

Designing Informative Metrics for Few-Shot Example Selection

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Abstract

Pretrained language models (PLMs) have shown remarkable few-shot learning capabilities when provided with properly formatted examples. However, selecting the “best” examples remains an open challenge. We propose a complexity-based prompt selection approach for sequence tagging tasks. This approach avoids the training of a dedicated model for selection of examples, and instead uses certain metrics to align the syntactico-semantic complexity of test sentences and examples. We use both sentence- and word-level metrics to match the complexity of examples to the (test) sentence being considered. Our results demonstrate that our approach extracts greater performance from PLMs: it achieves state-of-the-art performance on few-shot NER, achieving a 5% absolute improvement in F1 score on the CoNLL2003 dataset for GPT-4. We also see large gains of upto 28.85 points (F1/Acc.) in smaller models like GPT-j-6B.¹

1 Introduction

Pretrained language models (PLMs) have demonstrated impressive few-shot learning capabilities when prompted with examples for a particular task (Brown et al., 2020). In few-shot prompting, k examples that demonstrate the goal of the downstream task along with the test sample (collectively called the k -shot prompt) are provided to the PLM. However, the effectiveness of PLMs in few-shot learning depends on the “quality” of these prompts; achieving this quality is challenging due to the need for unambiguous instruction (Sclar et al., 2024), which is further complicated by the task of selecting appropriate examples. Appropriately selected examples will ensure that the PLM can generalize effectively and perform well across diverse natural language processing (NLP) tasks.

Recent work has shown that specific examples provided in-context can significantly impact the performance of PLMs (Min et al., 2022). Sorensen et al. (2022) notes that specific example combinations lead to better generalization, and connects this with the informativeness of these examples. This suggests that surfacing “specific” properties of prompts result in improved performance. Most prior work for prompt selection has either trained a prompt retriever to select examples, or used PLMs themselves to label examples (Rubin et al., 2022) to serve as a good prompt. However, both approaches require additional computation and task specific training. Liu et al. (2022) use nearest neighbours algorithms to select examples. However, this approach solely relies on embedding space properties, and does not consider other metrics which model label distribution such as entropy, leading to sub-optimal performance in some tasks.

In this work, we propose a new approach for example selection for sequence tagging tasks. These tasks are important because they enable the extraction of structured information from unstructured text data; this serves as a fundamental building block for various NLP tasks. Our approach, *complexity-based prompt retrieval* (CP retrieval), aims to select examples from the training data whose “properties” align with that of the test sentence. To this end, we use sentence- and word-level complexity measures to match prompt examples to evaluation sentences.

We conduct our experiments on named entity recognition (NER), part-of-speech (POS) tagging, and sentence chunking. We also create a new dataset involving tagging of Contextual Integrity (CI) parameters for privacy policies. We show that CP retrieval improves accuracy significantly in all cases.

The contributions of this work are as follows: (1) We propose CP retrieval to select prompts based on sentence and word level complexity metrics

¹Code and data used for the experiments in this paper is available at <https://github.com/RishabhAdiga/Complexity-based-prompt-retrieval.git>.

(§ 3); and (2) We demonstrate improved few-shot accuracy with CP retrieval. Our approach achieves state-of-the-art performance in few-shot NER with a 5% absolute improvement in F1 score on the CoNLL2003 dataset for GPT-4 and upto 28.85 points (F1/Accuracy) in smaller models (§ 5).

2 Related Work

To perform our experiments, we use the *Structured Prompting* paradigm introduced by Blevins et al. (2023) as our baseline for named entity recognition (NER), part-of-speech (POS) tagging, and sentence chunking. These are sequence tagging tasks—those that assign labels or tags to tokens or other units of text. This involves iteratively feeding the PLM a word and its predicted label to get it to label the next word. PLMs are also provided k pairs of (sentence, tagged sentence) as the task examples in a k -shot prompt. Experiments by Brown et al. (2020) show that PLMs can effectively solve these tasks with just a few demonstrations using this technique. We consider another task involving annotating contextual integrity (CI) parameters in privacy policies (Shvartzshnaider et al., 2019); we use a generic few-shot prompt as the baseline for this task as shown in Appendix A (Fig. 6).

