Decomposing Natural Logic Inferences in Neural NLI

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Abstract

In the interest of interpreting neural NLI models and their reasoning strategies, we carry out a systematic probing study which investigates whether these models capture the crucial semantic features central to natural logic: *monotonicity* and *concept inclusion*. Correctly identifying valid inferences in *downward-monotone contexts* is a known stumbling block for NLI performance, subsuming linguistic phenomena such as negation scope and generalized quantifiers. To understand this difficulty, we emphasize monotonicity as a property of a *context* and examine the extent to which models capture monotonicity information in the contextual embeddings which are intermediate to their decision making process. Drawing on the recent advancement of the probing paradigm, we compare the presence of monotonicity features across various models. We find that monotonicity information is notably weak in the representations of popular NLI models which achieve high scores on benchmarks, and observe that previous improvements to these models based on fine-tuning strategies have introduced stronger monotonicity features together with their improved performance on challenge sets.

1 Introduction

Large, black box neural models which achieve high scores on benchmark datasets designed for testing *natural language understanding* are the subject of much scrutiny and investigation.

It is often investigated whether models are able to capture specific semantic phenomena which mimic human reasoning and/or logical formalism, as there is evidence that they sometimes exploit simple heuristics and dataset artifacts instead (McCoy et al., 2019; Herlihy and Rudinger, 2021).

In this work, we consider the rigorous setting of *natural logic* (MacCartney and Manning, 2007). This is a highly systematic reasoning principle relying on only two abstract features, each of which is in itself linguistically complex: *monotonicity* and *concept inclusion relations*. It underlies the majority of symbolic/rule-based and hybrid approaches to NLI and is an important baseline reasoning phenomenon to look for in a robust and principled NLI model.

Downward monotone operators such as negations and generalized quantifiers result in the kinds of natural logic inferences which are often known to stump neural NLI models that demonstrate high performance on large benchmark sets such as MNLI (Williams et al., 2018).

By contrast, in this work we present a **structural** study: investigating to what extent the features relevant for identifying natural logic inferences, especially context monotonicty itself, are captured in the model's internal representations.

In this work, we carry out a systematic probing study to estimate and compare the extent to which the abstract features at the heart of monotonicity reasoning – i.e., context monotonicity and concept inclusion relations – are present in various NLI models' representations.

Our contributions are may be summarized as follows:

1. We perform a structural investigation as to whether the behaviour of *natural logic* formalisms are mimicked within popular transformer-based NLI models.

2. For this purpose, we present a joint NLI and semantic probing dataset format (and dataset) which we call NLI-XY: it is a unique probing dataset in that the probed features relate to the NLI task output in a very systematic way.

3. We employ thorough probing techniques to determine whether the abstract semantic features of *context monotonicity* and *concept inclusion relations* are captured in the models' internal representations.

4. We observe that some well-known NLI models demonstrate a systematic failure to model context monotonicity, a behaviour we observe to correspond to poor performance on natural logic reasoning in downward-monotone contexts. However, we show that the existing HELP dataset improves this behaviour.

5. We support the observations in the probing study with several *qualitative analyses*, including decomposed error-breakdowns on the **NLI-XY** dataset, representation visualizations, and evaluations on existing challenge sets.

2 Related Work

Natural logic dates back to the formalisms of Sanchez (1991), but has been received more recent treatments and reformulations in (MacCartney and Manning, 2007; Hu and Moss, 2018). Symbolic and hybrid neural/symbolic implementations of the natural logic paradigm have been explored in (Chen et al., 2021; Kalouli et al., 2020; Abzianidze, 2017; Hu et al., 2020).

The shortcomings of natural logic handling in various neural NLI models have been shown with several *behavioural* studies, where NLI challenge sets exhibiting examples of downward monotone reasoning are used to evaluate performance of models with respect to these reasoning patterns (Richardson et al., 2019; Yanaka et al., 2019b,a; Goodwin et al., 2020; Geiger et al., 2020).

