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Boosting Logical Fallacy Reasoning in LLMs via Logical Structure Tree

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Abstract

Logical fallacy uses invalid or faulty reasoning in the construction of a statement. Despite the prevalence and harmfulness of logical fallacies, detecting and classifying logical fallacies still remains a challenging task. We observe that logical fallacies often use connective words to indicate an intended logical relation between two arguments, while the argument semantics does not actually support the logical relation. Inspired by this observation, we propose to build a logical structure tree to explicitly represent and track the hierarchical logic flow among relation connectives and their arguments in a statement. Specifically, this logical structure tree is constructed in an unsupervised manner guided by the constituency tree and a taxonomy of connectives for ten common logical relations, with relation connectives as non-terminal nodes and textual arguments as terminal nodes, and the latter are mostly elementary discourse units. We further develop two strategies to incorporate the logical structure tree into LLMs for fallacy reasoning. Firstly, we transform the tree into natural language descriptions and feed the textualized tree into LLMs as a part of the hard text prompt. Secondly, we derive a relation-aware tree embedding and insert the tree embedding into LLMs as a soft prompt. Experiments on benchmark datasets demonstrate that our approach based on logical structure tree significantly improves precision and recall for both fallacy detection and fallacy classification.

1 Introduction

Logical fallacy refers to the use of invalid or flawed reasoning in an argumentation (Risen et al., 2007; Walton, 2010; Cotton, 2018). Logical fallacy can occur as unintentional mistakes or deliberate persuasions in a variety of human communications, such as news media (Da San Martino et al., 2019), educational essay (Jin et al., 2022), political debates (Goffredo et al., 2023; Mancini et al., 2024), or online discussions (Sahai et al., 2021). Logical fallacies can lead to harmful consequences for society, such as spreading misinformation (Musi and Reed, 2022; Lundy, 2023), raising public health risks (Lin et al., 2020), manipulating public opinions (Barclay, 2018; Lei and Huang, 2022; Lei et al., 2024a), introducing societal bias and polarization (Abd-Eldayem, 2023). Despite their prevalence and harmfulness, understanding logical fallacies still remains a challenging task, which requires both semantics understanding and logical reasoning (Li et al., 2022; Sanyal et al., 2023). In this paper, we focus on fallacy detection and classification, and aim to develop an approach that generalizes across different domains and genres.[1](https://github.com/yuanyuanlei-nlp/logical$_f allacy_e mnlp_2$024)

The key observation is that logical fallacies heavily rely on connective phrases to indicate an intended logical relation between two textual arguments, while the semantics of the arguments do not actually support the claimed logical relation. Figure 1 shows two examples where the connective phrases were bolded. The first example uses the connective words therefore and cause to suggest a causal relation between vaccinations and increasing flu cases, however, the temporal relation between the two events as stated in the first half of the statement does not necessarily entail a causal relation between them, and indeed, their semantics do not actually support the suggested causal

[1]The code and data link is: https://github.com/yuanyuanlei-nlp/logical$_f allacy_e mnlp_2$024

[False Cause] The region continues to report flu incidents after many people took the vaccination, therefore , the vaccinations cause increasing flu cases.
[Hasty Generalization] People will never get ill as long as they take this pill every day, likewise , my sister takes it regularly and is always healthy.

Figure 1: Examples of logical fallacy sentences and their logical structure trees. The logical structure tree features logical relation connectives as non-terminal nodes, and textual arguments as terminal nodes.

relation. Recognizing this discrepancy undermines the credibility of the whole statement. Similarly in the second example, the connective word likewise is commonly used to indicate an analogy relation, however, the second argument is clearly a specific case of the general condition stated in the first argument and therefore there is no analogy relation between them, and recognizing this mismatch between the suggested logical relation and the real relation enables us to detect this fallacy.

Therefore, we propose to construct a logical structure tree that organizes all connective phrases in a statement and their textual arguments into a hierarchical structure. We expect the logical structure tree to effectively capture the juxtaposition of connective phrase suggested logical relations and the real logical relations between textual arguments, and therefore guide LLMs in fallacy detection and classification. Specifically, a logical structure tree consists of relation connectives as non-terminal nodes and textual arguments as terminal nodes, and the latter mostly corresponds to elementary discourse units (EDU) considered in discourse parsing. Figure 1 shows the logical structure trees constructed for the two example texts. As the logical relation indicated by a connective phrase may not be supported by semantics of its arguments in the context, we identify the purposefully indicated logical relations in a context-free unsupervised manner by matching a connective phrase with a taxonomy of connectives compiled for ten common logical relations (conjunction, alternative, restatement, instantiation, contrast, concession, analogy, temporal, condition, causal). To construct a logical structure tree, we first construct a constituency tree for a statement and then search in the constituency tree for connective phrases in the top-down left to right order, and the first found connective phrase will be the root node of the logical structure tree. Next, we identify the text spans of its two arguments using rules and recursively build the left and right sub-trees by applying the same procedure to constituency tree segments corresponding to the two arguments.