Liu et al. (2022) have explored strategies for selecting examples to leverage GPT-3’s few-shot learning capabilities. They analyzed the sensitivity of GPT-3’s performance to randomly sampled examples and found significant variability (a phenomenon also explained by Min et al. (2022)). Liu et al. (2022) proposed a retrieval based approach called KATE that selects semantically similar examples by using k -nearest neighbors (in the embedding space of pre-trained sentence encoders like BERT and RoBERTa) which are used as the examples for the k -shot prompt. They found that KATE substantially improved GPT-3’s results over random sampling on natural language understanding and generation tasks.

3 Methodology

Our core idea is simple: *to select examples that closely resemble the test sample in both semantics and length while ensuring a diverse range of labels for the task*. We measure the “complexity” of a candidate example using 3 different sentence- and word-level metrics: (a) normalized sentence similarity score, (b) normalized smoothed length similarity, and (c) normalized label entropy.

Problem Setup: Assume we have a training dataset of the form $D = \{z_i = (x_i, y_i)\}_{i=1}^n$ and a test example x_{test} , our goal is to use a complexity score to select a subset of examples S of the training dataset ($S \subset D$) s.t. $|S| = k$.

3.1 Normalized Sentence Similarity

For a given test sentence, we calculate its similarity scores with each candidate sentence for the k -shot prompt. We convert each of the sentences into sentence embeddings using the all-MiniLM-L6-v2 sentence transformer (results do not vary drastically with alternate embedding methods). This produces an embedding size of 384 dimensions. To find the similarity score, we calculate cosine similarity between the embeddings.

$$\text{Similarity}(x_i, x_{test}) = \text{cosine_sim}(\text{emb}(x_i), \text{emb}(x_{test}))$$

These values are normalized to get our final sentence similarity scores. Formally, this is denoted as NormSentSimilarity².

3.2 Normalized Smoothed Length Similarity

This metric is based on the difference in sentence lengths between the candidate sentence and the test sentence. We use this metric since cosine similarity of sentence embeddings does not inherently factor sentence length. The smoothed length similarity (SLS) transforms the absolute length difference between two sentences using a sigmoid function to produce a smooth, tapered similarity curve rather than a hard threshold. The sigmoidal nature of SLS prevents stark drops in scores for small length divergences. This is important as, for few-shot prompting, some flexibility in length ranges is desirable to provide syntactic variety while maintaining coarse length matching. It is formulated as follows:

$$\text{SLS}(x_i, x_{test}) = (1 + \exp(\frac{|\text{len}(x_i) - \text{len}(x_{test})|}{T}))^{-1}$$

where T controls the sigmoidal shape ($T = 3$ in our experiments). Sentences with similar lengths achieve higher SLS scores, while increasingly divergent lengths taper down towards 0 in a continuous, non-binary fashion. These values are then normalized to provide our final Normalized Smoothed Length Similarity scores denoted as NormSLS².

²Normalization here is $N(s_i) = s_i / \max(S)$ where $S = \{s_1, \dots, s_n\}$ and $s_i \in \mathbb{R}$

3.3 Normalized Label Entropy

For a given task, let \mathcal{Y} define the space of possible labels. For sentence x_i , let y_i be the list of labels, and $\nu(y_i^j)$ is the frequency of label $j \in \mathcal{Y}$ in list y_i . We can calculate $\Pr(y_i^j) = \nu(y_i^j)/\text{len}(x_i)$. Entropy is then calculated as:

$$H(y_i) = - \sum_{j \in \mathcal{Y}} \Pr(y_i^j) \log_2 \Pr(y_i^j)$$

The intuition is that sentences where labels are more skewed provide less information gain for in-context learning compared to flatter distributions. Entropy can be used to quantify that skew difference. We normalize these entropy values to get our final NormEntropy² scores.

