Can BERT Reason? Logically Equivalent Probes for Evaluating the Inference Capabilities of Language Models

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Abstract

Pre-trained language models (PTLM) have greatly improved performance on commonsense inference benchmarks, however, it remains unclear whether they share a human's ability to consistently make correct inferences under perturbations. Prior studies of PTLMs have found inference deficits, but have failed to provide a systematic means of understanding whether these deficits are due to low inference abilities or poor inference robustness. In this work, we address this gap by developing a procedure that allows for the systematized probing of both PTLMs' inference abilities and robustness. Our procedure centers around the methodical creation of logically-equivalent, but syntactically-different sets of probes, of which we create a corpus of 14,400 probes coming from 60 logically-equivalent sets that can be used to probe PTLMs in three task settings. We find that despite the recent success of large PTLMs on commonsense benchmarks, their performances on our probes are no better than random guessing (*even with fine-tuning*) and are heavily dependent on biases—the poor overall performance unfortunately inhibits us from studying robustness. We hope our approach and initial probe set will assist future work in improving PTLMs' inference abilities, while also providing a probing set to test robustness under several linguistic variations—code and data will be released.[1]

1 Introduction

Pre-trained language models (PTLMs) such as BERT, RoBERTa, GPT-2, ALBERT, and BART (Liu et al., 2019; Radford et al.; Lan et al., 2019; Lewis et al., 2019) outperform previous state-of-the-art models on multiple natural language understanding (NLU) benchmarks, including those designed to test commonsense reasoning

[1]Our data and code is located at https://github.com/INK-USC/ReasonBERT. (Work in progress.)

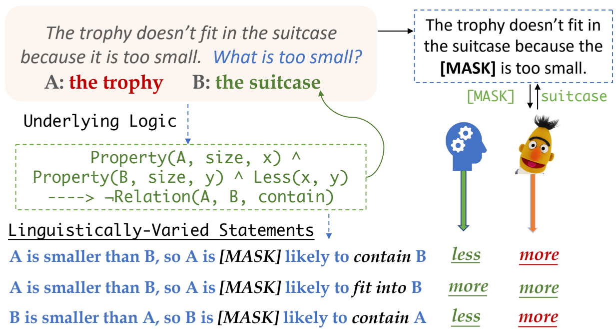

Figure 1: Humans solve inference questions by reasoning on the underlying logic of the question, thus linguistically variation has little affect on our abilities. Inconsistency in PTLMs' predictions when faced with linguistic variation caused us to attempt to provide a systematic approach of evaluating a model's understanding of the underlying logic in an inference question.

such as the `Winograd Schema Challenge` (WSC) (Levesque et al., 2012). Several studies have found that simply fine-tuning these PTLMs yield better performance than task-specific models (Trinh and Le, 2018; Kocijan et al., 2019). However, a growing body of work suggests this performance does not necessarily imply that PTLMs possess robust reasoning abilities (Talmor et al., 2019; Zhou et al., 2019; Kwon et al., 2019). Unfortunately, prior attempts at examining PTLMs' abilities to answer probes designed to expose human-like inference abilities been isolated to specific areas of knowledge and have not systematically tested the robustness of the PTLM's abilities. Thus, in this work we present a process to create probes that allow us to systematically understand if PTLMs posses inference abilities and if these abilities are robust.

We draw inspiration for our process from how humans approach inference problems. (Schank and Abelson, 1977) showed that humans translate natural language statements into underlying logical representations and then reason using these representations. These representations are robust to paraphrasing since diverse textual statements can lead to the same reasoning results, as shown in Fig. 1. Language models are often thought to have a similar ability to map statements into a representational space that achieves conceptual generalization (Bengio et al., 2003). However, we do not know if these mappings act in the same ways a human's does when faced with an inference task expressed in natural language—consistent **inferences** on linguistically diverse statements that share logical **equivalence**. We are thus motivated to design a new probing approach that evaluates whether PTLMs possess human-like reasoning capabilities.

We propose a systematic procedure to construct a *reasoning probe* set—a set of probes that would require human-like inference abilities to solve. The reasoning probes are defined in terms of first-order logic formulae, which capture the formalized logic of each probe, and thus can act as templates to generate probes. We also introduce a set of *linguistic perturbations* that can be applied to the logic underlying each reasoning probe to produce logically-equivalent statements with differing subject forms. Finally, we introduce novel entities that are random strings such as "prindag" to fill in the templates, allowing us to isolate entity knowledge from reasoning. A PTLM's performance on such probes would expose how close it's mapping function is to that of a human's.

To demonstrate the power and generality of our framework, we construct 60 sets of probes, each containing 24 types of perturbations, and involving 10 random strings, yielding a total of 14,400 logical statements to test PTLMs. We evaluate PTLM's performance on three different tasks: masked word prediction, sentence probability, and textual entailment (or Natural Language Inference, NLI) using probes constructed from the procedure shown in Figure 2. Surprisingly, the performances of SOTA models such as RoBERTa and GPT-2 are no better than random guessing on our probes while humans can reach around 85%. We then fine-tune on a partition of 80% our probes, validate using another 10%, and find that when testing the fine-tuned model on the rest, PTLMs still performs like random guessing. Furthermore, we identify a set of pervasive intrinsic biases in PTLMs that compromise their ability to effectively answer reasoning probes. We also use a gradient-based interpretation model to

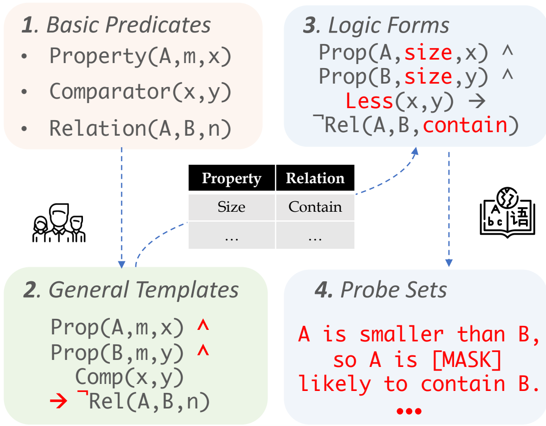

Figure 2: Overview of the workflow of our probe construction process. The output is a set linguistically-diverse of masked sentences that follow the same reasoning template.

try to find the contextual clues that PTLMs look at when making the predictions on our probes.

