Case-based Abductive Natural Language Inference

Marco Valentino, Mokanarangan Thayaparan, André Freitas
Department of Computer Science, University of Manchester, United Kingdom
Idiap Research Institute, Switzerland
marco.valentino@manchester.ac.uk

Abstract

Existing accounts of explanation emphasise the role of prior experience in the solution of new problems. However, most of the contemporary models for multi-hop textual inference construct explanations considering each test case in isolation. This paradigm is known to suffer from semantic drift, which causes the construction of spurious explanations leading to wrong conclusions. In contrast, we investigate an abductive framework for explainable multi-hop inference that adopts the retrieve-reuse-revise paradigm largely studied in case-based reasoning. Specifically, we present a novel framework that addresses and explains unseen inference problems by retrieving and adapting prior natural language explanations from similar training examples. We empirically evaluate the case-based abductive framework on downstream commonsense and scientific reasoning tasks. Our experiments demonstrate that the proposed framework can be effectively integrated with sparse and dense pre-trained encoding mechanisms or downstream transformers, achieving strong performance when compared to existing explainable approaches. Moreover, we study the impact of the retrieve-reuse-revise paradigm on explainability and semantic drift, showing that it boosts the quality of the constructed explanations, resulting in improved downstream inference performance.

1 Introduction

Multi-hop inference is the task of composing two or more pieces of evidence from external knowledge resources to address a particular reasoning problem. In the context of Natural Language Inference (NLI), this task is often used to develop and evaluate explainable systems, capable of performing transparent multi-step reasoning with natural language (Wiegrefe and Marasović, 2021; Thayaparan et al., 2020). While multi-hop reasoning has been largely explored for extractive problems such as open-domain question answering (Xiong et al., 2021; Fang et al., 2020; Yang et al., 2018), increasing attention is being dedicated to the abstractive setting, where the models are required to compose long chains of facts expressing abstract commonsense and scientific knowledge (Jhamtani and Clark, 2020; Xie et al., 2020; Khot et al., 2019; Jansen et al., 2018).

In this setting, multi-hop inference is often framed as an abductive natural language inference problem, where, for a given set of alternative hypotheses $H = \{h_1, h_2, \ldots, h_n\}$, the goal is to construct an explanation for each $h_i \in H$ and select the hypothesis supported by the best explanation. Existing approaches address abductive inference considering each test hypothesis in isolation, employing iterative and path-based methods (Yadav et al., 2019b; Kundu et al., 2019) or explicit con-
straints to guide the generation of a plausible explanation graph (Khashabi et al., 2018; Khot et al., 2017). However, this paradigm poses several challenges in the abstractive setting as: (1) the structure of the explanation is not evident from the decomposition of the hypothesis, that is, the type of facts required for the inference cannot be derived from the surface form of the reasoning problem; (2) central explanatory facts tend to be abstract, sharing a low number of terms with the hypothesis, making it hard to correctly estimate their relevance for the inference; (3) background knowledge sources contain a large amount of distracting information overlapping with the hypothesis, which can lead to the generation of spurious explanations. Consequently, existing approaches often suffer from a phenomenon known as semantic drift (Khashabi et al., 2019) – i.e., the tendency of composing incorrect reasoning chains leading to wrong conclusions. The example in Figure 1 illustrates some of these challenges. In contrast with the existing paradigm, we propose to integrate abductive natural language inference in a case-based reasoning framework (Schank et al., 2014; De Mantaras et al., 2005). Different accounts in philosophy and cognitive science emphasise the crucial role of prior knowledge in the generation of new explanations (Schank, 2013; Lombrozo, 2012; Thagard and Litt, 2008). Specifically, when presented with a new problem, humans use prior experience to guide the search of an appropriate solution, explicitly retrieving and adapting solutions from similar cases solved in the past. Case-based reasoning is built upon these findings, adopting a retrieve-reuse-revise paradigm to model inference over unseen problems. Following these observations, we hypothesise that the adoption of a case-based reasoning framework can help tackle some of the challenges involved in the abstractive setting since: (1) similar hypotheses tend to require similar explanations; (2) abstract facts tend to express general explanatory knowledge about underlying regularities, being frequently reused to explain a large variety of phenomena; (3) prior solutions from similar problems can explicitly help constrain the search space, reducing the risk of composing spurious inference chains including distracting information. To validate these hypotheses, we present a case-based abductive NLI model that retrieves and adapts natural language explanations from training examples to construct new explanations for unseen cases. Specifically, this paper provides the following contributions:

1. To the best of our knowledge, we are the first to propose a case-based abductive framework for multi-hop textual inference in an abstractive setting;

2. We empirically demonstrate the efficacy of the case-based framework on commonsense and scientific reasoning tasks, showing that the proposed model can be effectively integrated with different sentence encoders and downstream transformer-based models, achieving strong performance when compared to existing multi-hop and explainable approaches;

3. We study the impact of the retrieve-reuse-revise paradigm on explainability, and how this affects accuracy and robustness in downstream inference. Our results show that the case-based framework boosts the quality of the explanations for the most challenging hypotheses, resulting in improved downstream inference performance.

2 Related Work

Multi-hop Textual Inference. Performing multi-hop inference for abstractive reasoning tasks has been shown to be challenging as the general structure of the explanations cannot be derived from the surface form of the reasoning problem. Previous work has demonstrated that models in this setting are affected by semantic drift – i.e., the construction of spurious explanations leading to wrong conclusions (Fried et al., 2015; Khashabi et al., 2019). Existing approaches frame multi-hop inference as the problem of building an optimal graph, conditioned on a set of semantic constraints (Khashabi et al., 2018; Khot et al., 2017; Jansen et al., 2017; Khashabi et al., 2016), or adopting iterative methods, using sparse or dense encoding mechanisms (Yadav et al., 2019a,b; Pirtoaca et al., 2019; Kundu et al., 2019). To tackle semantic drift, recent datasets provide support with annotated explanations (Xie et al., 2020; Jansen et al., 2018). These resources have been used in explanation regeneration tasks (Jansen and Ustalov, 2019; Cartuyvels et al., 2020; Valentino et al., 2021), but their applicability on downstream predictions is yet to be explored. In contrast, in this paper, we study their impact on semantic drift for end-to-end inference problems.
Case-based Reasoning. Our approach is related to previous work on case-based reasoning (Schank et al., 2014; Schank, 2013; De Man
taras et al., 2005). Similar to the retrieve-reuse-revise paradigm adopted in case-based reasoning, we employ encoding mechanisms to retrieve explanations for cases solved in the past, and adapt them in the solution of new problems. Recent work in NLP investigates the use of a similar paradigm via k-NN retrieval on training examples. Khandelwal et al. (2020b,a) adopt k-NN search to retrieve similar training examples and improve pre-trained language models and machine translation without additional training. Similarly, Das et al. (2021, 2020) propose a case-based framework for knowledge base reasoning, while Kassner and Schütze (2020) reuse similar cases to improve BERT (Devlin et al., 2019) on cloze-style QA. To the best of our knowledge, this paper proposes the first application of case-based reasoning for multi-hop textual inference on end-to-end commonsense and scientific reasoning tasks.

3 Case-based Abductive NLI

Given a natural language hypothesis \( h \) (e.g., “Two sticks getting warm when rubbed together is an example of a force producing heat.”), we aim to construct an explanation supporting and estimating the validity of \( h \) by extracting and composing inference chains between multiple explanatory facts retrieved from an external corpus. To construct an explanation for \( h \), we adopt a case-based reasoning paradigm composed of three major phases (Fig. 2):

1. **Retrieve**: In the retrieve phase, we employ a sentence encoding mechanism to perform efficient k-NN search over two distinct embedding spaces. A first embedding space (Facts Embeddings) is adopted to retrieve a set of candidate explanatory sentences for the hypothesis. A second embedding space (Cases Embeddings) is used to retrieve similar cases solved in the past whose explanations can be useful to guide the search for a new solution.

2. **Reuse**: In the reuse phase, we condition the relevance of a given fact on the set of explanations retrieved from the top-K similar cases. Specifically, we reuse previously solved cases to estimate the explanatory power of a fact, representing the extent to which a given fact is used in explanations for past hypotheses.