3.4 Complexity Score

We propose a complexity score to align the syntactico-semantic complexity of prompts and examples. The three component metrics are weighted and summed to produce the final complexity score:

$$\begin{aligned} \text{CS}(z_i, x_{\text{test}}) = & w_1 * \text{NormSLS}(x_i, x_{\text{test}}) \\ & + w_2 * \text{NormEntropy}(y_i) \\ & + w_3 * \text{NormSentSimilarity}(x_i, x_{\text{test}}) \end{aligned}$$

We use this score to select the k highest scoring train sentences for a k -shot prompt. w_1, w_2, w_3 are weights that are set using grid search to optimize scores on the development set for each sequence tagging task. We found that $(w_1, w_2, w_3) = (0.25, 0.25, 0.5)$ is the best set for NER, $(w_1, w_2, w_3) = (0.2, 0.1, 0.7)$ is the best set for Chunking, $(w_1, w_2, w_3) = (0.1, 0.1, 0.8)$ is the best set for POS Tagging and $(w_1, w_2, w_3) = (0.1, 0.1, 0.8)$ is the best set for CI tagging. We see that the above set of values indicate that sentence similarity is most important. This is likely due to the presence of extremely similar examples in the test and training set.

4 Experimental Setup

Tasks: We perform our experiments on 3 different sequence tagging tasks namely NER, POS tagging, and sentence chunking. Each task involves the annotation of tokens in a sequence with specific labels, facilitating the extraction of valuable information and enhancing language understanding. For all datasets, we use a random set of 1000 test samples. For the CI task, we use 100 test samples.

1. *NER*: This focuses on classifying named entities within a text. The entities can range from persons and organization to locations and dates. For our experiments, we use the widely recognized CoNLL2003 dataset (Tjong Kim Sang and De Meulder, 2003).

2. *POS Tagging*: This involves assigning grammatical categories (e.g., nouns, verbs, adjectives) to each word in a sentence. We evaluate the POS tagging performance using the English Universal Dependencies (UD) treebank annotated on the GUM corpus (Zeldes, 2017). It employs the UPOS tagset introduced by Nivre et al. (2020).

3. *Sentence Chunking*: This aims to partition sentences into non-overlapping syntactic units. For our experiments, we use the CoNLL2000 dataset (Tjong Kim Sang and Buchholz, 2000) to frame chunking as a BIO tagging task.

4. *CI parameters*: We additionally created a custom dataset that involves the sequence tagging task of CI parameters for privacy policies. For more details on this dataset, refer to Appendix C.

Models: We perform our experiments on the GPT-Neo series of models which has parameter counts from 125 million to 20 billion (GPT-Neo-125M, GPT-Neo-1.3B, GPT-Neo-2.7B, GPT-j-6B, GPT-NeoX-20B) and additionally 2 black box models (Davinci-002 and GPT-4) for the sequence tagging tasks of NER, POS tagging and sentence chunking. For our custom dataset for CI parameters tagging, we use Llama2 variants.

5 Results

Table 1 compares the F1 and Accuracy scores (for NER, chunking and POS tagging) for different models while keeping the number of examples constant. Table 2 provides the same for the CI tagging task on Llama models (performance in a different domain). Our results show that CP retrieval significantly improves few-shot accuracy over the baseline across all models and considered tasks.

We observe substantial gains using our method, with the largest gains on GPT-j-6B which achieves a 28.85 point increase on NER, followed by GPT-Neo-2.7B which achieves a 24.82 point increase in chunking, and finally with GPT-Neo-125M which achieves a 15.56 point increase in POS tag-

³Accuracy has changed with respect to the original paper for this model probably because of the the reasoning in Chen et al. (2023)

	NER (F1)		Chunking (F1)		POS (Acc.)	
	Baseline	CP retrieval	Baseline	CP retrieval	Baseline	CP retrieval
GPT-Neo-125M	12.46	29.21	24.28	40.33	55.53	71.09
GPT-Neo-1.3B	31.49	52.44	25.44	44.19	65.30	75.58
GPT-Neo-2.7B	25.73	41.77	28.50	53.32	64.68	76.19
GPT-j-6B	25.88	54.73	35.85	54.56	79.96	84.37
GPT-Neox-20B	37.74	61.49	56.18	59.66	80.64	86.21
Davinci-002 (Black Box)	20.30	40.03	35.82	51.79	46.04 ³	52.20
GPT-4 (Black Box)	83.48*	88.76	79.78	84.52	92.93	93.47

