

# *Birds have four legs?!*

## NumerSense: Probing Numerical Commonsense Knowledge of Pre-trained Language Models

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### Abstract

Recent works show that pre-trained masked language models, such as BERT, possess certain linguistic and commonsense knowledge. However, it remains to be seen what types of commonsense knowledge these models have access to. In this vein, we propose to study whether *numerical commonsense knowledge* (i.e., commonsense knowledge that provides an understanding of the numeric relation between entities) can be induced from pre-trained masked language models and to what extent is this access to knowledge robust against adversarial examples? To study this, we introduce a probing task with a diagnostic dataset, NUMERSENSE<sup>1</sup>, containing 3,145 masked-word-prediction probes. Surprisingly, our experiments and analysis reveal that: (1) BERT and its stronger variant RoBERTa perform poorly on our dataset prior to any fine-tuning; (2) fine-tuning with distant supervision brings some improvement; (3) the best distantly supervised model still performs poorly as compared to humans (47.8% vs 96.3%).

## 1 Introduction

Pre-trained language models (PTLMs), such as BERT (Devlin et al., 2019), have yielded state-of-the-art performance on many natural language processing tasks. Given PTLMs’ cited ability to create general, yet useful text representations, an investigation into their ability to encode commonsense knowledge into representations is warranted—commonsense knowledge is often required to have a full understanding of language. Motivated by this and similar inquiries, probing tasks for analyzing PTLMs’ behaviors have been created. However, much prior probing work has primarily focused on the analysis of linguistic phenomena captured by PTLMs (Clark et al.; Tenney et al.).

<sup>1</sup><http://inklab.usc.edu/NumerSense/>

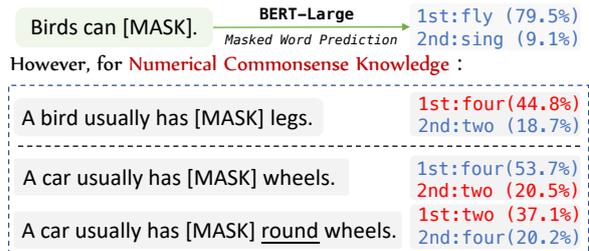


Figure 1: **Top:** PTLMs often cannot solve masked language modeling tasks needing *numerical commonsense knowledge*, hence our title. **Bottom:** Even when PTLMs seemingly succeed, they fail to stay consistent under small perturbations.

More recently though, there have been a few recent works that do investigate our original inquiry of whether PTLMs possess *commonsense knowledge*. For example, (Petroni et al., 2019; Davison et al., 2019; Bouraoui et al., 2020) find that it is feasible to use PTLMs as a commonsense knowledge base. They established this by converting triples from ConceptNet (Speer et al., 2017) into sentences for the purpose of creating a masked word prediction task to understand if the knowledge of the triple exists within the PTLMs—very often it did.

Overall, prior *commonsense knowledge* studies suggest that PTLMs are creating text representations that often have commonsense knowledge encoded in them. We therefore find it surprising that when posed with a similar reasoning-based masked word prediction task, PTLMs perform poorly in recalling the required *numerical commonsense knowledge* to solve the task. Thus, we propose to study whether PTLMs capture numerical commonsense.

We propose measuring this capability of PTLMs via a masked-word-prediction based probing task, where, the ranking of numeric words by what the model believes most probably fills the mask would expose the capabilities of PTLMs to capture *numeric commonsense knowledge*. For example, the masked position in the sentence “A bird usually

has [MASK] legs” is best filled by the number two when considering only numerical answers, as its commonsense knowledge that “birds usually have *two* legs”. Around this concept, we built a carefully crafted dataset, NUMERSENSE, of 1,131 probes that covers questions from 8 different categories.

