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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 classification¹.

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),

¹The code and data link is: https://github.com/yuanyuanlei-nlp/Logical_Fallacy_email_2024

educational essay (Jin et al., 2022), political debates (Goffredo et al., 2023; Mancini et al., 2024), or online discussions (Shai 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-Elgayed, 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; Sayal 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.

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 relation. Recognizing this discrepancy undermines the credibility of the whole statement. Similarly in the second example, the connective word *otherwise* 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.

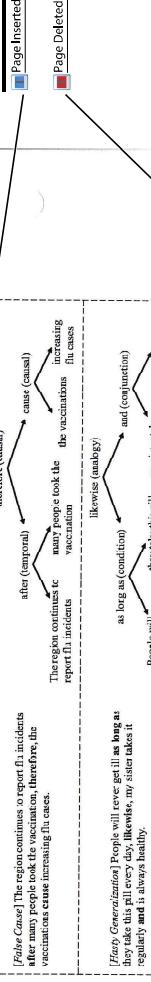


Figure 1: Examples of logical fallacy sentences and their logical structure trees. The logical structure tree features logical relation connectives as non-terminal nodes, and textual arguments as terminal nodes.

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 phrases 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 composed for ten common logical relations (excluding 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 use 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.

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- We propose to construct a logical structure tree to capture the juxtaposition of connective phrases 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%, and fallacy classification by up to 6.75% across various datasets.

2 Related Work

Logical Fallacy is erroneous patterns of reasoning (Walton, 1987; Fantino et al., 2003). Initial work explored the taxonomy of fallacies (Trinale, 2007; Greenwell et al., 2006; Walton et al., 2008). Recent works have focused on the automatic detection and classification of fallacies. Habernal et al. (2017) developed a software that deals with fallacies in

question-answering. Sheng et al. (2021) investigated *ac hominem* fallacy in dialogue responses. Habernal et al. (2018) explored the *ad hominem* fallacy from web argumentations. Sab and Gurevych (2017) recognized insufficient arguments in argumentation essays. Goiffred et al. (2022) categorized fallacies in political debates. Nakniih and Santini (2020) focused on fallacies in legal argumentations. Musi et al. (2022) researched fallacies about pandemics on social medias. (Alhindhi et al., 2022) proposed a multi-task prompting approach to learn the fallacies from multiple datasets jointly. Jin et al. (2022) proposed a structure-aware method to classify fallacies. Different from Jin et al. (2022) that masked out content words to form a sequence-based pattern, our paper proposes a tree-based hierarchical logical structure to unify both relation connectives and content arguments together.

Logical Reasoning abilities of large language models are gaining increasing research attention (Xu et al., 2023; Chen et al., 2021; Creswell et al., 2022; Pi et al., 2022; Jiao et al., 2023; Zhou et al., 2023; Sanyal et al., 2023; Parmar et al., 2024). Oauson et al. (2023) combined large language models with first-order logic. Pan et al. (2023); Zhang et al. (2023) empowered large language models with symbolic solvers. Pi et al. (2022) presented an adversarial pre-training framework to improve logical reasoning. Zhao et al. (2023) incorporated multi-step explicit planning into the inference procedure. Jiao et al. (2022) proposed a contrastive learning approach to improve logical question-answering. Different from these previous work, we particularly focus on logical fallacy reasoning, aiming to detect and classify fallacies.

Misinformation refers to the unverified or false information (Guerrero and Lyons, 2020; Armitage and Vacari, 2021; Ameir et al., 2023; Lei et al., 2024b). Misinformation detection was studied for years, such as fake news (Rashkin et al., 2017; Lei and Huang, 2023b; Ochiai et al., 2020), rumor (Ma et al., 2018; Lei et al., 2019), satire (Yang et al., 2017), political bias (Lei et al., 2022; Feng et al., 2023; Devadoss et al., 2023; Lei and Huang, 2024), propaganda (Da San Martino et al., 2019, 2020; Lei and Huang, 2023a). Logical fallacies are often employed within misinformation to present invalid claim as credible, facilitating the spread of misinformation (Beisseler et al., 2024; Pauli et al., 2022; Bonial et al., 2022). Developing automatic models to detect logical fallacies can also benefit the

identification and mitigation of misinformation.

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3 Logical Structure Tree

The logical structure tree consists of ‘relation’ connectives as non-terminal nodes, and textual arguments as terminal nodes. The relation connectives serve as parent nodes, and the two corresponding arguments are linked as left and right children nodes. Figure 1 illustrates example of the logical structure tree. The logical structure tree is constructed in an unsupervised manner, guided by the constituency tree and a taxonomy of connectives compiled for ten common logical relations.

3.1 Relation Connectives

The logical fallacies usually rely on relation connectives to indicate a logical relation. Inspired by the discourse relations proposed by Prasad et al. (2008), we define a taxonomy of ten logical relations which are commonly *separatist*, *conjunction*, *alternative*, *restatement*, *institution*, *contrast*, *connection*, *analog*, *temporal*, *condition*, and *causal* relations. Moreover, we build a set of connective words and phrases that correspond to each type of logical relation, as shown in Table 1. This set of connectives includes the explicit discourse connectives from the PPTB discourse relation dataset (Prasad et al., 2008), and is further expanded by maximally adding relevant connectives from the development set of the logic fallacy dataset (Jin et al., 2022).

We further conduct a statistical analysis on the distribution of ten logical relations and compare distributions between *fallacy* and *no fallacy* classes as well as across different fallacy classes, with the detailed results shown in Appendix A. The statistical analysis shows that both the *fallacy* and *no fallacy* classes contain many connective phrases and their distributions of the ten logical relations are also very similar. But as expected, different fallacy types tend to employ varying logical patterns, for example, *False Dilemma* uses more alternative relation, while *Deductive Fallacy* uses more analogy relation.

3.2 Tree Construction Algorithm

To construct a logical structure tree T_{Logic} , we first construct a constituency tree T_{Con} for a statement. We use the stanza library² to get the constituency

²<https://stanfordnlp.github.io/stanza/>

| Logical Relations | | Relation Connectives |
|-------------------|--|--|
| conjunction | | and as well as, as well, also, separately |
| alternation | | or, either, instead, alternatively, else, nor, neither |
| restatement | specifically, particularly, in particular, besides, additionally, moreover, furthermore, plus, not only, indeed, in other words, in fact, in short, in the end, overall, in summary, in details | |
| instantiation | for example, for instance, such as, including, as an example, as an instance, for one thing | |
| contrast | but, however, yet, while, unlike, rather than, rather than, on the contrary, on the other hand, on the contrary, contrary to, in contrast, by contrast, whereas, conversely, not, to, none, nothing, n't, although, though, despite, in spite of, regardless, regardless of, nevertheless, nonetheless, even if, even though, even as, even when, even after, even so, no matter | |
| concession | likewise, similarly, as if, as though, just as, just like, namely | |
| analogy | during, before, after, when as soon as, then next, until, till, meanwhile, in turn, meantime, afterwards, simultaneously, at the same time, beforehand, previously, earlier, later, thereafter, finally, ultimately | |
| temporal | if, as long as, unless, otherwise, except, whenever, wherever, once, only, only when, depend on | |
| condition | because, cause, as a result, result in, due to, therefore, hence, thus, thereby, since, new that, | |
| causal | consequently, in consequence, in order to, so that, why, for, accordingly, given, turn out | |

Table 1: Ten types of logical relations and their relation connectives.

tree (Qi et al., 2020). At the beginning, T_{Logic} is initialized as an empty tree. Then we traverse the constituency tree T_{Con} from top to bottom, and from left to right, and match relation connectives within each subtree of T_{Con} .