3. **Revise**: In this phase, the list of candidate explanatory facts is refined to build the final explanation. We model the construction of an explanation performing multi-hop reasoning between hypothesis and candidate facts via the composition of abstractive inference chains. This phase is aimed at quantifying the semantic plausibility of a given fact with respect to \( h \), and refine the explanation.

Additional details on the retrieve-reuse-revise phases are described in the following sections.
3.1 Retrieve

We perform k-NN search over two distinct embedding spaces: (a) an embedding space encoding individual commonsense and scientific facts that can be used to construct new explanations (Facts Embeddings); (b) an embedding space of true hypotheses associated with their respective explanations (Cases Embeddings). An explanation for a given hypothesis \( h_i \) is a composition of facts, \( E_i = \{f_1, \ldots, f_n\} \). To perform k-NN search, we employ a sentence encoder \( e(\cdot) \). Specifically, we use \( e(\cdot) \) to encode the whole corpus of facts and hypotheses into two distinct indexes of sentence vectors. At inference time, we use the encoder to derive a vector for the test hypothesis \( h \) and adopt cosine similarity to efficiently score and rank facts and hypotheses.

3.2 Reuse

We hypothesise that highly explanatory facts expressing underlying regularities tend to create explanatory patterns across similar hypotheses (Valentino et al., 2021). Therefore, we conjecture that explanations from similar cases can be used to estimate the explanatory power of a given fact \( f_i \), constraining the search space for the solutions of new hypotheses. Following this conjecture, given an unseen hypothesis \( h \) and a fact \( f_i \), we adopt the explanations retrieved from the top-K similar hypotheses to estimate the explanatory power of \( f_i \):

\[
\text{pw}(h, f_i) = \sum_{h_k \in k\text{NN}(h)} \text{sim}(e(h), e(h_k)) \cdot \mathbb{1}(f_i, h_k)
\]

where \( k\text{NN}(h) = \{h_1, \ldots, h_K\} \) represents the list of k-nearest hypotheses of \( h \) retrieved according to the cosine similarity \( \text{sim}(\cdot) \) between the embeddings \( e(h) \) and \( e(h_k) \), and \( \mathbb{1}(\cdot) \) is the indicator function verifying if \( f_i \) is included in the explanation \( E_k \) for the hypothesis \( h_k \). Therefore, for each hypothesis \( h_k \) in the set of k-nearest neighbours, the model accumulates the quantity \( \text{sim}(\cdot) \) only if \( f_i \) is used to explain \( h_k \). Since \( \text{sim}(e(h), e(h_k)) \) represents the similarity between \( h \) and \( h_k \), the more \( f_i \) explains past hypotheses that are similar to \( h \) the higher the explanatory power of \( f_i \). To condition the list of candidate explanatory facts on previously solved cases while controlling for relevance with respect to the test hypothesis \( h \), we compute the explanatory relevance of each \( f_i \) by interpolating the explanatory power with the similarity between the embeddings \( e(h) \) and \( e(f_i) \):

\[
\text{er}(h, f_i) = \lambda \cdot \text{sim}(e(h), e(f_i)) + (1 - \lambda) \cdot \text{pw}(h, f_i)  
\]

3.3 Revise

In the revise phase, the model considers the set of candidate explanatory facts retrieved in the previous stage to construct the final explanation for \( h \). We model the construction of an explanation through multi-hop reasoning between hypothesis and candidate facts via the composition of abstractive inference chains. To this end, we represent facts and hypothesis as sets of distinct concepts \( CP(s_i) = \{c_{p_1}, \ldots, c_{p_n}\} \) (e.g., “friction is a kind of force” is represented as the set \{friction, force\}). Given two generic sentences \( s_i \) and \( s_j \), we introduce a new chain between \( s_i \) and \( s_j \) for each shared concept in \( CP(s_i) \cap CP(s_j) \). We compose inference chains to construct an explanation graph starting with the hypothesis \( h \) as the only node. In the first step, the model extends the graph with facts that share concepts with \( h \) and that express taxonomic relations or synonymy. This step can be seen as an abstraction mechanism aimed at dealing with possible lexical variations of the hypothesis. We consider these facts as abstractive nodes. In the second step, the model extends the graph with all the remaining candidate explanatory facts that share at least one concept with previously added nodes (including \( h \)). We consider these facts as central nodes. After constructing the graph, we estimate the semantic plausibility of the central facts \( f_i \):

