## **Explaining Answers with Entailment Trees**

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#### **Abstract**

Our goal, in the context of open-domain textual question-answering (QA), is to explain answers by not just listing supporting textual evidence ("rationales"), but also showing how such evidence leads to the answer in a systematic way. If this could be done, new opportunities for understanding and debugging the system's reasoning would become possible. Our approach is to generate explanations in the form of entailment trees, namely a tree of entailment steps from facts that are known, through intermediate conclusions, to the final answer. To train a model with this skill, we created ENTAILMENTBANK, the first dataset to contain multistep entailment trees. At each node in the tree (typically) two or more facts compose together to produce a new conclusion. Given a hypothesis (question + answer), we define three increasingly difficult explanation tasks: generate a valid entailment tree given (a) all relevant sentences (the leaves of the gold entailment tree), (b) all relevant and some irrelevant sentences, or (c) a corpus. We show that a strong language model only partially solves these tasks, and identify several new directions to improve performance. This work is significant as it provides a new type of dataset (multistep entailments) and baselines, offering a new avenue for the community to generate richer, more systematic explanations.<sup>1</sup>

#### 1 Introduction

Explanation remains a formidable challenge in AI. While today's explanation systems are good at listing supporting evidence ("rationales") for an answer (DeYoung et al., 2019), they rarely explain the *chain of reasoning* from the evidence to the answer, i.e., *how* the answer follows, given the evidence – the goal of this work. Without this, it is hard to fully understand a system's response and/or pinpoint the source of errors if its conclusions are

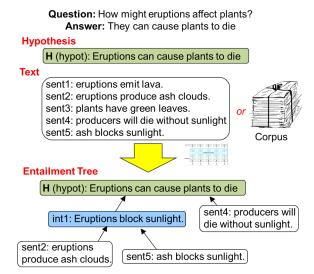


Figure 1: Given a hypothesis (green, summarizing a question+answer pair), and some partially relevant text (or a corpus), our goal is to generate an *entailment tree*, including intermediate nodes (blue), showing how the hypothesis follows from the text/corpus.

wrong. Conversely, if a system could support its answers with a chain of reasoning, new opportunities arise for interactively teaching the machine by debugging its mistakes.

Our approach is to generate explanations in the form of multistep entailment trees, such as shown in Figure 1, made up of individual textual entailment (TE) steps (Dagan et al., 2013). Unfortunately, although there are several single-step entailment datasets available (Bentivogli et al., 2011; Bowman et al., 2015) no dataset of multistep entailments exists, and so a significant contribution of this paper is the construction of such a dataset, called EntailmentBank. EntailmentBank contains 1,513 multistep entailment trees for accompanying QA pairs, constructed using expert annotators, and is the first dataset of its kind. We then define three increasingly difficult explanation tasks over this dataset, namely: generate a valid entailment tree for a given QA pair given (a) all rel-

<sup>&</sup>lt;sup>1</sup>ENTAILMENTBANK is available at https://allenai.org/data/entailmentbank

evant sentences (the leaves of the gold entailment tree), (b) all relevant and some distractor sentences, or (c) a full corpus.

Our focus here is on generating the **derivation** (line of reasoning) showing how the evidence leads to the answer, rather than the **pragmatics** of deciding which parts of that to then show the user. This allows us to separate two (typically confounded) explanation requirements, namely *correctness* (of the derivation) from *utility* (of the pragmatics), allowing us to evaluate derivations with a more objective measure (correctness). Our derivations also set the stage for future research on the pragmatics of what to show the user (Miller, 2019).

We also define and train a generative model for this task, adapting techniques used previously for generating deductive proofs (Tafjord et al., 2020). We find the model only partially solves the dataset, posing a challenge to the community. Our contributions are thus:

- A formulation of explanation as multistep textual entailment.
- ENTAILMENTBANK, the first dataset of multistep entailment trees for QA, to support entailment-based explanation. Each tree contains an average of 6.6 nodes and 2.7 entailment steps, with the full dataset of 1,513 trees including a range of small and large multi-step entailment problems.
- Baseline results using a state-of-the-art, generative model, showing that reasonable trees
  (42% with zero errors) can be generated in a
  restricted setting (all leaf sentences provided),
  but that the full task (tree from a corpus) remains hard. We include a detailed analysis
  identifying several avenues for future improvement.

This work is significant as it provides a new avenue, with a dataset and baseline models, for the community to generate richer, more systematic explanations.

