Old BERT, New Tricks: Artificial Language Learning for Pre-Trained Language Models

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Abstract

We extend the artificial language learning experimental paradigm from psycholinguistics and apply it to pre-trained language models – specifically, BERT (Devlin et al., 2019). We treat a pretrained model as a subject in an artificial language learning experimental setting: in order to learn the relation between two linguistic properties A and B, we introduce a set of new, non-existent, linguistic items, give the model information about their variation along property A, then measure to what extent the model learns property B for these items as a result of training. We show this method at work for degree modifiers (expressions like *slightly*, *very*, *rather*, *extremely*) and test the hypothesis that the degree expressed by the modifier (low, medium or high degree) is related to its sensitivity to sentence polarity (whether it shows preference for affirmative or negative sentences or neither). Our experimental results are compatible with existing linguistic observations that relate degree semantics to polarity-sensitivity, including the main one: low degree semantics leads to positive polarity sensitivity (that is, to preference towards affirmative contexts).

1 Introduction

One over-arching goal of linguistics is to describe and explain the limits of linguistic variation. What is impossible in natural language and why? Linguistic expressions can be characterized along a large set of properties: what they mean, what parts they consist of, how they combine with other expressions and so on. Delineating the space of possible natural languages amounts to uncovering non-trivial relations between these properties that constrain this space. Observations about these relations can come in the form of categorical implicational linguistic universals, for example, Greenberg's **Universal 37**: *A language never has more gender categories in nonsingular numbers than in the singular.* (Greenberg, 1963). Here, two properties of linguistic expressions are related: the grammatical number of an expression and how many gender distinctions are available for this expression. More complex generalizations may concern correlation between two continuous properties A and B.

Moving from observation towards explanation, one might also question the direction of this relation: does the extent of A affect the extent of B, or vice versa, or are they both affected by some other unobserved factor?

Interactions between linguistic properties can be studied (and potentially, found) on different scales: in one language, in a subset of natural languages, or universally.

In this paper, we study one particular linguistic generalization: the problem of polarity-sensitivity of degree modifiers (Israel, 1996, 2011; Solt, 2018; Solt and Wilson, 2021). Degree modifiers are words like *slightly*, *very*, and *extremely*. Property A, in this case, is the **degree** that these words convey, defined on a interval from very low to very high. For example, the degree of *slightly* is lower than the one of *very*. Property B here encodes distributional preferences of degree modifiers with respect to **polarity** of a sentence where they appear – roughly, whether they prefer to appear in negative or affirmative sentences, or show no polarity preference. Polarity preferences can also be represented as a continuous property from very low (negative polarity preference) to very high (positive polarity preference), with polarity-neutral in the middle.

Our study will focus on English, as represented in a pre-trained language model (LM), BERT (Devlin et al., 2019).

Interactions between linguistic properties have been subject to experimental studies. One prominent experimental method is artificial language learning, a framework actively used in psycholinguistics and cognitive science (Friederici et al., 2002; Motamedi et al., 2019; Kanwal et al., 2017; Culbertson et al., 2012; Ettlinger et al., 2014; Finley and Badecker, 2009). It has the following main

ingredients: (1) a fragment of an artificial language in the form of expressions that do not belong to the language that participants are speakers of; (2) training phase, where some information about the language fragment is given to the participants; (3) testing phase, where it is checked what other knowledge, beside the provided, was inferred during training. The main challenge for this method is that one only has limited access to the processes in the brain that underlie artificial language acquisition and use (although see Friederici et al. 2002). In particular, it is hard to control for the role of the participants' native language in the experiment. Another approach is artificial language learning using (artificial) neural networks (Piantadosi et al., 2012; Carcassi et al., 2019; van de Pol et al., 2021). Replacing human participants with neural networks as learning agents allows to examine the learning process in more detail, and to control for the learner's native language substrate, since the agent comes in a blank state with no prior knowledge. However, while this approach can make particular types of learnability statements, it raises questions about the extent to which its conclusions apply to natural language at all.

We propose a methodology that is middle ground between these two paradigms. It also involves an artificial language fragment and training to introduce knowledge about some property A, but it uses a *pre-trained* LM (Peters et al., 2018; Devlin et al., 2019; Brown et al., 2020) as the learning subject. More technically, we extend a pre-trained LM with a set of new tokens with randomly initialized embeddings and perform fine-tuning on a carefully constructed synthetic dataset. The dataset is constructed in a way to indirectly introduce different values along property A for different new tokens. Upon fine-tuning, we measure how the training affected property B and how variation along B depends on the values of property A introduced during training.

