Are Natural Language Inference Models IMPPRESSive?
Learning Implicature and PRESupposition

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Abstract

Natural language inference (NLI) is an increasingly important task for natural language understanding, which requires one to infer whether one sentence entails another. However, the ability of NLI models to make pragmatic inferences remains understudied. We create an IMPlicature and PRESupposition diagnostic dataset (IMPPRES), consisting of 32K semi-automatically generated sentence pairs illustrating well-studied pragmatic inference types. We use IMPPRES to evaluate whether BERT, BOW, and InferSent NLI models trained on MultiNLI (Williams et al., 2018) learn to make pragmatic inferences. Although MultiNLI contains vanishingly few pairs illustrating these inference types, we find that BERT learns to draw pragmatic inferences: it reliably treats implicatures triggered by “some” as entailments. For some presupposition triggers like only, BERT reliably recognizes the presupposition as an entailment, even when the trigger is embedded under an entailment canceling operator like negation. BOW and InferSent show weaker evidence of pragmatic reasoning. We conclude that NLI training encourages models to learn some, but not all, pragmatic inferences.

1 Introduction

One of the most foundational semantic discoveries is that systematic rules govern the inferential relationships between pairs of natural language sentences (Aristotle, De Interpretatione, Ch. 6). In natural language processing, Natural Language Inference (NLI)—a task whereby a system determines whether a pair of sentences instantiates in an entailment, a contradiction, or a neutral relation—has been useful for training and evaluating models on sentential reasoning. However, linguists and philosophers now recognize that there are separate semantic and pragmatic modes of reasoning (Grice, 1975; Clark, 1996; Beaver, 1997; Horn and Ward, 2004; Potts, 2015), and it is not clear which of these modes, if either, NLI models learn. We investigate two pragmatic inference types that are known to differ from classical entailment: scalar implicatures and presuppositions. As shown in Figure 1, implicatures differ from entailments in that they can be denied, and presuppositions differ from entailments in that they are not canceled when placed in entailment-cancelling environments (e.g., negation, questions).

To enable research into the relationship between NLI and pragmatic reasoning, we introduce IMPPRES, a fine-grained NLI-style diagnostic test dataset for probing how well NLI models perform implicature and presupposition. Containing 32K sentence pairs illustrating key properties of these pragmatic inference types, IMPPRES is automatically generated according to expert-crafted grammars, allowing us to create a large and lexically varied, but nonetheless controlled dataset isolating specific instances of both types.

To test whether NLI models learn to do well...
on IMPRES, we first need to determine if presuppositions and implicatures are present in our training data. We take MultiNLI (Williams et al., 2018) as a case study, and find it has very few instances of pragmatic inference (see §4). Given this, we ask whether training on MultiNLI is sufficient for models to generalize about these largely absent commonsense reasoning types. We find that generalization is possible: the BERT NLI model shows evidence of pragmatic reasoning when tested on the implicature from NLI model shows evidence of pragmatic reasoning when tested on the implicature from some to not all, as well as on several presupposition subdatasets (only, cleft existence, possessive existence, questions). We obtain some negative results, that are likely due to models lacking a sophisticated enough understanding of the meanings of the lexical triggers for implicature and presupposition (e.g., BERT treats several word pairs as synonyms, e.g., most notably, or and and).

Our contributions are: (i) we provide a new diagnostic test set to probe for pragmatic inferences, complete with linguistic controls, (ii) to our knowledge, we present the first work evaluating deep NLI models on specific pragmatic inferences, and (iii) we show that BERT models can perform some types of pragmatic reasoning very well, even when trained on NLI data containing very few explicit examples of pragmatic reasoning.

2 Background: Pragmatic Inference

We take pragmatic inference to be a relation between two sentences relying on the utterance context and the conversational goals of interlocutors. Pragmatic inference contrasts with semantic entailment, which instead captures the logical relationship between isolated sentence meanings (Grice, 1975; Stalnaker, 1977). We present implicature and presupposition inferences below.

