



Towards Generalizable NLP Models: A Prompt-Guided Inference Dataset with Integrated Reasoning Rules

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Abstract

Keywords

natural language inference (NLI), reasoning, inference scenario creation, paragraph-level inference, prompt engineering, chain-of-thought prompting

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Introduction

Natural Language Inference (NLI) tasks serve as a valuable benchmark for assessing the capabilities of new models within Natural Language Understanding (NLU) research. This is particularly significant as NLU plays a crucial role in the success of many actively studied NLP problems, including question answering, translation, and dialogue [1].

Interestingly, the field of Natural Language Processing (NLP) often overlooks the role of paragraphs despite their importance in discourse and text generation. The majority of NLI datasets and research focused only on sentence-level inference, where the premises and hypotheses are expressed in single, typically brief sentences. They are therefore inappropriate for use in other open-ended NLP situations. This is particularly crucial in tasks aimed at verifying the factual accuracy of summaries of documents [2]. Paragraphs, often described as "units of thought," go beyond the grammatical structure of individual sentences (syntax) [3]. Analyzing how sentences within a paragraph connect through cohesion (referential links) and coherence (logical flow of ideas) unlocks a deeper understanding of meaning [4, 5, 6]. This analysis of relationships between sentences is crucial for tasks like discourse generation, where sentences need to be arranged in a way that creates a clear and cohesive flow of information. Incorporating paragraph-level semantics into NLP models could significantly improve their ability to handle real-world language tasks.

In addition, many crowdsourced NLI datasets, while convenient, may not be well-suited for tackling real-world NLP problems due to their creation in isolation from specific downstream tasks and due to inherent annotator biases [7, 8]. Specif-

ically, as shown in the case of Multi-Genre Natural Language Inference (MultiNLI), crowd workers sometimes relied on certain strategies to form hypotheses of a specific label like adding negators for contradiction labels, and introducing bias into the dataset. This approach creates an unrealistically easy task, failing to capture the true complexity of real-world human reasoning [8]. Many analyses of the SNLI dataset conducted in recent years have revealed that models trained on it often lack significant compositionality in their representations. Instead, these models primarily rely on straightforward heuristics, such as word overlap, when making inferences (this phenomenon is commonly recognized as the "lexical overlap heuristic," as articulated by McCoy et al.(2019) [9]. For instance, a high overlap in words between premises and hypotheses typically predicts entailment, while contradictory sentence pairs usually exhibit minimal or no word overlap and/or the presence of negation words. This underscores the importance of developing models that can effectively incorporate external knowledge for more nuanced natural language inference tasks [10, 11].

What is emerging NLI's most pressing problem is their propensity for overfitting. While these models demonstrate impressive performance on the datasets they are trained upon, potentially exceeding human benchmarks, their ability to generalize to unseen data remains severely limited. This phenomenon, well-established in machine learning, is referred to as the generalization problem [12]. An underlying cause might be the focus on deductive reasoning in training data creation. Careful examination of crowd worker instructions for popular NLI datasets reveals an emphasis on logically guaranteed inferences, neglecting inductive reasoning, which

involves concluding unseen data.

To address these challenges and generate more realistic, nuanced data, we propose a novel paragraph scope scenario-inference pair elicitation method where each scenario is accompanied by multiple potential inferences. By incorporating various reasoning modes within the prompt creation stage, we aim to train an NLI model that can handle a broader spectrum of reasoning patterns, ultimately leading to a more robust and generalizable understanding of natural language inference.

Recent work

Pioneering datasets like The Stanford Natural Language Inference (SNLI) [13] and the Multi-Genre Natural Language Inference (MNLI) [1] established a benchmark with their large scale, balanced data, and clear labels. However, as the field matures, researchers are constantly innovating, recognizing limitations in existing datasets such as reliance on human-generated sentences and potential biases.