Our proposed approach combines the benefits of the two other approaches described above. First, learning happens on top of already existing linguistic knowledge, which makes these experiments more directly parallel to those with human participants. Second, like in other approaches involving computational modelling, the learning process is more directly controllable and explorable. Additionally, the factor of pre-existing linguistic knowledge can be more easily controlled for, compared to human experiments. Finally, our approach is scalable to a wide variety of languages, provided there is a LM of sufficient quality.

The idea of using counterfactual linguistic data is not new (Kaushik et al. 2020, 2021; Thrush et al. 2020 a.o.), but in this paper we do not use it for the purpose of bias mitigation or model evaluation. Our work contributes to the general agenda of establishing closer connections between learning in humans and artificial neural models (Futrell et al. 2019; Wilcox et al. 2020 a.o.).

We make the following contributions: we propose a new experimental methodology based on the artificial language learning paradigm; we use this methodology to explore the relation between two linguistic phenomena, degree and polarity-sensitivity, as represented in one pre-trained LM (BERT). We argue that, according to the experimental results, there is indeed a direct connection between the degree encoded by a degree modifier and its polarity-sensitivity.

The paper is structured as follows: Section 2 gives linguistic background about degrees and polarity. Section 3 describes the general method. In Section 4, we define a synthetic dataset and the measures we use to estimate degree and polarity. Section 5 presents the experiment. Section 6 discusses our results, the limitations of our set-up and suggestions for future work.

2 Background: Degree and polarity

In this section we provide background on the studied linguistic properties: we describe *degree* as a property of degree modifiers, and *polarity-sensitivity* as a property of linguistic items (words) that tend to appear in certain types of contexts. We outline the relation between these two properties, as discussed in theoretical linguistic literature. We will apply our proposed method to experimentally verify the hypothesised relation.

Degree

So-called gradable adjectives describe properties that can hold to a different degree. A classic example of a gradable adjective is *tall*. A classic example of a non-gradable one is *prime*. The former, as opposed to the latter, can be part of comparative and superlative constructions, and they can combine with **degree modifiers**: words like *slightly*, *very*, and *extremely*. Examples (1)-(2) illustrate this difference. We use * to denote all types of linguistic

deviancy, including ungrammaticality as well as semantic / pragmatic oddity:

(1) *7 is more prime than 3.
*13 is the most prime number in this set.
*1 is **somewhat / very / extremely** prime.

(2) Mary is taller than John.
Mary is the tallest person in this room.
Mary is **somewhat / very / extremely** tall.

For a statement with a simple base form of a gradable adjective – like *Mary is tall* – to be true, the property in question has to hold of the subject to some degree δ that is determined by linguistic and extra-linguistic contextual factors (Fara, 2000; Kennedy and McNally, 2005; Kennedy, 2007). When a gradable adjective appears in combination with a degree modifier, the degree δ that makes the statement true changes to a value that depends on the modifier. For Mary to count as 'somewhat tall', her height needs to be much lower than for 'extremely tall', for instance. The requirements on δ that degree modifiers encode can be used to order these modifiers along a scale of degrees, for example, *somewhat* $<$ *extremely*.

Polarity-sensitivity

For certain expressions, their acceptability and/or interpretation in a context is conditioned on the polarity of this context. Expressions with distributional preference[1] for negative contexts are called negative polarity items (NPIs). Expressions with preference towards positive contexts are called positive polarity items (PPIs). For example, *any* is an NPI (3), while *already* is a PPI (4). NPIs and PPIs are said to be **polarity-sensitive**. Like degree, we treat polarity-sensitivity as a continuous property on the [0,1] interval, where 0 is a very pronounced NPI, 1 a very pronounced PPI, with polarity-neutral items in the middle.

(3) *Mary bought **any** books. NPI
Mary didn't buy **any** books.

(4) John has arrived **already**. PPI
*John hasn't arrived **already**.

Sentences that are good contexts for NPIs and PPIs are said to have negative and positive polarity, respectively. Polarity of a sentence does not amount simply to the presence or absence of sentential negation, it is a way more complex semantic property (see Fauconnier 1975; Ladusaw 1979 and subsequent literature). However, we will focus on the presence or absence of negation as a proxy to polarity in the current discussion.

Relation between the two properties

Observations reported in linguistic literature suggest an interaction between these two properties (Israel, 1996, 2011; Solt, 2018; Solt and Wilson, 2021). Specifically, lower degrees associate with PPI behaviour. Low-to-moderate degree modifiers in English support this observation (Solt and Wilson, 2021), as examples in (5) demonstrate. This pattern is supported by other languages too (van Os, 1989; Nouwen, 2013; Ito, 2015).

(5) The issue is **fairly / pretty / somewhat / rather / kind of / sort of** important.
*The issue isn't **fairly / pretty / somewhat / rather / kind of / sort of** important.

