COMPS: Conceptual Minimal Pair Sentences for testing Property Knowledge and Inheritance in Pre-trained Language Models

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Abstract
A characteristic feature of human semantic memory is its ability to not only store and retrieve the properties of concepts observed through experience, but to also facilitate the inheritance of properties (can breathe) from superordinate concepts (ANIMAL) to their subordinates (DOG)—i.e. demonstrate property inheritance. In this paper, we present COMPS, a collection of minimal pair sentences that jointly tests pre-trained language models (PLMs) on their ability to attribute properties to concepts and their ability to demonstrate property inheritance behavior. Analyses of 22 different PLMs on COMPS reveal that they can easily distinguish between concepts on the basis of a property when they are trivially different, but find it relatively difficult when concepts are related on the basis of nuanced knowledge representations. Furthermore, we find that PLMs can demonstrate behavior consistent with property inheritance to a great extent, but fail in the presence of distracting information, which decreases the performance of many models, sometimes even below chance. This lack of robustness in demonstrating simple reasoning raises important questions about PLMs’ capacity to make correct inferences even when they appear to possess the prerequisite knowledge.

1 Introduction
The ability to learn, update, and deploy one’s knowledge about concepts (ROBIN, CHAIR) and their properties (can fly, can be sat on), observed during everyday experience is fundamental to human semantic memory (Quillian, 1967; Smith and Estes, 1978; Murphy, 2002). Knowledge of a concept’s properties, combined with the ability to infer category-inclusion or the ISA relation (Sloman, 1998; Murphy, 2003) leads to an important behavior known as property inheritance, where subordinates of a concept inherit its properties. For instance, one can automatically infer that luna can meow, has a tail, is a mammal, etc., even if all they know is that it is a cat (Murphy, 2002; Lake and Murphy, 2021). Computationally, property inheritance can be boiled down to implicitly representing the following symbolic rule:

\[
\forall x \text{ CAT}(x) \implies \text{CAN-MEOW}(x) \land \text{HAS-TAIL}(x) \land \text{MAMMAL}(x) \land \ldots ,
\]

where \( x \) is a subordinate of the concept \text{CAT}.

To what extent does experience with language contribute to behavior that is consistent with this ability? The recent empirical success of pre-trained language models (PLMs; Devlin et al., 2019; Brown et al., 2020, etc.) on tasks requiring access to complex semantic knowledge makes them perhaps the most powerful tools to answer this question. Consequently, recent works have established the promise of PLMs in capturing isomorphism with perceptual domains such as direction and color (Abdou et al., 2021; Patel and Pavlick, 2022), and capturing properties of real-world concepts (Weir et al., 2020; Grand et al., 2022). These results seem to serve as motivation for researchers to postulate that perhaps the study of meaning in PLMs should move beyond their inability to learn about reference from form (Bender and Koller, 2020) to instead focusing on the relations between models’ internal states (Piantadosi and Hill, 2022). If PLMs can indeed capture aspects of meaning by sidestepping the issue of explicit reference, and capture relational knowledge between internal states of contextual information (for instance, that luna is a cat), then they should also be able to learn the consequences that come with this knowledge, as shown above. It is therefore important to propose empirical tests that target whether PLMs can translate the knowledge they capture into inference-making capacities such as property inheritance, among others. These targeted tests can additionally shed light on the extent to which PLMs can approximate symbolic behavior, despite lacking explicit symbolic...
structure in their construction (Fodor and Pylyshyn, 1988; Smolensky, 1988).

In this work, we test PLMs on their ability to capture properties of concepts and jointly demonstrate property inheritance. To this end, we present Conceptual Minimal Pair Sentences (COMPS), a collection of English minimal pair sentences, where each pair attributes a property (can fly) to two noun concepts: one which actually possesses the property (ROBIN), and one which does not (PENGUIN). COMPS can be decomposed into two datasets that target different abilities in PLMs: COMPS-BASE, which tests PLMs’ ability to recall properties of real-world concepts in a minimal pair setting; and COMPS-WUGS, which we use to test models on their ability to demonstrate property inheritance. In order to be successful on COMPS-BASE, models must consistently show greater association of properties to concepts that possess them as compared to concepts that do not. For example, a model should rate (1a) to be more acceptable than (1b).

(1) a. A robin can fly.
   b. *A penguin can fly.