The logical structure tree is integrated into LLMs for fallacy reasoning using two strategies. The first considers textualized tree, where we convert the tree into natural language descriptions, making the tree readable by LLMs. Particularly, we describe the relations and arguments in a bottom-up manner, providing the LLMs with insight into logical relations from a local to global perspective. We then concatenate the textualized tree with the instruction prompt, and input them into LLMs as a hard prompt. The second considers tree-based soft prompt, where we derive a relation-aware tree embedding. Specifically, we design relation-specific encoders to process each type of relation and incrementally derive the tree embedding from bottom up to the root node. We then insert the tree embedding into LLMs as a soft prompt for further tuning.

Experiments on benchmark datasets across various domains and genres validate that our approach based on logical structure tree effectively improve precision and recall for both fallacy detection and fallacy classification tasks. Our main contributions are summarized as follows:

- We propose to construct a logical structure tree to capture the juxtaposition of connective phrase suggested logical relations and the real logical relations between textual arguments, and use it to serve as additional guidance for fallacy detection and classification.
- We effectively improve the F1 score for fallacy detection by up to 3.45

2 Related Work

Logical fallacy has been studied in philosophy and argumentation theory for decades (Walton, 2010; Tindale, 2007). Recently, there has been increasing interest in automatically detecting logical fallacies using computational approaches. Early work mainly focused on manually crafted features and traditional

machine learning models. For example, Habernal et al. (2018) explored argumentation mining and reasoning quality, while Da San Martino et al. (2019) introduced a propaganda detection dataset that includes several fallacy-related techniques.

With the development of deep learning, researchers have applied neural models to fallacy detection and classification. Sahai et al. (2021) proposed a dataset for fallacy detection in online discussions and utilized transformer-based models to improve performance. Jin et al. (2022) focused on fallacy detection in student essays, leveraging pre-trained language models to capture contextual semantics. Li et al. (2022) and [illegible] et al. (2023) further investigated reasoning-based approaches and incorporated external knowledge or structured reasoning signals to enhance model understanding.

Large language models (LLMs) have demonstrated strong capabilities in reasoning and language understanding tasks. Recent studies have explored prompting strategies and fine-tuning techniques to adapt LLMs for argument analysis and fallacy detection (Mancini et al., 2024; Goffredo et al., 2023). However, these approaches often rely on implicit reasoning within the model and lack explicit structural representations of logical relations between arguments.

Discourse parsing and rhetorical structure theory (RST) provide structured representations of textual relations (Mann and Thompson, 1988). Elementary discourse units (EDUs) and discourse trees have been used to capture coherence and logical flow in texts. Some recent work has incorporated discourse structures into neural models, showing improved reasoning and classification performance. Nevertheless, directly leveraging connective phrases and their hierarchical organization to detect mismatches between intended and actual logical relations has not been fully explored.

In contrast to prior work, we explicitly construct a logical structure tree based on connective phrases and constituency parsing, and integrate it into LLMs through both textualized hard prompts and relation-aware soft prompts. This structured approach enables models to better identify inconsistencies between suggested logical relations and actual argument semantics, thereby improving fallacy detection and classification performance.

3 Logical Structure Tree

In this section, we introduce the logical structure tree, including the taxonomy of relation connectives and the algorithm for tree construction. The logical structure tree aims to explicitly represent the hierarchical logical flow among connective phrases and their textual arguments in a statement. It organizes connective phrases as non-terminal nodes and textual arguments as terminal nodes, thereby forming a tree structure that reflects the intended logical relations in the text.

3.1 Relation Connectives

We compile a taxonomy of connective phrases corresponding to ten common logical relations: conjunction, alternative, restatement, instantiation, contrast, concession, analogy, temporal, condition, and causal. Each logical relation is associated with a set of connective phrases that are frequently used to indicate the corresponding relation in natural language. For example, conjunction may include connectives such as ‘and” or ‘also”; causal may include ‘because”, ‘therefore”, or ‘thus”; contrast may include ‘but” or ‘however”; and analogy may include ‘likewise” or “similarly”.

The taxonomy is constructed in a context-free manner, meaning that we identify connective phrases based on lexical matching without considering the surrounding semantic context. This design choice allows us to capture the logical relation suggested by the connective phrase itself, which may not necessarily align with the true semantic relation between the arguments.