On the other hand, modifiers in the moderate-to-high range show mild association with negative contexts (Israel, 1996). The association between negative polarity and degree modifiers from a certain range comes from the phenomenon of 'negative strengthening' (Gotzner et al., 2018; Mazzarella and Gotzner, 2021):

(6) John isn't **particularly** smart.

While the literal meaning of (6) is compatible with John being smart quite often these types of sentences are used to convey a stronger meaning: that John is not smart at all. This is a pragmatic asymmetry rather than a distributional constraint, but it contributes to the interaction patterns between degree and polarity-sensitivity.

Existing work proposes analyses of degree modification with built-in causal connection between the degree semantics of modifiers and their polarity profile (Israel, 1996; Solt and Wilson, 2021) – even though the extent, exact shape and direction of this connection is not established yet. We use this state of affairs as a chance to contribute to this discussion empirically and analytically, using the method proposed below.

3 Method

In this section, we describe the details of a method to conduct artificial language learning experiments

[1] We use the vague and permissive term 'preference' here to cover the whole spectrum of asymmetries between positive and negative contexts that an expression shows – from ungrammaticality to decreased prominence of a narrow scope reading. Gradations of polarity-sensitivity will play a crucial role in our discussion, but specifically for this reason we are looking for a unified way to describe the whole space of polarity sensitivity phenomena.

with pretrained LMs. Without loss of generality, we use BERT in our experiments, but other pretrained language models could be used instead.

We design our method to be applied to linguistic hypotheses of the form $A \Rightarrow B$, where A, B are some properties in a given language. In this study, we specifically focus on the relationship between adverbial degree modification and polarity-sensitivity. A in this context is low, medium or high degree of an adverbial modifier w, and B is negative, neutral or positive polarity of w. In general, we evaluate a hypothesis $A(w, i) \Rightarrow B(w, j)$ by showing that if A holds according to BERT for token w to an extent i, then so does B to some extent j, according to BERT.

We use the cloze test (a task where the participant is asked to recover a missing language item) adapted for BERT (see Warstadt et al. 2019, `[redacted for anonymity]` for the cloze test on LMs for polarity). The test uses BERT's probability distributions over tokens in masked positions in diagnostic contexts for property A or B.

To show that a hypothesis holds in general for an arbitatrary w, we:

(1) augment BERT's vocabulary with a set W of new tokens and randomly initialize the corresponding embeddings;

(2) fine-tune the corresponding embeddings on a dataset where the new tokens appear in contexts that distributionally select for particular values of A;

(3) test whether the knowledge that B holds was acquired, to the extent that follows the hypothesised association pattern with A.

As part of Step (1), we also verify that prior to training the initialized embeddings don't show any biases w.r.t. both properties A and B. This approach presupposes a set of contexts that distributionally select for a specific linguistic property X, denoted $\mathcal{S}(X)$. We describe a method to mine such contexts for the specific linguistic properties of our case study in Section 4.3. Part of future work is extending it to a more general case. The general structure of the synthetic dataset is described in Section 4.1. It is also tailored to the linguistic phenomenon under investigation.

4 Dataset and measures

First, we delineate a fragment of English that will be the basis of our experiment (Section 4.1): simple sentences with a gradable adjective predicated over a definite noun phrase (as in *The pizza is good*). We re-shape these sentences to create diagnostic contexts for properties A and B (Sections 4.2, 4.3). We also use it to exemplify values of A during training (Section 4.3).

4.1 Basic set of sentences

First, we automatically identified the set of gradable adjectives and nouns to build our training samples from. We started with `bert-base-uncased`[2] vocabulary and assigned all non-subword tokens a part of speech label with the SpaCy POS tagger[3]. We kept the top 1000 nouns. Using the CapitolWords dataset from `textacy`[4], we looked for co-occurrences of adjectives with degree modifiers *somewhat*, *very*, *really*, *extremely*, *rather* and picked 200 adjectives with the highest ratio of modified uses.

Second, we generated sentences with these nouns and adjectives using the following pattern:

$$\text{The } \texttt{noun}_x \texttt{ cop.PRS adj}_y$$

where `cop.PRS` is either singular or plural copula in the Present tense (*is* or *are*), $\texttt{noun}_x$ is one of the 1000 picked nouns, and $\texttt{adj}_y$ is one of the 200 gradable adjectives. The procedure gave us 400k sentences like these:

(7) The purpose is interesting.
The answer is simple.
The environment is large.

This 400k set varied in terms of naturalness, coherence and adherence to lexical selectional restrictions. To control for this, we ran the sentences through `GPT-2`[5] and kept the bottom 10k according to the assigned sentence perplexity.

The construction steps above aim to output 'natural' examples, based on insights from different sources (GPT-2, BERT, corpus-based statistics). Manual inspection of the resulting 10k dataset revealed some sentences that still sound intuitively 'weird'. We do not see this as a problem though, since the majority of sentences are natural enough.