If there is a subtree $S_{Con(w)}$ whose arguments α, β associated with w , then a new logical subtree $T_{Logic(c)}$ is created, with the matched relation connective c as a parent node, and the two arguments α, β as its left and right children. This new logical subtree $S_{Logic(c)}$ is added into the logical structure tree T_{Logic} . If the textual arguments α, β still contain other relation connectives, then we recursively match relation connectives in the arguments and replace the original argument node in the T_{Logic} with the newly created logical subtree. The termination condition is that all the relation connectives in the given text have been matched.

3.3 Textual Arguments Extraction

The textual arguments are the two content components linked by a relation connective. Given a matched relation connective c , its corresponding subtree in the T_{Con} is $S_{Con(w)}$. To extract the arguments of w , we find the parent tree of $S_{Con(w)}$ in the T_{Con} , denoted as $(S_{Con(w)})$. The text enclosed by $P(S_{Con(w)})$ is the concatenation of all its leaf node texts. If the text enclosed by parent tree $P(S_{Con(w)})$ contains content before and after the relation connective w , i.e., has the form of $\alpha + w + \beta$, then the left argument of w is α and the right argument is β . If the text enclosed by parent tree $P(S_{Con(w)})$ only contains content after the relation connective w , i.e., has the form of $w + \beta$, then the right ar-

gument of w is β , and the left argument α is the text enclosed as an grandparent tree $P(P(S_{Con(w)}))$ subtracted by the text enclosed by $P(S_{Con(w)})$.

4 Logical Fallacy Reasoning

We further design a framework to incorporate the logical structure tree into LLMs for fallacy detection and classification. This framework consists of two main components. The first is textualized tree, where we convert the logical structure tree into natural language descriptions, and feed it into LLMs as a hard text prompt. The second is tree-based soft prompt, where we derive a relation-aware tree embedding, and insert it into LLMs as a soft prompt for additional tuning. The hard and soft prompts are complementary: the hard prompt enriches the instruction with logical structure information, while the soft prompt facilitates direct tuning on tree embeddings. Figure 2 shows an illustration.

4.1 Textualized Tree

The textualized tree aims to transform the logical structure tree into the textual form, which can be interpretable by LLMs. As shown by the upper path of Figure 2, the textualized tree is represented as a table which consists of three columns: left argument, relation connective, right argument. Each row in the table represents a triplet (*left argument*, *relation connective*, *right argument*) corresponding to each logical relation in the tree. In particular, we organize the triples into the table in a bottom-up order, to provide this LLMs with insight into logical relations from a micro to macro perspective. The textualized tree is then input into the LLMs as a

Instruction prompt 1: Please classify the fallacy type of the Text. Choose one answer from these fallacy types: <fallacy type>. ext-<fallacy type>.

The definitions of each fallacy type are as follows: <fallacy type>: <fallacy type> ext-<fallacy type>.

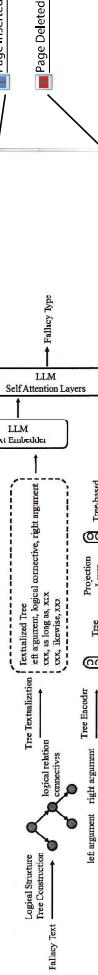


Figure 2: An illustration of logical fallacy classification informed by logical structure tree.

Part of the hard text prompt: bottom simple tree and up towards the root node:

$$h_t = \text{TreeEmbedder}(\text{textualize}(T_{\text{logic}})) \quad (1)$$

where $\text{textualize}(\cdot)$ denotes the textualization operation, TreeEmbedder refers to the text embedding layer of LLMs, h_t is the mapped embedding of the textualized tree.

4.2 Tree-based Soft Prompt

The tree-based soft prompt is e tree embedding which is projected into LLMs as a soft prompt for further using. As shown by the lower path of Figure 2, this process includes a tree encoder to derive the tree embedding, as well as a projection layer to transform the tree embedding into the same representation space of LLMs.

During the tree encoder stage, we aim to derive a relation-aware tree embedding. To integrate relation information into tree embedding, we design relation-specific encoders to process each type of logical relation. For a simple tree whose child-en nodes are leaf nodes without hierarchical layers, its embedding is computed as:

$$e_s = W^T(e_l \oplus e_c \oplus e_r) + b^T \quad (2)$$

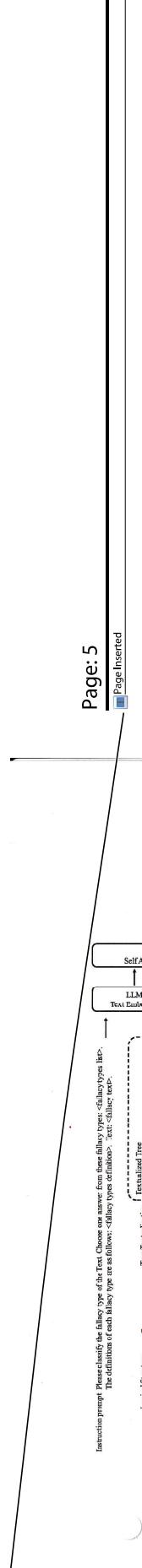
where e_s is the embedding of this simple tree, e_l , e_c , e_r are the embeddings of left argument, relation connective, and right argument, which are initialized as the average of word embeddings derived from RoBERTa language model [Liu et al., 2019], \oplus denotes feature concatenation, W^T , b^T are the trainable parameters of the encoder that corresponds to the relation type r , where $W^T \in R^{d \times d}$, $b^T \in R^d$, and $d = 768$ is the dimension of embedding space in RoBERTa. The relation type r is one of the ten logical relations associated with the relation connective.

For the tree with hierarchical structure, we derive the tree embedding incrementally, starting from the tree embedding of the root node. The tree embedding of the root node is the weighted sum of the tree embeddings of its children, plus a bias b_2 . The tree embedding of a child node is the weighted sum of the tree embeddings of its leaf nodes, plus a bias b_1 . The tree embedding of a leaf node is the result of the text embedding layer of the LLM, plus a bias b_0 .

Argotario (Habernal et al., 2017) collects fallacies from the general domain question-answering pairs. The dataset includes the following fallacy labels:

Ad Hominem, Appeal to Emotion, Hasty Generalization, Irrelevant Authority, Red Herring, and No

13161



| | Aggarwal | | | Reddit | | | Climate | | | | | |
|------------------------------|-----------|--------|-------|--------|-----------|--------|---------|-------|-----------|--------|-------|-------|
| Baselines | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc |
| Sohai et al. (2021) | - | - | - | - | 69.7 | 69.20 | - | - | - | - | - | - |
| GPT-3.5 | 92.86 | 14.61 | 25.24 | 41.67 | 54.7 | 15.38 | 23.96 | 50.00 | 79.00 | 7.61 | 13.72 | 33.83 |
| GPT-3.5 + T_{tagic} | 74.72 | 75.42 | 75.14 | 66.16 | 52.26 | 62.94 | 68.45 | 60.61 | 72.45 | 77.17 | 74.74 | 63.91 |
| RoBERTa | 31.18 | 83.42 | 82.29 | 75.65 | 63.00 | 76.02 | 70.08 | 66.86 | 67.77 | 83.13 | 76.59 | 63.16 |
| RoBERTa + T_{tagic} | 33.87 | 86.19 | 85.01 | 79.40 | 67.31 | 81.87 | 75.38 | 70.45 | 68.22 | 93.65 | 79.64 | 66.16 |
| Flan-T5 | 31.91 | 85.08 | 83.47 | 77.15 | 67.86 | 77.78 | 72.48 | 69.85 | 63.50 | 94.56 | 79.45 | 66.16 |
| Flan-T5 + T_{tagic} | 34.37 | 89.50 | 86.96 | 81.65 | 69.31 | 81.87 | 75.07 | 72.24 | 69.17 | 90.00 | 81.78 | 69.17 |
| Lama-2 | 33.52 | 83.98 | 83.15 | 77.90 | 68.53 | 79.41 | 73.57 | 70.96 | 68.90 | 93.48 | 79.26 | 66.16 |
| Lama-2 + T_{tagic} | 36.02 | 88.40 | 87.19 | 82.40 | 70.45 | 84.80 | 76.72 | 73.71 | 69.17 | 90.00 | 81.78 | 69.17 |