Table 1: Results of using complexity scores for retrieval of the best k examples (CP retrieval) for the few-shot prompt (here $k = 5$). The baseline is in the structured prompting paradigm (Blevins et al., 2023) with static prompt examples. **CP retrieval significantly surpasses the baseline using linguistic structure alone for the prompt (details in Appendix A) in all cases.** Best values are in boldface. * in the table shows the previously achieved state-of-the-art performance on few-shot NER by Ashok and Lipton (2023).

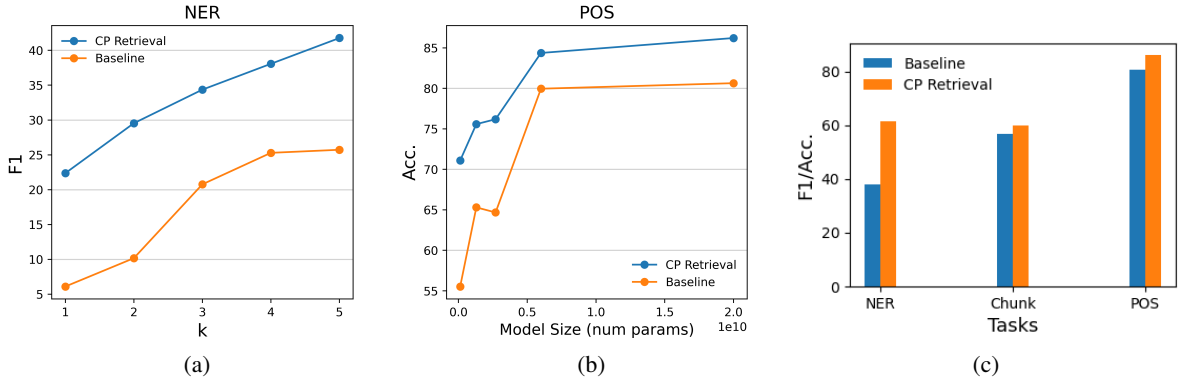


Figure 1: **CP retrieval demonstrates superior performance across all tasks.** (a) Performance while varying number of demonstrations k (GPT-Neo-2.7B) for NER. (b) Performance while varying model size for a fixed $k = 5$ for POS. (c) Performance for the various tasks on GPT-Neox-20B model with $k = 5$. Note that NER and chunking are evaluated based on the F1 score, and POS is evaluated based on accuracy as commonly done.

	CI tagging (Acc.)	
	Baseline	CP retrieval
Llama2-13B	36.07	51.82
Llama2-70B	43.29	55.95

Table 2: Results of using complexity score for retrieval (CP retrieval) on the CI parameters tagging task using Llama2 models. Best values are in boldface.

ging. It is also evident that the percentage gains of example selection drops with increasing model size in Fig. 1(b) (with GPT-4 having the least gains), and this is due to CP retrieval approaching overall accuracy saturation. Low gains in GPT-4 are also because larger models have seen more diverse training data, so random prompt selections are more than likely to cover the needed distribution. However, even with small gains, we achieve state-of-the-art performance on the CoNLL2003 dataset with a 5% increase over the previous state-of-the-

art by Ashok and Lipton (2023) for few-shot NER.

Impact of k : From Fig. 1(a), we see that our approach enables effective learning (larger gains) with smaller k . At $k = 2$, we see a gain of 19.37 points over the baseline which decreased when k is increased. The percentage gains consistently reduce as we increase the number of examples.

Discussion: What we want to put forth is that this approach can further boost performance when combined with more sophisticated prompting techniques. For example, CP retrieval can be used along with chain-of-thought (CoT) prompting (Wei et al., 2023). It can be used to identify the most information-rich examples for the initial context in CoT prompting.