The large quantity of examples in our dataset is crucial to make our experiments comparable to

[2] https://huggingface.co/bert-base-uncased
[3] https://github.com/explosion/spacy-models
[4] https://github.com/bdewilde/textacy-data
[5] https://huggingface.co/gpt2

psycholinguistic experiments. In the latter, one sentence gives rise to a multiple of observations about (roughly) one linguistic system, due to judgements to multiple participants with similar enough intuitions. In our setting, we have only one agent (BERT), so we compensate by increasing the number of sentences.

4.2 Estimating polarity

To assign polarity scores to degree modifiers, we follow the procedure in (Warstadt et al. 2019, `[redacted for anonymity]`). We use the 10k basic sentences (Section 4.1) to build a polarity contrast set. For each sentence in the basic set, a pair of sentences, one positive and one negative, with the `[MASK]` token in the modifier position:

The $\texttt{noun}_x$ `cop.PRS [MASK]` $\texttt{adj}_y$.
The $\texttt{noun}_x$ `cop.PRS.NEG [MASK]` $\texttt{adj}_y$.

We end up with 10k pairs of sentences like these:

(8) `The reason is [MASK] simple.`
`The reason isn't [MASK] simple.`

We use the generated sentence set to estimate polarity-sensitivity *pol(m)* of a degree modifier *m* using the probabilities that BERT assigns to each token in its vocabulary in the masked position:

$$\frac{\sum_{s \in D}[p(\textit{[MASK]} = m | s^{mskd}_{\text{AFF}}) > p(\textit{[MASK]} = m | s^{mskd}_{\text{NEG}})]}{|D|} \quad (1)$$

where D is the 10k dataset, s^{masked}_{pos} is a sentence s from the dataset in the positive form, with *[MASK]* in the degree modifier position, and s^{masked}_{neg} is its negative counterpart. So, we approximate polarity as the proportion of cases where token m got a higher probability in *pos* than in *neg* context.

Previous applications of this estimation method has shown its reliability for NPI detection (Jumelet and Hupkes 2018; Warstadt et al. 2019; Jumelet et al. 2021;`[redacted for anonymity]`). As an illustration, *slightly* gets a score of 0.99 (= is a PPI), *particularly* gets a score of 0.1 (is an NPI), while *incredibly* is a PPI again with score 0.94.

We use this polarity estimation method to get a reliable list of degree modifiers with polarity scores. For each of the 10k sentence pairs, we pick 100 tokens with highest probability in the masked position for a positive sentence and 100 tokens for its negative counterpart. Then we take two unions: one of all the "positive" tokens and one for the "negative" ones. We filter these two sets to only keep tokens that appear more than 100 times in one of them.[6] We use the resulting sets in the rest of the experiment.

4.3 Estimating and mining degree

To estimate polarity of tokens (Section 4.2), we relied on their patterns of occurrence in positive and negative contexts. To apply an analogous procedure to degree, we need contexts that associate with various degree semantics. We propose the following intuition. What does an answer to a yes/no-question with a gradable adjective – like *Is the pizza good?* – depend on? It certainly depends on how good the pizza is: the degree to which the property applies to the subject. Given that degree modifiers express exactly that, we can make a connection between their degree value and particles that answer the degree yes/no question.

For example, we expect particles to have different distribution in the masked position in (9) as an *effect* of the modifier:

(9) – Is the pizza good?
– [MASK], it is **somewhat** good.
– [MASK], it is **extremely** good.

We use this idea to mine particles that are associated with low and high degree. The mined particles can be used to assess degree of the modifiers, analogously to polarity measurement above. As low degree modifiers, we use *somewhat* and *slightly*; for high degree, *very* and *extremely*. We modify each of the 10k sentences to generate pairs of sentences like these, where MOD is one of the four modifiers of interest:

(10) `Is the question difficult?`
`[MASK], it is MOD difficult.`

As before, we run the resulting (40k) sentences through BERT and, for each sentence, we collect the top 100 tokens according to the probability of tokens in the masked position. We only keep those tokens that appear in this list 100 times or more. The particles in the resulting list are then tested their degree-diagnosing potential, as follows.

