Logical Reasoning with Span Predictions: Span-level Logical Atoms for Interpretable and Robust NLI Models

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Abstract

Current Natural Language Inference (NLI) models achieve impressive results, sometimes outperforming humans when evaluating on in-distribution test sets. However, as these models are known to learn from annotation artefacts and dataset biases, it is unclear to what extent the models are learning the task of NLI instead of learning from shallow heuristics in their training data. We address this issue by introducing a logical reasoning framework for NLI, creating highly transparent model decisions that are based on logical rules. Unlike prior work, we show that the improved interpretability can be achieved without decreasing the predictive accuracy. We almost fully retain performance on SNLI while identifying the exact hypothesis spans that are responsible for each model prediction. Using the e-SNLI human explanations, we also verify that our model makes sensible decisions at a span level, despite not using any span-level labels during training. We can further improve model performance and the span-level decisions by using the e-SNLI explanations during training. Finally, our model outperforms its baseline in a reduced data setting. When training with only 100 examples, in-distribution performance improves by 18%, while out-of-distribution performance improves on SNLI-hard, MNLI-mismatched, MNLI-matched and SICK by 11%, 26%, 22%, and 21% respectively.

1 Introduction

The task of Natural Language Inference (NLI) involves reasoning across a premise and hypothesis, determining the relationship between the two sentences. Either the hypothesis is implied by the premise (entailment), the hypothesis contradicts the premise (contradiction), or the hypothesis is neutral to the premise (neutral). NLI can be a highly challenging task, requiring lexical, syntactic and logical reasoning, in addition to sometimes requiring real world knowledge (Dagan et al., 2005). While neural NLI models perform well on in-distribution test sets, this does not necessarily mean they have a strong understanding of the underlying task. Instead, NLI models are known to learn from annotation artefacts (or biases) in their training data (Gururangan et al., 2018; Poliak et al., 2018). Models can therefore be right for the wrong reasons (McCoy et al., 2019), with no guarantees about the reasons for each prediction, or when the predictions are based on a genuine understanding of the task. We address this issue with our logical reasoning framework, creating more interpretable NLI models that definitively show the specific logical atoms responsible for each model prediction.

One challenge when applying a logical approach to NLI is determining the choice of logical atoms. When constructing examples from knowledge bases, the relationships between entities in the knowledge base can be used as logical atoms (Rocktäschel and Riedel, 2017). Whereas, in synthetic fact-based datasets, each fact can become a logical atom (Clark et al., 2020; Talmor et al., 2020). Neither approach would be suitable for SNLI (Bowman et al., 2015), which requires reasoning over gaps in explicitly stated knowledge (Clark et al., 2020), with observations covering a range of topics and using different forms of reasoning. Instead, our logical reasoning framework considers spans of the hypothesis as logical atoms. We determine...
the class of each premise-hypothesis pair based entirely on span-level decisions, identifying exactly which parts of a hypothesis are responsible for each model decision. By providing a level of assurance about the cause of each prediction, we can better understand the reasons for the correct predictions and highlight any mistakes or misconceptions being made. Using the e-SNLI dataset (Camburu et al., 2018), we assess the performance of our span-level predictions, ensuring that the decisions about each hypothesis span align with human explanations.

As no span labels are provided in the SNLI training data, we supervise our Span Logical Reasoning (SLR-NLI) model at a span level using logical rules, for example requiring a contradiction example to include at least one contradiction span. Inspired by previous work on error detection (Rei and Søgaard, 2018, 2019; Pislar and Rei, 2020; Bujel et al., 2021), we train models to detect both neutral and contradiction spans, jointly training on sentence labels while using auxiliary losses to influence the model behaviour at a span-level. Finally, we evaluate our model based on the span-level decisions for each logical atom.

To summarise our findings: 1) We introduce a logical reasoning framework (SLR-NLI) that almost fully retains performance on SNLI, while also performing well on the SICK dataset (Marelli et al., 2014). This contrasts with previous work, where the inclusion of logical frameworks results in substantially worse performance. 2) Our SLR-NLI model produces highly interpretable models, identifying exactly which parts of the hypothesis are responsible for each model prediction. 3) Evaluating the SLR-NLI predictions at a span level shows that the span-level decisions are consistent with human explanations, with further improvements if e-SNLI explanations are used during training. 4) SLR-NLI improves model robustness when training in a reduced data setting, improving performance on unseen, out-of-distribution NLI datasets.