2.1 Implicature

Broadly speaking, implicatures contrast with entailments in that they are inferences suggested by the speaker, but not included in the literal meaning of the sentence (Grice, 1975). Although there are many types of implicatures we focus here on scalar implicatures. Scalar implicatures are inferences, often optional,1 which can be drawn when one member of a memorized lexical scale (e.g., (some, all)) is uttered (see §6.1). For example, when someone utters Jo ate some of the cake, they suggest that Jo didn’t eat all of the cake, (see Figure 1 for more examples). According to Neo-Gricean pragmatic theory (Horn, 1989; Levinson, 2000), the inference Jo didn’t eat all of the cake arises because some has a more informative lexical alternative all that could have been uttered instead.

We expect the speaker to make the most informative true statement:2 as a result, the listener should infer that a stronger statement, where some is replaced by all, is false.

Implicatures differ from entailments (and, as we will see, presuppositions; see Figure 1) in that they are deniable, i.e., they can be explicitly negated without resulting in a contradiction. For example, someone can utter Jo ate some of the cake, followed by In fact, Jo ate all of it. In this case, the implicature (i.e., Jo didn’t eat all the cake from above) has been denied. We thus distinguish implicated meaning from literal, or logical, meaning.

2.2 Presupposition

Presuppositions of a sentence are facts that the speaker takes for granted when uttering a sentence (Stalnaker, 1977; Beaver, 1997). Presuppositions are generally associated with the presence of certain expressions, known as presupposition triggers. For example, in Figure 1, the definite description the cake triggers the presupposition that there is a cake (Russell, 1905). Other examples of presupposition triggers are shown in Table 1.

Presuppositions differ from other inference types in that they often project out of operators like questions and negation, meaning that they remain valid inferences even when embedded un-

| Type             | Example                      |
|------------------|------------------------------|
| Trigger          | Jo’s cat yawned.             |
| Presupposition   | Jo has a cat.                |
| Negated Trigger  | Jo’s cat didn’t yawn.        |
| Modal Trigger    | It’s possible that Jo’s cat yawned. |
| Interrog. Trigger| Did Jo’s cat yawn?           |
| Cond. Trigger    | If Jo’s cat yawned, it’s OK.  |
| Negated Prsp.    | Jo doesn’t have a cat.       |
| Neutral Prsp.    | Amy has a cat.               |

Table 1: Sample generated presupposition paradigm. Examples adapted from the ‘change-of-state’ dataset.

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1Implicature computation can depend on the cooperativity of the speakers, or on any aspect of the context of utterance (lexical, syntactic, semantic/pragmatic, discourse). See (Degen, 2015a) for a study of the high variability of implicature computation, and the factors responsible for it.

2This follows from: Grice’s (1975) cooperative principle; the assumption that speakers are opinionated (Gazdar, 1979).
der these operators (Karttunen, 1973). The inference that there is a cake survives even when the presupposition trigger is in a question (Did Jordan eat some of the cake?), as shown in Figure 1. However, in questions, classical entailments and implicatures disappear. Table 1 provides examples of triggers projecting out of several entailment canceling operators: negation, modals, interrogatives, and conditionals.

It is necessary to clarify in what sense presupposition is a pragmatic inference. There is no consensus on whether presuppositions should be considered part of the semantic content of expressions (see Stalnaker, 1977; Heim, 1983, for opposing views). However, presuppositions may come to be inferred via accommodation, a pragmatic process by which a listener infers the truth of some new fact based on its being presupposed by the speaker (Lewis, 1979). For instance, if Jordan tells Harper that the King of Sweden wears glasses, and Harper did not previously know that Sweden has a king, they would learn this fact by accommodation. With respect to NLI, any presupposition in the premise (short of world knowledge) will be new information, and therefore accommodation should be necessary to recognize it as entailed.