We use the same procedure as for polarity: for each particle, we check in what proportion of cases the probability that BERT assigns to the particle in the sentence with the high degree modifier is higher than with a low degree modifier. We perform this comparison for each of the four pairs of high vs. low degree modifiers: *very* vs. *somewhat*, *very*

[6] Among the tokens that survived the filter: *very*, *always*, *quite*, *so*, *really*, *too*, *all*, *actually*.

vs. *slightly*, *extremely* vs. *somewhat*, *extremely* vs. *slightly*. This procedure gives us a value from 0 to 1 for each particle from the list, depending on the extent to which it is associated with low degrees (the closer to 0, the more this holds) or high degrees (closer to 1). We fix the final set of top 10 particles that associate with **low** (11) degrees and with **high** degrees (12):

(11) `well, actually, now, but, however, still, so, why, anyway, sure`

(12) `yes, oh, sir, absolutely, god, damn, remember, wow, seriously, man`

Finally, we reverse the process and now use these particles to produce a degree score for degree modifiers. For each of the 10k sentences, we modify it to get 20 sentences like the following (where PRT ranges over the 20 particles in (11) and (12)):

(13) `Is the question difficult? PRT, it is [MASK] difficult.`

Comparing modifier probabilities across conditions defined by the distinction in (11) and (12) as before, we get a measure defined on the [0,1] interval that corresponds to the modifier's degree.

As a final step, we manually cleaned the resulting list of 415 tokens obtained from the `[MASK]` to get rid of syntactic junk and items whose selectional restrictions are too narrow, to end up with the list of 98 degree modifiers we will further use[7].

To validate our degree measure, we take five modifiers about which the literature agrees they introduce low or moderate degree (*barely*, *hardly*, *rather*, *fairly*, *merely*); same for high degree (*completely*, *totally*, *utterly*, *damn*, *bloody*) (Paradis (1997); Bennett and Goodman (2018) a.o.). There's no overlap with modifiers we used as seeds for our degree measure. Also, these are practically **all** modifiers with an undisputed degree profile discussed in the literature that are also whole BERT tokens. Our measure assigns the low degree class an average score of 0.22 (min 0.11; max 0.31); average of 0.56 for the high degree class (min 0.5; max 0.62). *Very*, which has some intensifying effect got a score of 0.45. We conclude that the measure is decent, albeit somewhat shifted to the left.

Fig. 1 shows the distribution of polarity-sensitivity and degree for these modifiers (we color-code them as moderate, medium and high degree). As the scatterplot and the fitted parabola show, the existing data is compatible with what is hypothesised in the linguistic literature: low degrees associate with positive polarity, while the rest is more varied – mid-range degrees gravitate towards more negative polarity somewhat, while the higher range again gravitates towards PPI behaviour.

[7]Code and data are at https://github.com/nlpsubmissions/artificial_language_learning_for_modifiers (anonymous).

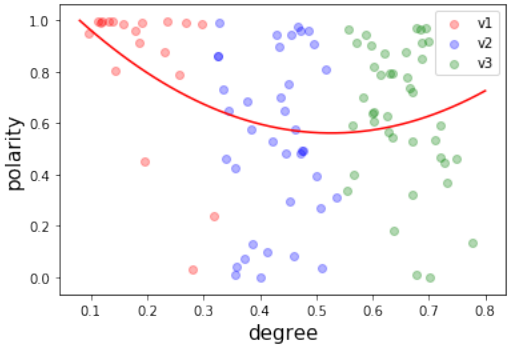

Figure 1: Degree and polarity of existing modifiers.

4.4 Degree and polarity in BERT embeddings

We use diagnostic classifiers to analyse how polarity-sensitivity and degree semantics are represented in BERT token embeddings for degree modifiers. Using embeddings of degree modifiers as features, we fit logistic regression with L1 regularization to demote non-zero coefficients for two binary classification tasks: 1) token classification into 'negative' ($< .5$) and 'positive' ($> .5$) with respect to polarity; 2) token classification into 'low degree ($< .4$, based on somewhat skewed score distribution) and 'high degree' ($> .4$).

On 5 folds, average accuracy for polarity on train data is 79.2%, and 74.7% on test. For degree, it's 73% and 72.3%, respectively. For each of the tasks, we find the most important part of the embedding that is responsible for the distinction, by taking coordinates that have non-zero coefficients in at least four of the folds. We found 20 important coordinates for polarity and 13 for degree. There was no overlap between these coordinates, indicating no representational overlap between polarity and degree at the level of token embeddings. If it turns out that the model encodes the dependency between the two properties, it would be on a level other than embeddings directly.

5 Experiment

This section describes how we teach BERT a new system of degree modifiers by only giving it information about their degree. Section 5.1 describes how we introduced new tokens into BERT's vocabulary and mined particles that signal the properties

we wish to teach BERT. Section 5.2 provides the details of the fine-tuning procedure and the experimental results.