2 Our logical framework

2.1 Span-level Approach

We consider each hypothesis as a set of spans $s_1, s_2, s_3, \ldots, s_m$ where each span is a consecutive string of words in the hypothesis. For example, in Figure 1 the hypothesis ‘A man poses in front of an ad for beer’ has the following spans: ‘A man’, ‘poses in front’, ‘of an ad’, ‘for beer’. Each span $s_i$ has a label of either entailment, contradiction or the neutral class. In practice, there are no pre-defined spans in NLI datasets, nor are there labels for any chosen spans. As a result, we propose a method of dividing hypotheses into spans, introducing a semi-supervised method to identify entailment relationships at this span level. In the example provided in Figure 1, $s_4$ = ‘for beer’ has a neutral class, while each other span has an entailment class. We observe that a hypothesis has a contradiction class if any span present in that hypothesis has a label of contradiction. Similarly, if a hypothesis contains a span with a neutral class and no span with a contradiction class, then the hypothesis has a neutral class. Therefore, a hypothesis only has an entailment class if there are no spans present with span labels of either contradiction or neutral (see Figure 2).

When evaluating a hypothesis-premise pair in the test-data, our model makes discrete entailment decisions about each span in the hypothesis, deciding the sentence-level class based on the presence of any neutral or contradiction spans. This method highlights the exact parts of a hypothesis responsible for each entailment decision.

2.2 Span Selection

We identify spans based on the presence of noun chunks in the hypothesis. Initially, the hypothesis is segmented into spans containing each noun chunk and its preceding text.

However, the most appropriate segmentation of
a hypothesis into spans may depend on the corresponding premise, and in some cases we may need to consider long range dependencies across the sentence. As a result, we also provide additional spans that are constructed from combinations of consecutive spans. We set the number of consecutive spans that we include as a hyper-parameter. For the example in Figure 1, this means also including spans such as ‘a man poses in front’ and ‘of an ad for beer.’

### 2.3 Modelling Approach

A BERT model is used for encoding the NLI premise together with each specific hypothesis span, masking the parts of the hypothesis that are not included in the given span. The BERT model provides a [CLS] representation \( h_i \) for each span \( i \). A linear layer is applied to these representations to provide logits \( L_{ni} \) and \( L_{ci} \) for each span, representing the neutral and contradiction classes respectively.

A separate attention layer is created for both the neutral and contradiction classes that attend to the different span-level outputs. The neutral attention layer attends more to neutral spans, while the contradiction attention layer attends more to contradiction spans. Both the neutral and contradiction attention layers consider the same [CLS] representation \( h_i \).

The two attention layers use the same architecture, with details provided below for the neutral \( (n) \) attention layer. Our span-level predictions will be based on the unnormalized attention weights \( \tilde{a}_{ni} \), which are calculated as:

\[
\tilde{a}_{ni} = \sigma(W_{n2}(\tanh(W_{n1}h_i + b_{n1}) + b_{n2}))
\]

where \( W_{n1} \) and \( W_{n2} \) are trainable parameters along with their respective bias terms. Equation (1) uses a sigmoid so that the output is in the range between 0 and 1 for binary classification. Upon normalisation, the attention weights \( \tilde{a}_{ni} \) define an attention distribution:

\[
a_{ni} = \frac{\tilde{a}_{ni}}{\sum_{k=1}^{n} \tilde{a}_{nk}}
\]

These weights are used to create a new weighted logit, \( L_n \):

\[
L_n = \sum_{i=1}^{n} a_{ni} L_{ni}
\]

Using a binary label \( y_n \), indicating if the example is neutral or not, we create a sentence-level loss to optimise using the sentence labels:

\[
L_{n}^{\text{Sent}} = (\sigma(W_{n3} \times L_n + b_{n3}) - y_n)^2
\]

We combine this with an auxiliary span loss on the model attention weights, \( L_{n}^{\text{Span}} \):

\[
L_{n}^{\text{Span}} = (\max_i (\tilde{a}_{ni}) - y_n)^2
\]

The auxiliary span attention loss has the effect of encouraging the span-level unnormalized attention weights to be closer to zero for entailment examples. This supports our logical framework, which states that all entailment examples must only consist of entailment spans. As neutral predictions require at least one neutral span, by supervising the maximum unnormalized attention weight we encourage one of the spans to be predicted as neutral. The contradiction-detection attention layer behaves in a similar way, detecting the presence of contradiction spans.