In an attempt to better identify features that neural models manage or fail to capture, researchers have employed *probing* strategies: namely, the *diagnostic classification* (Alain and Bengio, 2018) of auxiliary feature labels from internal model representations. Most probing studies in natural language processing focus on the *syntactic* features captured in transformer-based language models (Hewitt and Manning, 2019), but calls have been made for more sophisticated probing tasks which rely more on contextual information (Pimentel et al., 2020).

In the realm of semantics, probing studies have focused more on *lexical* semantics (Vulić et al., 2020): word pair relations are central to monotonicity reasoning, and thus form part of our probing study as well, but the novelty of our work is the task of classifying context monotonicity from contextual word embeddings. Due to its context-sensitive nature, it cannot be learnt by “memorizing" the labels of specific words in the training data, a key shortcoming in probing studies which focus on tasks such as POS tagging and word-pair relation classification, which have much less dependency on context.

3 Problem Formulation

3.1 Decomposing Natural Logic

Natural logic inferences (as formalized in Sanchez (1991); MacCartney and Manning (2007)) are usually described with respect to *substitution* operations. Certain word substitutions result in either forward or reverse entailment, while others result in neither. This is the basis for a calculus of determining entailment from substitution sequences (MacCartney and Manning, 2007; Hu et al., 2020; Hu and Moss, 2018).

Broadly speaking, we wish to determine whether well-known transformer-based NLI models mimic the reasoning strategies of natural logic. However, as neural NLI models are black box classifiers that only see a premise/hypothesis sentence pair as its input, it is not immediate how to compare its process to a rule-based system.

To this end, we consider a formulation of natural logic which describes its rules in terms of concept pair relations and *context monotonicity* (similar to (Rozanova et al., 2021)).

Consider the following example of a single step natural logic inference, which we will decompose into semantic components relevant to its entailment label:

		NLI Label
Premise	I did not eat any **fruit** for breakfast.	Entailment
Hypothesis	I did not eat any **raspberries** for breakfast.	

The hyponym/hypernym pair (raspberries, fruit) exemplifies a more general relation which we will refer to as the *concept inclusion* [1] relation $\sqsubset$, (and dually, *reverse concept inclusion* $\sqsupset$) in reference to the semantic interpretation of predicates related with subset inclusion, as in:

$$\{x \mid \text{raspberry}(x)\} \subset \{x \mid \text{fruit}(x)\}.$$

In the above example, they occur in a shared **context**, namely the sentence template

[1]In (MacCartney and Manning, 2007), this is treated as a “generalized entailment" relation which is defined on word/phrase pairs and extends to full sentences pairs using natural logic rules.

"I did not eat any ____ for breakfast".

Such a context may be treated as a *function* f

$$f : (\mathcal{X}, \sqsubseteq) \rightarrow (\mathcal{S}, \Rightarrow)$$

between a set of concepts $\mathcal{X}$ (ordered by the concept inclusion relation) and the set $\mathcal{S}$ of full sentences ordered by entailment. We say that f is *upward monotone* ($\uparrow$) if it is order *preserving*, i.e.

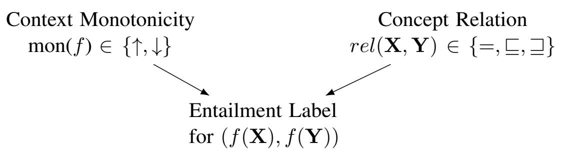
$$\forall_{X,Y}(X \sqsubseteq Y \text{ implies } f(X) \Rightarrow f(Y))$$

and that f is *downward monotone* ($\downarrow$) if it is order *reversing*, i.e.

$$\forall_{X,Y}(X \sqsupseteq Y \text{ implies } f(X) \Rightarrow f(Y)).$$

Given a natural language context f, any pair of grammatically valid insertions (X, Y) (e.g. ("raspberries", "fruit")) yields a sentence pair $f(X), f(Y)$. Treating $f(X)$ as a *premise* sentence and $f(Y)$ as a *hypothesis* sentence, a trained neural NLI model can provide a classification of whether $f(X)$ entails $f(Y)$.