5.1 Mining contexts for new degree modifiers

We partition the existing degree modifiers into three same-sized groups, based on the degree scale region they belong to: moderate, medium, high (or, v1, v2 and v3, respectively). This is shown as three vertical regions in Fig. 1. We use the identified groups to instantiate three classes of new degree modifiers. For each of the groups, we mine degree-region-specific particles, using the procedure described in Section 4.3. The resulting sets of particles are:

v1: `alternatively, myself, similarly, accordingly, otherwise, however, alternately, likewise, conversely, er, although, thus, nevertheless, nonetheless, still, hence`

v2: `yes, once, naturally, evidently, eventually, not, surely, nowadays, however, someday, fortunately, here, presumably, ideally, accordingly, hopefully`

v3: `god, gods, goddess, dammit, christ, goddamn, jesus, fucking, holy, kate, damn, skyla, lord, princess, love, daddy`

For each of the three groups, we instantiate 33 new modifiers. Then, for each sentence in the 10K set, we generate a v1 sentence, a v2 and a v3. The sentences are of the same question-answer form as in Section 4, and in each of them we insert a randomly picked particle corresponding to the degree class of the modifier (n = number id):

(14)
```
Is the reason simple?  [prt_v1],
it is [mod_v1_n] simple.
Is the reason simple?  [prt_v2],
it is [mod_v2_n] simple.
Is the reason simple?  [prt_v3],
it is [mod_v3_n] simple.
```

5.2 Fine-tuning BERT to new tokens

We split the dataset into training and validation parts with 0.85:0.15 ratio. Then we randomly mask 15% of tokens in the resulting dataset and fine-tune BERT for the task of masked token prediction. We use the same type of pretrained BERT model as in the previous steps. We use the Adam optimization algorithm with decoupled weight decay regularization (Kingma and Ba, 2014; Loshchilov and Hutter, 2017) and learning rate of `5e-5`. We use the batch size of 32 and fine-tune the model for three epochs.

	Before training		After training	
	degree	polarity	degree	polarity
v1	0.48, 0.06	0.42, 0.24	0.18, 0.02	0.99, 0.03
v2	0.50, 0.06	0.43, 0.21	0.40, 0.02	0.00, 0.00
v3	0.48, 0.06	0.39, 0.18	0.83, 0.02	0.85, 0.26
Baselines				
random	0.52, 0.06	0.38, 0.20	0.41, 0.09	0.83, 0.30
untrained	0.50, 0.06	0.39, 0.20	0.42, 0.08	0.00, 0.00

Table 1: Estimates of polarity and degree of new tokens before and after training. Each pair of numbers represents a mean and a standard deviation. v1, v2, v3 represent polarity and degree statistics for the new modifiers (low, medium, high) from our main experiment.

For the training, we freeze all weights except for the very first layer of token embeddings.[8]

We compare our method against two baselines:

- **random baseline:** 99 randomly initialized tokens are trained in contexts with particles randomly chosen from any of the three sets (v1, v2 and v3);
- **untrained baseline:** 99 new tokens to be randomly initialized before the training phase, but not fine-tuned.

Upon training, the three groups of tokens form three clusters, as shown in Fig. 2. Tokens that belong to groups v1 and v3 cluster in the PPI region, medium-degree tokens (v2) show NPI-like behaviour. This is generally in line with observations described in Sections 2 and 4. The two baselines (Figure 3), as expected, don't show pronounced degree profiles – but develop non-random polarity behaviour. The random baseline gravitates towards positive polarity, while the untrained baseline shows NPI behaviour. Means and standard deviations for degree and polarity before and after training are listed in Table 1.

6 Discussion and future work

6.1 Interpretation of the experimental results

We saw that the training organized the new tokens into three clusters. First, we observe that the tokens develop low, medium or high degree behaviour, as intended by dataset construction. This means that our procedure conveyed degree information to the model. Furthermore, polarity scores upon training show that the three groups generally follow

[8] This decision is based on the intuition that learning new words in an artificial language learning setting shouldn't lead to deep changes in prior linguistic knowledge of a native language for a realistic learner.

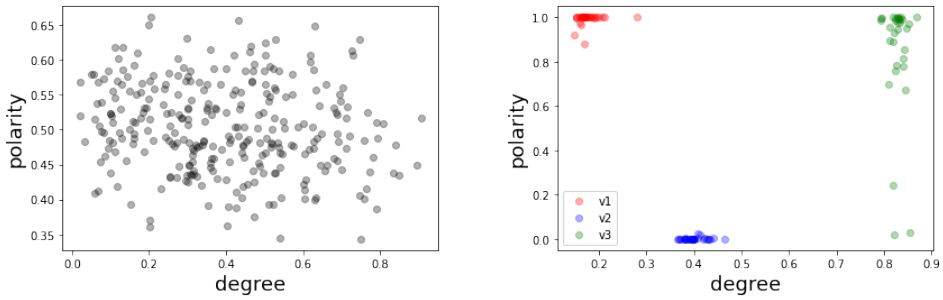

Figure 2: Target new tokens before (left) and after fine-tuning (right).