In summary, the contributions of our work are three-fold. First, we propose a systematic approach to generate logically-equivalent, but syntactically-different probes to evaluate PTLMs' logical inference capabilities. Then we construct 14,400 statements following our proposed approach to evaluate PTLMs using masked word prediction, sentence probability and NLI. Finally, we present results from an extensive set of experiments ablation studies and find that despite the success on existing benchmarks, SOTA PTLMs fails to correctly infer on our statements, even after fine-tuning.

2 Probe Construction Procedure

Our goal is to generate a set of linguistically-diverse commonsense statements that express the same underlying logical reasoning. In this section, we describe this construction process in detail. As shown in Figure 2, the process contains four steps. We first define a few general logical predicates. Next, we construct high-level first-order logic templates that capture a broad set of reasoning tasks. Third, we use background knowledge to partially ground templates into specific logic instances. Finally, we apply linguistic perturbation operators on the logical form to generate multiple paraphrases. These perturbations produce a diverse set of natural language sentences to probe PTLMs.

2.1 Define Basic Predicates

We start with defining three general predicates that serve as the basic building blocks for the logical formulations.

- $\textsc{Prop}(A, m, x)$ indicates that the property m of A is x, for example, $\textsc{Prop}(A, \text{size}, x)$ means the size of A is x.

- $\textsc{Rel}(A, B, n)$ indicates that A and B has a relation of n, for example, $\textsc{Rel}(A, B, \text{parent})$ means that A is B's parent.

- $\textsc{Cmp}(x, y)$ denotes that x is more or less than y.

Our procedure can work with any predicates, but in this work, we focus on these three due to their generality and the ability to produce multiple paraphrases expressing the same logic. Specifically, $\textsc{Prop}(A, m, x)$ and $\textsc{Rel}(A, B, n)$ are very common edge types in many knowledge bases like ConceptNet (Liu and Singh, 2004), so we can easily fill knowledge from them into our logic templates. As for linguistic diversity, $\textsc{Cmp}(A, B)$, for example, can be phrased as "A is more than B", "B is less than A", "A is not less than B", etc., and we can test PTLM's robustness on many more different types of linguistic variations.

2.2 Compose Logical Templates from Predicates

From the three defined basic predicates, we form logical templates by combining predicates using first order logical connectives like $\wedge$, $\rightarrow$, etc. We define a logical template to be a general form that can be grounded into many first order logical forms by filling the template with actual entities and relations.

For example, we consider the logical inference from a relation between two entities to a comparison of their properties. We can use $\rightarrow$ as the inference step, with the $\textsc{Rel}(A, B, n)$ predicate in the antecedent, indicating that the premise is A is of relation n to B. In the consequent, we compare a particular property of A and B, using the $\textsc{Cmp}(x, y)$ predicate to compare the two values of $\textsc{Prop}(A, m, x)$ and $\textsc{Prop}(B, m, y)$. Thus we can form the final first-order logical template for this inference as $\textsc{Rel}(A, B, n) \rightarrow \textsc{Prop}(A, m, x) \wedge \textsc{Prop}(B, m, y) \wedge \textsc{Cmp}(x, y)$. In the next section, we describe how these general templates are partially *grounded* by introducing specific commonsense knowledge, allowing us to produce reasoning tasks.

RELATION	PROPERTYCOMPARISON
priest	prays more
doctor	takes more care
parent	is older
teacher	is more informed
...	...

Table 1: Knowledge table to fill in the text template "A is B's [RELATION], so A [PROPERTYCOMPARISON] than B."

2.3 Fill Templates with Knowledge Tables

We use *knowledge tables* to ground the high-level templates to logic forms that represent a specific logical inference. We first construct a textual template corresponding to each first-order logical template with blanks that embed the underlying logic. Consider the template of property-comparison inference described above, the textual template can be "A is B's [RELATION], so A [PROPERTY-COMPARISON] than B." with [RELATION] and [PROPERTYCOMPARISON] being blanks that are filled. Table 1 shows examples of commonsense concepts used to generate specific instances. The generality of the predicates in our templates allows us to use many commonsense knowledge resources, such as ConceptNet (Liu and Singh, 2004) and ATOMIC (Sap et al., 2019), to automatically populate these knowledge tables. For example, ConceptNet contains the (priest, is_capable_of, praying) triplet in ConceptNet that can fill in the template above.

2.4 Generate Probe Sets Using Perturbation Operators

After grounding the logical templates, these logical relationships are expressed in natural language. In addition to a straightforward expression of the logical template directly into language, we define several *perturbations* that generate an equivalent logical statement but introduce linguistic variation. By defining multiple perturbation operators and applying them on logical atoms, we are able to form a diverse set of statements to probe PTLMs.

Linguistic Operators We define seven types of linguistic operators and the asymmetry operator to facilitate and formalize perturbations, shown in Table 2. We construct the last four operators by combining some of the single operators listed in the first three rows. Note that for "Negation", "Antonym", "Paraphrase Inversion", and "Negation Paraphrase" types, the logic of the original phrase is

LINGUISTIC OPERATOR	EXAMPLE
Negation	Neg(fit into) = not fit into
Antonym	Ant(fit into) = contain
Paraphrase	Para(fit into) = put into
Paraphrase Inversion	Para(Ant(fit into)) = Para(contain) = hold inside
Negation Antonym	Neg(Ant(fit into)) = Neg(contain) = not contain
Negation Paraphrase	Neg(Para(fit into)) = Neg(put into) = not put into
Negation Para_Inv	Neg(Para(Ant(fit into))) = Neg(para(contain))= Neg(hold inside) =not hold inside

Table 2: Linguistic operators with their logical equivalence and examples.

