Improving Neural Model Performance through Natural Language Feedback on Their Explanations

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Abstract

A class of explainable NLP models for reasoning tasks support their decisions by generating free-form or structured explanations, but what happens when these supporting structures contain errors? Our goal is to allow users to interactively correct explanation structures through natural language feedback. We introduce MERCURIE- an interactive system that refines its explanations for a given reasoning task by getting human feedback in natural language. Our approach generates graphs that have 40% fewer inconsistencies as compared with the off-the-shelf system. Further, simply appending the corrected explanation structures to the output leads to a gain of 1.2 points on accuracy on defeasible reasoning across all three domains.1

1 Introduction

Interactive Machine Learning allows humans to give feedback to the models, often leading to improved accuracy (Fails and Olsen, 2003; Raghavan, 2006; Settles, 2011). Interactive systems for NLP have used human-in-the-loop style interactions for helping refugee settlement (Brown and Grinter, 2016), aligning topic models (Yuan et al., 2018) and enhancing bilingual word embeddings (Yuan et al., 2020). Neural models have made advancements in explanation generation but are expensive to retrain. This paper aims to improve the model output through natural language feedback (e.g., on its explanation) without retraining.

One line of prior approaches (interactive semantic parsing approach) (Elgohary et al., 2021; Wang et al., 2016) parse natural language user feedback into a set of edit operations, which can then be executed on the incorrect explanation structure, thereby correcting the explanation. In these approaches, the feedback is specific to a semantic parsing schema and has to be specialized, i.e., directly mapped to specific instructions or literals, limiting its generalizability. Moreover, the feedback is expected to be actionable, containing a specific set of edit operations expressed in natural language. However, real-world human feedback is often imprecise and not directly actionable. Another line of prior approaches (interactive reasoning approach) (Talmor et al., 2020) explore interactivity by enriching the context of an input sample through human feedback. However, for the human giving the feedback, the model is a black box – so the human does not know what the model's internal belief is and how it will change based on the feedback.

These two lines of prior approaches inspire this paper – we provide more transparency to the human than the interactive reasoning approach as the model receives feedback on the explanation (similar to the interactive semantic parsing approach). We do this while relaxing the assumptions of the parsing approach – our feedback does not have a task-specific structure, and it is not assumed to be actionable (similar to the interactive reasoning approach).

We introduce MERCURIE, a pipeline system with two components, a previously trained neural model \mathcal{M} and a graph corrector \mathcal{G} . It takes as input any previously trained neural model \mathcal{M} capable of generating an explanation structure. The second input is a natural language human feedback on the generated explanation structure (for example, that some nodes are inconsistent with the rest of the graph). As output, it produces a better explanation structure.

The contributions of this work are:

^{*} authors contributed equally to this work. Ordering determined by dice rolling.

¹We release a dataset of over 450k graphs for defeasible reasoning generated by our system at https://tinyurl.com/mercurie.



Figure 1: Our pipeline: the output generated by \mathcal{M} is corrected by \mathcal{G} using human feedback.

- We demonstrate a system that shows that an explainable NLP model output can be improved through natural feedback on their explanations. Experiments show that MERCURIE can improve the consistency of explanation structures by up to 40% (§4).
- We also show downstream task (defeasible inference (Rudinger et al., 2020)) improvement for all domains by at least 1.2 points on accuracy (§6).

Algorithm 1: MERCURIE algorithm to correct explanations through human feedback

```
Given: \mathcal{M}: x \to \tilde{y}, \{x_i\}_{i=1}^N

Train \mathcal{G} on \mathcal{D}_{\mathcal{G}}:

\mathcal{D}_{\mathcal{G}} = \emptyset;

for i \leftarrow 1, 2, \dots, N do

\tilde{y}_i = \mathcal{M}(x_i);

I_i = \text{feedback}(\tilde{y}_i);

y_i = \text{human}(\tilde{y}_i);

\mathcal{D}_{\mathcal{G}} = \mathcal{D}_{\mathcal{G}} \cup (x_i, I_i, \tilde{y}_i, y_i);

end

Train \mathcal{G} on (x, I, \tilde{y}) \to y;
```