In summary, these two abstract linguistic features, *context montonicity* and *concept inclusion relation*, jointly determine the final gold entailment label of this type of NLI example.



3.2 NLI-XY Dataset Format

We follow this formalism as the basis for a *dataset format*, which we refer to as NLI-XY. This is the first probing dataset format (and consequently, dataset) in NLP where the auxiliary labels for intermediate semantic features influence the final task label in a rigid and determinate (yet simple) way, with these features being themselves linguistically complex. As such, it is as such a "decomposed" natural logic dataset format, where the positive entailment labels are further enriched with labels for the monotonicity and relational properties which gave rise to them. This allows for informative qualitative and structural analyses into natural logic handling strategies in neural NLI models.

The NLI-XY dataset format is comprised of the following:

			Auxilliary Label
Context	f	I did not eat any ____ for breakfast.	$\downarrow$ (downward monotone)
Insertion Pair	(X,Y)	(fruit, raspberries)	$\sqsupseteq$ (reverse concept inclusion)
			NLI Label
Premise	$f(X)$	I did not eat any fruit for breakfast.	Entailment
Hypothesis	$f(Y)$	I did not eat any raspberries for breakfast.	

Table 1: A typical NLI-XY example with labels for context monotonicity, lexical relation and the final entailment label.

1. A set of *contexts* f with a blank position indicated with an 'x', marked for the context monotonicity label.
2. A set of *insertion pairs* (X, Y), which are either words or phrases, labeled with the concept inclusion relation.
3. A derived set of premise and hypothesis pairs $(f(X), f(Y)$ made up of permutations of (X, Y) insertion pairs through contexts f, controlled for grammaticality as far as possible.

The premise/hypothesis pairs may thus be used as input to any NLI model, while the context monotonicity and insertion relation information can be used as the targets of an auxiliary probing task on top of the model's representations.

4 NLI-XY Dataset Construction

We make our NLI-XY dataset and all the experimental code used in this work is publically available [2]. We constructed the NLI-XY dataset used here as follows:

Context Extraction We extract context examples from two NLI datasets which were designed for the behavioural analysis of NLI model performance on monotonicity reasoning. In particular, we use the manually curated evaluation set MED (Yanaka et al., 2019a) and the automatically generated HELP training set (Yanaka et al., 2019b). By design, as they are collections of NLI examples exhibiting monotonicity reasoning, these datasets mostly follow our required $(f(X), f(Y))$ structure, and are labeled as instances of upward or downward monotonicity reasoning(although the contexts are not explicitly identified).

[2] Anonymized github link.

We extract the common context f from these examples after manually removing a few which do not follow this structure (differing, for example, in pronoun number agreement or prepositional phrases). We choose to treat determiners and quantifiers as part of the context, as these are the kinds of closed-class linguistic operators whose monotonicity profiles we are interested in. To ensure grammatically valid insertions, we manually identify whether each context as suitable either for a singular noun, mass noun or plural noun in the blank/x position.

Insertion Pairs Our (X, Y) insertion phrase pairs come from two sources: Firstly, the labeled word pairs from the MoNLI dataset (Geiger et al., 2020), which features only single-word noun phrases. Secondly, we include an additional hand-curated dataset which has a small number of *phrase-pair* examples, which includes intersective modifiers (e.g. (brown sugar, sugar)) and prepositional phrases (e.g. (sentence, sentence about oranges)). Several of these examples were drawn from the MED dataset. Each word in the pair is labelled as a singular, plural or mass noun, so that they may be permuted through the contexts in a reasonably grammatical way.