Table 2: The results of logical fallacy detection on three datasets. The precision, recall, F1 score of fallacy class, and accuracy are reported. The “rows + T_{tagic} ” represent incorporating the logical structure tree into the model.

| Dataset | Train | Dev | Test | Fallacy | Version | Types |
|----------|-------|-----|------|---------|---------|-------|
| Aggarwal | 963 | 261 | 267 | 309 | 422 | 5 |
| Reddit | 2313 | 668 | 335 | 1691 | 1625 | 8 |
| Climate | 436 | 114 | 133 | 477 | 206 | 9 |
| Logic | 1849 | 360 | 300 | 2449 | - | 13 |

Table 3: The number of samples in train/dev/test set, the number of fallacy and no fallacy (being) samples, and the number of fallacy types in each dataset.

Fallacy. We use this dataset for both fallacy detection and classification experiments, and follow the data split method in Alhindhi et al. (2022). **Reddit** (Sohai et al., 2021) collects user generated posts from Reddit, and annotates logical fallacies into: *Slippery Slope*, *Irrelevant Authority*, *Hasty Generalization*, *Black-and-White Fallacy*, *Ad Populum*, *Tradition Fallacy*, *Neutralistic Fallacy*, *Worse Problem Fallacy*, and *No Fallacy*. This dataset is used for both fallacy detection and classification.

Climate (Alhindhi et al., 2022) collects statements from articles in the climate change domain, and annotated the following fallacies: *Evaluating the Burden of Proof*, *Cherry Picking*, *Red Herring*, *Strawman*, *Irrelevant Authority*, *Hasty Generalization*, *Faulty Cause*, *False Analogy*, *Vagueness*, and *No Fallacy*.

Logic (Jin et al., 2022) annotates logical fallacies in the educational material into 13 types including *Ad Hominem*, *Ad Populum*, *False Dilemma*, *False Cause*, *Circular Reasoning*, *Deductive Fallacy*, *Appeal to Evident*, *Equivocation*, *Fallacy of Extension*, *Faulty Generalization*, *Intentional Fallacy*, *Fallacy of Credibility*, *Fallacy of Relevance*. This dataset does not include *No Fallacy* class and is only used for fallacy classification.

5.2 Experimental Settings

To validate our approach, we experiment on two types of language models: a decoder-only model

and an encoder-decoder model. For the decoder-only model, we choose the open-source large language model Llama-2 (Llama-2-7b-chat-hf) Zhou et al. (2023). For the encoder-decoder model, we choose the Flan-T5-large model (Chung et al., 2022). Both the models are trained via generative setting, where they take the instruction and given text as input, and generate a fallacy label as output. The fallacy detection task generates “Yes” or “No” label as output, while the fallacy classification task generates the name of each fallacy type. We follow Alhindhi et al. (2022) to unify the different names of the same fallacy across datasets, such as *False Dilemma* is converted into *Black-and-White Fallacy* since they are the same fallacy. We also follow Alhindhi et al. (2022) to feed the definitions of each fallacy type into the instruction prompt. The details of instruction prompt are explained in Appendix B.

The maximum input length is set to be 1024, number of epochs is 10, weight decay is 1e-2, the gradient accumulation step is 4, learning rate for Llama-2 is 3e-4, and learning rate for Flan-T5 is 3e-5. The Llama-2 model is trained with LORA (Hu et al., 2021), with rank 3, alpha 16, dropout 0.05, and trainable modules include c_proj and v_proj

5.3 Baselines

We compare our models with the baselines listed below. Besides the existing baselines, we also implement several additional baselines based on the GPT and RoBERTa (Liu et al., 2019) models; Sohai et al. (2021) a multi-granularity network is designed that trains sentence-level representation and the token-level representations jointly.

Jin et al. (2022); a structure-aware framework is developed that forms a sequence-based logical pattern for each text by masking out the content words. Sourati et al. (2022b); a prototype-based reason-

| Baselines | ArgoNLP | | | Reddit | | | Logic | | | Auc |
|-----------------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-----------------------------|
| | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc | Precision | |
| Jin et al. (2022) | - | - | - | - | - | - | - | - | 55.25 | 58.77 / 47.57 |
| Sourati et al. (2023a) | - | - | - | - | - | - | - | - | 63.18 | 63.1 / 62.7 / 63.1 |
| Sourati et al. (2023b) | - | - | - | - | - | - | - | - | 66.3 | 66.4 / 65.7 / 66.4 |
| Ahlini et al. (2022) | - | - | - | - | - | - | - | - | 66.3 | 66.4 / 65.7 / 66.4 |
| Sabai et al. (2021) | - | - | - | - | - | - | - | - | 66.3 | 66.4 / 65.7 / 66.4 |
| GPT-3.5 + T_{Logic} | 41.65 | 31.32 | 32.48 | 31.02 | 60.35 | 49.22 | 59.81 | 55.62 | 38.14 | 33.58 / 30.30 / 42.28 |
| RoBERT ₄ | 49.77 | 38.98 | 40.26 | 48.07 | 63.22 | 56.93 | 65.29 | 60.59 | 40.59 | 35.97 / 47.95 |
| RoBERT ₄ + T_{Logic} | 57.97 | 55.98 | 55.92 | 51.46 | 71.9 | 70.17 | 70.42 | 70.76 | 62.50 | 59.56 / 60.13 / 64.88 |
| Fian-T5 + T_{Logic} | 59.51 | 58.55 | 58.48 | 51.67 | 75.41 | 74.66 | 74.66 | 74.85 | 67.85 | 63.37 / 64.30 / 67.56 |
| Fian-T5 | 60.91 | 57.40 | 57.46 | 50.01 | 76.37 | 76.0 | 76.47 | 76.47 | 65.24 | 63.50 / 63.60 / 63.22 |
| Llama-2 + T_{Logic} | 65.23 | 62.12 | 62.35 | 62.78 | 81.98 | 81.14 | 81.25 | 81.29 | 70.90 | 69.14 / 69.37 / 73.45 |
| Llama-2 | 60.79 | 58.71 | 59.20 | 55.67 | 77.87 | 77.16 | 77.21 | 77.19 | 65.52 | 63.38 / 63.15 / 69.36 |
| Llama-2 + T_{Logic} | 65.63 | 63.29 | 63.22 | 64.09 | 84.84 | 83.68 | 83.95 | 83.63 | 70.70 | 69.55 / 74.16 |

Table 4: The results of logical fallacy classification on three datasets. The macro precision, recall, F1 score, and accuracy are reported. The rows “+ T_{Logic} ” represent incorporating the logical structure tree into the model.

ing method that injects background knowledge and explainable mechanisms into the language model. Sourati et al. (2023a): a case-based reasoning that retrieves similar cases from external sources based on goals, counterarguments, and explanation etc. Ahlini et al. (2022): a multi-task instruction tuning framework that learns the logical fallacies from multiple datasets collaboratively.