We then combine together the auxiliary span attention loss with the sentence-level loss:

\[
L_{n}^{\text{Total}} = L_{n}^{\text{Sent}} + L_{n}^{\text{Span}}
\]

While our model evaluation exclusively makes predictions from the unnormalized attention weights for each span, we find in practice that including a sentence level objective improves the span-level decisions. In particular, the sentence supervision influences the attention values directly as in (3), in addition to supervising the representations \( h_i \). The sentence-level supervision does not have access to the full hypothesis, separately considering each span representation \( h_i \).

### 2.4 Training Process

Our neutral and contradiction attention models have two class labels, with \( y_n \) and \( y_c \) taking values of 0 or 1. \( y_{n} = 0 \) when there are no neutral spans present, while \( y_{n} = 1 \) when there is at least one neutral span. \( y_c \) follows the same approach for the contradiction detection label.

For neutral NLI examples, we train our neutral-detection model using a sentence-level label of \( y_{n} = 1 \). Using our logical framework, we also know that a neutral example cannot contain a contradiction span, as any example with a contradiction span would have a contradiction label. We therefore train our contradiction-detection model using a sentence-level label of \( y_{c} = 0 \) for these examples. For contradiction examples, we do not
train our neutral-detection attention model, as there may or may not be neutral spans present in addition to the contradiction spans. For entailment examples, we train both neutral and contradiction detection models using the labels \( y_n = 0 \) and \( y_c = 0 \).

Therefore, for neutral or entailment examples we consider the total of both \( L^\text{Total}_n \) and \( L^\text{Total}_c \), whereas for the contradiction class we only consider \( L^\text{Total}_c \).

### 2.5 Logic-based Evaluation

We evaluate each NLI sentence based exclusively on our span-level decisions. Specifically, an NLI hypothesis is classified as the contradiction class if any of the unnormalized attention weights are classified as being contradiction (\( \tilde{a}_{ci} \geq 0.5 \)). If there are no contradiction spans present, an NLI example is classified as neutral if there exists at least one neutral span (\( \tilde{a}_{ni} \geq 0.5 \)). Otherwise, the NLI example is classified as entailment. The sentence-level logits \( L_n \) or \( L_c \) are only used during training and discarded for evaluation – they consider information across all the spans and therefore do now allow for a deterministic evaluation of which spans are responsible for the model predictions.

### 2.6 Span-level Supervision with Human Explanations

To provide our model with more information about individual spans, we can use the e-SNLI (Cam-buru et al., 2018) human explanations, with rationales highlighting the most important words for a given hypothesis and premise. Training models with the e-SNLI explanations can improve both model performance (Zhao and Vydiswaran, 2020; Stacey et al., 2021) and model robustness (Stacey et al., 2021), although not all prior work has found improvements (Kumar and Talukdar, 2020; Cam-buru et al., 2018; Carton et al., 2021; Hase and Bansal, 2021). We assess whether the human explanations can help our model make better decisions at the span level, and also whether the explanations further improve performance of our SLR-NLI model.

To incorporate the human explanations during training, we consider the highlighted word rationales for each hypothesis. If any of our SLR-NLI hypothesis spans contain all of the highlighted words in the e-SNLI explanation, we assign the overall sentence label as the individual span label. If the hypothesis rationale is not a single consecutive span then we do not provide any supervision with the explanation, as we observe that only single-span rationales consistently align with the desired span-level labels.

Let \( p_i \) be the value of 1 where the hypothesis rationale is fully contained within the \( i \)-th span, and 0 otherwise. Our neutral span loss \( L^\text{e-SNLI}_n \) is defined as:

\[
L^\text{e-SNLI}_n = \lambda^\text{e-SNLI} \sum_i p_i (\tilde{a}_{ni} - y_n)^2
\]

\( L^\text{e-SNLI}_c \) is defined in a similar way, using \( \tilde{a}_{ci} \) and \( y_c \).