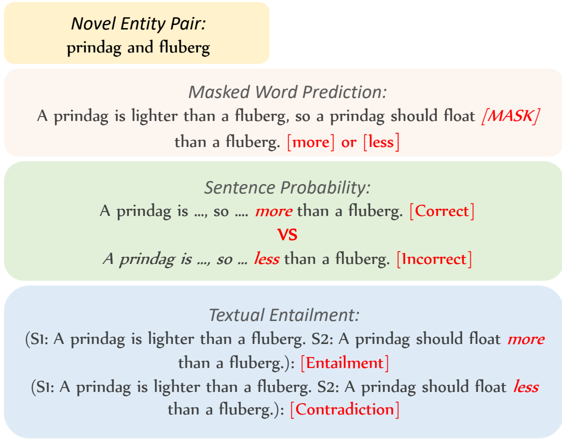

Figure 3: Illustration of our three considered evaluation settings to probe PTLMs with an example pair of novel entities.

changed, so words in the probe have to be replaced accordingly. For example, if we apply "Antonym" operator to the probe "A is smaller than B, so A is more likely to fit into B", we will get "A is smaller than B, so A is *less* likely to *contain* B".

Asymmetry Operator Our logical templates use several strongly-ordered comparisons and relationships. This strong ordering property allows us to introduce asymmetries that preserve meaning. For our predicates $\textsc{Rel}(A, B, n)$ and $\textsc{Cmp}(A, B)$, when we swap the positions of A and B, the meaning flips. For example, $\textsc{More}(A, B) = \neg\textsc{More}(B, A)$ and $\textsc{Rel}(A, B, parent) = \neg\textsc{Rel}(B, A, parent)$. Using this feature, we can swap the positions of two entities for these predicates and the logic will also be flipped, so we denote this perturbation as $\textsc{Asym}(\mathrm{P}(A, B)) = \mathrm{P}(B, A) = \neg\mathrm{P}(A, B)$.

Finally, we apply the defined operators to the parameters in the logic forms and manually write text templates for converting logic forms to sentences with diverse perturbations. We have eight forms of linguistic perturbations including the original (unperturbed) one, and we can apply the asymmetry operators either on the premise or conclusion or keep the original ordering. Thus we have in total of 24 types of perturbations.

3 Experiment Setup

This section presents our setup to probe LMs. We will describe our tasks and metrics to evaluate the LMs and then show the probes we construct following Section 2. Unlike most prior work that uses one task to probe the models, we use three tasks to test LMs' commonsense reasoning capability. We argue that each task evaluates some degree of the commonsense reasoning ability of the LMs, but does not provide a comprehensive picture. For example, in masked word prediction, the machine is asked to predict the most likely word to fill in the blank given the context, not necessarily test reasoning. However, we draw conclusions from experimental results on three distinct evaluation tasks, aiming to provide convincing and comprehensive probing insights.

3.1 Evaluation Tasks

A general illustration of three tasks is shown in Figure 3 and we will describe each task in the following paragraphs.

Masked Word Prediction We adopt the Masked LM pre-training objective from BERT (Devlin et al., 2019) to evaluate LMs on our constructed probes in a zero-shot setting to remove the effects of fine-tuning (Hewitt and Liang, 2019; Talmor et al., 2019) and probe only the pre-trained representations. We always mask words in the consequent of our probes to focus on the inference performance. Additionally, we choose to mask the words that not only require common-sense reasoning, but also restrict our masking to words where only a few options are appropriate logically and syntactically. For example, in the probe "A is B's parent, so A is *more* likely to care for B", we mask "more".

Sentence Probability We also evaluate LMs by feeding whole sentences into the model and comparing their probabilities by multiplying each word's probability conditioned on the previous words, i.e., the causal language modeling loss. For each probe, we pair it with a counterfactual statement by swapping the masked word in the above

LOGICAL TEMPLATE	EXAMPLE
$\text{PROP}(A, m, g) \wedge \text{PROP}(B, m, s) \rightarrow$ $\text{PROP}(A, t, x) \wedge \text{PROP}(B, t, y) \wedge \text{COMP}(x, y)$	A is made out of glass, B is made out of stone, so A is more transparent than B
$\text{REL}(A, B, p) \rightarrow \text{PROP}(A, p, x)$ $\wedge \text{PROP}(B, p, y) \wedge \text{COMP}(x, y)$	A is B's priest, so A spends more time praying than B
$\text{PROP}(A, v, x) \wedge \neg \text{PROP}(B, v, x) \rightarrow$ $\text{PROP}(A, s, x) \wedge \text{PROP}(B, s, y) \wedge \text{COMP}(x, y)$	A makes the varsity team while B does not, so A is more skilled than B
$\text{PROP}(A, c, x) \wedge \text{PROP}(B, c, y) \wedge \text{COMP}(x, y) \rightarrow$ $\text{PROP}(A, e, x) \wedge \text{PROP}(B, e, y) \wedge \text{COMP}(x, y)$	A is able to concentrate more than B , so A is more effective than B

Table 3: General first-order logical templates we construct for our probes and an example for each template in natural language.

evaluation setting with its opposite. In the example above, we create that probe's pair as: "A is B's parent, so A is *less* likely to care for B".

Textual Entailment The last evaluation we consider is the most challenging setting of the three. Since all of our probes can be separated into a premise and a conclusion, we treat them as pairs and ask LMs to classify their relationships from three classes: entailment, neutral, and contradiction, used in Natural Language Inference (NLI). Since vanilla pre-trained LM cannot directly be applied to this task, we use a version of the LM that is fine-tuned on the MultiNLI (Williams et al., 2018) dataset. Note that although the LMs are fine-tuned, we do not train or fine-tune on our probes.

3.2 Evaluation Metrics

Binary Accuracy For masked word prediction, we evaluate by simply comparing the rankings of the masked word and the other candidate with the opposite meaning. For example, in the masked probe: "A is B's parent, so A takes [MASK] care of B," "more" is the right answer and "less" is the wrong answer. In the binary setting, we feed the masked sentence to the LMs and give the model score 1 if the right answer appears higher than the wrong answer, and 0 otherwise. For the sentence probability task, the binary classification is comparing the probabilities of the sentence pair, one with the right answer and the other with the wrong answer. We assign scores similarly to the masked word prediction task and average across our probes to get the accuracy.