GPT-3.5: we prompt the GPT-3.5-turbo model to automatically choose one of the fallacy labels for each text, and the prompt is listed in Appendix C. GPT-3.5 + T_{Logic} : guide the gpt-3.5-turbo model to firstly reason the logical structure of each text, and then choose one of the fallacy labels through a chain-of-thought process (Wei et al., 2023).

RoBERT₄: the RoBERT₄ model is used to encode the text and the average of word embedding & asc as the text embedding. A classification head is built on top of the text embedding to classify labels. **RoBERT₄ + T_{Logic}** : we concatenate the text embedding with the logical structure tree embedding, and build classification head on top of the combine embedding to predict labels. The tree embedding is derived based on the method in Section 4.2.

5.4 Fallacy Detection

The fallacy detection task identifies whether a given text contains logical fallacy or not, which is a binary classification task. The macro precision, recall, and F1 score of the “fallacy” class, as well as the micro F1 score (i.e., accuracy) are used as evaluation metrics. Table 2 presents the performance on the Argotnet, Reddit, and Climate datasets.

The results demonstrate that incorporating the

logical structure tree effectively improves both precision and recall for logical fallacy detection. This observation is consistent for both types of Llama-2 and Fian-T5 models across all the three datasets, which span various domains and genres. Compared to the baselines that lack logical structure information, our approach based on the logical structure tree noticeably enhances the precision and recall, leading to the F1 score increased by up to 4.5%. This indicates that the logical structure tree is effective in capturing the difference in original flows between fallacious and benign texts.

Moreover, inferring the large language model GPT-3.5-turbo of logical structure information significantly improves fallacy detection under the zero-shot setting, resulting in a substantial improvement in the F1 score. This underscores the importance of integrating the logical structure information into LLMs for fallacy detection. Also, concatenating the logical structure tree embedding with the text embedding in the RoBERT₄ model also enhances the performance, which proves the usefulness of this logical structure tree embedding. Overall, incorporating the logical structure tree helps improve fallacy detection for various types of models.

5.5 Fallacy Classification

The fallacy classification task classifies the fallacy types for the fallacious text, which is a multi-class classification task excluding the “No Fallacy” class. The macro precision, recall, and F1 scores, as well as the micro F1 score (i.e., accuracy) are used as evaluation metrics. Table 4 shows the results on the Argotnet, Reddit, and Logic datasets.

The results demonstrate that integrating the logical structure tree into Llama-2 and Fian-T5 models

| Fallacy Detection | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc |
|--------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|---------------|--------------|--------------|
| Llama-2 | 83.52 | 83.98 | 83.75 | 77.90 | 68.55 | 79.41 | 73.57 | 70.96 | 68.30 | 93.48 | 79.26 | 66.16 |
| + tree-based tree | 83.25 | 86.19 | 83.46 | 77.91 | 69.54 | 80.12 | 75.46 | 70.52 | 67.70 | 97.83 | 87.67 | 67.67 |
| + tree-based soft prompt | 83.11 | 88.40 | 86.72 | 81.65 | 69.42 | 83.63 | 75.88 | 72.84 | 68.91 | 98.91 | 81.25 | 68.42 |
| + both (full model) | 84.02 | 88.40 | 87.19 | 82.40 | 70.05 | 84.30 | 76.72 | 73.73 | 69.17 | 100.00 | 81.78 | 69.17 |

| Fallacy Classification | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc | Precision | Recall | F1 | Acc |
|--------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------|
| Llama-2 | 60.79 | 58.71 | 59.20 | 59.67 | 77.87 | 77.16 | 77.21 | 77.19 | 65.52 | 63.38 | 63.38 | 69.36 |
| + tree-based tree | 62.63 | 61.32 | 61.86 | 61.67 | 80.98 | 80.45 | 80.59 | 80.71 | 66.09 | 66.38 | 71.24 | 72.54 |
| + tree-based soft prompt | 64.34 | 61.89 | 62.30 | 62.98 | 82.87 | 82.47 | 82.30 | 82.55 | 68.75 | 68.72 | 67.52 | 72.54 |
| + both (full model) | 65.63 | 63.29 | 63.32 | 64.69 | 84.84 | 83.68 | 83.95 | 83.63 | 70.70 | 69.55 | 74.16 | |

Table 5: The results of ablation study. The precision, recall, F1 score of ‘fallacy’ class are reported for fallacy detection (lower rows). The macro precision, recall, F1 score are reported for fallacy classification (upper rows).

| | Ad Hominem | Emotional | Generalization | Authority | Red Herrings | Macro F1 |
|-----------------------|------------|-----------|----------------|-----------|--------------|----------|
| Llama-2 | 60.79 | 57.33 | 55.38 | 63.16 | 49.35 | 59.20 |
| Llama-2 + T_{Logic} | 63.16 | 72.16 | 61.29 | 67.80 | 55.17 | 63.92 |

Table 6: The F1 score change across each fallacy type of fallacy classification on Agoraiato dataset. The fallacy types include Ad Hominem, Emotional Language, Hasty Generalizatio, Irrelevant Authority, and Red Herring.

notably enhances the performance of fallacy classification, with both precision and recall increased. This conclusion is valid across its three datasets from different domains and genres. Compared to the baselines without logical structure tree, our proposed approach significantly improves precision and recall, leading to an increase of up to 6.75% in the F1 score. This suggests that the logical structure tree effectively distinguishes the different logical patterns used in each fallacy type, and is applicable across various domains and genres.

In addition, our approach based on the logical structure tree outperforms the previous methods that may lack logical relations information. This highlights the necessity to induce the logical relations into LLMs for fallacy classification. Besides, our approach achieves higher performance than the baselines that overlook content words. This indicates that analyzing content words also plays an essential role in fallacy reasoning. The logical structure tree connects the logical relations and context arguments together to form a cohesive logical structure, representing the hierarchical logical flow and thereby improving fallacy classification.

5.6 Ablation Study

The ablation study of the two designed strategies to incorporate the logical structure tree into LLMs is shown in Table 5, where we take Llama-2 model as an example. The upper rows show the results of fallacy detection on the three datasets, and the lower rows show the results of fallacy classification. The results demonstrate that both the textualized

tree and tree-based soft prompt brings improvement for fallacy detection and classification across multiple datasets. This proves that the textualized tree and tree-based soft prompt are complementary with each other; the textualized tree enriches the instruction prompt with logical structure information and the tree-based soft prompt enables direct learning from the text embedding. Comparing across these two strategies, the soft prompt usually achieves better performance than the hard text prompt, and exhibits higher recall. Combining the two strategies neither leads to the best performance, achieving the highest precision and recall.