Cornerstone Datasets

The Stanford Natural Language Inference (SNLI) dataset, a cornerstone for NLI research, offers a large-scale, balanced dataset with clear labels, facilitating robust models for diverse logical relationships [13]. However, limitations exist. The simplistic sentence generation process from simple, static scenes limits reasoning style diversity, and the reliance on affirmative image captions restricts the ability to assess negation, a crucial aspect of natural language [14]. Building upon SNLI, the Multi-Genre Natural Language Inference (MNLI) dataset extends the scope by incorporating sentence pairs from various genres and domains (e.g., fiction, telephone conversations) [1]. This inclusion of diverse genres promotes model robustness by exposing them to a wider range of language styles and reasoning patterns. Additionally, MNLI facilitates transfer learning tasks, where models trained on this dataset can be adapted to perform well on different NLP applications. While MNLI offers significant advancements, it inherits limitations from SNLI, such as reliance on human-generated sentences, and suffers from genre imbalance within the dataset. Gururangan et al. [15] questioned whether SNLI-trained models are achieving genuine language comprehension or simply capitalizing on coincidental patterns (artifacts) within the dataset.

Domain-Specific and Challenging Datasets

There are many existing NLI training datasets, each with its strengths and weaknesses. SciTail [7] focuses on scientific language, training models for reasoning specific to scientific contexts, and encouraging understanding of contextual relevance but is limited in size. FEVER (Fact Extraction and VERification) tackles real-world fact-checking challenges with claims and evidence from Wikipedia. While valuable for these tasks, FEVER can be susceptible to biases and noise from imperfect evidence retrieval [16]. BioNLI is a dataset in biomedical natural language inference [17]. Interestingly, this research

addresses the automatic creation of meaningful negative examples by using rule-based and neural-based counterfactuals, potentially removing the need for expert involvement.

The development of NLI datasets is a continuous process. The paper of Liu et al. [18] introduced a new dataset called ConTRoL for contextual reasoning in natural language inference. It is a passage-level NLI dataset that focuses on complex reasoning types and is more challenging than previous benchmarks. Rather than evaluating a hypothesis versus a short passage, Koreeda and Manning [19] introduced an evaluation of the hypothesis against a whole document. The system is provided with a contract and a set of hypotheses, which could be statements about the contract's obligations, rights, or other key points. This approach applied to contracts, requires models to understand the broader context of the document. Worth noting is the study by Nie et al. (2020) which presented a large-scale NLI benchmark dataset collected through an iterative human-in-the-loop approach, resulting in a dataset that surpasses existing benchmarks in difficulty. Beyond the dataset itself, the authors proposed a novel data collection method that functions as a "moving target" for NLU. Unlike static benchmarks that models can quickly overfit on, this approach acts as a never-ending learning scenario that allows for continuous improvement and adaptation [20].

HANS (Heuristic Analysis for NLI Systems) [21] and ANLI (Adversarial NLI) [20] both aim to improve the robustness of NLI models. HANS achieves this by exposing model biases through pre-defined templates, while ANLI uses specially crafted adversarial examples.

Parlay creation

This project seeks to construct a comprehensive inference dataset for training a NLP model. The proposed dataset (Parlay) will be designed to promote model generalizability by encompassing five distinct categories, ranging from historical events to fictional narratives as inference pairs. To ensure the dataset's further diversity, each category will include inference pairs drawn from a wide range of contexts within its topic. Clear and concise prompts will be employed to introduce scenarios within each category. These scenarios will provide a brief description of a situation or event, offering essential context for the model to perform various inference tasks effectively.

The selection of scenario categories – historical events, scientific explanations, everyday life situations, news reports, and fictional stories – is strategically chosen to provide a comprehensive training ground for various reasoning modes. Each category offers unique advantages. Examining historical events allows the model to analyze complex cause-and-effect relationships, temporal reasoning (e.g., order of events), reasoning about counterfactuals ("what if" scenarios), and reasoning by analogy (using the law of recurring patterns and motivations that influence similar situations) [22, 23, 24, 25, 26, 27, 28]. Scientific explanations necessitate the understanding of deductive logical reasoning rules