Inference:

$$\begin{split} \tilde{y} &= \mathcal{M}(x);\\ \textbf{while } I: \textit{feedback}(\tilde{y}) \neq \emptyset \textit{ do}\\ \tilde{y} &= \mathcal{G}(x, I, \tilde{y});\\ \textbf{end}\\ y &= \tilde{y}; \end{split}$$

2 Related work

Interactive Learning: Interactive learning involves a human in the loop, as opposed to learning from datasets collected offline. Relevant approaches in NLP are wide-ranging from active learning (Raghavan, 2006; Wu et al., 2019) to

training dialogue systems that adapt to user utterances, spanning diverse domains (Holzinger, 2016). There are various modes of interaction (through labels (Raghavan, 2006; Fails and Olsen, 2003), utterance (Radlinski et al., 2019), imitation (Brantley et al., 2020), and language (Elgohary et al., 2020)). Our work uses language as the mode of interaction.

Language-based interactions: Natural language interaction allows for expressive human feedback to correct a model. In language-based interactions, controlled settings (Mehta and Goldwasser, 2019; Wang et al., 2016) give a better handle and are easy to evaluate. However, they do not generalize to real-world settings- human feedback is rich, and it is not desirable to be restricted to a vocabulary. Finally, the model being taught is treated either as (i) a black box (as in machine teaching (Dasgupta et al., 2019), (Talmor et al., 2020)) or (ii) the beliefs of the model are in some form exposed to feedback (as in interactive semantic parsing (Elgohary et al., 2021)). This paper is uniquely positioned because we present the first system, which has interaction through language by directly giving feedback on the model's beliefs (explanation) in a real-world, open domain setting.

Interactive Semantic Parsing: The common theme in prior approaches to this task based on interactive semantic parsing (such as (Elgohary et al., 2021; Wang et al., 2016)) is that user feedback is mapped into structure edit commands, which can then be executed on the incorrect structures to fix it. For example, (Elgohary et al., 2021) presented NL-EDIT to fix SQL queries using human feedback such as: replace course id with program id.. However:

• the feedback are syntactic with a certain taskspecific formal structure, e.g., NL-EDIT is known to struggle with natural feedback that does not describe an edit directly (Elgohary et al., 2021).

• the feedback is expected to be actionable. Rather than highlighting a problem or error, it is expected to contain a solution to fix the error. This feedback is then parsed using semantic parsing techniques into a set of structure edit commands.

Differences w.r.t. Interactive Semantic parsing Unlike NL-EDIT, we do not make assumptions about the structure of the feedback. Moreover, we assume that the feedback would be non-actionable (pointing out some local or global error without providing a solution to fix the error). This should especially hold with the growing complexity of the structure to give feedback because it is simpler for a human to point to the problem rather than enumerate (in natural language) the edits that might be required. Therefore, semantic parsing techniques do not apply to our problem as the feedback is nonactionable (i.e., our feedback only highlights that something is wrong, not how to fix it).

Interactive learning for reasoning tasks Our focus is a reasoning task that accounts for the context and requires commonsense to bridge between the feedback to a possible solution. In this, we are inspired by (Talmor et al., 2020) where the interaction is with a black box system (unlike this paper), and when the model incorrectly answers whether A whale has a belly button, then a user tells the model the explicit rule A mammal has a belly button, the model corrects its answer by combining the feedback with its implicit knowledge, e.g., that A whale is a mammal. Our work extends along this line of research by showing that a model can update a model's explanation structure in a reasoning task setting.

3 Task and Dataset

We focus on the task of generating graphs for defeasible inference queries. After presenting the task, we describe the graph generator \mathcal{M} that generates an inference graph for a defeasible inference query. Subsequently, we will use the feedback described in §4 to train \mathcal{G} , a system that fixes the output generated by \mathcal{M} .