In our initial experimentation, we found PTLMs to be brittle against adversarial attacks. As shown in the bottom section of Figure 1, BERT initially correctly predicts the masked word to be “four”, but it changes its top result to “two” in the slightly perturbed second sentence (a simple insertion of the word ‘round’). Thus to ensure a more comprehensive test, we added examples with manually verified adversarial attacks to NUMERSENSE, resulting in a final dataset size of **3,145** probes.

We finally analyze predictions from BERT and RoBERTa on our dataset (Section 3). We evaluate both models in two settings: (1) a zero-shot setting, meaning no probes from our dataset were used to fine-tune to the models before evaluation; (2) a distant supervision setting, where models were fine-tuned on examples from related commonsense reasoning datasets before being evaluated on ours. Our findings reveal that PTLMs are still much worse than humans on the task, although fine-tuning with distant supervision can help. We also provide some cursory analysis on why PTLMs perhaps preform so poorly, but we leave this to future work.

In summary, our contributions are a dataset of 3,145 probes designed to test the existence of numerical commonsense knowledge in PTLMs, as well as human and model evaluations on our dataset. We hope our work can help future work in: 1) improving PTLMs’ abilities to capture numerical commonsense, 2) populating numerical facts in current commonsense knowledge graphs, and 3) open-domain question-answering—“*How many legs do ants have?*” “*Six!*”

## 2 The NUMERSENSE Probing Task

We introduce our numerical commonsense reasoning probing task, as well as the creation process of the namesake dataset, NUMERSENSE. We also provide a breakdown of what types of knowledge are probes cover and finally include additional distant supervision data to test if fine-tuning on relevant data can improve performance.

Category	Example
Objects (35.2%)	A bicycle has <u>two</u> tires.
Biology (13.5%)	Ants have <u>six</u> legs.
Geometry (11.7%)	A cube has <u>six</u> faces.
Unit (6.3%)	There are <u>seven</u> days in a week.
Math (7.3%)	I will be <u>ten</u> next year, as I am <u>nine</u> now.
Physics (5.7%)	Water will freeze at <u>zero</u> degrees centigrade.
Geography (2.9%)	The world contains <u>seven</u> continents.
Misc. (17.5%)	There are <u>no</u> princes in the United States.

Table 1: NUMERSENSE examples of each category.

### 2.1 Task Formulation

We probe PTLMs via their masked word prediction task, but we do not use the standard evaluation procedure. Instead we use the of distribution of words a PTLM thinks could fill the masked position to rank words by their softmax scores (greatest to least). If the ranking demonstrates numerical commonsense knowledge—the highest ranked *number word* (e.g., “one”, “two”, and so on) is the correct answer—then that probe is successfully solved by the PTLM. The masked position in each probe is chosen such that a number word is an extremely probable way of filling in the blank.

Figure 1 has three such examples. The PTLMs are expected to be able to predict these masked number words, because the numerical knowledge about common concepts can be induced from *Wikipedia* where these PTLMs are trained.

### 2.2 Probing Data Collection

To build a suitable dataset for the proposed probing task, we make use of an existing corpus consisting of commonsense assertions, named *Open Mind Common Sense* (OMCS) (Singh et al., 2002). We first extracted the sentences from OMCS that had at least one of the following 12 *number words*: {“no”, “zero”, “one”, “two”, ..., “ten”}. We include “no”, as there exists statements involving numerical commonsense knowledge, where “no” is used in place of zero, “There are **no** princes in the United States.”

However, as to be expected, there were many noisy statements which were either 1) incorrect, 2) containing typos, or 3) having no numerical commonsense logic. We thus manually and pragmatically refined these sentences and did two rounds of vetting by different graduate students (who were not familiar with the task), from which we only kept the statements that were accepted by all students. After our strict filtration process, we ended up **1,131** cleaned statements or probes.

After our initial round of testing we observed that PTLMs can be brittle under a simple perturbation of inserting an adjective near the masked number word. Thus, in order to study the robustness of models in our proposed task, we also added adversarial examples to our dataset by adding adjectives before the noun involved in the numerical reasoning in each probe. The candidate adjectives are generated by querying related triples (e.g. <wheel, HasProperty, round> for the example in Fig. 1) in ConceptNet and further selected by human annotators to assure adversarial examples are valid and natural. We finally have **3,145** probes for our NUMERSENSE task.