like *modus ponens* and *modus tollens* [29]. Everyday scenarios provide a fertile environment for practical reasoning. The model encounters incomplete information, necessitating inductive reasoning based on patterns, experiences, and common sense [30]. Additionally, everyday scenarios require analogical reasoning, where the model identifies similarities to use knowledge from one situation to understand another [31]. This approach equips the model with transferable reasoning skills, allowing the model to adapt to novel situations. On top of that, informal language plays a significant role in everyday situations. As everyday life moves more and more into a virtual environment, understanding the diverse system of informal language is of great importance. Examples of everyday conversations in informal language will be included to cover the wide range of inputs and forms, in which informal language appears. News reports naturally require the model to exercise critical reasoning skills [32]. This involves evaluating source credibility, identifying potential biases, and distinguishing factual information from opinion. Fictional stories will provide a platform for exploring narrative reasoning, including understanding characters’ motivations, and emotions (theory of mind) [33, 34]. Furthermore, because stories often involve social interactions and dynamics the model can learn to reason about how characters behave in social contexts and predict their actions based on social norms (social reasoning) [35, 36].

We opted for an alternative approach utilizing prompt-driven scenario generation. While inspired by natural texts and ideas as prompt inputs, the scenarios themselves will be newly created based on those prompts. This approach addresses key challenges inherent in natural text-based datasets: citation management and authorship attribution difficulties. Including complete citations within the dataset itself might not be feasible due to space constraints or the chosen format (e.g., plain text pairs). Manually creating and managing citations for a large dataset can also be incredibly time-consuming. Prompt-driven scenarios eliminate this burden. Furthermore, natural texts often lack clear authorship. The collaborative nature of news production, frequent use of anonymous sources, and information aggregation approach in books make it difficult to trace the origin of specific ideas. Additionally, journalists’ interpretations and re-presentations of existing information can obscure the original author of underlying concepts. Unclear authorship makes it difficult to assess the potential biases associated with the information, and when creating inference pairs from different fields, you might inadvertently introduce biases based on the original authors’ viewpoints. This can ultimately impact the credibility of datasets constructed from natural texts. Our prompts allow for greater control over the information presented, mitigating bias.

The dataset will be built in Slovenian, contributing to the overall linguistic diversity of NLI resources. Each data point within the dataset will consist of two key components: a scenario paragraph to establish the context for a specific situation and the corresponding paragraph generated based on entail-

ment, contradiction, or neutral labels. Crucially, each data point will be further augmented with explanations detailing the specific and generalized reasoning that informs the categorization of each pair into entailment, neutral, or contradiction. This approach goes beyond simply labeling the data and provides valuable insights into the LLM’s underlying logic for each categorization.

These detailed explanations play a critical role in enabling efficient learning with few examples, also known as “few-shot learning” [37]. Analyzing the explanations allows us to gain a deeper understanding of the underlying logic the LLM used to establish the relationship between the paragraphs. This knowledge allows us to effectively guide the LLM when creating new scenario-inference pairs, even with a limited number of starting examples. The explanations essentially act as a training aid, helping the LLM apply similar reasoning patterns to novel scenarios. Additionally, by analyzing the explanations, we can identify broader reasoning principles that can be applied beyond specific scenarios. This empowers the LLM to generalize its reasoning skills and handle a wider range of inference tasks.

By utilizing prompt-driven scenarios, we will ensure the creation of a high-quality and well-controlled foundation for generating diverse inference pairs. We will achieve this through the following methods:

Reasoning Rule-Guided Prompt Engineering. We will develop prompts that incorporate established reasoning rules, such as *modus ponens*, *modus tollens*, causal reasoning, textual entailment, and predictive inference (Liu, Teng, Ning, Liu, Zhou, Zhang, 2023). Our focus will be on crafting effective prompts that integrate factual hints and guide the model towards specific inferences (entailment, contradiction, neutral). Factual hints refer to pieces of information embedded within the prompts that provide the model with essential knowledge about the scenario. These hints serve as anchors for the model’s reasoning process, allowing it to make inferences based on established facts. While factual hints provide a strong foundation, real-world inferences often rely on broader reasoning patterns beyond established rules. To address this, we will incorporate heuristics within our prompts. Heuristics can capture these general reasoning patterns, allowing our prompts to be more adaptable to diverse scenarios and inferences encountered in real-world situations. We will achieve this by exploring templates or conditional statements within the prompts based on the reasoning rule we want to target.

Chain of Thought Reasoning. We will investigate the application of chain-of-thought reasoning, where the model explicitly reveals its reasoning steps as it arrives at an inference. This will allow us to gain deeper insights into the model’s decision-making process, especially in relation to the applied reasoning rules, and further refine our prompt design for optimal performance [38].