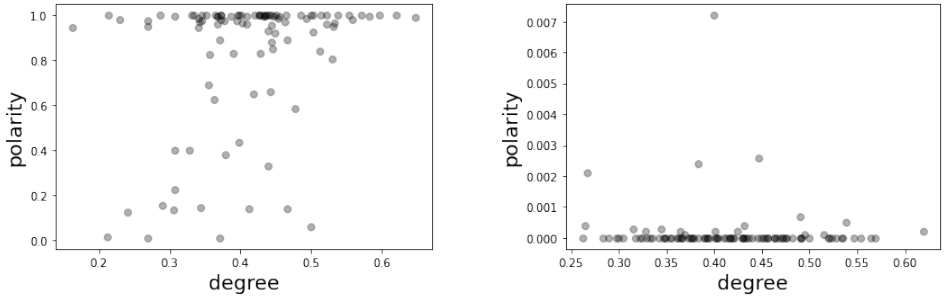

Figure 3: Baselines: contexts randomly mixed during training (left) and untrained tokens (right)

the hypothesis from Section 2 and analysis from Section 4.3: low and high degrees lead to PPI behaviour, while medium degrees are associated with negative polarity.

What is somewhat surprising though is how strong the association with negative polarity is for medium degrees. Here, looking at our baselines might provide a hint towards an explanation. The random baseline develops PPI behaviour: this is not particularly surprising given that a random pool of degree contexts is bound to contain a majority of PPI-associated low and high degree diagnostic particles. So, the model has prevailing evidence to treat random baseline items as PPIs. Untrained baseline is more interesting in this respect: new tokens that did not appear in the training dataset at all develop NPI behaviour. We do not know what leads to this, but, at the level of observation, a general shift in the direction of lower polarity scores for the whole lexicon might be some artefact of our training procedure. If this is true, the very low polarity scores that we see for some items should be interpreted as actually corresponding to somewhat higher scores. We leave exploration of this effect to future work.

6.2 Limitations and future work

Summing up Sections 5.2 and 6.1, our results are compatible with existing linguistic observations concerning the relation between degree and polarity. However, the biggest question to our approach is how much we can trust the obtained results in making conclusions about natural language. We could gain insight on this question by reproducing the experiment with human participants. The experiment with artificial LMs could serve as a preliminary step to polish the underlying hypothesis and the setup for the human experiment. We leave to future work as well.

Another question is whether there is a reliable way to introduce property A without leaking information about property B in the training data. Admittedly, the simple procedure we follow does not take specific precautions to convincingly show this did not happen. We hope that the version of the experiment that we present here will serve as a starting point for future work developing methods to address this question or recycling existing tools from other types of experiments.

7 Conclusions

We introduced a methodology to assess linguistic hypotheses using statistical and computational modeling methods (specifically, pretrained LMs). We applied it to a problem in linguistic semantics: relation between degree and polarity-sensitivity. We found that the experimental results are in line with the generalizations from the linguistic literature, indicating validity of our approach. We hope that this set-up can be applied to other types of models (trained on languages other than English, or multilingual) and other linguistic generalizations, both within individual languages and cross-linguistically (Greenberg, 1963; Corbett, 2010).

References

Erin D Bennett and Noah D Goodman. 2018. Extremely costly intensifiers are stronger than quite costly ones. *Cognition*, 178:147–161.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.

Fausto Carcassi, Shane Steinert-Threlkeld, and Jakub Szymanik. 2019. The emergence of monotone quantifiers via iterated learning. In *Proceedings of the 41st Annual Meeting of the Cognitive Science Society*.

Greville G. Corbett. 2010. *Implicational Hierarchies*. Oxford University Press.

Jennifer Culbertson, Paul Smolensky, and Géraldine Legendre. 2012. Learning biases predict a word order universal. *Cognition*, 122(3):306–329.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *NAACL-HLT*.

Marc Ettlinger, Ann R Bradlow, and Patrick CM Wong. 2014. Variability in the learning of complex morphophonology. *Applied psycholinguistics*, 35(4):807–831.

Delia Fara. 2000. Shifting sands: An interest-relative theory of vagueness. *Philosophical topics*, 28(1):45–81.

Gilles Fauconnier. 1975. Polarity and the scale principle. In *Proceedings of Chicago Linguistc Society 11*, pages 188–99.

Sara Finley and William Badecker. 2009. Artificial language learning and feature-based generalization. *Journal of Memory and Language*, 61(3):423–437.

Angela D Friederici, Karsten Steinhauer, and Erdmut Pfeifer. 2002. Brain signatures of artificial language processing: Evidence challenging the critical period hypothesis. *Proceedings of the National Academy of Sciences*, 99(1):529–534.

Richard Futrell, Ethan Wilcox, Takashi Morita, Peng Qian, Miguel Ballesteros, and Roger Levy. 2019. Neural language models as psycholinguistic subjects: Representations of syntactic state. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 32–42, Minneapolis, Minnesota. Association for Computational Linguistics.