Confidence Ratio To address the nuances in the ranking and probability scores given by the LMs, we further propose a metric called confidence ratio setting. Using the example above for masked word prediction, we denote the predicted score for "more" as $score_{right}$ and that for "less" as $score_{wrong}$. Then we calculate our final score using: $(score_{right} - score_{wrong})/(score_{right} + score_{wrong})$. The more positive the final score is, the better the performance according to this metric, and vice versa. The absolute value of this score indicates how confident the LM is for this prediction. Similarly, for the sentence probability task, we use the probability score of the correct input sentence from LMs as $score_{right}$, that of the incorrect sentence as $score_{wrong}$, and calculate the confidence ratio using the same formula. Note that for the textual entailment task, the model directly predicts a label for a pair of sentences, so we use accuracy of the labels predicted as other work on textual entailment and NLI.

3.3 Language Models

We evaluate a wide range of state-of-the-art language models covering both masked and unidirectional language models to fit in our different settings. For the masked word prediction task, we consider RoBERTa (Liu et al., 2019) with base and large versions and ALBERT (Lan et al., 2019), two recent masked language models that show good results on many benchmarks. For sentence probability, we consider GPT-2 (Radford et al.), a large language model for left-2-right language generation and COMET (Bosselut et al., 2019), a generative model with backbone being GPT-2 and is further trained on large knowledge bases such as ConceptNet (Liu and Singh, 2004) and ATOMIC (Sap et al., 2019) so we consider it as a commonsense knowledge-augmented model. For the task of textual entailment, we use one masked language model RoBERTa and one sequence-to-sequence model BART (Lewis et al., 2019), both fine-tuned on MultiNLI (Williams et al., 2018).

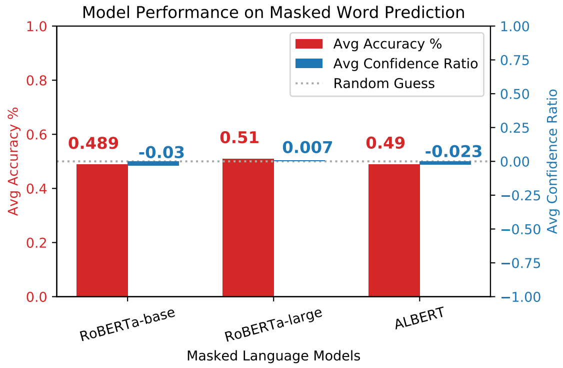

Figure 4: Results of average accuracy and confidence ratio of 3 masked language models on the masked word prediction setting. All the accuracies are close to 0.5, indicating that the models' performance is no better than random guessing. The associated confidence ratios are close to 0, as a result of the model being equally confident both when it is right or wrong.

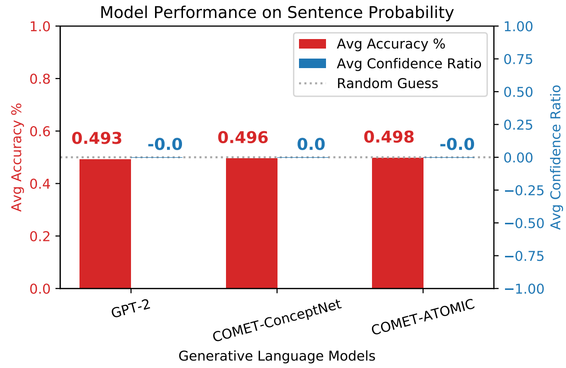

Figure 5: Results of average accuracy and confidence ratio of 3 generative language models on the sentence probability task. We see a similar pattern to the masked word prediction results.

3.4 Probing Data

Following the process in Section 2, we construct four logical templates from the basic predicates, shown in Table 3

Then we use knowledge tables to fill in each template and finally apply the perturbation operators as described before to form a final set of 1,440 linguistically-varied statements. To avoid conflating fact-based recall with commonsense reasoning, we use novel entities in all probing tasks. These entities are randomly generated character strings from length 3 to 12 that are assumed to be not seen in the training data of the LMs. By generating multiple instances of each template with different novel entities, we minimize the influence of our random generation of meaningful sub-words on the overall results. For each masked statement, we randomly generate 10 novel entities to fill in positions of A and B so we actually evaluate LMs using 14,400 probes.

4 Result Analysis and Discussion

We show the results of probing the state-of-the-art pre-trained language models, using the setup described above and provide analysis centered around the question raised in Section 1: can the LM ***consistently*** make ***correct*** predictions on a set of logically-equivalent, but syntactically-different statements? We will first examine the general performance of multiple language models on each task, show fine-tuning results on our probes, and present ablation studies to analyze the performances more thoroughly.

LM's performance is on par or worse than random guessing in all settings. As shown in Figure 4, the average binary accuracies of all three masked language models on the task of masked word prediction are around 0.5. Similarly, the confidence value of the predicted answer is close to 0, which is a result of the model being extremely confident in its guesses—confident incorrect guesses will have a confidence score near -1, while confident correct guesses will have a score near 1, thus the two cancel each other out and the average accuracy is close to 0. A random baseline that chooses between the two comparative words per probe would have an accuracy of 0.5 and a confidence score of 0, meaning that the tested masked language models barely beat a model that random guesses. Figure 5 shows the same statistics but with generative language models on the sentence probability task setting. We see the same pattern as the performances of masked language models: the average accuracies are around 0.5 and confidence ratios are 0, indicating that the inability to reason properly on our probes also applies to generative models. Moreover, COMET can be considered as a commonsense knowledge-augmented model since it is trained on commonsense knowledge bases (ConceptNet or ATOMIC), but we do not see a clear improvement from directly training on triplets from the knoweledge bases.

As for the textual entailment or NLI setting, Figure 6 presents the average accuracies of two models fine-tuned on MNLI dataset and tested on the textual entailment task. We only provide sentence pairs with entailment and contradiction labels by splitting the premises and the conclusions of our probes with the correct and incorrect comparatives, respectively, since recognizing neutral pairs is not related to our goal of probing reasoning. We find

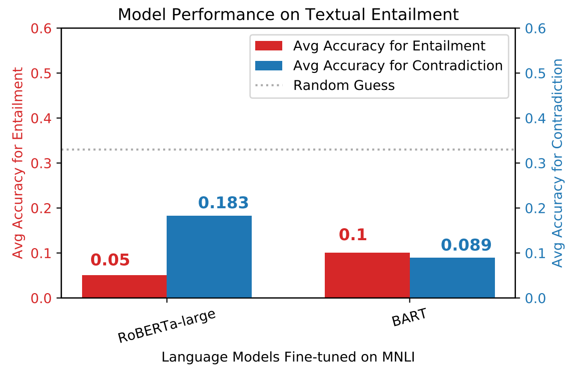

Figure 6: Results of average accuracies for predicting entailment and contradiction labels of 2 language models fine-tuned on MNLI. They are well below random guessing and for both models. We also notice a gap between the performance on entailment pairs and contradiction pairs for RoBERTa.