### 3 Related Work

#### 3.1 NLI with Neural Theorem Provers

Neural theorem provers can effectively solve a range of natural language tasks (Rocktäschel and Riedel, 2017; Weber et al., 2019; Minervini et al., 2020b,a), many of which could be recast in a similar form to NLI. These datasets are often built from knowledge graphs (Sinha et al., 2019; Bouchard et al., 2015; Kok and Domingos, 2007), for example identifying relationships between characters in short stories (Sinha et al., 2019). Non-neural theorem provers have also shown promising results on the SICK dataset (Martínez-Gómez et al., 2017; Abzianidze, 2020, 2017; Yanaka et al., 2018), although these methods cannot be easily translated to SNLI, which covers a wide range of topics and uses various forms of reasoning.

#### 3.2 Monotonic Reasoning with NLI

Using monotonic reasoning involves matching components of the hypothesis and premise, and using external knowledge from resources including WordNet (Miller, 1995) to determine the entailment relationships between corresponding parts of both sentences (Kaloulou et al., 2020; Hu et al., 2020; Chen et al., 2021). To improve performance, this logical approach can be combined with traditional neural models, learning which examples would benefit from a neural approach rather than using logical rules (Kaloulou et al., 2020), or using neural models to decide the likelihood of examples where entailment and contradiction are not detected (Hu et al., 2020). A hybrid approach can improve performance, but at the expense of the interpretability benefits. Logic models using monotonic reasoning are mostly evaluated on SICK and other datasets with a small number of differences between the premise and hypothesis. While our logical framework is not specifically designed for
these datasets, we show our performance on SICK still remains competitive with this prior work.

3.3 Logical Reasoning with SNLI

Previous work has applied logical reasoning techniques to SNLI, but with performance substantially below baseline levels. Feng et al. (2022) segment a hypothesis into spans, choosing one of seven logical relations for each hypothesis span. A logical relation is predicted for each span using a GPT-2 model (Radford et al., 2019) which considers the premise, the given span and all prior hypothesis spans, with reinforcement learning training this span-level behaviour (Feng et al., 2022). Previous work also predicts the seven logical relations for individual words rather than for hypothesis spans (Feng et al., 2020).

Closest to our work, Wu et al. (2021) label spans as entailment, neutral or contradiction, evaluating at a sentence level based on the presence of neutral or contradiction spans. Our substantial performance improvements compared to Wu et al. (2021) reflect our different approaches to supervising at a span level. Wu et al. (2021) provide each span model with information about the entire premise and hypothesis, in addition to a hypothesis span and a corresponding premise span. The span label is then predicted using a three class classifier. In comparison, we create separate additional attention layers for neutral and contradiction span detection, combining together multiple different losses to supervise at both the sentence and span level. As we consider neutral and contradiction span detection as separate binary tasks, we also introduce logical rules during training which include not supervising our neutral detection model for contradiction examples, and how a neutral label means there are no contradiction spans present.

We directly compare our results to Feng et al. (2020), Wu et al. (2021) and Feng et al. (2022).

4 Experiments

We experiment with training the SLR-NLI model on either SNLI (Bowman et al., 2015) or SICK (Marelli et al., 2014). SNLI is a larger corpus, with 570k observations compared to 10k in SICK. SNLI involves a diverse range of reasoning strategies between the premise and hypothesis, where annotators have been asked to create a hypothesis for each class for each premise, with the premises provided from image captions. In contrast, SICK initially uses sentence pairs from image captions and video descriptions, with additional sentence pairs generated by applying a series of rules, including replacing nouns with pronouns and simplifying verb phrases. As a result, entailment and contradiction examples in SICK are often the same except with one or two small changes. Previous work exploits this similarity, using logical reasoning to identify the contradiction and entailment examples (Chen et al., 2021; Hu et al., 2020). Compared to this setting, SNLI provides a more challenging dataset for applying logical reasoning approaches.

We further experiment with training our model in a reduced data setting, motivated by the hypothesis that forcing our model to learn at a span-level will make better use of a smaller number of examples. We expect SLR-NLI to also be more robust in a reduced data setting, with existing models known to rely on dataset biases when overfitting to small datasets (Utama et al., 2020b). For the reduced data setting, we train SLR-NLI with either 100 or 1,000 examples from SICK or SNLI, evaluating out-of-distribution performance on other unseen NLI datasets including SNLI-hard (Gururangan et al., 2018), MNLI (Williams et al., 2018) and HANS (McCoy et al., 2019). As no explanations are provided for SICK, we only use explanations when training on SNLI (described as SLR-NLI-esnli).