#### 2 Related Work

In the context of QA, there are multiple notions of explanation/justification, including showing an authoritative, answer-bearing sentence (Perez et al., 2019), an attention map over a passage (Seo et al., 2016), a synthesized phrase connecting question and answer (Rajani et al., 2019), or the syntactic pattern used to locate the answer (Ye et al., 2020;

Hancock et al., 2018). These methods are primarily designed for answers to "lookup" questions, to explain where and how an answer was found in a corpus.

For questions requiring inference, the focus of this paper, an explanation is sometimes taken as the chain of steps (typically sentences) leading to an answer. Because of the difficulty of generating detailed decomposition steps, existing datasets typically include one or more simplifications that ultimately limit their utility (see Table 1 for a comparison). For example, HotpotQA's support task goes partway towards this goal by asking for answer-supporting sentences (Yang et al., 2018) or triples (in the derivative R4C dataset (Inoue et al., 2020)), but neither dataset describes how these sentences combine to arrive at the answer. Similarly, WorldTree V2 (Xie et al., 2020) contains supporting sentences but no information about how they combine. More recently, StrategyQA goes further by including derivations for its answers, but using deductive steps and at a coarse granularity (Geva et al., 2021). Similarly, eQASC (Jhamtani and Clark, 2020) includes reasoning annotations but limited to a single entailment step. In this work we generalize to tasks requiring multi-step entailment trees. Table 1 illustrating these comparisons in more detail.

Our dataset also differs from human-authored explanation datasets, e.g., e-SNLI (Camburu et al., 2018), and CoS-E (Rajani et al., 2019). These datasets were primarily designed for (explanation) language generation (without an associated explanation semantics), while our goal is to assemble explanations from an authoritative corpus so that they have credible provenance.

Recent work in deductive reasoning has shown that transformers can generate formal proofs with high reliability, both in a formal setting (Polu and Sutskever, 2020; Wang and Deng, 2020) and with rules expressed in natural language (Saha et al., 2020). Inspired by this, we apply similar ideas to generating entailment trees, in particular leveraging the generative techniques used in the ProofWriter system (Tafjord et al., 2020) (Section 5).

Finally, our task extends textual entailment (TE) in two ways. First, as well as asking if text T entails hypothesis H, we wish to know which part(s) of T entail H. Second, ours is the first dataset containing multistep entailment trees, in contrast to earlier TE datasets where typically a single sentence

Property $\downarrow$ , Dataset $\rightarrow$	WorldTree V2	eQASC	R4C	StrategyQA	ENTAILMENTBANK
Semantics of Inference	(informal)	1-Step Entailment	(informal)	Deduction	Entailment Tree
Average Facts per Inference	6	2	2	3	7
Average Edges per Inference	9 <sup>‡</sup>	1	2 <sup>‡</sup>	2	6
Granularity of Inference	Fine	Coarse	Coarse	Coarse	Fine
Explicit Ordering of Inference	No	No	No	Yes	Yes
Authoring Method	Expert	Crowd	Crowd	Crowd	Expert

Table 1: A comparison of ENTAILMENTBANK with other similar datasets. In general, ENTAILMENTBANK contains larger inference problems, at a finer level of granularity than existing datasets, while being the only dataset to include multi-step entailments that make the reasoning steps explicit. <sup>‡</sup> WT2 and R4C explanations are implied (unannotated) graphs based on overlapping words or entities – values here are inferred by constructing graphs based on lexical overlap.

entails *H* through (typically) paraphrasing (Bentivogli et al., 2011; Bar-Haim et al., 2014; Bowman et al., 2015).

#### 3 The EntailmentBank Dataset

#### 3.1 Overview

ENTAILMENTBANK contains two parts: 1,513 entailment trees, each tree showing *how* a question-answer pair (QA) is entailed from a small number of relevant sentences (e.g., Figure 1); and a general corpus C, containing those and other sentences of domain-specific and general knowledge relevant to the QA domain. We use these two parts shortly to define a simpler task (generate the tree given the leaf sentences, without/with distractors) and a harder task (generate the tree from the corpus). While ENTAILMENTBANK is geared towards the science domain, the construction techniques could also be applied to construct entailment trees in other domains.

ENTAILMENTBANK uses multiple-choice questions (and the correct answer option) from the ARC dataset of grade-school science questions (Clark et al., 2018), and a corpus of science- and general knowledge derived from WorldTree V2 (Xie et al., 2020; Jansen et al., 2018). WorldTree includes a knowledge-base of science-relevant knowledge, expressed as a collection of tables, but is easily converted to a corpus of sentences for ENTAILMENTBANK as each table row is (by design) readable as a fluent English sentence. WorldTree was created with ARC questions in mind, making it an ideal source for ENTAILMENTBANK's corpus.