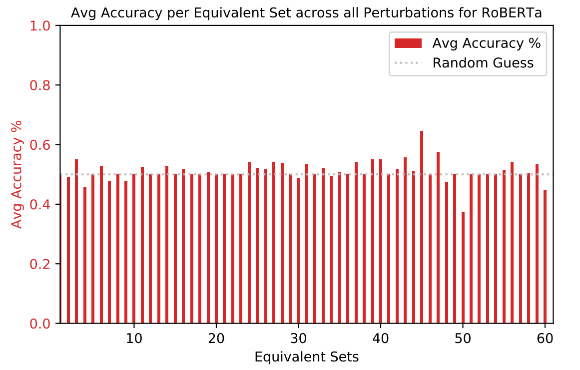

Figure 7: Results of average accuracy of RoBERTa-large on the masked word prediction task. We can see that the PTLM consistently makes random-guessing like predictions across all logically-equivalent sets.

that RoBERTa and BART fine-tuned on MNLI perform far below the random guessing (0.33) for three-way classification. After looking at their predictions, we find that they are mostly predicting the neutral label, showing that they do not understand the underlying logic in most of the probes, regardless of being correct or not, and they predict that the sentence pairs do not entail or contradict at all. We also find that RoBERTa fine-tuned on MNLI has a much higher accuracy on predicting the contradiction labels compared to entailment, while BART does not show this gap.

Furthermore, when we look into the average performance for each logically-equivalent but syntactically-different probe set, Figure 7 shows that the average accuracies for all sets are close to 0.5. The same pattern also applies to other models on the two other settings, indicating that the random guessing like performance is consistent across different probes.

These unsatisfactory results of multiple SOTA language models on three different settings is at sharp contrast to their substantial performance improvements on many commonsense reasoning benchmarks. From these results, we deduce that while PTLMs can be fine-tuned to perform well on many commonsense reasoning tasks, they do not show this same performance on our probes in the settings tested.

Fine-tuning does not help Given this deviation from previous results in a zero-shot setting, the natural next step is to investigate LM's performance on our probes after fine-tuning. We follow the standard 80/10/10 split for train/valid/test, making sure that all probes from the same logically equivalent sets appeared in the same split to prevent boosted performance resulting from overfitting to the training data. We fine-tune RoBERTa-base and RoBERTa-large on the masked language modeling task and GPT-2 on the causal language modeling task for 30 epoches. After each epoch we test the fine-tuned model on our validation set, and save the model with the highest validation set performance.

However, all this fine-tuning provides no real aid to RoBERTa's ability to perform well on our probe set, as seen in Figure 8. Again the accuracies hover around 0.5 like random guessing, indicating RoBERTa and GPT-2 are as confused as it was before the fine-tuning. Even though they have now been shown the majority of our probe set, meaning that they have seen many sentences that are very similar in syntax to the test set, it still fails to reason correctly, strengthening the conclusion from previously observed results of PTLM's reasoning abilities. We also believe that this inability to improve after fine-tuning shows the challenging nature of our dataset, which cannot be trivially solved by fine-tuning.

Diagnosing PTLMs: heavy language biases Surprised by LM's poor performance even after fine-tuning, we want to dive deeper into the predictions to see what is happening. In our experiment setups, we center the evaluation around pairs of comparative words: we ask models to predict the mask comparative, find the sentence containing the right word, and predict the relationship (entailment or contradiction) of sentence pairs with different comparatives. We use three distinct pairs

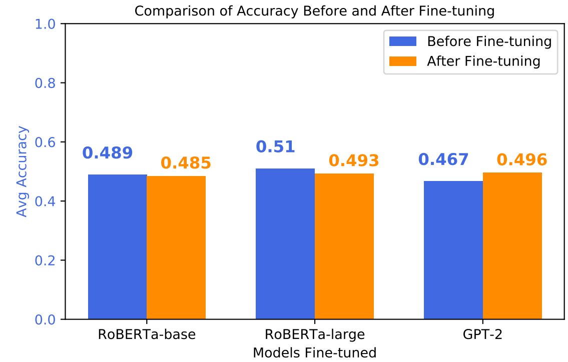

Figure 8: Fine-tuning results of average accuracy with 80/10/10 split for train/valid/test. We see that there is no clear different between the performance before and after fine-tuning and it is still like random guessing.

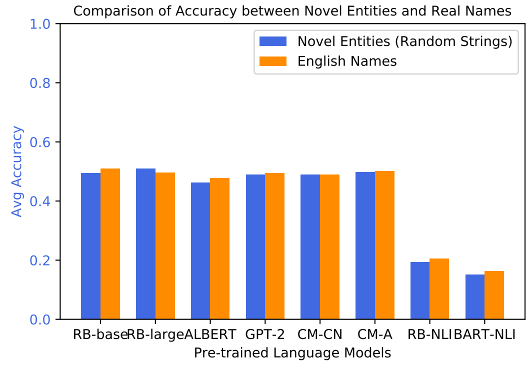

Figure 9: Ablation study results of average performance of PTLMs across one third of the probes. These probes involve social interactions where we replaced our usual novel entities with real names. We still see the consistent poor performance, indicating that using random strings is not hindering PTLMs' ability.

of comparative words in evaluation, 'more' or "less","easier" or "harder" and "better" or "worse". The seeming randomness of PTLM's performance prompted us to inspect our results more closely, and we subsequently uncovered a strong bias in model's response. We initially found that PTLMs heavily favor predicting "more" over "less", in 94% of statements, "better" over "worse" in 93%, and "easier" over "harder" in 81%. These results indicate a heavy bias as there are equal number of statements where each word in a given pair is the correct answer.