Premise/Hypothesis Pairs Premise/Hypothesis pairs are constructed by permuting insertion pairs through the set of contexts within the grammatical constraints. Note that the data is split into train, dev and test partitions *before* this permutation occurs, so that there are **no shared contexts or insertion pairs** between the different data partitions, in an attempt to avoid overlap issues such as those discussed in (Lewis et al., 2021)

5 Experimental Setup

Our experiments are designed to investigate the following questions: Firstly, to what extent do different NLI models differ in their encoding of context monotonicity and lexical relational knowledge? Secondly, if a model successfully captures these features, to what extent do they correspond with the model's predicted entailment label? We investigate these questions with a detailed probing study and a supporting qualitative analysis, using decomposed error break-downs and representation visualization.

		Context Monotonicity		
Partition	**(X,Y) Relation**	Up ↑	Down ↓	Total
train	$\sqsubseteq$	671	543	1214
	$\sqsupseteq$	671	543	1214
	None	244	222	466
	Total	1586	1308	**2894**
dev	$\sqsubseteq$	598	389	987
	$\sqsupseteq$	598	389	987
	None	220	242	462
	Total	1416	1020	**2436**
test	$\sqsubseteq$	1103	1066	2169
	$\sqsupseteq$	1103	1066	2169
	None	502	516	1018
	Total	2708	2648	**5356**

Table 2: Dataset statistics for the NLI-XY dataset. We employ an **aggressive** $30, 20, 50$ train-dev-test split for a more impactful probing result.

5.1 Models and Representations

We consider a selection of neural NLI models based on transformer language models (such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019) and BART (Lewis et al., 2020)) which are fine-tuned on one of two benchmark training sets: either SNLI (Bowman et al., 2015) or MNLI (Williams et al., 2018). Of particular interest, however, is the case where these models are trained on an additional dataset (the HELP dataset from (Yanaka et al., 2019b)) which was designed for improving the overall balance of upward and downward monotone contexts in NLI training data. We use our own random $50-30-20$ train-dev-test split of the HELP dataset (ensuring unique contexts in every split), so that there is no overlap of contexts between the fine-tuning data and the few HELP-test examples we used as part of our NLI-XY dataset[3].

5.2 Probing

The NLI-XY dataset is equipped with two auxiliary feature labels which are the targets of the probing task: context monotonicity and the relation of the (X, Y) phrase pair (referred to henceforth as either concept inclusion relation or lexical relation).

5.2.1 Models and Representations

For each auxiliary task, we use simple linear model architectures as the probes. We train 50 probes of varying complexities using the *probe-ably* framework (Ferreira et al., 2021). The target of the probing study is the classification token of the final

[3]We use the *transformers* library (Wolf et al., 2020) and their available pretrained models for this work.