#### 3.2 Guidelines

Expert graduate and undergraduate annotators were trained to construct entailment trees for QA pairs, given a small number of potentially relevant sentences for each QA pair (drawn from the WorldTree corpus). Specifically, they were trained to author

trees:

- where each step is an **entailment** (a conclusion that "a person would typically infer" (Dagan et al., 2013)), i.e., the knowledge expressed in each node reasonably follows from the content of its immediate children.
- at a **fine-grained granularity**, where each step encodes a single inference, e.g., making a single taxonomic inference, conjoining two facts, or applying a single rule in the corpus.
- that are explicit, with the informal goal of including all the knowledge that a young child would need to answer the question.
- that are compositional, where more complex conclusions can be drawn from simpler leaf facts.
- that are **accurate**, concluding (a declarative version of) the QA pair of interest.

## 3.2.1 Tool and Authoring Procedure

Constructing detailed entailment trees meeting the above desiderata is challenging, even for expert annotators, and in pilot experiments we found that authoring trees directly, from scratch, was extremely difficult. To make authoring easier, we designed a web-based graphical drag-and-drop authoring tool (see Figure 2) that allows explanation authors to construct, iterate, and review explanations quickly.<sup>2</sup>

For each question, the tool presents the user with a pool of top-ranked relevant facts from the corpus that might be relevant to building an explanation. To assist the tree construction process, the user first populates an "explanatory worksheet", identifying facts from the pool in a small number of specific categories (e.g., "core facts", "grounding facts") that they anticipate will be included in the

<sup>&</sup>lt;sup>2</sup>The ENTAILMENTBANK authoring tool was implemented as a Javascript browser client and npm back-end, and is released as open source at https://github.com/cognitiveailab/entailmentbanktools/.

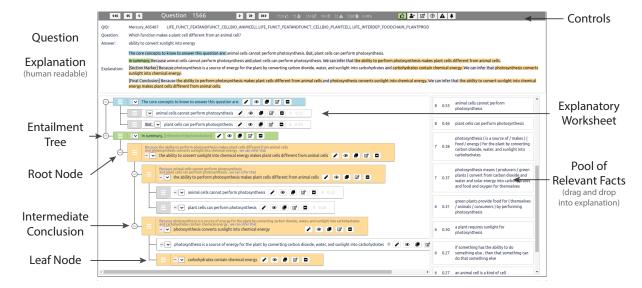


Figure 2: The web-based authoring tool developed to enable authoring entailment trees. (top) The question and a human-readable version of the semi-structured explanation are provided to the user. (bottom) The semi-structured explanation, including the entailment tree, as currently authored by the user. Nodes (facts) can be dragged-and-dropped to change their ordering. White nodes represent facts from the corpus, while orange nodes were authored by the user. (right) A shortlist (or pool) of top-ranked relevant facts from the corpus that the user can choose to drag-and-drop into the explanation.

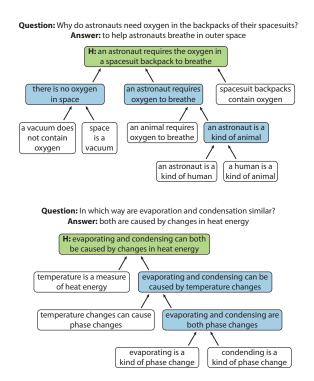


Figure 3: Two example medium-complexity entailment trees, paired with their questions. The root nodes of each tree (hypotheses) are denoted by **H** (green), and intermediate conclusions are blue. (top) An entailment tree with 4 entailment steps and 10 nodes describing the reasoning required to determine why an astronaut requires oxygen in spacesuit backpacks. (bottom) An entailment tree with 3 entailment steps and 7 nodes describing the reasoning required to answer a question about the similarity of two concepts (evaporation and condensation).

tree. From this worksheet, the user then begins constructing the entailment tree – typically starting at the bottom-most leaf nodes, authoring intermediate

conclusions from them, then progressively working on higher levels of the tree until they author a conclusion that directly answers the question, and all branches of the tree meet detail and decomposition requirements. If the user requires a fact not present in the pool of provided facts, e.g., a missing science fact or a question-specific statement, the user can quickly compose their own facts and add these to the tree. Once completed, the individual entailment steps are then separately reviewed by a different author for quality and suggested edits. In total, this process takes an average of approximately 20 minutes per question. Two example trees authored using this process are shown in Figure 3.