We generalize this pattern to the fact that when PTLMs are asked to infer a comparative relationship between the property of two entities, the model is heavily biased towards predicting the *positive valence* words regardless of what property we are comparing—i.e. regardless of the logic in the statement. Table 4 shows that the accuracy for "positive valence"words is a lot higher than "negative valence" words. Fine-tuning on the our probes, which have a balanced number of sentences containing positive and negative comparatives, does not help mitigate this bias for RoBERTa, but help for GPT-2. This bias towards positive valence is further evidence that PTLMs tested do not reason on our probes like humans in these settings, but rather attempts to pattern match.

Comparison with humans In order to ensure that our probe set is truly testing commonsense, we conducted a small human evaluation on a portion of our dataset. If our probe set is indeed testing commonsense, humans should be able to perform quite strongly on the test we devise. Our human evaluation was conducted on a 5% sample of our probes, where 20 people were asked to choose the more probable word between a pair of opposite comparative words (such as "more" and "less") that best completed the logic in a sentence—the comparative word would fill in a blank in the sentence. The results is shown in the last column in Table 4. While the number of datapoints (20) isn't large enough to be fully confident in our summary statistics, the average human performance is 85% with inter-annotator agreement 0.768 which is substantial agreement, showing that humans are generally able to perform this task, thus suggesting we are indeed testing commonsense. We also have reason to believe this number is not too far off a larger sample's mean, as 16 out of 20 people scored above an 85%. It is also worth noting that humans do not exhibit the same bias towards positive valence words observed in PTLMs

Ablation study and observations of novel entity usage As mentioned in the previous section, we use pairs of novel entities to prevent information about the correct logic of the sentence being leaked by real entities. While we do conduct an ablation study on a portion of our probes to test the effect of novel entities, it is important to mention that the dominant trend is that no matter what pair of novel entities were substituted into the probes, the machine's answer rarely changed. In fact out of the 1440 probes we constructed, 1343 (over 93%) of them always resulted in the same answer across all ten trials regardless of the novel entities being used. This strongly suggests that our novel entity generation and substitution process has had little

Model	Acc on "Pos"	Acc on "Neg"
RB-base	0.872	0.125
RB-large	0.899	0.122
ALBERT	0.734	0.246
RB-base-ft	0.878	0.092
RB-large-ft	0.775	0.158
GPT-2	0.777	0.209
GPT-2-ft	**0.509**	**0.483**
CM-CN	0.698	0.294
CM-A	0.664	0.332
Human	**0.831**	**0.863**

Table 4: Summary of PTLMs performances on probes that contain a positive valence word such as "more", "better", and "easier" versus that contains a negative valence words such as "less", "worse", and "harder". We see a clear gap between the accuracy of the two types of probes, even after the models are fine-tuned, with one exception: fine-tuning GPT-2 seems not remove this bias. We also find that humans do not exhibit such bias.

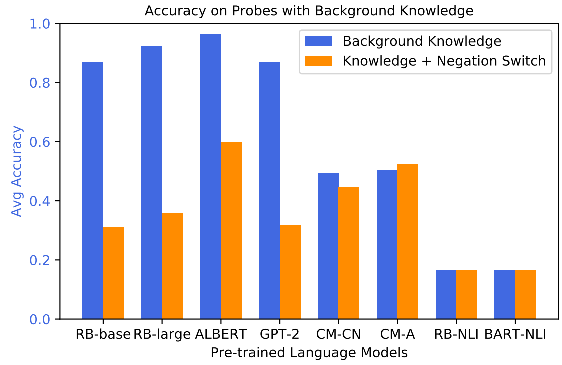

Figure 10: Results of average performance of PTLMs when we provide background knowledge in our probes. For RoBERTa, ALBERT, and GPT-2, we notice a huge increase in accuracy when provided knowledge. However, we find that they are merely parroting what appears in the context since when we apply a negation in the probe, which should change the prediction, they are simply predicting the same as the context shows, resulting in performance drop. For COMET moddels and models tested on the NLI setting, we do not observe the same pattern and it seems that adding knowledge does not help or hurt.

to no effect on LM's reasoning ability—which is exactly what we wanted.

In order to ensure our novel entity usage wasn't hindering LM's ability to reason, we conducted an ablation study on 480 of our probes, one third of our full dataset. These 480 probes involved social commonsense and so the novel entities were being used instead of people's names. We conduct ablation by switching back to common real people's names so that the probes look like normal sentences. As Figure 9 shows, the performances of all the models on three settings do not change much, again strongly suggesting that the novel entities are of little concern to PTLMs when making the decision as to what words should fill in the masked word. Our usage of novel entities does not seem to introduce helpful or distracting sub-words, nor does the introduction of novel entities seem to bother the models, as there is no difference in performance with or without them.

Does explicitly providing commonsense knowledge help? Shocked by the severe bias observed in PTLMs, we construct an easier set of probes, where we explicitly state all knowledge needed to make the correct logical inference. We have two settings for this test, one where parroting the now-provided commonsense fact is all that is needed to correctly answer the probe, and the other where a simple negation switch of the commonsense fact is needed to solve the probe:

- A is made of glass, B is made of stone, *and glass is more transparent than stone*, so A is [MASK] transparent than stone. (parrot)
- A is made of glass, B is made of stone, *and glass is more transparent than stone*, so A is **not** [MASK] transparent than stone. (negation switch)

We do this so to investigate whether RoBERTa is actually able to use the provided commonsense fact, or is it possibly just pattern matching.

We add this piece of background knowledge to the 60 original (unperturbed) statements along with their corresponding negated statements to form an "easier" setting of our task. As shown in Figure 10, we find two patterns PTLMs exhibit. For RoBERTa, ALBERT, and GPT-2, there is a stark difference in performance between the two settings. When they are being asked to parrot the commonsense fact, the performances jump up to near perfect scores, however when all they have to do is the equivalent of applying a negation operator on the fact, they fail even worse than when they are not provided the fact. These results suggest that in the parrot easier setting, it is likely RoBERTa, ALBERT, and GPT-2 are just parroting the commonsense fact they see in the sentence and not utilizing some sort of reasoning ability, as when asked to perform the simplest of logical operations they fail. The other pattern we notice is that providing background knowledge does not help or hurt the performances for COMET and models tested on the textual entailment task.