3 Related Work

NLI has been framed as a commonsense reasoning task (Dagan et al., 2006; Manning, 2006). One early formulation of NLI defines “entailment” as holding for sentences $p$ and $h$ whenever, “typically, a human reading $p$ would infer that $h$ is most likely true...[given] common human understanding of language [and] common background knowledge” (Dagan et al., 2006). Although this sparked lively debate regarding the terms inference and entailment—and whether a coherent notion of “inference” could (and should) be defined (Zaenen et al., 2005; Manning, 2006; Crouch et al., 2006)—in recent work on NLI common sense formulations of “inference” have been widely adopted (Bowman et al., 2015; Williams et al., 2018) largely for practical reasons, i.e., they enable untrained annotators to easily participate in dataset creation.

NLI itself has been steadily gaining in popularity; many datasets for training and/or testing systems are now available including: FraCaS (Cooper et al., 1994), RTE (Dagan et al., 2006; Mirkin et al., 2009; Dagan et al., 2013), Sentences Involving Compositional Knowledge (Marelli et al., 2014, SICK), large scale imaging captioning as NLI (Bowman et al., 2015, SNLI), recasting other datasets into NLI (Reisinger et al., 2015; White et al., 2017; Poliak et al., 2018), ordinal common sense inference (Zhang et al., 2017, JOCI), Multi-Premise Entailment (Lai et al., 2017, MPE), NLI over multiple genres of written and spoken English (Williams et al., 2018, MultiNLI), adversarially filtered common sense reasoning sentences (Zellers et al., 2018, 2019, (Hella)SWAG), explainable annotations for SNLI (Camburu et al., 2018, e-SNLI), cross-lingual NLI (Conneau et al., 2018, XNLI), scientific questioning answering as NLI (Khot et al., 2018, SciTail), NLI recast-question answering (part of Wang et al. 2019, GLUE), NLI for dialog (Welleck et al., 2019). Other NLI datasets are created specifically to identify where models fail (Glockner et al., 2018; Naik et al., 2018; McCoy et al., 2019; Schmit and Schütze, 2019), many of which are also automatically generated (Geiger et al., 2018; Yanaka et al., 2019a,b; Kim et al., 2019; Nie et al., 2019).

As datasets for NLI become increasingly numerous, one might wonder, do we need yet another NLI dataset? In this case, the answer is clearly yes: despite NLI’s formulation as a common sense reasoning task, no extant NLI dataset has been created to explicitly probe pragmatic inferences in contrast with entailment. IMPRES allows us to ask whether NLI models trained on common sense reasoning perform well on specific types of pragmatic inference, without explicit training.

Beyond NLI, several recent works evaluate sentence understanding models for knowledge of pragmatic inferences. de Marneffe et al. (2019) introduce the CommitmentBank, a dataset of human judgments measuring how strongly presuppositions of clause embedding verbs project, and Jiang and de Marneffe (2019) find that an LSTM with supervision on this dataset can predict human judgments well. Outside the topic of sentential inference, Cianflone et al. (2018) create sentence-level adverbal presupposition datasets and train a binary classifier to detect contexts in which presupposition triggers (e.g., too, again) can be used.
### Table 2: Paradigm for the scalar implicature datasets, with \(\langle\text{some, all}\rangle\) as an example.

| Premise | Hypothesis | Relation type | Logical label | Pragmatic label | Item type |
|---------|------------|---------------|---------------|----------------|-----------|
| some    | not all    | implicature (+ to −) | neutral | entailment | target |
| not all | some       | implicature (− to +)  | neutral | entailment | target |
| some    | all        | negated implicature (+) | neutral | contradiction | target |
| all     | some       | reverse negated implicature (+) | neutral | contradiction | target |
| not all | none       | negated implicature (−)  | neutral | contradiction | target |
| none    | not all    | reverse negated implicature (−) | neutral | contradiction | target |
| all     | none       | opposite | contradiction | contradiction | control |
| none    | all        | opposite | contradiction | contradiction | control |
| some    | none       | negation | contradiction | contradiction | control |
| none    | some       | negation | contradiction | contradiction | control |
| all     | not all    | negation | contradiction | contradiction | control |
| not all | all        | negation | contradiction | contradiction | control |