## 3.2.2 Identifying Relevant Facts

To identify the pool of relevant facts to show the annotator for each question, we could simply perform information retrieval over the corpus, using the QA pair as the query. However, for this dataset, we are able to do better than this: First, we train two "relevant sentence" classifiers (using BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) respectively) using additional WorldTree annotations.<sup>3</sup> Then, for each question, both models exhaustively

<sup>&</sup>lt;sup>3</sup>WorldTree includes annotations about which WorldTree table rows are relevant to which questions, i.e., which rows are supporting evidence ("rationales") for which question. Although these rationales do not identify *all* relevant sentences, they can be used as distant supervision (along with random negative facts drawn from the corpus) to train a "relevant sentence" classifier.

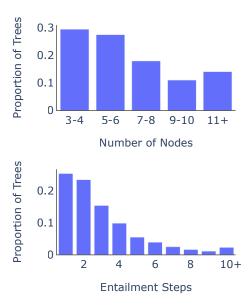


Figure 4: Histograms of entailment tree complexity, measured on the training set. (*top*) Proportion of trees with a given number of nodes (facts). (*bottom*) Proportion of trees with a given number of entailment steps. The average entailment tree contains 6.6 nodes (facts) across 2.7 entailment steps.

	Train	Dev	Test	All
Questions Entailment reasoning steps	1079	163	271	1513
	2857	408	703	3968

Table 2: Summary statistics for the dataset splits.

score each fact in the corpus, and the top 20 facts from each are retrieved, reranked using Tensorflow-Ranking-BERT (Han et al., 2020), and presented as a ranked list to the entailment tree annotator based on their final scores.

#### 3.3 Overall Dataset

Due to the large time investment required to generate detailed entailment trees, we author trees for 1,513 randomly selected questions, which include a total of 3,968 discrete entailment steps. Overall, approximately 600 (paid) work hours were used to build the dataset.

Summary statistics for the train, development, and test sets are shown in Table 2. On average, each entailment tree includes 6.6 nodes across 2.7 entailment steps, where each entailment step typically involves 3 facts (two leaves, that combine to entail a conclusion). Figure 4 shows histograms of entailment tree size (measured in terms of the number of nodes, and number of entailment steps). Entailment Bank includes a diverse range of problem sizes, with approximately half (49%) of entailment trees representing short entailment prob-

lems with one or two entailment steps (typically composed of 3-5 nodes), while the remaining 51% of trees contain 3-16 entailment steps (up to 27 nodes).

## 3.4 Dataset Analysis

To understand the entailment challenges in EN-TAILMENTBANK, we analyzed 100 randomly sampled entailment steps from trees in the training set. We identified 6 common high-level categories of inference, shown in Table 3. Substitution types refer to entailments that require a model to perform taxonomic, merynomic, or other forms of chaining that substitute one entity for another in one of the input sentences. Inference from Rules entailments require the application of a specific rule, specified as one of the input sentences, to the other input sentence. Our analysis suggests that approximately one-third (33%) of all entailments require the application of domain-specific rules to complete. Further Specification or Conjunction entailments require a model to combine the details of both input facts into a single output fact. Less frequent types require inferring an object's class from it's properties, inheriting properties of objects, or determining orders for sequential reasoning. As a whole, this analysis shows diverse forms of reasoning are required to successfully complete the entailment steps in ENTAILMENTBANK.

## 4 Task Definitions

Because producing correct entailment trees from a corpus is challenging, we define three tasks of increasing difficulty (named no-distractor, distractor, and full-corpus, respectively) that simplify the retrieval and evaluation problems inherent in the task. The inputs to all three are a hypothesis H, namely a declarative form of a question + answer (QA),<sup>4</sup> and some sentences S expressing (both relevant and irrelevant) knowledge about the world. The desired output is a valid entailment tree T where the leaves are sentences selected from S, the intermediate nodes  $int_i$  are intermediate conclusions (new sentences, not part of the input), and the root node (conclusion) is the hypothesis H. T is valid if every node  $n_i$  in the tree is *entailed* by its children. Examples are shown in Figures 1 and 3.