5.1 Ablation Study

Impact of Individual Complexity Metrics: Table 3 shows the performance of each individual

	NER (F1)	Chunking (F1)	POS (Acc.)
Normalized Sentence Similarity	25.39	38.16	66.82
Normalized Smoothed Length Similarity	17.22	31.50	59.91
Normalized Label Entropy	15.08	28.11	60.43
Baseline	12.46	24.28	55.53

Table 3: **Results of performing ablations to analyze the performance of each individual metric when used for retrieval of k examples for a few-shot prompt (here $k = 5$).**

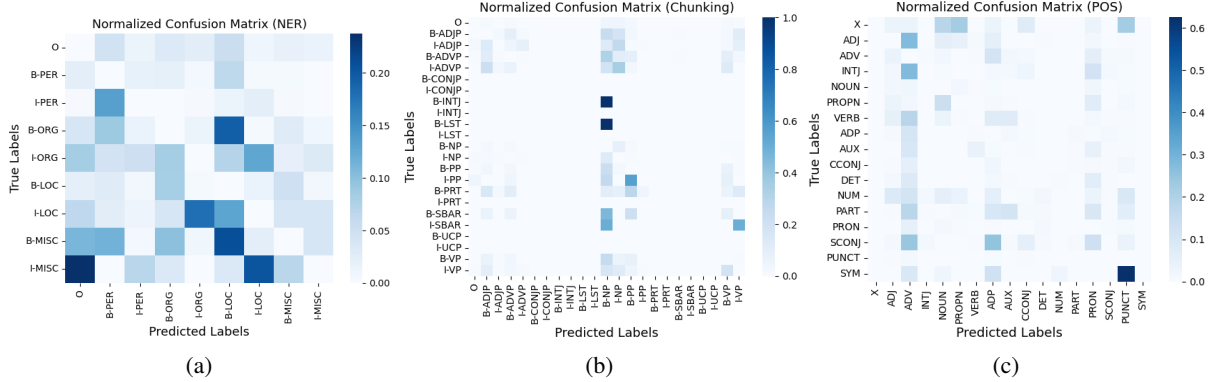


Figure 2: **Normalized confusion matrices for (a) NER (b) Chunking and (c) POS**

metric in isolation to retrieve the best k examples for the few-shot prompt. It is evident that all 3 metrics lead to gains in accuracy/F1 scores for each of these datasets. It is also important to observe that the Normalized Sentence Similarity metric leads to the highest gains in performance over the baseline. This is also directly reflected in the optimal values for the weights (w_1, w_2, w_3) in seen in § 3.4 which have a higher value associated with w_3 .

Other Baselines: We also compared our methodology with the k NN baseline in Appendix B demonstrating that CP retrieval consistently outperforms k NN-based example retrieval. For example, it results in a 4.27% absolute gain in F1 score over the k NN baseline for the task of sentence chunking when using GPT-Neo-2. 7B model.

Number of Samples: In Appendix D, we show that CP retrieval helps in improving performance *even when* the number of samples to retrieve from in the train set is reduced. Specifically, when the number of available samples for the NER task is reduced to 1000 (from 11079), CP retrieval achieves an F1 score of 25.98 compared to the baseline random selection score of 12.46. Even with just 30 samples, CP retrieval attains an F1 score of 18.19.

5.2 Error Analysis

In this subsection, we analyze the common errors made by PLMs using our methodology to identify patterns and potential areas for improvement. We

do so by looking at the confusion matrices shown in Fig. 2. To plot these, we have zeroed out the diagonal values which represent correct predictions and then perform normalization, making it easier to compare error rates across different classes.

We see that error rate is more evenly spread out for NER (with a max of around 0.25) (c.f. Fig. 2(a)), whereas Chunking (c.f. Fig. 2(b)) and POS (c.f. Fig. 2(c)) have more localized errors. We see vertical bands in the confusion matrices of Chunking and POS, and these vertical bands can indicate systematic biases or recurring mistakes in the model which can be targeted for correction. Specifically, the model over predicts many words as "B-NP" (Beginning of a Noun Phrase) in chunking and incorrectly predicts the "SYM" (Symbol) tag as "PUNCT" (Punctuation) in POS tagging.