5.7 Effect on Different Fallacy Types

We further analyze the F1 score change across each fallacy type in the fallacy classification task. The Llama-2 model is used as an example to show the performance change before and after incorporating the logical structure tree. Table 6 presents the F1 score change across each fallacy type on Agoraiato dataset. The performance change across each fallacy type on the Reddit and Logic dataset are shown in the Table 7 and Table 8. We observe that the logical structure tree brings bigger improvements for the fallacy types such as *Red Herring*, *Hasty Generalization*, *Irrelevant Authority*, *Ad Populum*, *Extension Fallacy*, *Equivocation*, *Circular Reasoning* etc. One possible explanation is that these fallacy types usually employ certain logical relations or logical patterns to persuade the readers. However, the performance increase is less noticeable for the fallacy types such as *Appeal to*

| | Slippery Authority | Generalization | Black-White | Ad Populum | Tradition | Naturalistic | Worse Problem | Others |
|---------------|--------------------|----------------|-------------|------------|-----------|--------------|---------------|--------|
| Liami-2 | 84.56 | 83.05 | 69.57 | 63.41 | 63.29 | 91.82 | 94.00 | 75.56 |
| Liami-2+Topic | 88.89 | 92.31 | 71.27 | 63.22 | 62.91 | 87.18 | 92.25 | 82.61 |

Table 7: The F1 score change across each fallacy type of fallacy classification on Reddit dataset. The fallacy types include Slippery Slope, Irrelevant Authority, Hasty Generalization, Black-and-White Fallacy, Ad Populum, Tradition Fallacy, Naturalistic Fallacy, and Worse Problem Fallacy.

| | Ad Hominem | Ad Populum | False Dilemma | False Cause | Circular | Deductive | Emotional |
|---------------|------------|------------|---------------|-------------|----------|-----------|-----------|
| Liami-2 | 82.35 | 72.41 | 73.57 | 68.42 | 61.90 | 62.07 | 66.67 |
| Liami-2+Topic | 80.46 | 37.50 | 73.57 | 66.67 | 75.68 | 66.67 | 65.22 |
| Liami-2 | 25.90 | 50.00 | 73.13 | 34.48 | 65.71 | 65.00 | 63.05 |
| Liami-2+Topic | 44.44 | 72.22 | 81.03 | 38.71 | 68.97 | 73.05 | 69.55 |

Table 8: The F1 score change across each fallacy type of fallacy classification on Logic dataset. The fallacy types include Ad Hominem, Ad Populum, False Dilemma (Black-and-White Fallacy), False Cause, Circular Reasoning, Deductive Fallacy, Appeal to Emotion (Emotional Language), Equivocation, Fallacy of Extension, Faulty Generalization (Hasty Generalization), Intentional Fallacy, Fallacy of Credibility (Irrelevant Authority), Fallacy of Relevance (Red Herring).

Emotion and Ad Hominem. It may due to the reason

that these fallacies rely more on the emotional or sentimental language instead of logical relations.

6 Limitations

We have compiled a set of connective words and phrases for the ten logical relations, as detailed in Table 1. While we have included the common connectives in this set, it may not contain all the possible connectives. The logical structure tree that is constructed based on this connective words set demonstrates its usefulness in fallacy reasoning. Future work can be expanding this connectives set and investigating the effects of various connectives.

7 Conclusion

This paper detects and classifies fallacies. We propose a logical structure tree to explicitly represent and track the hierarchical logic flow among relation connectives and their arguments. We also design two strategies to incorporate this logical structure tree into LLMs for fallacy reasoning. Extensive experiments demonstrate the effectiveness of our approach based on the logical structure tree.

Ethical Considerations

This paper aims to detect and classify logical fallacies. Logical fallacy is the error or flaws in the reasoning, and can occur in various human communications. Logical fallacies can lead to harmful consequences for society, such as spreading misinformation or introducing societal bias. The goal of this research is to understand logical fallacies,

so that we can better identify and mitigate them. The release of cyclic datasets, ~~are mode~~, should be used for mitigating logical fallacies, instead of expanding or disseminating the misinformation

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References

- Rehab Mohamed Ahmed Abd-Eldayem. 2023. The relationship between cognitive bias and logical fallacies in egyptian society. *Social Science*, 12(6):281–293.
- Esma Ahmed, Sabine Aumi, and Gilles Brassard. 2023. Fake news, disinformation and misinformation in social media: a review. *Social Network Analysis and Mining*, 13(1):30.
- Tariq Alihindi, Tuhin Chakrabarty, Elena Musi, and Simaranta Muresan. 2022. Multitask instruction-based prompting for fallacy recognition. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 8172–8187, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Rachele Armitage and Cristian Vacari. 2021. Misinformation and disinformation. In *The Routledge companion to media disinformation and populism*, pages 38–48. Routledge.

- Donald A Berchay. 2018. *Fake news propaganda, and plain old lies: how to find trustworthy information in the digital age*. Rowman & Littlefield.
- Sven Beisecker, Christian Schröter, and Sebastian Hein. 2024. Shades of fake news: How fallacies influence consumers' perception. *European Journal of Information Systems*, 33(1):41–60.
- Claire Bonial, Austin Blodgett, Taylor Hudson, Stephanie M. Lakin, Jeffrey Michler, Douglas Summers-Say, Peter Subor, and Clare Voss. 2022. The search for agreement on logical fallacy annotation of an infodemic. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 4430–4438. Marseille, France: European Language Resources Association.
- Zenning Che, Qiuyue Guo, and Lawrence S. Moss. 2021. NeuralLog: Natural language inference with joint neural and logical reasoning. In *Proceedings of *SEM@2021: The Tenth Joint Conference on Logical and Computational Semantics*, pages 78–88. Online: Association for Computational Linguistics.
- Hyung Won Chung, Le Hou, Shayne Longire, Barrett Zoph, Yi Tay, William Fedus, Yunxian Li, Xuezhi Wang, Moustafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shuai, Guo Zhiyuan, Dabir Mirza, Xinyang Chen, Akanksha Chowdhury, Alex Castro-Ros, Manu Pella, Kevin Robinson, Dusha Valler, Sharun Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanning Huang, Andrew Dai, Hongyan Yu, Suxin Petrov, Ed H. Chi, Jeff Dean, Jacob Devitt, Adam Roberts, Danny Zhou, Quoc V. Le, and Jason Wei. 2022. Scaling instruction fine-tuned language models. *Preprint*, arXiv:2210.1.416.
- Christian Crotton. 2018. Argument from fallacy: *Bad arguments: 100 of the most important fallacies in Western philosophy*, pages 125–127.
- Antonia Creswell, Murray Shanahan, and Irina Ziegls. 2022. Selection-inference: Exploiting large language models for interpretable logical reasoning. *Preprint*, arXiv:2205.09712.
- Giovanni Da San Martino, Alberto Barrón-Cedeño, Henning Wachsmuth, Rostislav Patrov, and Preslav Nakov. 2020. SemEval-2020 task 11: Detection of propaganda techniques in news articles. In *Proceedings of the Fourteenth Workshop on Semantic Evaluation*, pages 137–141.4, Barcelona (online). International Committee for Computational Linguistics.
- Giovanni Da San Martino, Saenghat Ya, Alberto Barrón-Cedeño, Rostislav Patrov, and Preslav Nakov. 2019. Fine-grained analysis of propaganda in news articles. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5336–5346, Hong Kong, China: Association for Computational Linguistics.
- Nicolas Devaivre, Philippe Muller, and Chloe Braud. 2023. An integrated approach for political bias prediction and explanation based on discursive structure. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 11196–11211, Toronto, Canada: Association for Computational Linguistics.
- Edmund Favatino, Stephanie Schäfer-Fantiro, and Antoni Navarro. 2003. Logical fallacies: A behavioral approach to teaching. *The Behavior Analyst Today*, 4(1):109.
- Shangbin Feng, Chan Young Park, Yuhua Liu, and Yulia Tsvetkov. 2023. From pietraining: coda to language models to downstream tasks: Tracking the trials of political biases leading to unfair NLP models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1, Long Papers)*, pages 11757–11762, Toronto, Canada: Association for Computational Linguistics.
- Pierpaolo Goffredo, Mariana Chaves, Serena Villata, and Elena Cabri. 2023. Argument-based detection and classification of fallacies in political debates. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 11101–11112, Singapore: Association for Computational Linguistics.
- Pierpaolo Goffredo, Shekhar Hadzicar, Venkkit Varkishan, Elena Cabri, and Serena Villata. 2022. Fallacies, argument classification in political debates. In *IJCAI*, pages 4143–4149.
- William S Greenwell, John C Knight, C Michael Holcaway, and Jacob J Pease. 2006. A taxonomy of fallacies in system safety arguments. In *24th International System Safety Conference*.
- Andrew M Guess and Zeynajean A Lyons. 2020. Misinformation, disinformation, and online propaganda. *Social media and democracy: The state of the field, prospects for reform*, 10.
- Ivan Habernal, Rafia Hannemann, Christian Pelzlak, Christopher Klaunn, Patrick Pauli, and Iryna Gurevcz. 2017. Argotanic: Computational argumentation meets serious games. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 7–12, Copenhagen, Denmark: Association for Computational Linguistics.
- Ivan Habernal, Henning Wachsmuth, Iryna Gurevcz, and Benno Stein. 2018. Before name-calling: Dynamics and triggers of ad hominem fallacies in web argumentation. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 386–396, New Orleans, Louisiana: Association for Computational Linguistics.
- Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shaen Wang, Li Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models. *Preprint*, arXiv:2106.09685.