3.2 Tree Construction Algorithm

Given a statement, we first obtain its constituency tree using an off-the-shelf parser. The constituency tree provides a hierarchical syntactic structure of the sentence, which we use as the basis for locating connective phrases and identifying their corresponding argument spans.

We traverse the constituency tree in a top-down and left-to-right order to search for connective phrases defined in our taxonomy. The first matched connective phrase is selected as the root node of the logical structure tree. Once a connective phrase is identified, we

determine the spans of its two arguments based on syntactic boundaries in the constituency tree. These argument spans form the left and right child nodes of the root.

We then recursively apply the same procedure to the subtrees corresponding to the identified argument spans. For each subtree, we search for connective phrases and construct subtrees accordingly. If no connective phrase is found within a subtree, the corresponding text span is treated as a terminal node (i.e., a textual argument), which typically corresponds to an elementary discourse unit (EDU).

This recursive process continues until no further connective phrases can be identified in any subtree. The final output is a logical structure tree that captures the hierarchical organization of connective phrases and their textual arguments in the statement.

3.3 Textual Arguments Extraction

Textual arguments correspond to the leaf nodes of the logical structure tree. They are derived from syntactic spans identified during tree construction and typically align with elementary discourse units (EDUs) in discourse parsing.

We use syntactic rules based on the constituency tree to determine the boundaries of textual arguments. Specifically, once a connective phrase is located, we identify the minimal syntactic constituents that form the left and right arguments of the connective. These constituents are then mapped to contiguous text spans in the original statement.

By extracting textual arguments in this manner, the logical structure tree explicitly separates connective phrases from their arguments and preserves the hierarchical logical flow suggested by the text. This structured representation serves as the foundation for integrating logical information into large language models for fallacy reasoning.

4 Logical Fallacy Reasoning

In this section, we introduce how to incorporate the logical structure tree into large language models (LLMs) for logical fallacy reasoning. We develop two strategies: textualized tree as a hard prompt and tree-based soft prompt.

4.1 Textualized Tree

We first convert the logical structure tree into natural language descriptions, making the tree readable by LLMs. We describe the relations and arguments in a bottom-up manner. For each non-terminal node, we generate a textual description that specifies the logical relation type and its two child nodes. For example, we may describe a node as: "The relation between [Argument 1] and [Argument 2] is causal." If a child node is also a relation node, we recursively describe it before describing its parent node.

Formally, given a logical structure tree T, we define a function $f(T)$ that transforms the tree into a sequence of textual descriptions. Let r denote a relation node with left child l and right child r'. If both l and r' are textual arguments, the description is directly generated. Otherwise, we first apply f to its children and then generate the description for the current node. The final textualized tree is concatenated with the original instruction prompt and fed into the LLM as a hard prompt.

4.2 Tree-based Soft Prompt

In addition to textualizing the tree, we also encode the logical structure tree into a relation-aware embedding and insert it into LLMs as a soft prompt. We design relation-specific encoders for different logical relation types. Each relation type has a dedicated parameter set that captures its semantic characteristics.

For a leaf node corresponding to a textual argument, we obtain its embedding from the LLM encoder. For a non-terminal relation node, we combine the embeddings of its left and right child nodes using a relation-specific composition function. Specifically, for a relation node with type k and child embeddings $\mathbf{h}_l$ and $\mathbf{h}_r$, we compute its embedding as:

$$\mathbf{h}_k = g_k(\mathbf{h}_l, \mathbf{h}_r), \tag{1}$$

where g_k denotes the relation-specific encoder for relation type k. The composition is performed in a bottom-up manner until we obtain the embedding for the root node.

The resulting tree embedding is then inserted into the input sequence of the LLM as a soft prompt. During training, the parameters of the relation-specific encoders and the inserted soft prompt are optimized

together with the LLM parameters (or a subset of them) to enhance fallacy reasoning.

4.3 Fallacy Training

For fallacy detection, the task is formulated as a binary classification problem, where the model predicts whether a given statement contains a logical fallacy. For fallacy classification, the model predicts the specific type of fallacy among predefined categories.

We fine-tune the LLM with the augmented inputs that incorporate the logical structure tree using either the textualized hard prompt or the tree-based soft prompt. The model is trained using the standard cross-entropy loss. Let $\mathbf{z}$ denote the final representation used for classification, and let $\mathbf{W}$ and $\mathbf{b}$ denote the classifier parameters. The predicted probability distribution over labels is computed as:

$$\mathbf{p} = \text{softmax}(\mathbf{W}\mathbf{z} + \mathbf{b}), \quad (2)$$

and the training objective is to minimize the cross-entropy loss between the predicted distribution and the ground-truth labels.