\[
\text{sp}(h, f_i) = \frac{\sum_{cp_j \in CP(h)} \text{path}(cp_j, f_i)}{|CP(h)|}
\]

where \( \text{path}(cp_j, f_i) \) verifies whether there exists an inference chain in the graph connecting the concept \( cp_j \) in the hypothesis with the fact \( f_i \). Therefore, the semantic plausibility of a fact \( f_i \) is represented by the percentage of concepts in the hypothesis \( h \) that have an inference chain leading to \( f_i \). To derive the final explanation, we sum the explanatory relevance computed during the reuse phase with the semantic plausibility, pruning the graph considering only the top \( n \) central facts and their linked abstractive nodes (see Fig. 2).
Table 1: Accuracy on WorldTree (test-set) for easy and challenge questions. The parameter \( n \) corresponds to the number of explanatory sentences considered by the models to compute the scores for each hypothesis.

| Model                        | Overall | Easy | Challenge |
|------------------------------|---------|------|-----------|
| **Sparse Retrieval Solver**  |         |      |           |
| BM25 \((n = 1)\)             | 41.21   | 44.96| 32.99     |
| BM25 \((n = 2)\)             | 43.62   | 48.54| 32.73     |
| BM25 \((n = 3)\)             | 45.87   | 50.76| 35.05     |
| **Dense Retrieval Solver**   |         |      |           |
| Sentence-BERT \((n = 1)\)    | 44.91   | 50.99| 31.44     |
| Sentence-BERT \((n = 2)\)    | 45.79   | 51.45| 33.25     |
| Sentence-BERT \((n = 3)\)    | 44.51   | 49.82| 32.73     |
| **Path-based Solver**        |         |      |           |
| PathNet                      | 41.50   | 43.32| 36.42     |
| **Transformers**             |         |      |           |
| BERT-large                   | 46.19   | 52.62| 31.96     |
| RoBERTa-large                | 50.20   | 57.04| 35.05     |
| **Case-based Abductive NLI** |         |      |           |
| CB-ANLI BM25 \((n = 1)\)     | 52.13   | 56.34| 42.78     |
| CB-ANLI BM25 \((n = 2)\)     | 55.17   | 60.42| 43.56     |
| CB-ANLI BM25 \((n = 3)\)     | 52.69   | 58.56| 39.69     |
| CB-ANLI Sentence-BERT \((n = 1)\) | 54.45 | 61.23| 39.43     |
| CB-ANLI Sentence-BERT \((n = 2)\) | 52.77 | 59.60| 37.62     |
| CB-ANLI Sentence-BERT \((n = 3)\) | 51.64 | 58.67| 36.08     |

4 Empirical Evaluation

**Experimental Setup.** We evaluate the Case-based Abductive NLI (CB-ANLI) framework on WorldTree (Jansen et al., 2018) and AI2 Reasoning Challenge (ARC) (Clark et al., 2018), two multiple-choice science question answering datasets designed to test abstractive commonsense and scientific inference. To perform the experiments, we transform each question-candidate answer pair into a hypothesis following the methodology described in (Demszky et al., 2018). Given a set of alternative hypotheses \( H = \{h_1, \ldots, h_n\} \), we adopt the model for abductive inference by generating an explanation for each hypothesis and selecting as an answer the one supported by the best explanation. To this end, we assign a score to each hypothesis \( h_i \) in \( H \) equal to the sum of the scores for the facts included in the explanation for \( h_i \). The knowledge bases required for the inference are populated using the WorldTree corpus (Jansen et al., 2018). The corpus contains a large set of commonsense and scientific facts (\( \approx 10^5 \)) that are used to construct explanations for multiple-choice science questions. The explanations include an average of 6 facts (and as many as \( \approx 20 \)), requiring challenging multi-hop inference to be generated. We store the individual facts in our KB and consider the training questions (\( \approx 1K \)) and their explanations as the set of previously solved cases. For the refine phase, we dynamically extract the concepts in facts and hypotheses using WordNet with NLTK\(^1\). Specifically, given a sentence, we define a concept as a maximal sequence of words that corresponds to a valid synset in WordNet. This allows us to consider multi-words expressions such as “living thing” that frequently occur in the scientific domain.