For SICK, when we consider out-of-distribution performance we evaluate on the corrected SICK dataset (Hu et al., 2020), with labels manually corrected by Hu et al. (2020); Kalouli et al. (2017). However, for a fair comparison to previous work, we use the original SICK dataset when evaluating in-distribution performance from SICK.

To validate that the model is making sensible decisions at a span level, we compare the span-level predictions to the e-SNLI human explanations. For each single-span hypothesis rationale in e-SNLI, we consider each model span containing this entire rationale. Each span that does contain the e-SNLI rationale is evaluated, with its span predictions compared to the sentence-level label. As the e-SNLI test data contains three human explanations for each observation, the hypothesis spans are compared to each of these three explanations.

In summary, we consider the following research questions: 1) Does our interpretable SLR-NLI model retain performance on SNLI? 2) Is SLR-NLI a flexible approach that can also work on SICK?
Table 1: Performance (accuracy) on the SNLI test-set from our SNLI-NLI model, with and without the additional e-SNLI supervision during training. Each condition is tested across 5 random seeds, including the baseline.

| Accuracy | SNLI | ∆   |
|----------|------|-----|
| BERT (baseline) | 90.77 |     |
| Feng et al. (2020) | 81.2 | -9.57 |
| Wu et al. (2021) | 84.53 | -6.24 |
| Feng et al. (2022) | 87.8 | -2.97 |
| SLR-NLI | 90.33 | -0.44 |
| SLR-NLI+esnli | 90.49 | -0.28 |

3) Does the SLR-NLI model improve performance in a reduced data setting? 4) In the reduced data setting, does SLR-NLI also improve robustness? 5) Does SLR-NLI make sensible decisions at a span level?

### 4.1 Hyper-parameter Settings

We use a BERT-base (Devlin et al., 2019) model, providing a direct comparison to previous work. We choose the best learning rate for the baseline, SLR-NLI and SLR-NLI-esnli from \{10^{-6}, 2.5 \times 10^{-6}, 5 \times 10^{-6}, 7.5 \times 10^{-6}, 10^{-5}\}. Each SNLI model is trained over 2 epochs, using a linear learning schedule with a warmup and warmdown period of a single epoch. For the SICK dataset, we train with 3 warmup and warmdown epochs to reach a baseline comparable with previous work. \(\lambda^{e\text{-SNLI}}\) is set as 0.1. We also consider spans that consist of up to 3 smaller, consecutive spans. Hyper-parameters are selected based on SNLI, with the same hyper-parameters applied to SICK. A separate hyper-parameter search is conducted for the reduced data setting, with models evaluated with early stopping across 10 epochs. Each hyper-parameter is tested across 5 random seeds, comparing the mean results.

### 5 Results

#### 5.1 Performance on SNLI and SICK

On the SNLI test set, the SLR-NLI model achieves in-distribution results very close to the standard BERT model, with 90.33% accuracy compared to the baseline of 90.77% (Table 1). This result outperforms prior work on logical reasoning in SNLI, as the inclusion of logical frameworks has previously been accompanied by large performance drops (Feng et al., 2022; Wu et al., 2021; Feng et al., 2020). We achieve this level of performance without ever training or evaluating on the full premise and hypothesis pairs.

When training with the e-SNLI explanations, we see an additional small improvement in accuracy (reaching 90.49%). SLR-NLI also compares favourably to prior logical reasoning work on the SICK dataset, despite the benchmarks being specifically designed for this dataset (Table 2). In particular, Chen et al. (2021) is specifically designed to bridge the differences between a hypothesis and premise, which is not possible for SNLI. Kalouli et al. (2020) also outperforms SLR-NLI, however this is a hybrid approach that uses logic for some examples and a standard neural network for other examples without the same interpretability benefits. The strong performance on both SNLI and SICK shows the flexibility of SLR-NLI, which can be applied to a range of different NLI datasets.