3.1 Task: Defeasible Inference

Defeasible inference (Rudinger et al., 2020) is a mode of reasoning in which given a premise \mathbf{P} , a hypothesis \mathbf{H} may be strengthened or weakened in light of new evidence. For example, given a premise *ocean causes erosion*, the hypothesis *rocks become smaller* will be strengthened by the situation *waves are bigger*, and weakened by the situation \mathbf{S} *no waves*. We use **PHS** to refer to a defeasible query and **T** to the answer (strengthened or weakened).

This problem has been widely studied in cognitive science by supporting defeasible inference through argumentative frameworks (Pollock, 1987). Humans have found argumentations helpful in defeasible reasoning, and this insight has led to models that simulate argumentations through an inference graph, e.g., Pollock (2009) supplement defeasible queries PHS with an inference graph. An inference graph contains events as nodes and the causal relationship between the nodes as edges. The motivation behind using inference graphs is to provide additional context for each PHS query that might help the humans understand the nature of the effect that an update situation \mathbf{S} has on the hypothesis. Being costly to construct by hand, inference graphs have only been studied at a small scale.

In the absence of a large repository of inference graphs for defeasible queries, we propose their automatic generation by learning from WIQA (Tandon et al., 2019) - a repository of graphs that are similar to an inference graph (Section 3.1.2). The main challenge in learning from these graphs is that they are narrowly focused on the procedural text domain. In contrast, defeasible inference task has a wide scope– thus requiring the transfer technique that we present in 3.2. Given the central role that the WIQA dataset plays in our work, we provide a brief description next.

3.1.1 WIQA

WIQA comprises of 2107 pairs of (P, G) where Pis a paragraph that describes a process (e.g., the spread of a virus). The influence graph G corresponding to P is a directed acyclic graph (DAG) that captures the interactions between the events and their influences within the context of the process described by P. Let G = (V, E), where Vdenotes the set of vertices and E the set of edges. The nodes $n \in V$ are events relevant to the process. Each node n is described by a sequence of text tokens. The edge set E contains two types of edges: *helps* and *hurts*, denoted by green and red arrows respectively. A *helps* edge between a source node n_c and a target node n_e signifies that the source event n_c positively influences the target event n_e and a *hurts* edge stands for n_c negatively influencing n_e . Figure 2 shows an example influence graph for the process of "spread of a virus during a pandemic."



Figure 2: A sample influence graph about spread of a virus during a pandemic

3.1.2 WIQA as a repository of inference graphs

We show that the nodes of an influence graph in WIQA are similar to the inference graph for defeasible reasoning proposed in (Pollock, 2009), by showing a semantic mapping between the components of a defeasible query and an influence graph.

- The premise of a defeasible query **P** and the passage in WIQA both play a similar role of providing more context for the influence graph.
- Each WIQA graph has two hypothesis nodes, which capture either the strengthening or weakening of a hypothesis. Thus, there is a natural correspondence between the hypothesis nodes in WIQA and the hypothesis in defeasible.
- Each influence graph consists of a node S, which contains an event grounded in P that signifies a change. This is similar to the update S in the defeasible query.

3.2 Designing \mathcal{M} for Defeasible Reasoning

Given these similarities, we train a graph-generator on WIQA and transfer it for defeasible reasoning. Our goal is to supplement each defeasible query **PHS** with an inference graph. We first train a graph generator \mathcal{M} using WIQA. As discussed, each example in WIQA consists of a (P, G) pair, where P is the passage, and G is the influence graph. We extract the hypothesis node H and the situation node S from G (using the last two nodes in Figure 2). We then train a sequence-to-sequence generation model (based on T5-11B), where the input is the string $P \| H \| S$ and the output is the corresponding influence graph G encoded as a string. During inference, we obtain a graph for the defeasible query **PHS** by setting passage = **P**, hypothesis = \mathbf{H} , and situation = \mathbf{S} , as discussed. Figure 3 shows the details of the training process.