We also manually annotated the category label for each instance so that we can better understand the covered topics and their percentage. We found 8 types of numerical commonsense knowledge ranging from tangible everyday objects (e.g., car, guitar, and table) to geometry (e.g., cube). Table 1 lists some concrete examples of each category.

### 2.3 Distant Supervision for Fine-Tuning

We were interested in looking into if distant supervision for fine-tuning could help performance. In order to answer this question, we collected a large number of sentences from Wikipedia where each sentence contains a common object in an everyday scenarios as well as one of our **number words**. We choose Wikipedia as most PTLMs are trained on it.

We collected these sentences by first obtaining a list of frequent nouns from various caption corpora such as MSCOCO (Lin et al., 2014), VATEX (Wang et al., 2019), etc. Then, we filtered the sentences in each noun’s Wikipedia article so that the final collected sentences contained at least one number word of interest. We ended up collecting **13,800** sentences for fine-tuning and believe these sentences, if used correctly, can improve PTLMs’ ability to recall the necessary numerical commonsense knowledge to solve our probes.

## 3 Empirical Analysis

In this section, we introduce the set-up of the experiments and then present results from different PTLMs in both a zero-shot setting and a distantly supervised fine-tuned performance. We will also provide some analysis on the robustness and biases in the various models, and finally a study of the performance of a state-of-the-art open-domain question-answering model.

Models	Core			Core + Adversarial		
	hit@1	hit@2	hit@3	hit@1	hit@2	hit@3
BERT-Base	31.98	55.92	70.58	25.24	48.66	64.81
RoBERTa-Base	36.04	60.42	72.08	28.39	51.91	67.29
BERT-Large	37.63	62.01	76.77	27.18	52.89	70.22
RoBERTa-Large	<b>45.85</b>	66.70	80.04	<b>35.66</b>	58.52	74.44
Ft. BERT-L.	41.78	62.37	74.56	28.13	53.94	69.71
Ft. RoBERTa-L.	<b>47.79</b>	67.49	78.09	<b>36.20</b>	59.44	73.55
Human Bound	89.7 <sup>(<math>\alpha</math>)</sup> / 96.3 <sup>(<math>\beta</math>)</sup>			88.3 <sup>(<math>\alpha</math>)</sup> / 93.7 <sup>(<math>\beta</math>)</sup>		

Table 2: Results (%) of PTLMs on NUMERSENSE. ‘Ft.’ stands for ‘Fine-tuned.’ The human performance is shown by closed testing ( $\alpha$ =‘no external information’) / open testing ( $\beta$ =‘Wikipedia is allowed’).

### 3.1 Experiment Set-up

We run our experiments in two settings, *zero-shot inference* and distant supervision via fine-tuning. In the first setting, we probe PTLMs without any modifications, specifically we use BERT and RoBERTa with pre-trained masked-word-prediction heads.

In our second setting, we use our collected distant supervision dataset (Sec. 2.3) and mask the *number words* in each sentence. We then proceed to fine tune the models above on these masked sentences, before evaluating them on NUMERSENSE.

### 3.2 Evaluation Metric and Human Bound

A masked-word-prediction head (either fine-tuned or not) produces a probability distribution over its whole vocabulary via a SoftMax function. As mentioned in (Sec. 2.1), NUMERSENSE is the task of using this probability distribution to rank all number words, and evaluating this ranking. To evaluate, we use hit@1/2/3 accuracy, which calculates the percentage of predictions where the correct number word is ranked in the top  $k$  number words.

To estimate human performance on the task, we sampled 300 examples and asked two groups of three people to fill in the masked word, where one group had access to external information (**open-book** test) and the other did not (**closed-book** test). We take the majority label as the final label for the human performance.