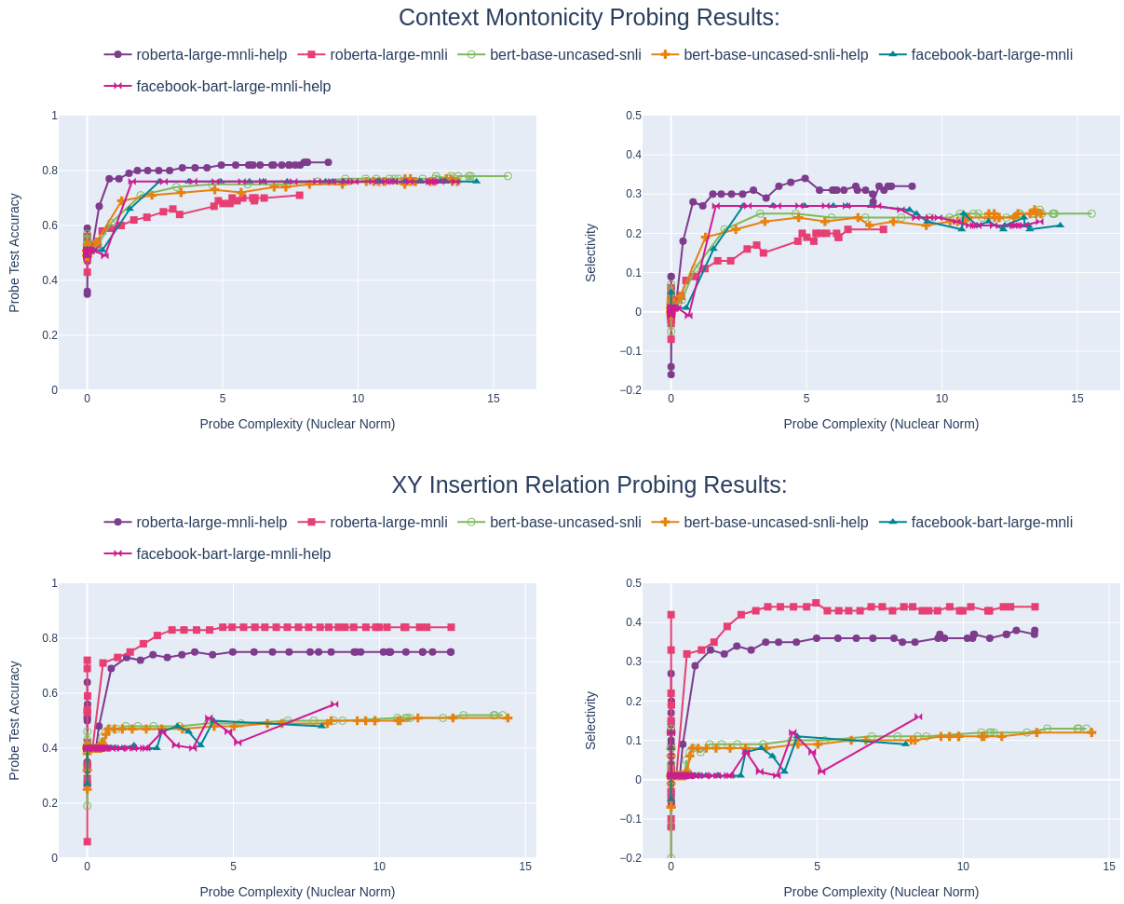


Figure 1: Probing results for all examined models.

layer of each model, as is used for the final NLI classification decision.

5.2.2 Probe Complexity Control

The complexities are represented and controlled as follows: For linear models $\hat{y} = W\mathbf{x} + \mathbf{b}$, we follow (**?**) in using the nuclear norm

$$||\mathbf{W}||_* = \sum_{i=1}^{min(|\mathcal{T}|,d)} \sigma_i(\mathbf{W}).$$

of the matrix W as the approximate measure of complexity. In cases where the auxiliary task has a relatively large number of classes, the rank has been used as the proxy measure of model complexity (Hewitt and Manning, 2019). As the nuclear norm is a convex approximation of the *rank* of the transformation matrix, it is used in (Pimentel et al., 2020), where this allows for a larger number of informative values.

5.2.3 Metrics and Control Tasks

Accuracy and Selectivity Naively, a strong accuracy on the probing test set may be understood to indicate strong presence of the target features within the learned representations, but there has been much discussion about whether this evidence is compelling on its own. In fact, certain probing experiments have found the same accuracy scores for random representations (Zhang and Bowman, 2018), indicating that high accuracy scores are meaningless in isolation. Hewitt and Liang (2019) describe this as a dichotomy between the representation's encoding of the target features and the probe's capacity for *memorization*, and propose the use of the *selectivity* measure to always place the probe accuracy in the context of a controlled probing task with shuffled labels on the same vector representations. For each fully trained probe, we report both the test accuracy and the *selectivity* measure: tracking the selectivity ensures that we are not using a probe that is complex enough to be *overly expressive* to the point of having the capacity to overfit the randomised control training set.