4 Human feedback on \mathcal{M}

In this section, we propose a method to take feedback on the output of \mathcal{M} .

4.1 Human feedback

We evaluate the graphs produced by \mathcal{M} for defeasible reasoning using human evaluators. Two human judges evaluated 100 graphs produced by \mathcal{M} . The judges found that all the graphs had the correct structure, but 70% of them had *repeated* nodes with the same information.

Each node in an influence graph plays a specific role (e.g., positive contextualizer or mediator). Thus, repeated nodes violate the semantic structure of a graph. Additionally, they also reduce the amount of information carried by each graph. For defeasible reasoning, we focus on reducing this repetition of nodes in each graph. We note that we do not utilize the edge structure of the graph for this work or take feedback on it. The structure of the graphs is assumed to be fixed. Our intuition is that reducing the number of repeated nodes will improve the quality of these graphs, making them more useful for downstream tasks. To be consistent across tasks, we refer to such graphs with repeated nodes as being *incorrect graphs*.

4.2 Automating human-like feedback

We observed that humans found it cognitively challenging to look at multiple nodes and check for the consistency of nodes and repetition of content across multiple unrelated or opposite polarity



Figure 3: Training the graph generator \mathcal{M} for defeasible reasoning.

Algorithm 2: Generating training data for \mathcal{G} using human feedback.

```
Given: Inference graphs G generated by \mathcal{M},
           and G* generated by \mathcal{M} *
Result: Training data for \mathcal{G}
Init: \mathcal{D} \leftarrow []
for i \leftarrow 1, 2, \ldots, |\mathcal{M}| do
     F_{G_i} = feedback(G_i);
     F_{G_i} * = feedback(G_i *);
     if F_{G_i} \neq \emptyset and F_{G_i} * = \emptyset then
          /* G_i has problems, G_i*
                is good
                                                        */
          \mathcal{D} = \mathcal{D} \cup (G_i, F_{G_i}, G_i *);
     else if F_G = \emptyset and F_G * = \emptyset then
          /* Both G_i and G_i* are
                qood
                                                        */
          \mathcal{D}=\mathcal{D}\cup
           (G_i, \text{No issues, looks good}, G_i*);
end
return \mathcal{D}
```

nodes. In contrast, prior work on assembling structure edit commands relies on the relative simplicity of the structure (such as in an SQL query), allowing targeted feedback. This is not possible in our case, owing to the sizeable cognitive load of manually labeling each node while maintaining structural consistency. Therefore, using human annotations, we devised a simple rule-based system F that uses token-based overlap to detect repetitions while preventing spurious matches due to negation. Figures 8, 10, and 9 show examples of various kinds of inconsistencies and the corresponding feedback.

4.3 Automating expected corrected graph

Ideally, it would be desirable to have training data that provides a *fixed graph* corresponding to each incorrect graph. However, we realized that manually fixing incorrect graphs is not scalable, as it requires identifying repeated nodes and then coming up with a label that would remove the repetitions across the graph. We circumvent this issue by training another version of graph generator \mathcal{M}^* . The training process of \mathcal{M}^* closely follows that of \mathcal{M} : we set the input to P ||H||S||T and the output to G. Note that the only difference here from \mathcal{M} is that the generation is now additionally conditioned on the edges, leading to more diverse and possibly less noisy graphs.

During inference, we obtain a graph for the defeasible query **PHS** by setting passage = **P**, hypothesis = **H**, and situation = **S**, as discussed. Figure 3 shows the details of the training process.

We further note that such conditioning is not possible for the general case since the graph edges are not available with defeasible queries.

We use T5-11B (Raffel et al., 2020) as our graph generator \mathcal{M} , feedback graph generator \mathcal{M}^* , as well as graph corrector \mathcal{G} .

5 Correcting explanation structure through human feedback

Can we make use of the feedback described §4? We show that we can train a model, \mathcal{G} , that takes that feedback and improves \mathcal{M} . That is, given **PHS**, \mathcal{M} generates a potentially noisy graph (§3.2) - and \mathcal{G} learns to correct this graph using the automatic human-like feedback (§4.2) and compute loss over the expected corrected graph (§4.3). First, we show this graph correction system \mathcal{G} , followed by empirically measuring the effectiveness of \mathcal{G} .