6 Conclusions

In summary, CP retrieval is a flexible technique that can be used to enhance the accuracy of existing few-shot approaches using example scoring. Additionally, it provides a task-agnostic quantification of the informativeness of examples for improved model performance. The relative weights of the components of the complexity score can be tuned on a per-task basis. Our approach allows us to extract the most out PLMs without any fine-tuning of model parameters.

7 Limitations

Our methodology focuses on sequence tagging tasks and cannot be applied to tasks outside this domain such as question answering. This is because the normalized entropy metric is specifically designed for encouraging selection of sentences with a wider label variety on the token level; this helps increase the sampling of underrepresented labels. Further, we have conducted all experiments for the sequence tagging tasks in only the English language. Performance with other languages has not been analyzed.

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Appendix

A Prompts

Context: The Finance Ministry raised the price for tap sales of the Dutch government 's new 5.75 percent bond due September 2002 to 99.95 from 99.90 .

Tagged: The_O Finance_B-ORG Ministry_I-ORG raised_O the_O price_O for_O tap_O sales_O of_O the_O Dutch_B-MISC government_O 's_O new_O 5.75_O percent_O bond_O due_O September_O 2002_O to_O 99.95_O from_O 99.90_O ._O

Context: Swiss bonds ended mostly higher in generally quiet activity , with the September confederate bond futures contract holding just above 113.00 .

Tagged: Swiss_B-MISC bonds_O ended_O mostly_O higher_O in_O generally_O quiet_O activity_O ,_O with_O the_O September_O confederate_O bond_O futures_O contract_O holding_O just_O above_O 113.00_O ._O

Context: The Brent crude futures market on the Singapore International Monetary Exchange (SIMEX) was closed on Monday in respect for a U.K. national holiday .

Tagged: The_O Brent_B-ORG crude_O futures_O market_O on_O the_O Singapore_B-ORG International_I-ORG Monetary_I-ORG Exchange_I-ORG (_O SIMEX_B-ORG)_O was_O closed_O on_O Monday_O in_O respect_O for_O a_O U.K._B-LOC national_O holiday_O ._O

Context: European bourses closed mixed on Tuesday with London clawing back most of the day 's losses despite an unsteady start on wall Street , hit by inflation worries .

Tagged: European_B-MISC bourses_O closed_O mixed_O on_O Tuesday_O with_O London_B-LOC clawing_O back_O most_O of_O the_O day_O 's_O losses_O despite_O an_O unsteady_O start_O on_O wall_B-ORG Street_I-ORG ,_O hit_O by_O inflation_O worries_O ._O

Context: No closures of airports in the Commonwealth of Independent States are expected on August 24 and August 25 , the Russian Weather Service said on Friday .

Tagged: No_O closures_O of_O airports_O in_O the_O Commonwealth_B-LOC of_I-LOC Independent_I-LOC States_I-LOC are_O expected_O on_O August_O 24_O and_O August_O 25_O ,_O the_O Russian_B-ORG Weather_I-ORG Service_I-ORG said_O on_O Friday_O ._O

Context: Hungarian overnight interest rates closed higher on Friday as market liquidity tightened before the December 10 social security contribution payment deadline, dealers said.

Tagged:

Figure 3: Prompt generated for a specific test sample after retrieval of 5 examples (5-shot prompt) from the training dataset for **Named Entity Recognition** using our approach. The test sentence that we want the model to label is provided at the end of the prompt and is shown in bold

Context: Shearson is offering the notes as 6 34 % securities priced to yield 6.15 % .

Tagged: Shearson_B-NP is_B-VP offering_I-VP the_B-NP notes_I-NP as_B-PP 6_B-NP 34_I-NP %_I-NP securities_I-NP priced_B-VP to_B-VP yield_I-VP 6.15_B-NP %_I-NP ._O

Context: Bonds due 1991-1996 carry 6.70 % coupons and bonds due 1997-2000 carry 6 34 % coupons .

Tagged: Bonds_B-NP due_B-ADJP 1991-1996_B-NP carry_B-VP 6.70_B-NP %_I-NP coupons_I-NP and_O bonds_B-NP due_B-ADJP 1997-2000_B-NP carry_B-VP 6_B-NP 34_I-NP %_I-NP coupons_I-NP ._O

Context: Their price falls further than that of other bonds when inflation and interest rates kick up .