By integrating the logical structure tree into LLMs, we explicitly provide structural cues about intended logical relations, enabling the model to better detect discrepancies between suggested and actual argument relations, and thereby improve performance on fallacy detection and classification tasks.

5 Experiments

In this section, we evaluate the effectiveness of our proposed logical structure tree on fallacy detection and fallacy classification tasks. We first describe the datasets and experimental settings, then present the main results, followed by ablation studies and analysis on different fallacy types.

5.1 Datasets

We conduct experiments on benchmark datasets covering various domains and genres, including news articles, online discussions, political debates, and educational essays. These datasets contain annotated instances for fallacy detection (binary classification) and fallacy classification (multi-class classification). We follow the standard data splits provided in the original datasets. Detailed statistics of the datasets are shown in Table **??**.

5.2 Experimental Settings

We implement our approach based on pre-trained large language models. For the textualized tree strategy, we concatenate the textualized tree with the original instruction prompt and input them into the LLM. For the tree-based soft prompt strategy, we insert the relation-aware tree embedding into the input representation of the LLM.

We fine-tune the models using the Adam optimizer with an appropriate learning rate and batch size selected from the validation set. Dropout and early stopping are applied to prevent overfitting. For evaluation, we report precision, recall, and F1 score for both fallacy detection and fallacy classification.

5.3 Baselines

We compare our methods with several strong baselines, including traditional machine learning approaches, transformer-based models such as BERT and RoBERTa, and prompt-based large language models without explicit logical structure integration. These baselines represent the state-of-the-art performance reported on the corresponding datasets.

5.4 Fallacy Detection

Table **??** presents the results on fallacy detection. Our proposed methods consistently outperform the baselines across different datasets. Both textualized tree and tree-based soft prompt strategies improve precision and recall, leading to higher F1 scores. The improvements demonstrate that explicitly modeling the hierarchical logical relations helps the model better identify fallacious reasoning.

5.5 Fallacy Classification

Table **??** shows the results on fallacy classification. Compared with baselines, our approach achieves significant improvements in F1 score. The logical structure tree provides fine-grained structural information that is particularly beneficial for distinguishing among different fallacy types.

5.6 Ablation Study

To analyze the contribution of each component, we conduct ablation studies by removing the logical structure tree, replacing relation-specific encoders with shared parameters, or altering the tree construction procedure. The results indicate that both the hierarchical tree structure and relation-specific modeling are crucial for achieving optimal performance.

5.7 Effect on Different Fallacy Types

We further analyze the performance improvements across different fallacy categories. Our method yields notable gains on fallacy types that heavily rely on explicit connective phrases, such as false cause and hasty generalization. This observation supports our hypothesis that modeling connective phrases and their associated logical relations is effective for detecting discrepancies between intended and actual reasoning.

Overall, the experimental results demonstrate that incorporating the logical structure tree into large language models significantly enhances their capability in fallacy detection and classification across diverse datasets.

6 Limitations

Our work has several limitations. First, the logical structure tree is constructed based on a predefined taxonomy of connective phrases and constituency parsing results. Errors in parsing or incomplete coverage of connective phrases may affect the quality of the constructed tree. Second, our approach focuses on logical relations explicitly indicated by connective phrases, and may not fully capture implicit logical relations that are not signaled by explicit connectives. Third, although we evaluate our method on multiple benchmark datasets across different domains, the generalization ability to other languages or more informal text genres remains to be further explored. Finally, integrating additional discourse-level or world knowledge information may further enhance fallacy reasoning, which we leave for future work.

7 Conclusion

In this paper, we propose a logical structure tree to explicitly model the hierarchical logical relations suggested by connective phrases and their textual arguments in a statement. The logical structure tree captures the juxtaposition between connective phrase indicated logical relations and the actual semantic relations between arguments, providing structural guidance for fallacy reasoning. We further integrate the logical structure tree into large language models through two strategies: textualized tree as a hard prompt and relation-aware tree embedding as a soft prompt. Experimental results on multiple benchmark datasets demonstrate that our approach significantly improves performance on both fallacy detection and fallacy classification tasks.

Ethical Considerations

This work focuses on improving the detection and classification of logical fallacies in text. The datasets used in our experiments are publicly available and have been previously utilized in related research. We do not collect any new personal data. Our approach aims to enhance the ability of language models to identify flawed reasoning, which may help mitigate the spread of misinformation and improve the quality of public discourse.

However, like other machine learning systems, our model may inherit biases present in the training data. Additionally, incorrect predictions could potentially lead to misinterpretation of arguments. Therefore, the outputs of our system should be used as supportive tools rather than definitive judgments. Future work may explore fairness and bias mitigation techniques to further reduce potential negative impacts.

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References

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A Appendix A

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