**Sentence Encoders.** We evaluate CB-ANLI using sparse and dense sentence encoders without additional training. The sparse version adopts BM25 vectors (Robertson et al., 2009), while the dense version employs Sentence-BERT (large) (Reimers and Gurevych, 2019; Thakur et al., 2020), which has demonstrated state-of-the-art performance in semantic textual similarity tasks.

4.1 Multiple-choice Science Questions

In this section, we present the results achieved on the WorldTree test-set (1247 questions). We report the accuracy of the case-based framework with different numbers \( n \) of facts in the explanations. We compare the proposed framework against different

\(^1\)https://www.nltk.org/_modules/nltk/corpus/reader/wordnet.html
Table 2: Results for RoBERTa large fine-tuned on the WorldTree test-set and augmented with different evidence retrieval models.

| Model                  | Over. | Easy  | Chal. |
|------------------------|-------|-------|-------|
| BM25 \((n = 1)\)      | 57.06 | 60.88 | 48.57 |
| BM25 \((n = 2)\)      | 61.07 | 66.82 | 48.32 |
| BM25 \((n = 3)\)      | 61.23 | 65.54 | 51.12 |
| S-BERT \((n = 1)\)    | 55.85 | 61.46 | 43.41 |
| S-BERT \((n = 2)\)    | 60.91 | 66.82 | 47.80 |
| S-BERT \((n = 3)\)    | 56.96 | 62.04 | 45.73 |
| CB-ANLI BM25 \((n = 1)\) | 61.71 | 66.92 | 50.38 |
| CB-ANLI BM25 \((n = 2)\) | 63.48 | 69.38 | 50.38 |
| CB-ANLI BM25 \((n = 3)\) | 62.43 | 67.77 | 50.63 |
| CB-ANLI S-BERT \((n = 1)\) | 59.99 | 65.54 | 47.45 |
| CB-ANLI S-BERT \((n = 2)\) | 63.32 | 67.98 | 52.97 |
| CB-ANLI S-BERT \((n = 3)\) | 62.27 | 67.63 | 50.38 |

Table 3: Performance on the AI2 Reasoning Challenge (ARC). We compare CB-ANLI with published explainable approaches that are fine-tuned only on ARC.

| Model                  | Accuracy |
|------------------------|----------|
| CB-ANLI BM25 \((n = 1)\) | 33.45    |
| CB-ANLI BM25 \((n = 2)\) | 34.39    |
| CB-ANLI BM25 \((n = 3)\) | 33.79    |
| CB-ANLI Sentence-BERT \((n = 1)\) | 36.77    |
| CB-ANLI Sentence-BERT \((n = 2)\) | 35.75    |
| CB-ANLI Sentence-BERT \((n = 3)\) | 34.30    |
| CB-ANLI S-BERT \((n = 1)\) + RoBERTa | 44.02    |
| CB-ANLI S-BERT \((n = 2)\) + RoBERTa | 47.86    |
| CB-ANLI S-BERT \((n = 3)\) + RoBERTa | 42.40    |

4.2 Evidence Retrieval

We evaluate CB-ANLI as an evidence retrieval model by combining it with downstream Transformers. To perform this experiment, we augment the input of RoBERTa large with the explanations constructed for each hypothesis, and fine-tune the model to maximise the score for the correct one. Table 2 reports the accuracy achieved with RoBERTa large when adopting CB-ANLI and stand-alone models as evidence retrievers. We observe that RoBERTa augmented with CB-ANLI achieves better overall results for each value of \(n\), suggesting that the proposed framework is able to generate more discriminating evidence for downstream reader models.