### 3.3 Experimental results

We show our experimental results in Table 2. The first four lines are results from PTLMs in the zero-shot inference setting. We see that size matters, as there is a clear performance gain when the model sizes increases. Also, RoBERTa’s results are consistently better than BERT’s (37.63 vs 41.78), which is probably because RoBERTa uses a larger

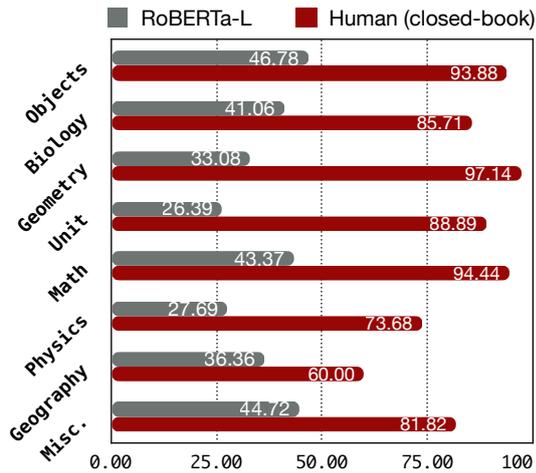


Figure 2: Performance of RoBERTa-Large V.S. human performance (closed-book tests) on different categories of numerical commonsense knowledge.

training corpora and focuses more on masked language modeling in its pre-training stage.

We see that our fine-tuning efforts do help improve model performance: “37.63  $\rightarrow$  41.78” for BERT-large and “45.85  $\rightarrow$  47.79” for RoBERTa-large. However, both are still far from the human’s closed-book evaluation. Figure 2 shows PTLMs performance is poor across all categories within the core set of NUMERSENSE.

Comparing the performance of a PTLM on the “Core” set versus the “Core+Adversarial” set, we can measure the robustness of the model. We found all models incur a significant performance drop when being evaluated on the “Core+Adversarial” dataset. This suggests that PTLMs (even when fine-tuned) can be brittle towards adversarial attacks, and future direction in pre-training language models should consider more structured inductive biases such as dependencies and semantic roles.

### 3.4 Case Study about the Number Bias

Recall the example in Fig. 1, “a bird usually has [MASK] legs,” which BERT-Large predicts to be “four”. Does BERT-Large always predict “four” as long as the adjacent word after the [MASK] is ‘legs’? To investigate if the bias exists, we show some case studies in Table 3. As different randomly generated words fill the ‘[x]’s we see that both BERT and RoBERTa have a bias towards a certain answer, evidenced by the existence of a dominant answer in the softmax distribution. However, it seems that RoBERTa’s (Liu et al., 2019) modified pre-training strategy helps it have less bias. We

<b>Template:</b>	<b>a [x] usually has [MASK] legs.</b>
BERT-L	four: 39.3%, two: 18.3%, three: 10.1%
RoBERTa-L	four: 20.8%, two: 9.0%, three: 8.1%
<b>Template:</b>	<b>most [x] have [MASK] wheels.</b>
BERT-L	four: 25.3%, two: 14.1%, three: 5.1%
RoBERTa-L	four: 9.2%, two: 7.8%, three: 4.6%
<b>Template:</b>	<b>all [x] have [MASK] sides.</b>
BERT-L	two: 28.3%, three: 12.9%, four: 12.9%
RoBERTa-L	two: 16.6%, no: 2.9%, three: 2.3%

Table 3: The average Softmax of top 3 predictions in templates where ‘[x]’ is filled with 1k random words.

argue that future studies should further control the bias in masked language modeling.

### 3.5 Open-Domain How-many Questions

The examples in the NUMERSENSE can be seen as open-domain questions targeting ‘how-many’ commonsense—“how many legs does a fly usually have?” Answering these open-domain numerical commonsense questions is a practical downstream application of models that are successful in the NUMERSENSE. Thus, as a side note, we also report the performance of the state-of-the-art open-domain QA model (Asai et al., 2020).