As an approximation to make automated evaluation feasible, we ensure that S includes all the

 $<sup>^4</sup>$ For convenience we provide both H and QA as inputs, although in principle H may be generated from QA automatically, e.g., using the QA2D model (Demszky et al., 2018)

Inference Type	Prop.	Example Entailment
Substitution	42% s s in	
Inference from Rule	33% s s in	
Further Specification or Conjunction	15% s s in	
Infer Class from Properties	s	
Property Inheritance	4% s s in	
Sequential Inference	3% s s s in	transcription is when genetic information flows from DNA to RNA translation is when genetic information flows from RNA to proteins

Table 3: The prevalence of 6 common reasoning methods required to solve individual entailment tree steps, sampled from 100 random entailment steps in the training corpus. Discrete entailment steps in ENTAILMENTBANK require diverse forms of reasoning to solve, from forms of taxonomic or merynomic chaining (substitution) to application of domain-specific rules. Here,  $s_n$  denotes input sentences, while int denotes entailed conclusions (intermediate nodes in the trees).

leaf sentences  $S_{gold}$  that are in the gold entailment tree  $T_{qold}$ , and treat  $T_{qold}$  (+ valid reorderings) as the only valid entailment tree constructable from that input. This allows us to check validity by comparing the generated tree with  $T_{qold}$ . This approximation is reasonable for tasks 1 and 2 below, because their limited input makes it unlikely that an alternative valid tree is constructable from the input. For task 3, though, to avoid alternative valid trees being buildable from the input corpus, we remove the few sentences similar to  $S_{gold}$  from the corpus on a per-question basis. Although these steps are not fool-proof, they do allow entailment tree validity to be reasonably approximated by comparison with  $T_{qold}$ , a critical methodological requirement for automatic evaluation.

The three tasks, in increasing order of difficulty, are as follows:

**Task 1 (no-distractor):** Inputs = H + QA + leaf sentences  $S_{gold}$ 

**Task 2 (distractor):** Inputs = H + QA + leaf sentences  $S_{gold}$  + 20-30 distractor sentences

Task 3 (full-corpus): Inputs = H + QA + a corpus C (that includes  $S_{gold}$  and excludes other sentences similar to  $S_{gold}$ )

Task 3 (full-corpus) represents the full task where C is large, potentially requiring one or more information retrieval (IR) steps to construct a valid

tree. In principle, C is simply the WorldTree corpus of general facts. However, in practice there are two question-specific deviations from this ideal. First, annotators sometimes included non-WorldTree facts in the gold entailment tree, either to express question-specific scenario facts (e.g., "A ball rolls down a hill.") or additional world knowledge missing in WorldTree. To accommodate this, these extra facts are added to C on a per-question basis. Second, as noted earlier, we remove corpus sentences similar to  $S_{gold}$  to discourage alternative valid trees being found, so comparison with  $T_{gold}$  is a reasonable evaluation.

The desired output in all cases is a valid entailment tree T, approximated as being the gold entailment tree  $T_{qold}$  (+ valid reorderings).

#### 5 Model

Inspired by the "All-at-once" sequence-to-sequence model in the ProofWriter system (Tafjord et al., 2020), we train a T5-based generative model for our task, called EntailmentWriter.

#### 5.1 Entailment Tree Encoding

We encode entailment trees as a linear structure that can be output by a generative model. To do this, the input sentences S are labeled with identifiers (sent1, sent2, ...), and the hypothesis H is labeled

with the special identifier 'hypot' (Figure 1). All nodes in the output tree are then identifiers: sent\* for leaf nodes, int\* for internal nodes, and 'hypot' for the conclusion (root node). As the int\* nodes denote new sentences (not in the input), we include those sentences in the output immediately after their int\* identifier is first introduced.

When linearizing the tree, we start from leaf facts and work towards proving the root of the tree (hypot). We use the symbol "&" to denote "and", and "->" to denote "entails". Thus the depth 2 entailment tree in Figure 1 would be encoded as:

```
sent2 & sent5 -> int1: Eruptions block
sunlight ; sent4 & int1 -> hypot
```

Note here that the new sentence "Eruptions block sunlight" that intermediate node int1 denotes is explicitly part of the to-be-generated output. The task for the models is to output valid entailment trees encoded in this way, given the input.

#### 5.2 Model Details

The EntailmentWriter model is built on top of the text-to-text pretrained T5 transformer (Raffel et al., 2020), where the inputs are as described in Section 4 for Task 1 (no-distractor) and Task 2 (distractor). For Task 3 (full-corpus), the corpus exceeds T5's token limit, so we add a retrieval step of 30 sentences from the corpus C using the hypothesis H as query. The retrieved sentences are then labeled with identifiers and input to the model. This may mean that only a subset of the required sentences  $S_{qold}$  is recalled and provided to the model, hence the generated entailment tree will necessarily be incomplete in such situations, given this strategy. (Note that other strategies - for future work - could avoid this problem, e.g., using multiple retrieval steps).