- Fangkai Jiao, Yangyang Guo, Xueming Song, and Liqiang Nie. 2022. MEBit: Meta-Pyth Guided Contrastive Learning for Logical Reasoning. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 3,956–3,959, Dublin, Ireland. Association for Computational Linguistics.
- Zhijing Jin, Abhinav Lalwani, Tejas Vaidhya, Xiaoyu Shen, Yiven Ding, Zhiliang Lyu, Minmeng Sacian, Rada Mihalcea, and Bernhard Schölkopf. 2022. Logical fallacy detection. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 7,180–7,198, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yuanyuan Lei and Ruihong Huang. 2022. Few-shot (dis)agreement identification in online discussions with regularized and augmented meta-learning. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 5,581–5,593, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yuanyuan Lei and Ruihong Huang. 2023a. Discourse structures guided fine-grained propaganda identification. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 33–342, Singapore. Association for Computational Linguistics.
- Yuanyuan Lei and Ruihong Huang. 2023b. Identifying conspiracy theories news based on event relation graph. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 9811–9822, Singapore. Association for Computational Linguistics.
- Yuanyuan Lei and Ruihong Huang. 2024. Sentence-level media bias analysis with event relation graph. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5,225–5,236, Mexico City, Mexico. Association for Computational Linguistics.
- Yuanyuan Lei, Md Messal Monem Niazi, Ayesha Qamar, Sai Rupena Reddy, Jonathan Tong, Haoran Xu, and Ruihong Huang. 2024a. ENCoNA: Event-level moral opinions in news articles. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5,239–5,251, Mexico City, Mexico. Association for Computational Linguistics.
- Yuanyuan Lei, Kaiqiang Song, Sangwoo Cho, Xinyang Wang, Ruihong Huang, and Dong Yu. 2024c. Poetry calibration for opinion summarization. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5,211–5,224, Mexico City, Mexico. Association for Computational Linguistics.
- Quanzhi Li, Qiong Zhang, Luo Si, and Yingchi Liu. 2019. Rumor detection on social media: Datasets, methods, and opportunities. In *Proceedings of the Second Workshop on Natural Language Processing for Internet Freedom: Censorship, Disinformation, and Propaganda*, pages 66–75, Hong Kong, China. Association for Computational Linguistics.
- Yitian Li, Jidong Tan, Wenjing Chen, Caoyun Fan, Han He, and Yuchan Lin. 2022. To what extent do natural language understanding datasets correlate to legal reasoning? a method for diagnosing logical reasoning. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 1,708–1,717. Gwangju, Republic of Korea. International Committee on Computational Linguistics.
- Tirroto PH Lin, Kelvin H Wu, Suber S Huang, Lost B Jonas, David SC Fui, and Dennis SC Lam. 2020. Death tolls of covid-19 where come the fallacies and ways to make them more accurate. *Global Public Health* 15(10):1542–1557.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *Preprint*, arXiv:1907.11692.
- Morgan Lundy. 2023. TikTok and covid-19 vaccine misinformation: New avenues for misinformation spread, popular infodemic topics, and dangerous logical fallacies. *International Journal of Communication* 17:124.
- Jing Ma, Wei Gao, and Jian-Fai Wong. 2018. Rumor detection on Twitter with tree-structured recursive neural networks. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1,880–1,889, Melbourne, Australia. Association for Computational Linguistics.
- Eleonora Mancini, Federico Reggioli, and Paolo Torroni. 2024. Multimodal fallacy classification in political debates. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 170–178, St. Julian's, Malta. Association for Computational Linguistics.
- Elena Musi, Myro Alourpi, Elinor Carmi, Simeon Yates, and Kay O'Halloran. 2022. Developing fake news immunity: fallacies as misinformation traps during the pandemic. *Online Journal of Communication and Media Technologies*, 12(3).

- Elena Musi and Chris Reed. 2022. From fallacies to semi-fake news: Improving the identification of misinformation triggers across digital media. *Discourse & Society*, 33(3):349–370.
- Callistus Irenaeus Nakpah and Simone Santini. 2020. Automated discovery of logical fallacies in legal argumentation. *International Journal of Artificial Intelligence and Applications (JAI),* 1.
- Theo Oluussen, Alex Gu, Ben Liphin, Cedegao Zhang, Armando Solar-Lezama, Joshua Tenenbaum, and Roger Levy. 2023. LINC: A nonsymbolic approach for logical reasoning by combining language models with first-order logic provers. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 5153–5176, Singapore. Association for Computational Linguistics.
- Ray Oshikawa, Jing Qian, and William Yang Wang. 2020. A survey on natural language processing for fake news detection. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 6036–6093, Marseille, France. European Language Resources Association.
- Liangming Pan, Alon Albalak, Xinyi Wang, and William Yang. 2023. Logic-LM: Empowering large language models with symbolic savers for faithful logical reasoning. In *Fairings of the Association for Computational Linguistics: EMNLP 2023*, pages 3806–3824, Singapore. Association for Computational Linguistics.
- Mhiri Parmar, Nisarg Patel, Neeraj Varshney, Mumtazi Nakamura, Man Luo, Sathosh Mastety, Arindam Mitra, and Chitra Baral. 2024. LogEbench: Towards systematic evaluation of logical reasoning ability of large language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13673–13707, Bangkok, Thailand. Association for Computational Linguistics.
- Amalie Pauli, Lechu Derczynski, and Ira Asentij. 2022. Modelling persuasion through misuse of rhetorical appeals. In *Proceedings of the Second Workshop on NLP for Positive Impact (NLPImp)*, pages 89–100, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.
- Xinyu Pi, Wanjin Zhong, Jian Gao, Nan Duan, and Jian-Guang Lou. 2022. Loggan: Learning logical reasoning via adversarial pre-training. *Preprint*, arXiv:2205.08794.
- Rashmi Prasad, Nikhil Dineh, Alan Lee, Eleni Miltsevaki, Lijo Robaldo, Aravind Joshi, and Bonnie Webber. 2008. The Penn Discourse TreeBank 2.0. In *Proceedings of the Sixth International Conference on Language Resources and Evaluation (LREC'08)*, Marrakech, Morocco. European Language Resources Association (ELRA).
- Peng Qi, Yuhui Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Starza: A Python System. 266:110–118.
- natural language processing toolkit for many human languages. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*.
- Hannah Rashkin, Eunsol Choi, Jim Yea Jung, Svetlana Volkova, and Ye-in Choi. 2017. Truth of varying shades: Analyzing language in fake news and political fact-checking. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2351–2357, Copenhagen, Denmark. Association for Computational Linguistics.
- Jane Risen, Thomas Giowich, R. Sternberg, D. Halber, and J. Roediger. 2007. Informal logical fallacies. *Critical Thinking in Psychology*, 110.
- Sounya Saha, Oura Balala, and Roxana Hornigar. 2021. Breaking down the invisible wall of informal fallacies in online discussions. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, page 644–557, Online. Association for Computational Linguistics.
- Sounya Saha, Yichong Xu, Shuohang Wang, Ziyi Yang, Rechit Yan, Yenhai Yu, Chenggang Zhu, and Xiansh Ren. 2024. AFOLLC: A simple approach for adaptive pretraining of language models for logical reasoning. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6303–6321, Toronto, Canada. Association for Computational Linguistics.
- Faily Sheng, Kai-Wei Chang, Peen Narasimhan, and Nanyan Pei. 2021. “nice try, kiddo”: Investigating ad heminums in dialogue responses. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 750–767. Online. Association for Computational Linguistics.
- Zhiyar Sourati, Filip Ilievski, Hong-An Sandin, and Alain Mernoud. 2023a. Causa-based reasoning with language models for classification of logical fallacies. *arXiv preprint arXiv:2310.11872*.
- Zhiyar Sourati, Vishnu Priya Pasanna Venkatesh, Da-stan Deshpande, Himaanshu Rawlani, Filip Ilievski, Hong-An Sandin, and Alain Mernoud. 2023b. Robust and explainable identification of general fallacies in natural language arguments. *Knowledge-Based Systems*, 266:110–118.
- Christian Stab and Iryna Gurevych. 2017. Recognizing insufficiently supported arguments in argumentative essays. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics, Volume 1, Long Papers*, pages 980–990, Valencia, Spain. Association for Computational Linguistics.