Control Task The *selectivity* score is calculated with respect to a *control task*. At its core, this is

		Feature Probing		NLI Monotonicity Challenge Sets		
NLI Models	Fine-Tuning Data	Context Monotonicity (%*)	XY Insertion Relation (%*)	HELP-Test (%)	MED (%)	NLI-XY (%)
roberta-large-mnli	-	71.0	84.0	36.69	46.10	59.01
roberta-large-mnli	HELP	82.0	78.0	**97.63**	**78.22**	**80.68**
roberta-large-mnli	HELP, HELP-Contexts	84.0	76.0	87.17	76.44	79.29
facebook/bart-large-mnli		76.0	48.0	43.61	46.54	60.59
facebook/bart-large-mnli	HELP	76.0	56.0	88.99	77.16	79.3417
bert-base-uncased-snli		77.0	50.0	63.55	0.4938	49.09
bert-base-uncased-snli	HELP	77.0	51.0	66.80	0.4613	44.79

Table 3: Summary NLI challenge test set and probing results for all considered models. *Probing results are summarized with the *accuracy at max selectivity*.

just a balanced random relabelling of the auxiliary data, but (Hewitt and Liang, 2019) advocate for more targeted control tasks with respect to the features in question and a hypothesis about the model's possible capacity for *memorization*. For example, in their control task for POS tagging, they assign the same label to each instance of a word's surface form ("word type") to account for possible lexical memorization. By construction, our context monotonicity classification task is much more context-dependant and balanced: a given X insertion will occur about as often in upward and downward monotone contexts, making it harder for a probe to exploit meaningless heuristics, such as associating a given word with a context monotonicity label. For the lexical relation classification control task, we assign a shared random label for all identical insertion pairs, regardless of context.

5.3 NLI Challenge Set Evaluations

As well as the NLI-XY dataset (which can function as an ordinary NLI evaluation set), for completeness we report NLI task evaluation scores on the full MED dataset (Yanaka et al., 2019a), which was designed as a thorough stress-test of monotonicity reasoning performance. Furthermore, we report scores on the HELP-test set (from the dataset split in (Rozanova et al., 2021)): this data partition was not used in the fine-tuning of models on HELP, but we include the test scores here for insight.

5.4 Qualitative Analyses

To complement the probing and NLI results, we make two additional comparisons that may qualify the observations.

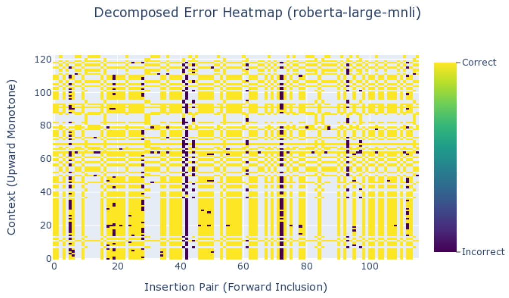
Decomposed Error Analysis The compositional structure and auxiliary labels in the NLI-XY dataset allow for extensive qualitative analysis. Firstly, we construct decomposed error analysis heatmaps which indicate whether a given premise-hypothesis data point $f(X), f(Y)$ is correctly classified by an entailment model. For brevity (and because this is representative of our observations), we include only the error breakdowns for the two sublasses of the positive entailment label: where the context monotonicity is upward and lexical relation is forward incusion, and where the context monotonicity is downward and the lexical relation is reverse inclusion.

Representation Visualization We store the classification token ([CLS]) of the model's last hidden layer and project it into a lower-dimensional space using the *umap* library (McInnes et al., 2018) with the default configuration. To qualify the context monotonicity probing results, we label the points according to the *gold* context monotonicity / concept relation labels.