Nicole Gotzner, Stephanie Solt, and Anton Benz. 2018. Scalar diversity, negative strengthening, and adjectival semantics. *Frontiers in Psychology*, 9:1659.

Joseph H Greenberg. 1963. Some universals of grammar with particular reference to the order of meaningful elements. *Universals of language*, 2:73–113.

Michael Israel. 1996. Polarity sensitivity as lexical semantics. *Linguistics and Philosophy*, 19(6):619–666.

Michael Israel. 2011. *The grammar of polarity: Pragmatics, sensitivity, and the logic of scales*, volume 127. Cambridge University Press.

Satoshi Ito. 2015. *Bias and Prosody in Japanese Negative Polar Questions*. Ph.D. thesis, Cornell University.

Jaap Jumelet, Milica Denic, Jakub Szymanik, Dieuwke Hupkes, and Shane Steinert-Threlkeld. 2021. Language models use monotonicity to assess NPI licensing. *CoRR*, abs/2105.13818.

Jaap Jumelet and Dieuwke Hupkes. 2018. Do language models understand anything? on the ability of lstms to understand negative polarity items. In *BlackboxNLP@ EMNLP*.

Jasmeen Kanwal, Kenny Smith, Jennifer Culbertson, and Simon Kirby. 2017. Zipf's law of abbreviation and the principle of least effort: Language users optimise a miniature lexicon for efficient communication. *Cognition*, 165:45–52.

Divyansh Kaushik, Eduard Hovy, and Zachary Lipton. 2020. Learning the difference that makes a difference with counterfactually-augmented data. In *International Conference on Learning Representations*.

Divyansh Kaushik, Amrith Setlur, Eduard Hovy, and Zachary C. Lipton. 2021. Explaining the efficacy of counterfactually augmented data.

Christopher Kennedy. 2007. Vagueness and grammar: The semantics of relative and absolute gradable adjectives. *Linguistics and philosophy*, 30(1):1–45.

Christopher Kennedy and Louise McNally. 2005. Scale structure, degree modification, and the semantics of gradable predicates. *Language*, pages 345–381.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

William A Ladusaw. 1979. *Polarity sensitivity as inherent scope relations*. Ph.D. thesis, Austin, TX: University of Texas at Austin.

Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*.

Diana Mazzarella and Nicole Gotzner. 2021. The polarity asymmetry of negative strengthening: dissociating adjectival polarity from facethreatening potential. *Glossa: a journal of general linguistics*, 6(1).

Yasamin Motamedi, Marieke Schouwstra, Kenny Smith, Jennifer Culbertson, and Simon Kirby. 2019. Evolving artificial sign languages in the lab: From improvised gesture to systematic sign. *Cognition*, 192:103964.

Rick Nouwen. 2013. Best nogal aardige middenmoters: de semantiek van graadadverbia van het middenbereik. *Nederlandse Taalkunde*, 18(2):204–214.

Carita Paradis. 1997. *Degree modifiers of adjectives in spoken British English*. Lund University Press.

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In *Proc. of NAACL*.

Steven T Piantadosi, Joshua B Tenenbaum, and Noah D Goodman. 2012. Bootstrapping in a language of thought: A formal model of numerical concept learning. *Cognition*, 123(2):199–217.

S. Solt and E.C. Wilson. 2021. M-modifiers, attenuation and polarity sensitivity. In *Proceedings of Sinn und Bedeutung*, volume 25.

Stephanie Solt. 2018. Not much: On the variable polarity sesitivity of 'much' words cross-linguistically. In *Proceedings of Sinn und Bedeutung*, volume 23.

Tristan Thrush, Ethan Wilcox, and Roger Levy. 2020. Investigating novel verb learning in bert: Selectional preference classes and alternation-based syntactic generalization. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 265–275.

Iris van de Pol, Paul Lodder, Leendert van Maanen, Shane Steinert-Threlkeld, and Jakub Szymanik. 2021. Quantifiers satisfying semantic universals are simpler. In *Proceedings of the 43rd Annual Meeting of the Cognitive Science Society*.

Charles van Os. 1989. *Aspekte der Intensivierung im Deutschen*, volume 37. Narr Tübingen.

Alex Warstadt, Yu Cao, Ioana Grosu, Wei Peng, Hagen Blix, Yining Nie, Anna Alsop, Shikha Bordia, Haokun Liu, Alicia Parrish, et al. 2019. Investigating bert's knowledge of language: Five analysis methods with npis. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2877–2887.

Ethan Wilcox, Peng Qian, Richard Futrell, Ryosuke Kohita, Roger Levy, and Miguel Ballesteros. 2020. Structural supervision improves few-shot learning and syntactic generalization in neural language models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4640–4652, Online. Association for Computational Linguistics.