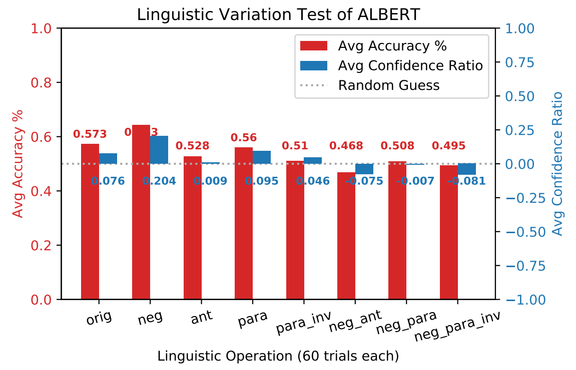

Figure 11: Results of average accuracy and confidence ratio across all the probes separated by the type of linguistic perturbations of ALBERT on masked word prediction. We do not see much variance for differnet perturbations, mainly due to the strong bias of predicting positive valence comparative words.

For COMET models, this may be due to the fact that COMET is trained on triplets from knowledge bases: given a head entity and a relation, predict the tail entity, so it is not used to taking auxiliary knowledge into its input. As for models fine-tuned on MNLI, the performance stays unchanged because they still think most of the sentence pairs of our probes are neutral, failing to grasp the embedded logical inference step.

Are PTLMs robust to perturbations? We cannot say for certain due to poor general performance and severe bias. Since the overall performances are close to random and the heavy bias towards positive valence words, we can only say that there are some variations for each perturbation applied. As Figure 11 shows, average performance for each perturbation type does not have much variation and we find a similar phenomenon for other models. This does not show that PTLMs are robust to linguistic perturbations since the accuracies are all random guessing like. We do like to note that the linguistically-varied nature of our probe sets still provides robustness test for models, but here due to the overall unsatisfactory results of current PTLMs, we do not get much insights from this perspective.

What contextual clues do the models use when making predictions on our probes? We want to dive into PTLMs' behaviors on our probes more by trying to find what are the most important words in the probes when they make predictions. We use the SmoothGrad (Smilkov et al., 2017) algorithm from AllenNLP Interpret (Wallace et al., 2019) on masked word prediction on our probes with real people's names (the same set as our ablation study) using BERT. We find that the interpretations are not very consistent as the most important words change when we input the same sentence for multiple times and will also change when different names are used, so we conduct 5 trials with different names for each probe and pick the words that appear in the majority of the trials. We have the following preliminary findings.

When aggregated across all probe sets, we find that the three most frequent words BERT finds most important when making the predictions according to SmoothGrad are: "than", "not", and "so", which makes sense because "than" indicates that we are asking for a comparative, "not" is the negation indicator, and "so" hints the causal relationship in our probes. However, noticing these clues does not necessarily mean that the model comprehends the logical implication of them. In other words, PTLM, in this case BERT, knows that these words are important when making a decision, but it does not know how to properly answer the questions based on these lexical signals.

5 Related Work

Machine commonsense logic has been studied for a long history. Most classical works primarily focus on executing symbolic rules as hand-crafted programs for machines to learn (Mccarthy, 1960). Recent attempts mainly generate templatic questions, such as those in the bAbI dataset (Weston et al., 2015), to test whether neural networks are able to reason via executing long chains of logic operations. Given the huge success of PTLMs (Devlin et al., 2019; Liu et al., 2019) in natural language processing, we want to study whether, or to what extent, PTLMs can reason with commonsense.

Prior works in analyzing the (commonsense) reasoning ability of PTLMs have primarily focused on creating probing tasks by generating ad-hoc masked sentences either from knowledge bases (Petroni et al., 2019; Feldman et al., 2019) or existing datasets. The first line of works aim to test if PTLMs can work as knowledge bases (e.g. ConceptNet, Freebase) in terms of retrieving factual or commonsense knowledge by triple prediction tasks. LAMA and its following work (Petroni et al., 2019; Jiang et al., 2019) designed relational templates as masked sentences and then test if pre-trained PTLMs such as BERT or RoBERTa can correctly recover the missing one-hop relations. Correctly retrieving factual triples does not necessarily mean that PTLMs can *reason* with them. Our work, in contrast, focuses on higher-order reasoning chains, which requires PTLMs to capture logical rules to answer all different linguistic variations. We explicitly test if PTLMs can consistently predict missing tokens in a set of paraphrases sharing the same logical patterns.

The goal of the second line of work (Zhou et al., 2019; Talmor et al., 2019; Kwon et al., 2019) is to reuse existing datasets as probe tasks, such as `SWAG`, `PIQA` (Bisk et al., 2019), and so on. Though these kinds of probing tasks can directly show the reasoning performance of PTLMs on downstream tasks, it is still not clear if PTLMs really enjoy the ability of mapping utterance to underlying logical patterns for predicting masked tokens. The success of PTLMs on these tasks may come from simple statistical matching instead of reasoning. As we seek to investigate whether PTLMs have human-like reasoning ability, the probing tasks are supposed to be centered around logical templates. Our proposed logical templates assures that our probing examples focus on reasoning instead of retrieving frequent linguistic patterns.

6 Conclusion

In summary, we propose a systematic approach to construct logically-equivalent, but syntactically different masked statements to probe PTLMs. Following this approach, we generate in total 14,400 masked statements from 60 sets of probes, 24 types of perturbations, and 10 fictitious entities and test 8 PTLMs on three different evaluation tasks. We find that PTLM's performance is comparable to random guessing, has a strong bias towards predicting comparative words with positive valence, and fine-tuning does not help. We further present ablation studies strengthening the conclusion that PTLMs fail to make human-like inferences on our probes. Our approach and initial probe set can assist future work in improving PTLMs' inference abilities, while also providing a probing set to test model's understanding of logical equivalence.