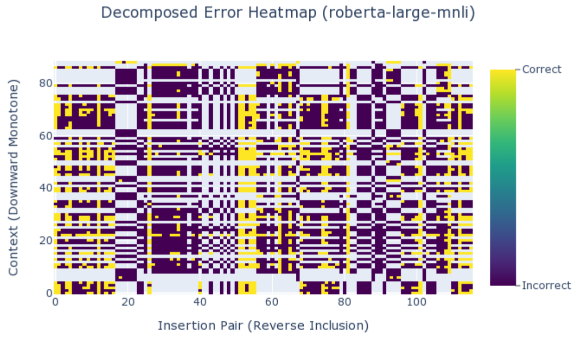
6 Results and Discussion

6.1 Probing Results

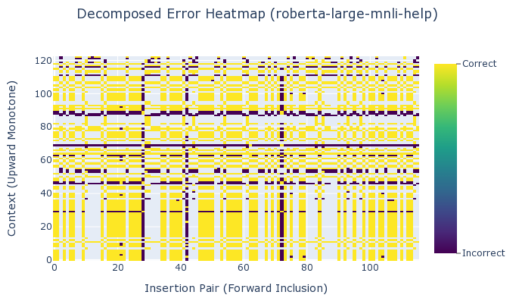
The results for the linear probing experiments for both the *context monotonicity classification* task and the *lexical relation* classification task may be found in figure 1. The results of the control tasks are taken into account as part of the selectivity measure, which is represented on the right hand plot for each experiment. It is particularly notable that large datasets trained only on the MNLI dataset have inferior performance on context monotonicity classification. This corresponds with the further qualitative studies, suggesting that even in some of



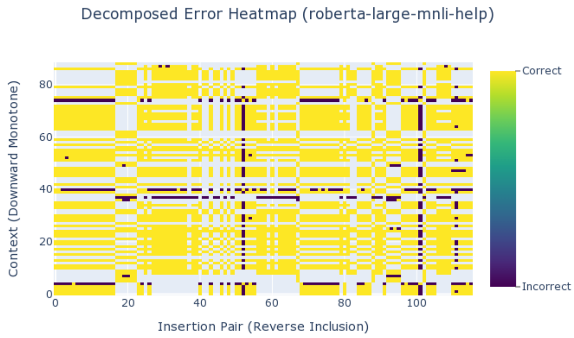
(a)



(b)



(c)



(d)

Figure 2: Decomposed error heat maps for portions of the NLI-XY dataset corresponding to the indicated context monotonicity and insertion relations (blank positions are present as only grammatical insertions were included in the dataset.)

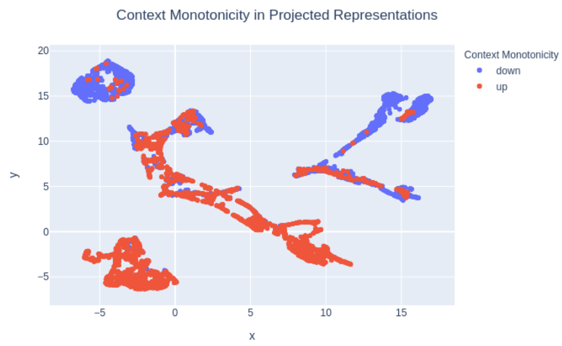
the most successful transformer-based NLI models, *there is a poor "understanding" of the logical regularities of contexts and how these are altered with downward monotone operators.*

6.2 Comparison to Challenge Set Performance

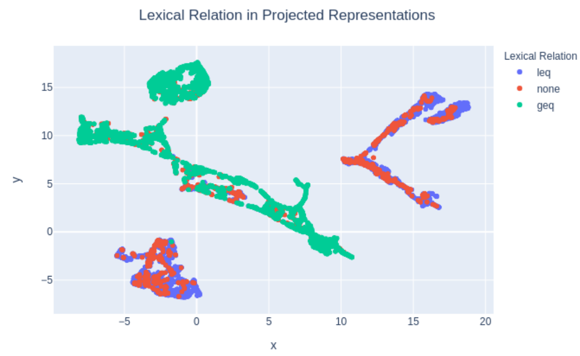
Evaluation on the challenge test sets is relatively consistent with monotonicity probing performance, in the sense that there is a correspondence between poor/successful modeling of monotonicity features and poor/successful performance on a targeted natural logic test set. As these challenge sets are focused on testing monotonicity reasoning, this is a result which strongly bolsters the suggestion that explicit representation of the context monotonicity feature is crucial, especially for examples involving negation and other downward monotone operators. Furthermore, we generally confirm previous results that additional fine-tuning on the HELP data set has been helpful for these specialized test sets, and add to this that it similarly improves the explicit extractability of relevant context montonicity features from the latent vector representations.