Tagged: Their_B-NP price_I-NP falls_B-VP further_B-ADVP than_B-PP that_B-NP of_B-PP other_B-NP bonds_I-NP when_B-ADVP inflation_B-NP and_O interest_B-NP rates_I-NP kick_B-VP up_B-PRT ._O

Context: Serial bonds were priced at par to yield to 6.90 % in 2000 .

Tagged: Serial_B-NP bonds_I-NP were_B-VP priced_I-VP at_B-PP par_B-NP to_B-VP yield_I-VP to_B-PP 6.90_B-NP %_I-NP in_B-PP 2000_B-NP ._O

Context: At the auction of six-month U.S. Treasury bills on Monday , the average yield fell to 7.61 % from 7.82 % .

Tagged: At_B-PP the_B-NP auction_I-NP of_B-PP six-month_B-NP U.S._I-NP Treasury_I-NP bills_I-NP on_B-PP Monday_B-NP ,_O the_B-NP average_I-NP yield_I-NP fell_B-VP to_B-PP 7.61_B-NP %_I-NP from_B-PP 7.82_B-NP %_I-NP ._O

Context: The rate on six-month bills rose to 7.53 % for a bond-equivalent yield of 7.92 % .

Tagged:

Figure 4: Prompt generated for a specific test sample after retrieval of 5 examples (5-shot prompt) from the training dataset for **Sentence Chunking** using our approach. The test sentence that we want the model to label is provided at the end of the prompt and is shown in bold

Context: Many forms of culture are passed down through a combination of deliberate and unconscious processes .
Tagged: Many_ADJ forms_NOUN of_ADP culture_NOUN are_AUX passed_VERB down_ADP through_ADP a_DET combination_NOUN of_ADP deliberate_ADJ and_CCONJ unconscious_ADJ processes_NOUN ._PUNCT
Context: Cognitive psychology is the field of psychology dedicated to examining how people think .
Tagged: Cognitive_ADJ psychology_NOUN is_AUX the_DET field_NOUN of_ADP psychology_NOUN dedicated_VERB to_SCONJ examining_VERB how_ADV people_NOUN think_VERB ._PUNCT
Context: Having been a psychologist for a number of years gives me a leg up on it .
Tagged: Having_AUX been_AUX a_DET psychologist_NOUN for_ADP a_DET number_NOUN of_ADP years_NOUN gives_VERB me_PRON a_DET leg_NOUN up_ADV on_ADP it_PRON ._PUNCT
Context: Do they get mad or irritated if the centre of attention moves to someone else ?
Tagged: Do_AUX they_PRON get_VERB mad_ADJ or_CCONJ irritated_VERB if_SCONJ the_DET centre_NOUN of_ADP attention_NOUN moves_VERB to_ADP someone_PRON else_ADV ?_PUNCT
Context: When thoughts are formed , the brain also pulls information from emotions and memories (Figure 7.2) .
Tagged: When_ADV thoughts_NOUN are_AUX formed_VERB ,_PUNCT the_DET brain_NOUN also_ADV pulls_VERB information_NOUN from_ADP emotions_NOUN and_CCONJ memories_NOUN (_PUNCT Figure_PROPN 7.2_NUM)_PUNCT ._PUNCT
Context: Psychologists have examined the mental processes that underpin conscious and unconscious biases [6] ;
Tagged:

Figure 5: Prompt generated for a specific test sample after retrieval of 5 examples (5-shot prompt) from the training dataset for **Part-of-Speech** tagging using our approach. The test sentence that we want the model to label is provided at the end of the prompt and is shown in bold