The output of the model is the full predicted entailment tree encoded as described earlier (Section 5.1).

We fine-tune the models on the training set using the default hyperparameters (including the Adafactor optimizer) in the T5 library.<sup>5</sup> We use the largest T5-11B model, fine-tuned for 20k steps (batch size 8), selecting the checkpoint with highest validation score.

## 6 Experiments

#### 6.1 Evaluation Metrics

We score the generated entailment trees along four dimensions: Do they use the right input sentences (for leaf nodes of the tree)? Is the tree structurally correct? Are the generated conclusions valid? Is the overall entailment tree correct?

We approach evaluating entailment trees as a two step problem. First, nodes in the predicted tree  $T_{pred}$  are aligned with nodes in gold tree  $T_{gold}$ . Then, we compare both the structure (edges) of the gold and predicted trees, as well as the content of the gold and predicted nodes. To perform the alignment, accounting for partial overlap and different valid ways of writing the same entailment tree, we proceed as follows:

- First, for each intermediate conclusion int<sub>pred</sub> in T<sub>pred</sub>, and int<sub>gold</sub> in T<sub>gold</sub>, we gather their ancestor leaf sentences.
- Then, we align each intermediate node  $int_{pred}$  to the first  $int_{gold}$  for which the Jaccard similarity of their respective ancestor sentences is maximum. For any  $int_{pred}$  with zero Jaccard similarity to all gold nodes  $int_{gold}$ , it is aligned to a dummy gold node with a blank conclusion.

Once aligned, the aligned tree  $T_{pred}^{'}$  is scored against gold tree  $T_{gold}$  using the metrics below. The F1/BLEURT metrics score elements of the tree (micro-averaging the results), while "AllCorrect" checks if *all* the elements are correct (1=yes, 0=no), i.e., the predicted tree is perfect along the dimension being considered. Our metrics are:

**Leaf Nodes (F1, AllCorrect):** Does the predicted tree use the correct leaf sentences? We compute an F1 score by comparing leaf sentences  $S_{pred}$  to  $S_{gold}$ . The "AllCorrect" score is 1 if the entire set of nodes is identified correctly (F1=1.0), 0 otherwise.

**Steps (F1, AllCorrect):** Does the tree have the correct entailment step structure? Here we compute F1 and "AllCorrect" scores in a way similar to leaf nodes by comparing the set of entailment steps in the aligned proof  $T_{pred}'$  with  $T_{qold}$ .

Intermediates (BLEURT, AllCorrect): Are the synthesized intermediate nodes  $Int_{pred}^{'}$  All-Correct. For this metric, we use the state-of-the-art BLEURT metric for evaluating generations, using the off-the-shelf BLEURT-

<sup>&</sup>lt;sup>5</sup>https://github.com/google-research/text-to-text-transfertransformer

		Leaves AllCorrect		Entailment T Steps AllCorrect	Intern	nediates AllCorrect	Overall AllCorrect
Task 1 (no-distractor)	99.3	93.4	60.0	48.7	0.74	58.7	42.4
Task 2 (distractor)	87.9	47.6	47.0	33.2	0.68	56.1	29.5
Task 3 (full-corpus)							
(Lower bound)	34.9	2.2	0.3	0.0	0.00	21.0	0.0
(Upper bound, Task 2)	87.9	47.6	47.0	33.2	0.68	56.1	29.5

Table 4: Baseline scores of the generated entailment trees from EntailmentWriter, along four different dimensions (test set). F1/BLEURT scores measure predicted/gold overlap, while AllCorrect scores 1 when *all* the predictions are correct for a tree, 0 otherwise.

Large-512 model.<sup>6</sup> (Sellam et al., 2020). Our analysis based on 300 hand-labelled examples from the development set suggests that it correlates well with human ratings (correlation = 0.67, sensitivity = 0.88, specificity = 0.80). Further, we define generation correctness as 1 if an aligned pair of  $int'_{pred}$ ,  $int_{gold}$  gives BLEURT > 0.28, 0 otherwise. Note that a correct intermediate doesn't necessarily imply a correct entailment, as the ancestor nodes may be wrong.

Finally, "Intermediates AllCorrect" per question is 1 if *all* the generated intermediates in the tree are correct, 0 otherwise.