- Christopher W Tindale. 2007. *Fallacies and argument appraisal*. Cambridge University Press.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Anjali Almehairi, Yasmine Bahaei, Nikolay Bashlykov, Sonnya Barra, Prajwal Bhargava, Shruqi Bhoosale, Dan Bikel, Lukas Blecic, Cristian Canton Ferrer, Moya Chen, Guillermo Cucurull, David Esteban, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuerst, Cynthia Gao, Vedant Goswami, Namita Govai, Anthony Harborth, Saeid Hosseini, Rui Hou, Jason Wei, Ian Marcu, Kardas, Viktor Kerzenc, Madian Khabsa, Isabel Kloumann, Artem Korenev, Amit Singh Kour, Marie-Anne Lachaux, Thibaut Lavril, Janya Lee, Diana Lisickovych, Yinghai Lu, Yuning Mao, Xavier Martinet, Tolo Mihaylov, Pushkar Misra, Igor Molchanov, Yixin Nie, Andrew Polton, Jeremy Reichenstein, Rusth Rungta, Kalyan Saladi, Alan Schellen, Ruan Silva, Eric Michael Smith, Rajtan Subramanian, Xiaoping Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Khan, Puxin Xu, Zheng Yan, Ilyyan Zarow, Yuchen Zhang, Angelia Fan, Melanie Kambedar, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edanov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models. *Preprint*, arXiv:2307.09288.
- Douglas Walton. 2010. Why fallacies appear to be better arguments than they are. *Informal logic*, 30(2):159–184.
- Douglas Walton, Christopher Reed, and Fabrizio Macagno. 2008. *Argumentation schemes*. Cambridge University Press.
- Douglas N Walton. 1987. What is a fallacy? *Eemeren, Frans H. vanGrootendorst, RobBlair, J. AnthonyWillard, Charles A.Gaels,; Argumentation: Across the lines of discipline, Dordrecht/Providencia, Foris Publications*, pages 323–350.
- Jason Wei, Xiechi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. 2023. Chain-of-thought prompting elicits reasoning in large language models. *Preprint*, arXiv:2301.11903.
- Fangzhi Xu, Qika Lin, Jiawei Han, Tianzhe Zhao, Jun Liu, and Erik Cambria. 2023. Are large language models really good logical reasoners? a comprehensive evaluation and beyond. *Preprint*, arXiv:2306.09841.
- Fan Yang, Arun Mukherjee, and Edith Dragut. 2017. Satirical news detection and analysis using attention mechanism and linguistic features. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1979–1985, Copenhagen, Denmark. Association for Computational Linguistics.
- Hailin Zhang, Jian Huang, Zhyang Li, Mayur Naik, and Eric Xing. 2023. Improved logical reasoning of language models via differentiable symbolic programming. In *Finding’s of the Association for Computational Linguistics: ACL 2023*, pages 3062–3077.

A Statistical Analysis of Logical Relations

Table 9 presents the ratio of samples that contain the ten logical relations in *fallacy* and *no fallacy* classes, when we take the Argotario (Habernal et al., 2017) and Reddit (Sahai et al., 2021) datasets as examples. Further, Table 10 shows the ratio of samples that contain the ten logical relations in each fallacy type, where we take the Logic dataset (Jin et al., 2022) as an example.

B Instruction Prompt for Fallacy Detection and Classification**B.1 Prompt for Fallacy Detection**

The instruction prompt for the Llama-2 or Flan-T5 baseline model is: "The task is to detect whether the Text contains logical fallacy or not. The logical fallacy can be <fallacy name (fallacy definition)>. Please answer Yes if the Text contains logical fallacy, else answer No. Text: <text>. Answer:"

The instruction prompt that incorporates the textualized tree into the Llama-2 or Flan-T5 model is: "The task is to detect whether the Text contains logical fallacy or not. The logical fallacy can be <fallacy name (fallacy definition)>. The logical relations in the Text are presented in this table: argument 1, logical relation, argument 2 <textualized tree>. Please answer Yes if the Text contains logical fallacy, else answer No. Text: <text>. Answer:"

B.2 Prompt for Fallacy Classification

The instruction prompt for the Llama-2 or Flan-T5 baseline model is: "The task is to classify the fallacy type of the Text. Choose one answer from these fallacy types: <fallacy names list>. The definitions of each fallacy type are as follows. <fallacy name: fallacy definition>. Please classify the fallacy type of the Text. Text: <text>. Answer:"

The instruction prompt that incorporates the textualized tree into the Llama-2 or Flan-T5 model is: "The task is to classify the fallacy type of the Text. Choose one answer from these fallacy types: <fallacy names list>. The definitions of each fallacy type are as follows. <fallacy name: fallacy definition>. Please classify the fallacy type of the Text. Text: <text>. Answer:"

C Prompt for GPT-based baselines**C.1 Prompt for Fallacy Detection**

The instruction prompt for the gpt-3.5-turbo baseline model is: "The task is to detect whether the Text contains logical fallacy or not. The logical fallacy can be <fallacy name (fallacy definition)>. Please answer Yes if the Text contains logical fallacy, else answer No. Text: <text>. Answer." The instruction prompt that incorporates the logical structure into gpt-3.5-turbo model through a chain-of-thought process is: "The task is to detect whether the Text contains logical fallacy or not. The logical fallacy can be <fallacy name (fallacy definition)>. Please answer Yes if the Text contains logical fallacy, else answer No. Let's think step by step. Firstly, explain the logical relations and logical structure in the text. Secondly, choose the answer. Please mimic the output style in the Example. Example: <example text>. Output: Firstly, explain the logical relations and logical structure in the text. <explanation of logical relations and logical structure in the example>. Secondly, choose the answer. Answer: <fallacy label of the example>. Text: <text>. Output:"