We use the model that is trained on the Natural Question (NQ) dataset (Kwiatkowski et al., 2019), where we replace the ‘[MASK]’s in our examples with ‘how many’, so that our probes are in a similar format to NQ examples. For example “a fly usually has [MASK] legs” is converted to “*how many legs* a fly usually has?”<sup>2</sup> The accuracy of the state-of-the-art model is only **15.4%**, which is even lower than using BERT-base without fine-tuning. This indicates that improving performance on NUMERSENSE can help improve the performance on answering open-domain “how-many” questions.

## 4 Related Work

**Probing Tasks for PTLMs.** Prior work in probing language models have primarily focused on analysis of linguistic phenomena. Clark et al. (2019) investigated the relationship between BERT’s attention weights and syntactic structures, while such as dependency (e.g. direct objects, noun modifiers), coreference, and sentence segmentation. Tenney et al. (2019) was able to display where certain types of linguistic information is captured within

<sup>2</sup>We also manually test some queries such as “*how many legs* does a fly usually have?”, which have similar results.

BERT—they in fact find the layers in a PTLM represent the steps of a classical NLP pipeline: POS tagging, parsing, NER, semantic roles, and coreference. This line of work has indeed helped us understand the ability of PTLMs to capture *linguistic knowledge* via self-supervised learning from unlabeled data. We are interested in the numerical commonsense knowledge of PTLMs.

**Probing Commonsense Knowledge.** Besides the works that we have discussed in Section 1, Zhou et al. (2020) and Talmor et al. (2019a) also proposed to probe the commonsense knowledge of pre-trained language models. They both utilized various existing language understanding datasets targeting commonsense knowledge to test if PTLMs can capture certain commonsense knowledge. Lin et al. (2019a) also show that PTLMs can retrieve paths from ConceptNet that aid in interpreting the decision made by the PTLMs on the CommonsenseQA dataset (Talmor et al., 2019b). Lin et al. (2019b) probe the commonsense knowledge in pre-trained language generation models via a constrained text generation task. However, they do not consider numerical commonsense knowledge, which is relatively under-explored area.

**Numerical Commonsense Knowledge.** Forbes and Choi (2017) and Goel et al. (2019) studied commonsense comparisons between two physical objects (e.g., a house is usually bigger than a person) in pre-trained word embeddings. Elazar et al. (2019) and Yamane et al. (2020) propose to induce the commonsense distribution of quantitative attributes (e.g., mass, length, and currency) of objects. Their goal is to extract or crowd-source such numerical attributes, and then obtain distributions that reflect commonsense knowledge. NUMERSENSE, however, mainly focuses on exact numerical commonsense facts (e.g., a bird has *two* legs) instead of a range of values (e.g., a tiger weighs *around 120kg*), and have a larger number of arguments besides physical attributes.

**Encoding Numerics for Computation.** Wallace et al. (2019) probe PTLMs in terms of the ability to represent numeracy tokens by a regression task (e.g., “71”  $\rightarrow$  71.0), and also find that BERT is not good at encoding numerical tokens. Some works focus on incorporate algebra computation ability in PTLMs (Zou and Lu, 2019; Geva et al., 2020), thus making them able to answer math reasoning tasks such as MAWPS (Koncel-Kedziorski et al., 2016) and DROP (Dua et al., 2019). Note that

these models and tasks are not targeting numerical commonsense knowledge but only the numerical-related computation within text.

## 5 Conclusion

We present a probing task, NUMERSENSE, to induce numerical commonsense knowledge from pre-trained language models. To initiate this research direction, we collect a new diagnostic dataset carefully verified by human annotators, which covers 8 different topics. Powerful pre-trained models such as BERT and RoBERTa perform surprisingly poorly, even after fine-tuning with high-quality distant supervision. We hope our findings and probing dataset will provide a basis for improving pre-trained masked language models’ *numerical common sense*, as this knowledge is beneficial for tasks such as knowledge base completion and open-domain question answering.

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