)

```
I want you to act as an annotator for a
↪ question answering system. You will
↪ be given the title and abstract of a
↪ biomedical research paper, along
↪ with a list of biomedical entities
↪ mentioned in the abstract. Your task
↪ is to determine which entity should
↪ replace the placeholder (XXXX) in
↪ the title.

Here's how you should approach this
↪ task:

Carefully read the title and abstract of
↪ the paper.
```

Dataset	Metric	GPT-3.5				GPT-4
		0 shot	1 shots	3 shots	10 shots	
CUAD	Accuracy	0.6404	0.8048	**0.8293**	0.8178	0.8837
BioMRC	Accuracy	0.4067	**0.5169**	0.5040	0.4532	0.8259
Unfair_tos	F1	0.4201	0.3847	0.3758	**0.4206**	0.4863
ContractNLI	Accuracy	0.4580	0.5990	0.5750	**0.6420**	0.8240
Casehold	Accuracy	0.3040	0.3020	0.3330	**0.4010**	0.6970

Table 2: Hyper-parameter tuning experiment results for GPT-3.5 and GPT-4.

Dataset	Domain	Task	# Test Data
BioMRC Pappas et al. (2020)	Biomed.	Multi-Choice	6, 250
CUAD Hendrycks et al. (2021)	Law	Classification	4, 182
Unfair_tos Lippi et al. (2019)	Law	Classification	1, 620
ContractNLI Koreeda and Manning (2021)	Law	NLI	1, 991
Casehold Zheng et al. (2021)	Law	Multi-Choice	3, 600

Table 3: Datasets involved in our empirical study.

Dataset	1-shot	10-shot	50-shot	max-shot (avg. # of shots)
BioMRC	0.835	0.810	-	0.760 (13 shots)
Unfair_tos	0.441	0.488	0.567	0.563 (137 shots)
ContractNLI	0.715	0.750	-	0.740 (47 shots)
CUAD	0.795	0.790	-	0.82 (18 shots)
CaseHOLD	0.660	0.790	-	0.735 (19 shots)

Table 5: GPT-4 result with different number of few-shot examples

```
Pay close attention to the context in
↪ which the placeholder (XXXX) appears
↪ in the title.
Review the list of biomedical entities
↪ mentioned in the abstract.
Determine which entity from the list
↪ best fits the context of the
↪ placeholder in the title.
Output only the identifier for the
↪ chosen entity (e.g., `@entity1`). Do
↪ not output anything else.

<INPUT>:
<title>:
[[TITLE]]
<abstract>:
[[ABSTRACT]]
<entities>:
[[ENTITY]]
<OUTPUT>:
```

D.2 UnfairTOS (Lippi et al., 2019)

```
I want you to act as an annotator for a
↪ Term of Service (ToS) review system.
↪ You will be given a piece of a Term
↪ of Service. Your job is to determine
↪ whether the ToS contains any of the
↪ following unfair terms:

Limitation of liability
Unilateral termination
Unilateral change
Content removal
Contract by using
Choice of law
Jurisdiction
Arbitration

If none of the above terms are present,
↪ you should output "None".

Here's how you should approach this
↪ task:

Carefully read the ToS.
Review the list of unfair terms.
For each unfair term, determine whether
↪ it is present in the ToS.
Output only the unfair terms that are
↪ present in the ToS. A ToS may have
↪ multiple unfair terms. \
You should output all of them, separated
↪ by a semicolon (;).
Do not output anything else.

<text>:
[[TEXT]]
<OUTPUT>:
```

D.3 ContractNLI (Koreeda and Manning, 2021)

```
I want you to act as an annotator for a question answering system. You will be given a contract and a hypothesis. Your task is to determine the hypothesis is contradictory, entailed or neutral to the contract.

Here's how you should approach this task:

Carefully read the contract.
Carefully read the hypothesis.
Determine whether the hypothesis is contradictory, entailed or neutral to the contract.
Output only the label (contradiction, entailment, neutral). Do not output anything else.

<INPUT>:
<premise>:
[[PREMISE]]
<hypothesis>:
[[HYPOTHESIS]]
<OUTPUT>:
```

D.4 CUAD (Hendrycks et al., 2021)

```
I want you to act as an annotator for a question answering system. You will be given the question and a piece of a contract. You will need to answer the question based on the contract. There are only two possible answers, "Yes" or "No".

Here's how you should approach this task:

Carefully read the question.
Carefully read the contract.
Determine the answer to the question is true or not.
Output only the exact answer (one of "Yes" or "No") of the questions. Do not output anything else.
<INPUT>:
<text>:
[[TEXT]]
<question>:
[[QUESTION]]
<OUTPUT>:
```

D.5 Casehold (Zheng et al., 2021)

```
I want you to act as an annotator for a Question Answering system. You will be given the question and several answers. Your job is to determine which answer best answers the question.

Here's how you should approach this task:

Carefully read the question.
Carefully read the answers.
Output the numeric index of the answers that best answers the question.
Do not output anything else.

<INPUT>:
<question>:
[[QUESTION]]
<answer>:
[[ANSWER]]
<OUTPUT>:
```