Context: Classify each word in the the sentence to its contextual integrity parameter (Sender, Attribute, Receiver, None, TP, Subject)
Example1:
Input Sentence:
[We, will, also, disclose, nonpersonally, identifiable, information, to, our, partners, and, other, third, parties, about, how, our, users, collectively, use, the, Sites]
Output:
[[We, Sender], [will, None], [also, None], [disclose, None], [nonpersonally, Attribute], [identifiable, Attribute], [information, Attribute], [to, None], [our, Receiver], [partners, Receiver], [and, None], [other, Receiver], [third, Receiver], [parties, Receiver], [about, TP], [how, TP], [our, TP], [users, TP], [collectively, TP], [use, TP], [the, TP], [Sites, TP]]
Example2:
Input Sentence:
[If, you, choose, to, use, our, referral, service, to, tell, a, friend, about, Military, or, refer, other, information, on, Military, to, a, friend, we, will, ask, you, for, your, friends, name, and, email, address]
Output:
[[If, TP], [you, TP], [choose, TP], [to, TP], [use, TP], [our, TP], [referral, TP], [service, TP], [to, TP], [tell, TP], [a, TP], [friend, TP], [about, TP], [Military, Attribute], [or, TP], [refer, TP], [other, Attribute], [information, Attribute], [on, TP], [Military, Attribute], [to, TP], [a, TP], [friend, TP], [we, Receiver], [will, None], [ask, None], [you, Sender], [for, None], [your, Subject], [friends, Subject], [name, Attribute], [and, None], [email, Attribute], [address, Attribute]]
Question: Now perform the same task on the input given below and provide output in the same format as above:
Input Sentence:
[Insert Input]

Figure 6: Prompt structure for the **CI** tagging task (2-shot prompt shown here)

B k NN Baseline

	NER (F1)		Chunking (F1)		POS (Acc.)	
	k NN Baseline	CP retrieval	k NN Baseline	CP retrieval	k NN Baseline	CP retrieval
GPT-Neo-125M	25.39	29.21	38.16	40.33	66.82	71.09
GPT-Neo-2.7B	36.44	41.77	49.05	53.32	73.71	76.19

Table 4: Results of using complexity score retrieval (CP retrieval) of the best scoring k examples for the few-shot prompt (here $k = 5$). The baseline here is picking the k -nearest neighbors + structured prompting paradigm (Blevins et al., 2023). Best values are in boldface which demonstrates that CP retrieval aids in significant performance gains.

C Contextual Integrity Dataset Details

The Contextual Integrity (CI) parameter tagging task (Shvartzshnaider et al., 2019) involves classifying the words in relevant sentences of privacy policies into the following classes - Sender, Receiver, Subject, Attribute and Transmission Principle. The total counts for each of these classes in the dataset is shown in Table 5. The dataset has a total of 600 samples (sentences) which have been extracted from The OPP-115 Corpus (Online Privacy Policies, set of 115) (Wilson et al., 2016) and labelled for this sequence tagging task. We utilize GPT-4 to create this dataset in a few-shot scenario (the examples for the few-shot prompts are manually labelled). Following this, we obtain the labelled outputs from GPT-4 which is then passed through human verification and relabelling. 3 annotators performed this task such that each sample is verified by 2 annotators and we achieve an average inter-annotator agreement of 0.64 using the popular Cohen’s Kappa metric (McHugh, 2012) on the relabelled classes. We have used 100 samples in the test set and the remaining 500 samples as part of the train set.

Class	Frequency
O	4817
SENDER	481
RECEIVER	1058
SUBJECT	509
ATTRIBUTE	3152
TP	6798

Table 5: Total class counts in the CI dataset

D Dependence on Number of Training Samples Available for Retrieval

While most practical tasks nowadays usually have a large set of examples present to select from, we wanted to check the viability of our methodology as the number of examples for selection reduced. The experiment was performed on GPT-Neo-125M with a 5-shot prompt on the NER dataset. It is evident from Table 6 that reducing the number of examples for selection reduces the F1 score gradually, but there are still significant gains even with a small set of examples to select from when it is compared to the random selection baseline.

No. of samples to select from	CP retrieval (F1)
11079 (Entire train data)	29.21
1000	25.98
500	24.38
100	23.74
30	18.19
Baseline-random sample selection (F1)	
11079 (Entire train data)	12.46

Table 6: Performance when number of samples to select from (train set) is reduced gradually. Even with just 30 samples to select from, CP retrieval provides a 5.73% absolute gain in F1 score.