#### 5.2 Reduced data setting

In a reduced data setting training with 1,000 SNLI observations, there is a small in-distribution improvement from SLR-NLI-esnli, with larger improvements observed out-of-distribution (see Table 3). When training with only 100 observations we also see substantial improvements in-

Table 2: Performance (accuracy) of SLR-NLI compared to previous work. Results for SLR-NLI-esnli are not provided as the e-SNLI explanations are specific to SNLI. Results for SLR-NLI and the baseline are an average from across 5 random seeds.

| Accuracy | SICK | ∆   |
|----------|------|-----|
| BERT (baseline) | 85.52 |     |
| Hybrid systems | | |
| Hu et al. (2020)+BERT | 85.4 | -0.1 |
| Kalouli et al. (2020) | 86.5 | +1.0 |
| Logic-based systems | | |
| Hu et al. (2020) | 77.2 | -8.3 |
| Abzianidze (2017) | 81.4 | -4.1 |
| Martínez-Gómez et al. (2017) | 83.1 | -2.4 |
| Yanaka et al. (2018) | 84.3 | -1.2 |
| Abzianidze (2020) | 84.4 | -1.1 |
| Chen et al. (2021) | 90.3 | +4.8 |
| SLR-NLI | 85.43 | -0.09 |
Table 3: Performance of SLR-NLI compared to a BERT baseline in a reduced data setting. We use SLR-NLI-esnli (SLR-e) when training on SNLI, whereas for SICK we train SLR-NLI without any human explanations (SLR). Results in bold outperform the corresponding results in either the baseline or from SLR-NLI. When training on SICK, we use the original SICK dataset, whereas the out-of-distribution evaluating on SICK uses the SICK-corrected dataset. All results are an average across 5 random seeds.

| Model          | SNLI           | SICK           |
|----------------|----------------|----------------|
|                | SLR-e Base.    | SLR-e Base.    | SLR Base. | SLR Base. |
| Data-set size  | 1,000          | 1,000          | 100       | 100       |
| OOD datasets:  |                |                |
| SNLI-dev       | 74.22          | 73.98          | 61.45     | 46.96     |
| SNLI-test      | 74.05          | 73.90          | 60.95     | 46.88     |
| SNLI-hard      | 59.51          | 59.25          | 50.46     | 44.85     |
| MNLI-mismat.   | 57.05          | 49.17          | 43.70     | 47.85     |
| MNLI-mat.      | 54.76          | 48.46          | 42.50     | 45.61     |
| SICK           | 52.23          | 52.19          | 45.77     | 52.33     |
| HANS           | 50.00          | 50.27          | 49.99     | 50.61     |

Table 4: Span-level performance of our SLR-NLI-esnli model compared to SLR-NLI without the supervision with the human explanations. A version of SLR-NLI with a dropout mechanism applied is also included. All results are an average across 5 random seeds.

|                          | Sent. acc. | Span acc. | F-macro | F-ent | F-neut | F-cont |
|--------------------------|------------|-----------|---------|-------|--------|--------|
| Zero-shot:               |            |           |         |       |        |        |
| SLR-NLI                  | 90.33      | 84.75     | 84.61   | 81.74 | 84.80  | 87.27  |
| SLR-NLI + dropout        | 90.33      | 87.91     | 87.81   | 85.96 | 86.52  | 90.94  |
| Supervised:              |            |           |         |       |        |        |
| SLR-NLI-esnli            | 90.49      | 88.29     | 88.17   | 86.24 | 86.99  | 91.28  |

distribution, with SLR-NLI-esnli outperforming the baseline by 18% for SNLI-test, with improvements on SNLI-hard, MNLI-mismatched, MNLI-matched and SICK of 11%, 26%, 22% and 21% respectively. Training on a reduced SICK dataset shows the same findings, with in-distribution improvements accompanied by out-of-distribution improvements on the SNLI and MNLI datasets. The improved out-of-distribution performance in the reduced data setting suggests that both SLR-NLI and SLR-NLI-esnli are less reliant on database biases compared to the baseline model (Belinkov et al., 2019; Mahabadi et al., 2020; Stacey et al., 2020; Utama et al., 2020a; He et al., 2019; Clark et al., 2019).

The only dataset where SLR-NLI underperformed compared to the baseline was HANS. This dataset contains syntactic heuristics, with each hypothesis consisting of words that are also words in the corresponding premise. For example, the premise of ‘the doctor was paid by the actor’ is accompanied by the hypothesis ‘the doctor paid the actor’ (McCoy et al., 2019). In these examples, evaluating on the smaller spans provides no additional benefit.