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7 Appendix

7.1 Probing Data Samples

We show all perturbations for one probe in Table 5 and all of our probe set's unperturbed statement in Table 6. We will release full data upon acceptance.

linguistic perturbation	asymmetric perturbation	probe
original	original	A is wider than B, so A finds it harder to slip through cracks than B
original	asymmetric_premise	B is wider than A, so A finds it easier to slip through cracks than B
original	asymmetric_conclusion	A is wider than B, so B finds it easier to slip through cracks than A
negation	original	A is wider than B, so A does not find it easier to slip through cracks than B
negation	asymmetric_premise	B is wider than A, so A does not find it harder to slip through cracks than B
negation	asymmetric_conclusion	A is wider than B, so B does not find it harder to slip through cracks than A
antonym	original	A is wider than B, so A finds it easier to be blocked by cracks than B
antonym	asymmetric_premise	B is wider than A, so A finds it harder to be blocked by cracks than B
antonym	asymmetric_conclusion	A is wider than B, so B finds it harder to be blocked by cracks than A
paraphrase	original	A is wider than B, so A is worse at fitting into openings than B
paraphrase	asymmetric_premise	B is wider than A, so A is better at fitting into openings than B
paraphrase	asymmetric_conclusion	A is wider than B, so B is better at fitting into openings than A
paraphrase_inversion	original	A is wider than B, so A is more impeded by small openings than B
paraphrase_inversion	asymmetric_premise	B is wider than A, so A is less impeded by small openings than B
paraphrase_inversion	asymmetric_conclusion	A is wider than B, so B is less impeded by small openings than A
negation_antonym	original	A is wider than B, so A does not find it harder to be blocked by cracks than B
negation_antonym	asymmetric_premise	B is wider than A, so A does not find it easier to be blocked by cracks than B
negation_antonym	asymmetric_conclusion	A is wider than B, so B does not find it easier to be blocked by cracks than A
negation_paraphrase	original	A is wider than B, so A is not better at fitting into openings than B
negation_paraphrase	asymmetric_premise	B is wider than A, so A is not worse at fitting into openings than B
negation_paraphrase	asymmetric_conclusion	A is wider than B, so B is not worse at fitting into openings than A
negation_paraphrase_inversion	original	A is wider than B, so A is not less impeded by small openings than B
negation_paraphrase_inversion	asymmetric_premise	B is wider than A, so A is not more impeded by small openings than B
negation_paraphrase_inversion	asymmetric_conclusion	A is wider than B, so B is not more impeded by small openings than A

Table 5: An example probe set—24 logically equivalent, but semantically different statements.

template	probe
1	A is made out of glass and B is made out of stone, so A is more transparent than B
1	A is made out of cotton and B is made out of glass, so A is less sharp than B
1	A is made out of concrete and B is made out of paper, so A should be more heavy than B
1	A is made out of metal and B is made out of rubber, so A should float worse than B
1	A is made out of glass and B is made out of copper, so A is more fragile than B
1	A is made out of steel and B is made out of wool, so A is less soft than B
1	A is made out of wood and B is made out of glass, so A is more combustible than B
1	A is made out of sponge and B is made out of nylon, so A is worse for water resistance than B
1	A is made out of copper and B is made out of concrete, so A is more ductile than B
1	A is made out of metal and B is made out of cloth, so A is less foldable than B
1	A is made out of chocolate and B is made out of metal, so A is harder to keep frozen than B
1	A is made out of metal and B is made out of dirt, so A is a better electrical conductor than B
1	A is made out of stone and B is made out of helium, so A has a harder time flying than B
1	A is made out of honey and B is made out of water, so A is more viscous than B
1	A is made out of titanium and B is made out of rubber, so A is less elastic than B
1	A is made out of water and B is made out of methane, so A is more safe to store than B
1	A is made out of mercury and B is made out of oxygen, so A is worse for your health to consume than B
1	A is made out of wood and B is made out of fur, so A will more easily expand when heated than B
1	A is made out of concrete and B is made out of wood, so A is less penetrable than B
1	A is made out of glass and B is made out of tar, so A will reflect light better than B
3	A makes the varsity team while B does not, so A is more skilled than B
3	A is going to perform for people while B is not, so A finds it harder to be relaxed than B
3	A won the competition while B did not, so A finds it easier to be happy than B
4	A is able to concentrate more than B, so A finds it easier to be productive than B
3	A bullies people while B does not, so A is less kind than B
2	A is B's boss, so A commands more respect than B
4	A has more work than B, so A finds it harder to be at ease than B
2	A has a crush on B, so A finds it harder to be relaxed around B
4	A has more dedication than B, so A will have a harder time failing than B
2	A is B's parent, so A initially takes more care of B
2	A is B's doctor, so A takes more care of B
2	A hurt B's feelings, so A must be more insensitive than B
2	A is B's priest, so A spends less time sinning than B
2	A is B's lawyer, so A is less ignorant of the law than B
4	A has a lot less money than B, so A is less financially secure than B
4	A watches more tv shows than B, so A is more capable of understanding pop-culture references than B
2	A always loses to B in tennis, so A is a less proficient tennis player than B
2	A makes B late, so A has less reason to be annoyed at B
4	A is a better friend than B, so A is more thoughtful than B
2	A is B's teacher, so A should be more informed than B
4	A is smaller than B, so A is easier to put into a box than B
4	A is heavier than B, so A is better at sinking than B
4	A is denser than B, so A should withstand piercing more easily than B
4	A is wider than B, so A finds it harder to slip through cracks than B
4	A is hotter than B, so A should be easier to melt than B
4	A is more elastic than B, so A should bounce better than B
4	A is tougher than B, so A is harder to rip apart than B
4	A is harder than B, so A is less comfortable than B
4	A is taller than B, so A will cast a more lengthy shadow than B
4	A is lighter than B, so A finds it harder to support weight than B
4	A has less momentum than B, so A has a worse ability to damage on impact than B
4	A is more luminous than B, so A is more dangerous to look at than B
4	A is more soluble than B, so A is harder to discern in water than B
4	A is more pungent than B, so A is easier to detect than B
4	A is smaller than B, so A finds it harder to displace liquid in a tub than B
4	A is shorter than B, so A is worse for keeping things out of reach than B
4	A is larger than B, so A is more difficult to carry than B
4	A is more taut than B, so A is worse at withstanding additional force than B
4	A is much hotter than B, so A will be more painful to hold onto than B
4	A is more magnetic than B, so A is harder to separate from another magnet than B

Table 6: The sixty probes we constructed and their corresponding templates