4 **Annotating MultiNLI for Pragmatics**

Although Williams et al. (2018) reports that 22% of the MultiNLI development set sentence pairs contain lexical triggers (such as *regret* or *stopped*) in the premise and/or hypothesis, the mere presence of presupposition-triggering lexical items in the data is insufficient to answer the question, since the sentential inference may focus on other types of information. To address this, we randomly selecting 200 sentence pairs from the MultiNLI matched development set and presented them to three expert annotators with a combined total of 17-years of training in formal semantics and pragmatics. Annotators answered the following questions for each pair: (1) are the sentences \(P\) and \(H\) related by a presupposition/implicature relation (entails/is entailed by, negated or not); (2) what subtype of inference (e.g., existence presupposition, \(\langle\text{some, all}\rangle\) implicature); (3) is the presupposition trigger embedded under an entailment-cancelling operator?

Very few MultiNLI pairs relied on pragmatic inferences. We find only eight presupposition pairs and three implicature pairs on which at least two annotators agreed. Moreover, of the inference subtypes tested in IMPRES, we only found one possession presupposition. All others were tagged as existence presuppositions and conversational implicatures. We conclude that any positive pragmatic results from models trained on MultiNLI and tested on IMPRES can reasonably be assumed to derive from generalization from basic semantic entailment relations and independent semantic knowledge acquired in the original training data seen by these models.

5 **Methods**

**Data Generation.** IMPRES consists of semi-automatically generated pairs of sentences with NLI labels illustrating key properties of implicatures and presuppositions. Generating data lets us control the lexical and syntactic content so that we can guarantee that the sentence pairs in IMPRES evaluate the desired phenomenon (see Ettinger et al., 2016, for related discussion). We generate IMPRES according to expert-crafted grammars using a codebase developed by Warstadt et al. (2019). The codebase includes a vocabulary of over 3000 lexical items annotated with grammatical features needed to ensure morphological, syntactic, and semantic well-formedness. The same codebase is used for both the implicature and presupposition parts of IMPRES (see §6.1 and 7.1 for detailed descriptions of the implicature and presupposition data). We will release our generation code upon acceptance.

**Models.** We create IMPRES for the purpose of evaluating what NLI models learn from standard datasets like MultiNLI. We intend IMPRES to be used only for evaluation, since supervised classifiers trained on automatically generated data may learn to exploit simple regularities in the data. Accordingly, our experiments evaluate NLI models trained on MultiNLI and built on top of three sentence encoding models: a Bag of Words (BOW) model, InferSent (Conneau et al., 2017), and BERT-Large (Devlin et al., 2018). The BOW and InferSent models use 300D GloVe embeddings as word representations (Pennington et al., 2014). For the BOW baseline, word embeddings for premise and hypothesis are separately summed to create sentence representations, which are con-
concatenated to form a single sentence-pair representation which is fed to a logistic regression softmax classifier. For the InferSent model, GloVe embeddings for the words in premise and hypothesis are respectively fed into a bidirectional LSTM, after which we concatenate the representations for premise and hypothesis, their difference, and their element-wise product (Mou et al., 2015). BERT is a multilayer bidirectional transformer pretrained with the masked language modelling and next sequence prediction objectives, and finetuned on the MultiNLI dataset. We concatenate the premise and hypothesis after a special [CLS] token and separated them with the [SEP] token. The BERT representation for the [CLS] token is fed into classifier. For the BERT model, we use the pre-trained model weights from a transformer trained on Toronto books and Wikipedia from its Huggingface Pytorch implementation.