6.3 Qualitative Analyses

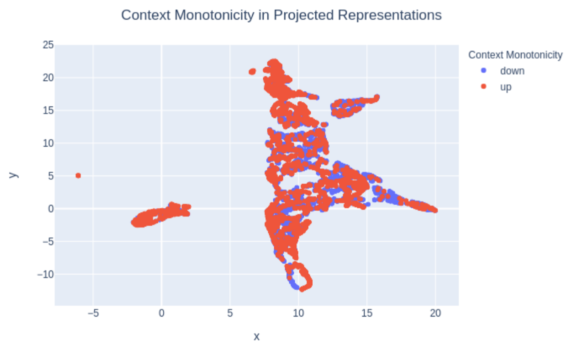
Error Break-Downs We are less concerned with the accuracy score (on NLI challenge sets) of a given model as with the behavioural *systematicity* visible in the errors, as we are not interested in noisy errors which may be due to words or phrases from outside the training domain. Consistent mis-classification for all examples derived from a fixed context or insertion pair are actually *also* strongly suggestive of a regularity in reasoning. The decomposed error analyses paint a striking picture: we generally see that models trained on MNLI routinely fail to distinguish between the expected behaviour of upward and downward monotone contexts, despite generally achieving high accuracies on large benchmark sets. This is in accordance with observations in Yanaka et al. (2019b) Yanaka et al. (2019a), where low accuracy on the downward-monotone reasoning sections of challenge sets points to this possibility. Howver, they show consistently show strong behavioural regular-



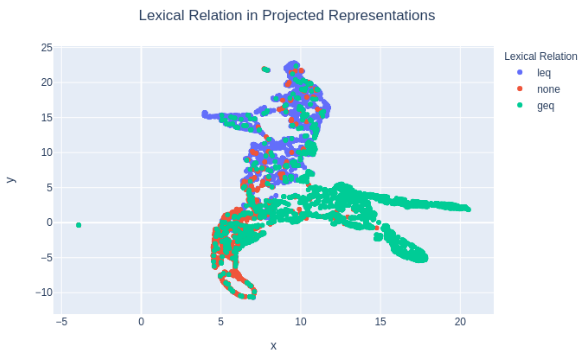
(a) `roberta-large-mnli-help`



(b) `roberta-large-mnli-help`



(c) `roberta-large-mnli`



(d) `roberta-large-mnli`

Figure 3: UMAP projections of selected classification token representations comparing `roberta-large-mnli` and the improved `roberta-large-mnli-help`, which shows greater distinction between context monotonicity features.

ity with respect to concept inclusion. Even when the contexts are downward monotone, they still treat them systematically as if they were *upward* monotone, echoing the concept insertion pair relation *only*: they completely fail to discriminate between upward/downward monotone contexts and their opposite behaviours.

Visualization Each data point corresponds to an embedded example ([CLS]) in the NLI-XY dataset, with the left and right columns colored with the *gold* auxiliary labels for context monotonicity and concept inclusion relations respectively. These illustrate the probing observations: in the well-known `roberta-large-mnli` model, concept inclusion relation features are distinguishable, whereas context monotonicity is very randomly scattered, with no emergent clustering. However, the `roberta-large-mnli-help` model shows an improvement in this behaviour, demonstrating a stronger context monotonicity distinction.

7 Conclusion

In summary, the NLI-XY has enabled us to present evidence that explicit context monotonicity feature clustering in neural model representations seems to correspond to better performance on natural logic challenge sets which test downward-monotone reasoning. In particular, many popular models trained on MNLI seem to lack this behaviour, accounting for previous observations that they systematically fail in downward-monotone contexts.

Furthermore, the probes' labels also have some explanatory value: both entailment and non-entailment labels can each further be broken down into sub-regions. This qualifies the classification with the observations that the data point occurs in a cluster of examples with a) upward (resp. downward) contexts and b) a forward (resp. backward) containment relation between the substituted noun phrases. In this sense, the analyses in this work can thus be interpreted as an explainable "decomposition" of the treatment natural logic examples in neural models.

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