Overall Proof (AllCorrect): We define the overall "AllCorrect" score for a generated proof as 1 only if all of the leaves, steps, and intermediates are all correct, i.e., the tree completely matches  $T_{gold}$ . Otherwise it scores 0. This is a strict metric: any error in the generated tree will result in a score of 0.

#### **6.2** Main Results

Table 4 shows performance of the EntailmentWriter model on each of the three subtasks. In the easiest setting, Task 1 (no-distractor), where only the gold leaves are provided as input, the model correctly structures these into gold entailment steps in 49% of cases, and generates 58% of intermediate conclusions correctly. In total, EntailmentWriter is able to generate gold entailment trees for only 42% of questions in this easiest setting, highlighting the difficulty of this task.

Task 2 (distractor) increases the difficulty of

identifying relevant leaves by adding distractors to the input gold leaf sentences until a total of 30 sentences are supplied as input to the model<sup>8</sup>. In this setting, the model is able to correctly identify gold leaf nodes only about half the time (47%), which significantly reduces overall task performance from 42% (no-distractor) to 30% (distractor). In spite of this reduction in overall task performance due to the loss of correct leaf nodes, correctness at generating intermediate conclusions for each entailment step remains nearly the same as in the no-distractor setting at 56%, suggesting that when EntailmentWriter has meaningful input facts, it is able to make use of them equally well.

In Task 3 (full-corpus), the input is the entire WorldTree corpus, augmented with additional question-specific and general facts used in gold entailment trees but not part of WorldTree. Given this input is too large for a transformer, a retrieval step is needed. Here, we provide upper- and lower-bound results corresponding to perfect and weak retrieval results respectively.

**Upper bound:** As the Task 2 input contains exactly the required sentences  $S_{gold}$  (+ distractors), it is equivalent to the perfect retrieval scenario. Hence Task 2 results can be used as an upper bound for Task 3.

Lower bound: We run our Task 2 model using sentences retrieved from WorldTree alone (using Tensorflow-Ranking-BERT retrieval, Section 3.2.2). As this retrieval does not see any required non-WorldTree facts, the model is necessarily disadvantaged, hence we use this score as a lower bound on Task 3.

As Table 4 shows, the lower bound result is poor, even struggling to select the right leaf nodes (F1 = 34%), and not generating any perfectly correct trees. Although this model is disadvantaged, it

<sup>&</sup>lt;sup>6</sup>We fine-tuned and evaluated the BLEURT metric further using 300 hand-labeled examples, however it performs similarly to the vanilla model.

<sup>&</sup>lt;sup>7</sup>The BLEURT threshold was picked using a subset of 300 manually labeled pairs. When we test this threshold on the rest of the labeled pairs we get a high (89%) F1 score, indicating the threshold is reasonable.

<sup>&</sup>lt;sup>8</sup>On average, each input in the distractor setting has 25 distractor sentences

suggests that performing well on the full task is difficult.

## 6.3 Error Analysis

To better understand the challenges in generating multistep entailment trees, we performed error analyses both at the level of individual entailment steps, as well as failures associated with generating full trees.

## **6.3.1 Individual Entailment Steps**

We first analyze cases where the model is failing at individual entailment reasoning steps. For this we sampled 100 entailment steps from the development set where the predicted tree had overall AllCorrect = 0 based on the automated evaluation metrics, i.e., the automated metrics detected at least one error somewhere in the tree. Manually evaluating the sampled entailments, we obtain the statistics shown in Table 5. The analysis suggests that even though these trees are invalid overall, 30% of their individual entailment steps *are* valid.

AllCorrect	% Entailment steps
Incorrect	57%
Nearly correct	13%
Correct	30%

Table 5: Human evaluation of individual entailment steps in (development set) trees automatically scored as (overall) not correct, i.e., contain *some* error. Although the overall trees are invalid, 30% of their contained entailment steps are correct.

In cases where an entailment step was invalid, we identify three common kinds of failure:

- The entailed conclusion simply repeats one of the input sentences (41%): This can be attributed to the fact that the model has seen a lot of instances in the training data where the intermediate conclusions have high word overlap with input sentences. In the future, we would like to explore a training regime where the loss function encourages the model to add something novel compared with the input sentences.
- The entailed conclusion does not follow from input sentences (47%): In these cases, the model is using knowledge unstated in the input for this particular entailment step but present somewhere else in the input context.

In future, we would like to address this by exploring an iterative generation approach that focuses on one entailment step at a time and that can distinguish good vs bad entailment.

• The entailed conclusion is correct, but either different from gold or irrelevant to prove the hypothesis (12%).