The BOW and InferSent models have development set accuracies of 49.6% and 67.6%. The development set accuracy for the BERT-Large model on MultiNLI is 86.6%, similar to the results achieved by (Devlin et al., 2018), but somewhat lower than state-of-the-art (currently 90.8% on test from the ensembled RoBERTa model with long pretraining optimization, Liu et al. 2019).

6 Experiment 1: Scalar Implicatures

6.1 Scalar Implicature Datasets

The scalar implicature portion of IMPRES includes six datasets, each isolating a different scalar implicature trigger from six types of lexical scales (of the type described in §2): determiners ⟨some, all⟩, connectives ⟨or, and⟩, modals ⟨can, have to⟩, numerals ⟨2,3⟩, ⟨10,100⟩, scalar adjectives, and verbs, e.g., ⟨good, excellent⟩, ⟨run, sprint⟩. Examples pairs of each implicature trigger can be found in the Appendix. For each type, we generate 100 paradigms, each consisting of 12 unique sentence pairs, as shown in Table 2.

Since implicature computation is dependent on the context of utterance (see §2.1), we anticipate two possible behaviors, i.e., the model may: (a) be pragmatic, and compute the implicature and conclude that the premise and hypothesis are in an ‘entailment’ relation, (b) be logical, i.e., consider only the literal content, and not compute the implicature, concluding they are in a ‘neutral’ relation. Thus, we measure both possible conclusions, by tagging sentence pairs for scalar implicature with two sets of NLI labels to reflect the behavior expected under “logical” and “pragmatic” modes of inference, as shown in Table 2.
6.2 Implicatures Results & Discussion

We first evaluate model performance on the controls, shown in Figure 2. If models do not give correct outputs on the controls, they either do not understand the basic function of the negative items used (not, none, neither), or do not correctly diagnose the scalar relationship between terms like some and all. We find that the NLI BERT model performs at ceiling on control conditions for all implicature types, in contrast with InferSent and BOW, whose performance is very variable. Since BERT is the only model that passes all controls, its results on the target items are most interpretable.

For connectives, scalar adjectives and verbs, the BERT model results show neither the hypothesized pragmatic or logical behavior (see Appendix for breakdown of results). In fact, it evaluates sentence pairs as entailment in both directions, meaning it treats scalemates (e.g., and and or; good and excellent) as synonyms, revealing a coarse-grained knowledge of these meanings that lacks information about asymmetric informativity relations between scalemates. Results for modals (can and have to) are split between the three labels, not showing any predicted logical or pragmatic pattern. We conclude that the models do not have sufficient knowledge of the meaning of these words.

In addition to pragmatic and logical interpretations, numerals can also be interpreted as exact cardinalities. We thus predict three different behaviors: logical “at least n”, pragmatic “at least n”, “exactly n”. We observe that results are inconsistent: neither the “exact” nor “at least” interpretations hold across the board.

For the determiner dataset (some-all), the results in Figure 4 break down the results by condition and show that BERT clearly behaves as though it performs pragmatic and logical reasoning in different conditions. It has a preference for pragmatic over logical interpretations overall (55% vs. 36%), and only 9% of results are consistent with neither mode of reasoning. Furthermore, we observe that the proportion of pragmatic reasoning shows consistent effects of sentence order (i.e., whether the implicature trigger is in the premise or the hypothesis), and the presence of negation in one or both sentences.

Pragmatic reasoning is consistently higher when the implicature trigger is in the premise, which we can see in the results for negated implicatures. We observe more pragmatic reasoning in the some and all condition compared to the all and some condition (a similar behavior is observed with the not all-none conditions).

Generally, the presence of negation lowers rates of pragmatic reasoning. First, the negated implicature conditions can be subdivided into pairs with and without negation. Among the negated ones, pragmatic reasoning is lower than for non-negated ones. Second, having negation in the premise rather than the hypothesis makes pragmatic reasoning lower: among pairs tagged as direct implicatures (some vs. not all), there is higher pragmatic reasoning with non-negated some in the premise than with negated not all. Finally, we observe that pragmatic rates are lower for some vs. not all than for some vs. all. In this final case, pragmatic reasoning could be facilitated by explicit presentation of the two items on the scale.