4.3 ARC Challenge

To evaluate the generalisation of CB-ANLI on a broader set of challenge questions, we run additional experiments on the AI2 Reasoning Challenge (ARC) (Clark et al., 2018). Here, we keep the same configuration and set of hyperparameters. Table 3 reports the results achieved on the test-set (1172 challenge questions). We observe that CB-ANLI with Sentence-BERT can generalise better on ARC. We attribute these results to the ability
of Sentence-BERT to go beyond lexical overlaps for case retrieval, supporting generalisation on new hypotheses with different surface forms. To show the impact of evidence retrieval on ARC, we fine-tune RoBERTa with the explanations constructed by the Sentence-BERT version. We compare CB-ANLI against published explainable approaches that are fine-tuned only on ARC, without additional pre-training on related datasets (e.g. OpenBookQA (Mihaylov et al., 2018), RACE (Lai et al., 2017)). The results show that CB-ANLI (Sentence-BERT) is third in the ranking, outperforming existing explainable systems based on Integer Linear Programming (ILP) (Khot et al., 2017; Khashabi et al., 2016) and pre-trained embeddings (Yadav et al., 2019a). At the same time, CB-ANLI obtains competitive results when compared with most of the fine-tuned neural approaches, including ET-RR (Ni et al., 2019). Moreover, when combined with RoBERTa, CB-ANLI achieves the best results among the considered approaches, improving on AutoROCC (Yadav et al., 2019b) by $\approx 6\%$.

4.4 Ablation Study

We carried out an ablation study to investigate the impact of the case-base reasoning framework on downstream inference performance. To this end, we consider different versions of CB-ANLI by alternatively removing the impact of the reuse and revise phase. For the first, we remove the explanatory power term in equation 3. For the latter, we simply skip the revise phase ignoring the semantic plausibility to filter the central facts. The results of the study, reported in Table 4, clearly show the impact of each phase on the final inference performance.

4.5 Explainability

In this section, we investigate the impact of the retrieve-reuse-revise paradigm on explainability, and how this affects the results on downstream reasoning tasks. To this end, we measure the performance of CB-ANLI when considering a different number $K$ of previously solved hypotheses during the retrieve and reuse phases. To evaluate explainability, we use the annotated explanations in the WorldTree corpus as gold standards, computing the accuracy of the explanations constructed by CB-ANLI (i.e., the percentage of selected central facts that are part of the gold explanations). Since the gold explanations in the test-set are masked, we perform this analysis on the dev-set. Figure 3 (a) illustrates the change in answer and explanation accuracy on WorldTree with an increasing number $K$ of similar cases. The graph demonstrates that the improvement in answer prediction is associated with better explanation generation (with a peak at $K = 20$). Specifically, by conditioning the inference on an increasing number of similar hypotheses, CB-ANLI is able to construct more accurate explanations.
What force is needed to help stop a child from slipping on ice? (A) gravity, (B) friction, (C) electric, (D) magnetic

What causes a change in the speed of a moving object? (A) force, (B) temperature, (C) change in mass, (D) change in location

Weather patterns sometimes result in drought. Which activity would be most negatively affected during a drought year? (A) boating, (B) farming, (C) hiking, (D) hunting

Beryl finds a rock and wants to know what kind it is. Which piece of information about the rock will best help her to identify it? (A) The size of the rock, (B) The weight of the rock, (C) The temperature where the rock was found, (D) The minerals the rock contains

Jeannie put her soccer ball on the ground on the side of a hill. What force acted on the soccer ball to make it roll down the hill? (A) gravity, (B) electricity, (C) friction, (D) magnetism

Table 5: Examples of explanations constructed for the predicted answers. The underlined choices represent the correct answers. Accurate indicates whether the central fact (bold) is labelled as a gold explanation in the corpus.

Figure 4: Impact of the case-based reasoning framework on the robustness of CB-ANLI (WorldTree test-set).
the task of discriminating between alternative hypotheses. The graph shows that higher values of $K$ have a positive impact on robustness. While the performance of CB-ANLI with $K = 0$ degrades immediately, we observe that increasing values of $K$ help maintain the performance stable until $\approx 80\%$ of overlaps. The positive impact of the case-based mechanism is confirmed when considering hypotheses with higher number of distinct concepts (Figure 4 (b)). The longer the hypotheses, in fact, the higher the probability of distracting concepts causing semantic drift.

5 Conclusion

This paper presented CB-ANLI, a model that integrates multi-hop and case-based reasoning in a unified framework. We empirically demonstrated the efficacy of the case-based framework for abductive natural language inference in commonsense and scientific reasoning tasks. As future work, we plan to investigate the efficacy of the framework on neural architectures, combining the retrieve-reuse-revise phases in an end-to-end differentiable fashion.

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