# **6.3.2** Failure Analysis of Generated Entailment Trees

We analyzed 50 generated entailment trees in the development set where the automated metrics gave an "AllCorrect" score of 0, signifying there is (at least) one error *somewhere* in the tree. We observe the following classes of errors:<sup>9</sup>

- Incorrect leaves results in invalid/missing entailment steps (56%): For example, for the question "Why do mosquitoes instinctively move towards carbon dioxide...? A: It helps mosquitoes find food", the predicted tree misses using the critical input fact that "mosquitoes eat animal blood", hence cannot infer "animals are a source of food for mosquitoes", hence cannot infer the importance of moving towards carbon dioxide.
- Correct leaves, but invalid steps (18%): For example, for a question asking "Can a person see someone in a dark room? A: No", the model selects the correct leaf sentences but stitches them together in the wrong order. As a result, an invalid intermediate conclusion is generated. Specifically, it incorrectly tries to draw an entailment from "a person is in a dark room" and "a person is looking into the dark room", producing "the person outside can see the person in the dark room", an invalid step and one that directly contradicts the target QA pair.
- Correct steps, but incorrect intermediate conclusions (2%): For example, for a question with H: "compression waves cause objects to move in the same direction of the wave", the model gets the proof structure right in terms of placement of relevant leaves. But instead of concluding a gold intermediate conclusion "int1<sub>gold</sub>: longitudinal waves are also called

<sup>&</sup>lt;sup>9</sup>Note that some error classes are not mutually exclusive, so proportions do not add to 100%

Number of steps	Number of questions	F1	Leaves AllCorrect	F1	Steps AllCorrect	Intern BLEURT	nediates AllCorrect	Overall AllCorrect
1	84	95.1	83.3	81.3	79.8	0.95	86.9	79.8
2	83	88.6	43.4	40.0	22.9	0.69	54.2	12.0
3	43	85.8	37.2	27.3	9.3	0.51	44.2	7.0
4	27	83.8	25.9	26.1	0.0	0.51	29.6	0.0
≥5	34	74.2	0.0	20.8	0.0	0.32	20.6	0.0
Any	271	87.9	47.6	47.0	33.2	0.68	56.1	29.5

Table 6: Results on Task 2 (distractor) broken down by the number of entailment steps in the gold tree, indicating that scores drop rapidly as trees get larger (more steps).

compression waves" it prematurely predicts the final conclusion H for the intermediate  $int1_{pred}$  (and then re-predicts it in the final entailment step).

- Disconnected trees (4%): We found 2 examples where the generated entailment tree had intermediate conclusions that were not used later towards proving the hypothesis. E.g. for question with H: "the plants in the gardens will receive the most sunlight in summer to grow during the day", the model accurately compose leaf facts to reach the intermediate conclusion "the plants in the gardens will receive sunlight to grow" but the predicted proof does not then use it in later steps. One way to avoid this would be to apply structural constraints on the output, enforcing a (single) tree structure (Saha et al., 2020).
- Imperfect evaluation (24%): For these cases we found that the generated entailment tree was correct but our metrics could not detect the equivalence in the predicted vs gold tree. Failure cases included 1) alternate valid entailment trees missing in our gold annotations 2) the generated proof is finer-grained or coarsegrained with respect to the gold proof. An improved evaluation metric would help alleviate these scoring discrepancies.

## 6.3.3 Performance wrt. Tree Size

Finally, we grouped the Task 2 results according to the size (number of steps) in the gold tree. The results are shown in Table 6, and demonstrate that the scores drop significantly as the number of steps in the gold proof increases.

## 7 Summary and Conclusion

Our goal is to enable machines to generate richer, more systematic explanations. To this end, we have developed a novel formulation of explanations as *multistep entailment trees*, and created ENTAIL-MENTBANK, the first large-scale dataset of such trees.

We have also presented baseline results for automatically generating entailment tree explanations for answers to science questions, trained on EN-TAILMENTBANK. These initial results suggest that such generation is possible in restricted settings (leaf sentences are provided), but that the full task (explanation from a corpus) remains challenging. As new mechanisms are developed to guide and validate tree construction, we expect the quality of the resulting explanations to improve significantly. If this were possible, new opportunities for understanding and debugging a system's reasoning would arise, allowing users to not just receive answers, but also have meaningful dialogs with the machine about those answers by exploring its line of reasoning. ENTAILMENT-BANK contributes to this direction, offering a new resource for developing richer, more systematic explanations. ENTAILMENTBANK is available at https://allenai.org/data/entailmentbank

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