6 Analysis

6.1 Evaluating span performance

Even without additional supervision from e-SNLI, SLR-NLI performs well at a span level, with 84.75% accuracy in a zero-shot setting (Table 4). This shows that human explanations are not required for the model to make sensible decisions at a span level. With the additional e-SNLI supervision, SLR-NLI-esnli reaches a span-level accuracy of 88.29%. We observe that without the additional e-SNLI supervision, the model tends to rely more on the longer spans that consist of consecutive smaller spans. To mitigate this issue, we experiment with a dropout mechanism during training which ran-
Contradiction span | Neutral span
---|---

**Example 1 (SNLI-test):**

**Premise:** a woman with a green headscarf, blue shirt and a very big grin.

**Hypothesis:** the woman is young.

**Example 2 (SNLI-dev):**

**Premise:** two women are embracing while holding to go packages.

**Hypothesis:** the sisters are hugging goodbye while holding to go packages after just eating lunch.

**Example 3 (MNLI-mismatched):**

**Premise:** your contribution helped make it possible for us to provide our students with a quality education.

**Hypothesis:** your contributions were of no help with our students’ education.

**Example 4 (MNLI-mismatched):**

**Premise:** a few months ago, carl newton and i wrote a letter asking you to consider a financial contribution to graduate endodontics at indiana university.

**Hypothesis:** carl newton and i have never had any previous contact with you.

Figure 3: Span and sentence level predictions for SNLI-test, SNLI-dev and MNLI-mismatched (out-of-distribution). Each of the four examples above are correctly predicted by SLR-NLI-esnli (the first two examples are neutral, while the second two examples are contradiction).

domly masks large spans consisting of consecutive smaller spans, encouraging the model to also make sensible decisions at the most granular span level. In 10% of observations, all such large spans are masked, leaving only smaller spans as the model input. This dropout mechanism improves span performance to 87.91%, although the sentence level performance does not improve in tandem (Table 4).

### 6.2 Model Interpretability

The main advantage of our span-level approach is the interpretability of the model predictions, allowing us to understand which specific parts of the hypothesis are responsible for each predicted label. We define explanation spans as the set of the smallest neutral and contradiction spans such that any longer span that is predicted as neutral or contradiction contains one of these spans. As a result, we only choose longer, multi-segment spans when there are no smaller spans that explain the model decisions. For contradiction predictions, we only include contradiction spans in our explanations.

As shown in Figure 3 - Example 1, SLR-NLI-esnli consistently makes sensible span-level predictions for easier, shorter hypotheses. We therefore show the results of a longer, more challenging example (Example 2), along with two examples from the unseen, out-of-distribution MNLI-mismatched validation set (Examples 3 and 4). In each case, the model is making correct decisions in line with our human expectations. To provide an unbiased sample of the span-level explanations, we also show the first four neutral and contradiction examples from SNLI-test in the Appendix.

### 7 Conclusion

We introduce SLR-NLI as a logical framework that predicts the class of an NLI sentence pair based on span-level predictions. We achieve this span-level supervision by combining together a sentence-level loss with span losses based on logical rules. SLR-NLI almost fully retains performance on SNLI, outperforming previous logical methods, whilst also performing well on the SICK dataset. The model also outperforms the baseline in a reduced data setting, with substantially better model robustness. Finally, we create a highly interpretable model whose decisions can easily be understood, highlighting why these predictions are made and the reasons for any misclassifications.
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Example 1 (SNLI-test):

**Premise:** this church choir sings to the masses as they sing joyous songs from the book at a church.

**Hypothesis:** the church has cracks in the ceiling.

Example 2 (SNLI-test):

**Premise:** this church choir sings to the masses as they sing joyous songs from the book at a church.

**Hypothesis:** a choir sing at a baseball game.

Example 3 (SNLI-test):

**Premise:** a woman with a green headscarf, blue shirt and a very big grin.

**Hypothesis:** the woman has been shot.

Example 4 (SNLI-test):

**Premise:** an old man with a package poses in front of an advertisement.

**Hypothesis:** a man poses in front of an ad for beer.

Figure 4: Span and sentence level predictions for the first four neutral and contradiction examples in SNLI-test. While the first example is incorrectly predicted as being contradiction (instead of neutral), the other three predictions are correct and show that the model is making sensible span-level decisions. Entailment examples have not been displayed, as unless these examples have been misclassified no neutral or contradiction spans would be displayed. As the fourth example was displayed in Figure 3, we instead show the first, second, third and fifth SNLI-test examples.