5.1 Training the graph corrector G

We now proceed to train the graph corrector \mathcal{G} using Algorithm 2. The \mathcal{G} is also trained as a sequence-to-sequence model. For a given query **PHS**, the graphs generated by \mathcal{M} and \mathcal{M}^* are first paired. From these pairs, we only retain those



Figure 4: *C*-, *C*+ and *S*,*S*- are overlapping.

Figure 5: C-, C+, S, S- and M-, M+, H+ are overlapping.

Figure 6: Incorrect graphs generated by \mathcal{M} for SNLI (left) SOCIAL domains of Defeasible. The feedback on each graph is mentioned in caption, and we provide the fixed versions of these graphs in the Appendix.



Figure 7: The graphs generated by \mathcal{M} (left), \mathcal{M}^* (middle), and \mathcal{G} (right). The input graph has repetitions for nodes $\{C-, S-\}, \{C+, H+\}, \text{ and } \{M-, M+\}$. The corrected graph replaces the repetitions with meaningful labels.

cases where the \mathcal{M} graph is incorrect, whereas \mathcal{M}^* graph is not, as identified by our rule-based feedback system F. We record each such example as $(G', F(G'), G^*)$. We also retain pairs where both G' and G'' are correct, and in those cases, the feedback F(G') is set to *no issues, looks good*. This is then fed to our generation model, which is trained to generate G^* from G', F(G').

Training \mathcal{G} completes our pipeline for obtaining high-quality graphs for each defeasible query. First, given a defeasible query **PHS**, we generate a potentially incorrect graph. G' using \mathcal{M} . We then use the feedback generator F to obtain feedback F(G') on G'. The tuple (G', F(G')) is then fed to \mathcal{G} to obtain a corrected graph G.

6 Results

In this section, we answer two questions: i) Does \mathcal{G} reduce the inconsistencies in the graphs? ii) Does using graphs generated by \mathcal{G} help the end task?

6.1 Does G reduce the inconsistencies in the graphs?

We evaluate the repetitions in the graphs using two metrics:

- **rep. per graph:** the average number of repeated nodes in the graphs produced by \mathcal{M} and \mathcal{G} .
- % with repetitions: the percentage of graphs with at least one repeated node.

As Table 1 shows, G reduces the average repetitions by 40% (2.11 to 1.25) and reduces the fraction of graphs with at least one repetition by 25.7 on average.

	Metric (repeti- tions)	no feedback (\mathcal{M})	w/ feedback (G)
ATOMIC	per graph	2.05	1.26
	% graphs	72	48
SNLI	per graph	2.09	1.18
	% graphs	73	46
SOCIAL	per graph	2.2	1.32
	% graphs	75	49
Average	per graph	2.11	1.25
	% graphs	73.3	47.6

Table 1: \mathcal{G} reduces the inconsistencies in the graphs. The number of repetitions on average per graph and percentage of graphs with some repetition, both improve.

6.2 Does using graphs generated by G help the end task?

We now evaluate the efficacy of the graphs generated by \mathcal{M} and corrected by \mathcal{G} on the defeasible inference task. As mentioned in Section 3, the goal of the defeasible inference task is to classify an update **S** as a strengthener or weakener of a hypothesis **H** in the context of premise **P**.

Let M be the graph generated by \mathcal{M} for the query **PHS**. The graph M and the feedback F on M are then supplied to \mathcal{G} to obtain G. We overload the notation and use M and G to refer to the nodes of the graphs generated by \mathcal{M} and \mathcal{G} , respectively. Thus, given each defeasible query **PHS**, we obtain M: the set of nodes generated \mathcal{M} and G: the set of nodes generated by \mathcal{G} .