To conclude, only the determiner dataset was informative in showing the extent of the NLI BERT model’s pragmatic reasoning, since it alone showed a fine-grained enough understanding of the semantic relationship of the scalemates, like some and all. For the other datasets, scalemates

| Presuppositions | Hypothesis | Label | Item Type |
|-----------------|------------|-------|-----------|
| Neg. Trigger    | Trigger    | contradiction | control   |
| Modal Trigger   | Trigger    | neutral      | control   |
| Interrog. Trigger| Trigger    | neutral      | control   |
| Cond. Trigger   | Trigger    | neutral      | control   |

Table 3: Paradigm for the presupposition target (top) and control datasets (bottom). For space, *Trigger refers to either plain, Negated, Modal, Interrogative, or Conditional Triggers as per Table 1.
were mostly treated as synonymous (except for modals, where knowledge of any semantic relationship between can and need to seemed absent). Within the determiner dataset, however, BERT returned impressive results showing a high proportion of pragmatic reasoning compared to logical reasoning, which was affected by sentence order and presence of negation in a predictable way.

7 Experiment 2: Presuppositions

7.1 Presupposition Datasets

The presupposition portion of IMPRES includes eight datasets, each isolating a different kind of presupposition trigger. The full set of triggers is shown in the Appendix. For each type, we generate 100 paradigms, with each paradigm consisting of 19 unique sentence pairs. (Examples of the sentence types are in Table 1).

Of the 19 sentence pairs, 15 contain target items. The first target item tests whether the model correctly determines that the presupposition trigger entails its presupposition. The next two items alter the presupposition, either negating it, or replacing a constituent, leading to contradiction and neutrality, respectively. The remaining 12 target items show that the relation between the trigger and the (altered) presupposition is not affected by embedding the trigger under various entailment-canceling operators. 4 control items are designed to test the basic effect of entailment-canceling operators—negation, modals, interrogatives, and conditionals. In each control, the premise is a presupposition trigger embedded under an entailment-canceling operator, and the hypothesis is an unembedded sentence containing the trigger. These controls are necessary to establish whether models learn that presuppositions behave differently under these operators than classical semantic entailments.

7.2 Presupposition Results & Discussion

The results from presupposition controls are in Figure 5. We find that the BERT NLI model performs well above chance on each control (accuracy > 0.33), whereas the BOW and InferSent models perform at or below chance. In the “negated” condition, the BERT NLI model correctly identifies that the trigger is contradicted by its negation 100% of the time, e.g., Did Bill’s handyman win? is neutral with respect to Bill’s handyman won. This indicates that the BERT model mostly learns that negation, modals, interrogatives, and conditionals cancel classical entailments. On the other hand, the BOW and InferSent models do not grasp the ordinary behavior of these common operators.

Next, we test whether models identify presuppositions of the premise as entailments, e.g., that Bill’s handyman won entails that Bill has a handyman. Recall from §2.2 that this would be akin to what a listener does when they accommodate a presupposition. The results in Figure 6 show that each of the three models accommodates some presuppositions, but this depends on both the nature of the presupposition and the model. For instance, the BOW and InferSent models accommodate presuppositions of nearly all trigger types at well above chance rates (accuracy ≫ 0.33). In the case of the uniqueness presupposition of cleft sentences, these models almost always correctly predict an entailment (i.e., at over 90% accuracy), but for most triggers, performance is much less reliable. By contrast, the BERT model’s behavior is much more bimodal. It always accommodates the existence presuppositions of clefts and possessed definites, as well as the presupposition of only, but almost never accommodates any presupposition involving numeracy, e.g. Both flowers that bloomed died entails There are exactly two flowers that bloomed.