We will detail the specifics of this approach and its advantages in the following section.

Preliminary Results

For the purpose of sending in the first draft we have decided to each do some examples in order to get familiar with the process, to gather new ideas and to give our mentors an insight into how the dataset will look like.

Iterative Prompting and Human Expertise

This section of the report details the process undertaken by team member 1 to create a Natural Language Inference (NLI) dataset utilizing the large language model GPT-3.5.

The prompting process began by familiarizing the LLM with the concept of an NLI dataset. The team member inquired about the concept and requested an example. Following GPT-3.5's initial attempt (which exhibited issues regarding the "neutral" label), the team member clarified the concept of neutrality within the examples. To establish a consistent structure for the dataset, the team member presented an example from the Stanford NLI (SI-NLI) dataset. This served as a foundation for prompting GPT-3.5 to generate its examples. The structure of the generated examples was refined to achieve a consistent format encompassing premise, hypothesis, particular and generalized explanation, outlining the reasoning process. The primary focus was on prompting GPT-3.5 to create diverse NLI examples across various categories. On a few occasions, the team member provided prompts based on specific quotes or ideas but primarily relied on GPT-3.5's generation capabilities.

The most problems regarding the content arose when creating the 'neutral' part of the example, for it often understood neutral as "the subject of the premise not being in favour of one or the other option". That is why often the team member had to manually correct the examples to make an example functional or clearer. There were, however, examples, in which the link that was created by the LLM at first seemed a bit unclear, e.g. the link between the premise and the hypothesis seemed somewhat hard to detect, but upon further investigation the underlying reasoning provided by GPT-3.5 was recognized as sound and logical in a more direct sense, taking into consideration the meaning of each word and the connection between them. That is why these examples were retained as well because it is an addition to the diversity of the dataset.

Curated Few-Shot Learning with Chain of Thought Prompting

The second approach followed a two-stage methodology: first, compiling high-fidelity data points using the large language model Gemini, and second, training and inferencing the LLM using chain-of-thought prompting (again using LLM Gemini).

The project's foundation was built on crafting high-quality data points. Team member 2 carefully manually chose well-known historical occurrences, everyday life situations, and natural phenomena or processes as the core themes for these data points. To make sure they effectively prompted the LLM, each data point went through a rigorous process of refinement

using a trial-and-error approach. This involved creating, testing, and then revising the data points until they consistently produced good results. Data points were crafted to incorporate rich contextual information surrounding the concept. This might have involved narrative framing and the inclusion of multiple perspectives within the scenario. This selection encouraged diverse reasoning applications by encompassing concepts with varying domains, complexities, and reasoning technique requirements. The second stage explored the application of one-shot or few-shot learning techniques for LLM training. This approach involved training the LLM on a limited set of thoroughly prepared data points. The goal of this technique was to leverage the rich information content embedded within each data point to enable the LLM to effectively generalize its learnings. Following training, a prompting technique termed chain of thought prompting was employed. This approach involved crafting prompts that explicitly guide the LLM through a series of logical steps. The prompts referenced the underlying factors and relationships that define the concepts presented in the data points. Conditioned by these prompts, the LLM was then tasked with inferring related concepts or situations. Crucially, the LLM was also expected to clarify the reasoning behind its inferences, thereby revealing the connections between the original concept and the inferred one. This prompting technique employed a crucial feedback loop. The initial prompts were crafted, and the LLM's responses were analyzed. Based on these outcomes, the prompts were iteratively refined to better guide the LLM's reasoning process and elicit more insightful explanations. This back-and-forth process ensured the prompts became progressively more effective in unlocking the LLM's ability to perform chain-of-thought reasoning.

To optimize the LLM's training process, we translated the data points and prompts into English (and finally translated the outcomes back into Slovenian). This decision stemmed from the fact that languages with fewer resources require more tokens to represent the same information. This increased tokenization could have compromised the LLM's ability to effectively simulate understanding of the concepts. Another interesting observation was that LLMs often favor short, two-sentence outputs. To address this, we implemented techniques that encourage the generation of longer and more coherent paragraphs.

Discussion

Acknowledgments

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