Following Rudinger et al. (2020), we prefix a given sequence of tokens T with a special beginning-of-sequence (BOS) token. T is then encoded using RoBERTa-base (Liu et al., 2019)², and the hidden representation corresponding to BOS is passed to a classifier (single-layer MLP). We train three classifiers, each following the above-described architecture with different inputs: (i) Baseline: T = P ||H||S, (ii) \mathcal{M} : T = P ||H||M||S, and (iii) \mathcal{G} : T = P ||H||G||S. We report the results in Table 2, and observe that: (i) Despite the relative simplicity of our approach (concatenating nodes with the query), both \mathcal{M} (concatenates noisy graph) and \mathcal{G} (concatenates cleaner graph) improve over the baseline. This shows that these explanation structures help enrich the context in the defeasible reasoning task. (ii) \mathcal{G} outperforms both the baseline and \mathcal{M} , showing that reducing the inconsistencies and repetitions improves end task performance.

	Baseline	\mathcal{M}	${\mathcal G}$
ATOMIC	78.3	78.8	79.5
SNLI	81.6	82.1	83.1
SOCIAL	86.2	86.7	87.2
average	82.03	82.53	83.26*

Table 2: Results on Defeasible inference without using graphs (Baseline (Rudinger et al., 2020)), using graphs generated by \mathcal{M} , and graphs corrected with feedback by \mathcal{G} . * indicates statistical significance

7 Discussion and Conclusion

We present MERCURIE, a system that improves the explanation structure (graphs) generated by a model without requiring expensive humanannotated feedback. Our approach generates graphs that have 40% fewer inconsistencies as compared with the off-the-shelf system. Further, simply appending the corrected explanation structures to the output leads to a gain of 1.2 points on accuracy on defeasible reasoning across all three domains.

This work paves a new path towards exciting future research direction of constantly improving explainable NLP models by applying human feedback.

Acknowledgments

This material is partly based on research sponsored in part by the Air Force Research Laboratory under agreement number FA8750-19-2-0200. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright notation thereon. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily

²We use the implementation by (Wolf et al., 2019)

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A Appendix

A.1 Examples of errors in the explanation structures generated by \mathcal{M}

- Figure 8 shows an example of incorrect graph generated for Defeasible SNLI data.
- Figure 9 shows an example of incorrect graph generated for Defeasible Social data.
- Figure 10 shows an example of incorrect graph generated for Defeasible ATOMIC data.

A.2 Reproducibility

A.2.1 $\mathcal{M}, \mathcal{M}^*, \mathcal{G}$

T5-11B models has 11B parameters with 24-layers, 1024-hidden-state, 65,536 feed-forward hiddenstate, 128 attention heads. We use TPU (v3-8) on Google cloud platform. It takes 3 hours in average to train \mathcal{M} and \mathcal{M}^* , and 4 hours to train \mathcal{G} .

A.2.2 Classifier for defeasible tasks

We build on the implementation by Wolf et al. (2019), using the default hyperparameters. For optimization, we use AdamW (Loshchilov and Hutter, 2017) with a learning rate of 2e-5, a batch size of 16, and a linear rate scheduler with warm up for the first 3 (10%) of the epochs. We use accumulate gradients for two batches, and clip gradients at 1. We also experimented with a block size of 300 and a batch size of 2. All of our experiments were done on a single Nvidia GeForce RTX 2080 Ti.



Figure 8: Incorrect graph generated by \mathcal{M} (left) and fixed by \mathcal{G} (right) for Defeasible-SNLI dataset. The feedback is 'C-, C+ are overlapping, and S, S- are overlapping.'



Figure 9: Incorrect graph generated by \mathcal{M} (left) and fixed by \mathcal{G} (right) for Defeasible-SOCIAL dataset. The feedback is 'C-, C+,S,S- are overlapping, and M-, M+, H+ are overlapping.'



Figure 10: Incorrect graph generated by \mathcal{M} (left) and fixed by \mathcal{G} (right) for Defeasible-ATOMIC dataset. The feedback is 'S-, M+ are overlapping.;