Finally, we evaluate whether models predict that presuppositions project out of entailment canceling operators (e.g., that Did Bill’s handyman win? entails that Bill has a handyman). We can only consider such a prediction as evidence of projection if two conditions hold: (a) the model correctly identifies that the relevant operator cancels entailments in the control from the same paradigm (e.g.,
Figure 6: Results for the unembedded trigger paired with positive presupposition.

Did Bill’s handyman win? is neutral with respect to Bill’s handyman won, and (b) the model identifies the presupposition as an entailment when the trigger is unembedded in the same paradigm (e.g. Bill’s handyman won entails Bill has a handyman). Otherwise, a model might correctly predict entailment essentially by accident if, for instance, it systematically ignores interrogatives. For this reason, we filter out results for the target conditions that do not meet these criteria.

Figure 7 shows results for the target conditions after filtering. While InferSent almost never understands that presuppositions can project, we find strong evidence that the BERT and BOW models do. Specifically, they correctly identify that the premise entails the presupposition (over 80% of the time for BERT, and over 90% of the time for BOW). Furthermore, BERT is the only model to reliably identify (i.e., over 90% of the time) that the negation of the presupposition is contradicted. These results hold irrespective of the entailment canceling operator. No model reliably performs above chance when the presupposition is altered to be neutral (e.g., Did Bill’s handyman win? is neutral with respect to John has a handyman).

It is somewhat counterintuitive that the simple BOW model can learn some of the projective behavior of presuppositions. One explanation for this finding is that projection is essentially a phenomenon insensitive to word order. In other words, if a presupposition trigger is present at all in a sentence, a presupposition will generally arise irrespective of its position in the sentence.4

8 Conclusion

This work is an initial step towards rigorously investigating the extent to which NLI models learn semantic versus pragmatic inference types. We have introduced a new dataset IMPRES for probing this question, which can be reused to evaluate pragmatic performance of any NLI given model.

We find strong evidence that BERT learns scalar implicatures associated with determiners. Pragmatic or logical reasoning was not diagnosable for the other implicature trigger pairs, whose meaning was not fully understood by our models (as most scalar pairs were treated as synonymous). In the case of presuppositions, the BERT NLI models, and BOW to some extent, perform well on a number of our subdatasets (only, cleft existence, possessive existence, questions). For the other datasets, the models did not perform as expected on the basic unembedded triggers, again suggesting the model’s lack of knowledge of the basic meaning of these words. Though their behavior is far from systematic, this is suggestive evidence that some NLI models have the capacity to perfectly true, in which the presupposition fails to project due to “local satisfaction” (Heim, 1983).

4There is an exception to this, which we expect to be in-
form in ways that correlate with human-like pragmatic behavior, generalizing from data that does not have explicit information on the tested inference types.

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### Table 4: Examples of automatically generated sentences pairs from each of the six datasets for the scalar implicatures experiment. The pairs belong to the “Implicature (+ to −)” condition.

| Type          | Premise                        | Hypothesis                        |
|---------------|--------------------------------|-----------------------------------|
| Connectives   | These cats or those fish appear. | These cats and those fish don’t both appear. |
| Determiners   | Some skateboards tipped over.    | Not all skateboards tipped over.   |
| Numerals      | Ten bananas were scorching.     | One hundred bananas weren’t scorching. |
| Modals        | Jerry could wake up.            | Jerry didn’t need to wake up.     |
| Scalar adjectives | Banks are fine.                  | Banks are not great.              |
| Scalar verbs  | Dawn went towards the hills.    | Dawn did not get to the hills.    |

### Table 5: Examples of automatically generated sentences pairs from each of the eight datasets for the presupposition experiment. The pairs belong to the “Plain Trigger / Presupposition” condition.