C.2 Prompt for Fallacy Classification

The instruction prompt for the gpt-3.5-turbo baseline model is: "The task is to classify the fallacy type of the Text. Choose one answer from these fallacy types: <fallacy names list>. The definitions of each fallacy type are as follows. <fallacy name: fallacy definition>. Please classify the fallacy type of the Text. Text: <text>. Answer." The instruction prompt that incorporates the logical structure into gpt-3.5-turbo model through a chain-of-thought process is: "The task is to classify the fallacy type of the Text. Let's think step by step. Firstly, explain the logical relations and logical structure in the text. Secondly, choose the answer. Please mimic the output style in the Example. Example: <example text>. Output: Firstly, explain the logical relations and logical structure in the text. <explanation of logical relations in the example>. Secondly, choose the answer. Answer: <fallacy label of the example>. Text: <text>. Output"

D The Names and Definitions of Fallacies

D.1 Argotario dataset

The Argotario dataset (Habernal et al., 2017) includes five fallacy types: Ad Hominem, Appeal to Emotion, Hasty Generalization, Irrelevant Authority, Red Herring. The name of Appeal to Emotion is converted into Emotional Language. The definitions of these fallacy types which are used in the instruction prompt are:

- Ad Hominem: the text attack a person instead of arguing against the claims.
- Emotional Language: the text arouse non-rational emotions.
- Hasty Generalization: the text draw a broad conclusion based on a limited sample of population.
- Irrelevant Authority: the text cite an authority but the authority lacks relevant expertise.
- Red Herring: the text diverge the attention to irrelevant issues.

D.2 Reddit dataset

The Reddit dataset (Sahai et al., 2021) includes eight fallacy types and their label names are: Slippery Slope, Irrelevant Authority, Hasty Generalization, Black-and-White Fallacy, Ad Populum, Tradition Fallacy, Naturalistic Fallacy, Worse Problem Fallacy. The definitions of these fallacy types which are used in the instruction prompt are:

- Slippery Slope: the text suggest taking a small initial step leads to a chain of related events culminating in significant effect.
- Irrelevant Authority: the text cite an authority but the authority lacks relevant expertise.
- Hasty Generalization: the text draw a broad conclusion based on a limited sample of population.
- Black-and-White Fallacy: the text present two alternative options as the only possibilities.
- Ad Populum: the text affirm something is true because the majority thinks so.
- Tradition Fallacy: the text argue the action has always been done in the tradition.

D.4 Logic dataset

The Logic dataset (Jin et al., 2022) annotates 13 types of fallacy: Ad Hominem, Ad Populum, False Dilemma (Black-and-White Fallacy), False Cause, Circular Reasoning, Fallacy of Logic (Deductive Fallacy), Appeal to Emotion (Emotional Language), Equivocation, Fallacy of Extension (Extension Fallacy), Fainty Generalization (Hasty Generalization), Intentional Fallacy, Fallacy of Credibility (Irrelevant Authority), Fallacy of Relevance

(Red Herring). The names in the parenthesis are the replaced names used in the instruction prompt. The definitions of these fallacy types which are used in the instruction prompt are:

- Ad Hominem: the text attack a person instead of arguing against the claims.
- Ad Populum: the text affirm something is true because the majority thinks so.
- Black-and-White Fallacy: the text present two alternative options as the only possibilities.
- False Cause: the text assume two correlated events must also have a causal relation.
- Circular Reasoning: the end of the text come back to the beginning without having proven itself.
- Deductive Fallacy: the text has an error in the logical reasoning.
- Emotional Language: the text arouse non-rational emotions.
- Equivocation: the text use a key term in multiple senses, leading to ambiguous conclusions.
- Extension Fallacy: the text attack an exaggerated version of the opponent's claim.
- Hasty Generalization: the text draw a broad conclusion based on a limited sample of population.
- Intentional Fallacy: the text show intentional action to incorrectly support an argument.
- Irrelevant Authority: the text cite an authority but the authority lacks relevant expertise.
- Red Herring: the text diverge the attention to irrelevant issues.

| % | conjunction | alternative | restatement | instantiation | contras. | concession | temporal | condition | causal |
|------------|-------------|-------------|-------------|---------------|----------|------------|----------|-----------|--------|
| fallacy | 37.96 | 46.72 | 1.46 | 0.3 | 48.91 | 1.46 | 6.57 | 10.95 | 16.06 |
| no fallacy | 28.13 | 40.63 | 3.13 | 0.60 | 42.19 | 3.13 | 1.56 | 7.81 | 15.63 |
| fallacy | 64.04 | 75.44 | 4.39 | 2.42 | 67.54 | 8.19 | 16.67 | 26.90 | 34.80 |
| no fallacy | 50.31 | 69.63 | 3.37 | 1.53 | 67.18 | 7.98 | 19.94 | 25.46 | 33.44 |
| | | | | | | | | | 73.01 |

Table 9: The ratio (%) of samples that contain the ten logical relations in *fallacy* and *no fallacy* classes in the development set of Argotaino (the first two rows) and Redicit (the latter two rows) datasets.

| % | conjunction | alternative | restatement | instantiation | contras. | concession | temporal | condition | causal |
|----------------|-------------|-------------|-------------|---------------|----------|------------|----------|-----------|--------|
| Ad Hominem | 30.22 | 60.44 | 0.44 | 0.44 | 64.44 | 2.22 | 7.55 | 12.00 | 12.44 |
| Ad Populum | 20.88 | 47.46 | 0.63 | 1.89 | 27.21 | 1.89 | 10.76 | 5.06 | 76.89 |
| False Dilemma | 18.34 | 79.81 | 0.91 | 0.00 | 36.69 | 2.75 | 1.83 | 15.59 | 10.12 |
| False Case | 46.74 | 62.72 | 0.00 | 0.00 | 36.68 | 1.18 | 3.55 | 37.87 | 30.45 |
| Circular Claim | 24.24 | 38.63 | 0.00 | 0.75 | 37.87 | 0.00 | 3.03 | 11.36 | 36.98 |
| Deductive | 28.09 | 63.63 | 0.00 | 0.00 | 39.67 | 0.82 | 19.83 | 17.35 | 8.33 |
| Emotional | 41.86 | 59.68 | 2.32 | 0.00 | 50.38 | 1.55 | 7.75 | 18.60 | 24.79 |
| Equivocation | 42.10 | 71.05 | 0.00 | 0.00 | 63.15 | 7.89 | 5.26 | 31.57 | 17.35 |
| Extension | 54.71 | 73.38 | 0.00 | 1.88 | 62.25 | 0.94 | 11.32 | 18.86 | 76.31 |
| Generalization | 38.99 | 52.33 | 0.94 | 0.63 | 39.91 | 1.88 | 8.49 | 21.27 | 87.73 |
| Intentional | 29.46 | 48.21 | 2.67 | 0.89 | 60.71 | 4.46 | 5.36 | 18.75 | 31.13 |
| Authority | 39.25 | 66.35 | 2.80 | 4.67 | 41.12 | 2.80 | 3.73 | 16.82 | 69.49 |
| Relevance | 35.96 | 67.54 | 0.87 | 0.00 | 55.25 | 0.00 | 20.17 | 13.28 | 25.60 |
| Overall | 34.49 | 58.97 | 0.87 | 0.82 | 45.39 | 1.85 | 6.91 | 18.22 | 67.85 |

Table 10: The ratio (%) of samples that contain the ten logical relations in each fallacy type in the Logic dataset. The fallacy types include Ad Hominem, Ad Populum, False Dilemma, Black-and-White Fallacy, False Cause, Circular Reasoning, Destructive Fallacy, Appeal to Emotion (Emotional Language), Equivocation, Fallacy of Extension, Faulty Generalization (Hasty Generalization), Intentional Fallacy, Fallacy of Credibility (Irrelevant Authority), Fallacy of Relevance (Red Herring).