| Type          | Premise                        | Hypothesis                        |
|---------------|--------------------------------|-----------------------------------|
| All N         | All six roses that bloomed died. | Exactly six roses bloomed.        |
| Both          | Both flowers that bloomed died. | Exactly two flowers bloomed.      |
| Change of State | The cat escaped.                | The cat used to be captive.       |
| Cleft Existence | It is Sandra who disliked Veronica. | Someone disliked Veronica.        |
| Cleft Uniqueness | It is Sandra who disliked Veronica. | Exactly one person disliked Veronica. |
| Only          | Only Lucille went to Spain.     | Lucille went to Spain.            |
| Possessed Definites | Bill’s handyman won.           | Bill has a handyman.              |
| Question      | Sue learned why Candice testified. | Candice testified.                |

### Adjectives Implicature Results (Accuracy)

- **Excellent/good**
  - Logical: 1, Pragmatic: 0.69
  - Logical: 1, Pragmatic: 0
- **Good/excellent**
  - Logical: 0.033, Pragmatic: 0.12
  - Logical: 0, Pragmatic: 0.27
- **Good/not excellent**
  - Logical: 0.098, Pragmatic: 0
  - Logical: 0, Pragmatic: 0.031
- **Not excellent/good**
  - Logical: 0.034, Pragmatic: 0
  - Logical: 0.013, Pragmatic: 0.85
- **Not excellent/not good**
  - Logical: 0.88, Pragmatic: 0
  - Logical: 1, Pragmatic: 0.11
  - Logical: 0, Pragmatic: 0.79

Figure 8: Results for the scalar implicatures triggered by adjectives, by target condition.
Figure 9: Results for the scalar implicatures triggered by adjectives, by target condition.
Figure 10: Results for the scalar triggered by determiners, by target condition.
### Modals Implicature Results (Accuracy)

| Condition                      | BERT | BOV model | InferSent | Logical/Pragmatic |
|-------------------------------|------|-----------|-----------|-------------------|
| can/have to                   | 0.37 | 0.11      | 0.00      | logical           |
| can/have to                   | 0.41 | 0.17      | 0.00      | pragmatic         |
| can/not have to               | 0.12 | 0.01      | 0.00      | logical           |
| can/not have to               | 0.08 | 0.05      | 0.07      | pragmatic         |
| cannot/not have to            | 0.48 | 0.07      | 0.11      | logical           |
| cannot/not have to            | 0.31 | 0.91      | 0.89      | pragmatic         |
| have to/can                   | 0.3  | 0.83      | 1.00      | logical           |
| have to/can                   | 0.22 | 0.14      | 0.00      | pragmatic         |
| not have to/can               | 0.03 | 0.02      | 0.00      | logical           |
| not have to/can               | 0.4  | 0.88      | 0.17      | pragmatic         |
| not have to/cannot            | 0.01 | 0.01      | 0.00      | logical           |
| not have to/cannot            | 0.25 | 0.19      | 0.79      | pragmatic         |

Figure 11: Results for the scalar triggered by modals, by target condition.
Figure 12: Results for the scalar triggered by numerals, by target condition.
Figure 13: Results for the scalar triggered by verbs, by target condition.

| Condition          | BERT | BOV | InferSent | Logical/Pragmatic |
|--------------------|------|-----|-----------|-------------------|
| not run/not sprint | 0.99 | 0.028 | 1         | 0.94/0             |
| not sprint/not run | 0.095 | 0.019 | 0         | 0.019/0           |
| not sprint/run     | 0.019 | 0.065 | 0         | 0.065/0           |
| not sprint/run     | 0.33 | 0.77 | 0.32      | 0.33/0.32         |
| run/not sprint     | 0.33 | 0.0088 | 0 | 0.0088/0        |
| run/not sprint     | 0    | 0    | 0.069     | 0.069/0           |
| run/sprint         | 0.32 | 0.13 | 0         | 0.32/0            |
| sprint/run         | 0.0095 | 0.31 | 0.057     | 0.0095/0.057      |
| sprint/run         | 1    | 0.65 | 1         | 1/0               |