To test property inheritance, we introduce a novel subordinate concept, WUG, for a subset of the concepts in the original COMPS-BASE task, and then test whether models can endow that concept with the properties of its superordinate. Success on COMPS-WUGS requires models not only to know properties of a concept, but also to perform the reasoning to associate subordinate concepts with the properties of their superordinates. That is, given that models successfully rated (1a) to be relatively more acceptable than (1b), they should also rate (2a) as more acceptable than (2b):

(2) a. A wug is a robin. Therefore, a wug can fly.
   b. *A wug is a penguin. Therefore, a wug can fly.

We use COMPS to analyze property knowledge and property inheritance in 22 different PLMs, ranging from small masked language models to billion-parameter auto-regressive language models. Our analyses suggest that PLMs are reasonably adept at distinguishing between certain concepts on the basis of properties. Their performance peaks when the concepts being compared are trivially different (e.g., LION and TEA for the property is a mammal), but substantially declines (by as much as 25%) when the concepts share semantic relations across different representational mechanisms (taxonomy, property norms, co-occurrence). When models are correct in attributing properties to the right concepts, they tend to also extend those properties to subordinates of those concepts, thereby demonstrating behavior that is compatible with accurate property inheritance. Additionally, models also tend to fail at property inheritance on a majority of instances where they failed to reflect ground-truth property knowledge, showcasing a general consistency in the use of property knowledge that is locally accessible to them. Our post-hoc analyses, however, reveal that a majority of PLMs struggle to demonstrate property inheritance in presence of competing and distracting information—on processing concatenated sentences such as “a wug is a robin. a dax is a penguin,” models are more likely to attribute can fly to “dax” than to “wug,” despite correctly attributing the property to the correct superordinate (“robin”) in the original setting. This lack of robustness in the face of distracting content is especially observed in larger models, which operate at or below chance performance. Together, these findings suggest that the capacity of contemporary ‘mid-sized’ PLMs to extract relational information from their context and make consistent inferences is largely coarse grained, especially in presence of competing or distracting information. We make our code and data available at: https://github.com/kanishkamisra/comps

2 Conceptual Minimal Pair Sentences (COMPS)

2.1 Connections to prior work

Prior work in exploring property knowledge in PLMs has adopted two different paradigms: one which uses probing classifiers to test if the applicability of a property can be decoded from the representations of LMs (Forbes et al., 2019; Da and Kasai, 2019; Derby et al., 2021); and the other which uses cloze-testing, in which LMs are tasked to fill in the blank in prompts that describe specific properties/factual knowledge about the world (Petroni et al., 2019; Weir et al., 2020). We argue that both approaches—though insightful—are fundamentally limited for evaluating property knowledge, and that minimal pair testing overcomes these limitations to a beneficial extent.

Apart from ongoing debates surrounding the validity of probing classifiers (see Hewitt and Liang, 2019; Ravichander et al., 2021; Belinkov, 2022), the probing setup does not allow the testing of prop-
property knowledge in a precise manner. Specifically, several properties are often perfectly correlated in datasets such as the one we use here (see §2.2). For example, the property of being an animal and being able to breathe, having a face, etc., are all perfectly correlated with one another. Even if the model’s true knowledge of these properties is highly variable, probing its representations for them would yield the exact same result, leading to conclusions that overestimate the model’s capacity for some properties, while underestimating for others. Evaluation using minimal pair sentences overcomes this limitation by allowing us to explicitly represent the properties of interest in language form, thereby allowing precise testing of property knowledge.

Similarly, standard cloze-testing of PLMs (Petroni et al., 2019; Weir et al., 2020; Jiang et al., 2021) also faces multiple limitations. First, it does not allow for testing of multi-word expressions, as by definition, it involves prediction of a single word/token. Second, it does not yield faithful conclusions about one-to-many or many-to-many relations: e.g. the cloze prompts “Ravens can ___” and “___ can fly,” do not have a single correct answer. This makes our conclusions about models’ knowledge contingent on choice of one correct completion over the other. The minimal pair evaluation paradigm overcomes these issues by generalizing the cloze-testing method to multi-word expressions—by focusing on entire sentences—and at the same time, pairing every prompt with a negative instance. This allows for a straightforward way to assess correctness: the choice between multiple correct completions is transformed into one between correct and incorrect, at the cost of having several different instances (pairs) for testing knowledge of the same property. Additionally, the minimal pairs paradigm allows us also to shed light on how the nature of negative samples affects model behavior, which has been missing in approaches using probing and cloze-testing. The usage of minimal pairs is a well-established practice in the literature, having been widely used in works that analyze syntactic knowledge of LMs (Marvin and Linzen, 2018; Futrell et al., 2019; Warstadt et al., 2020). We complement this growing literature by introducing minimal-pair testing to the study of property knowledge in PLMs.

Our property inheritance analyses (over the COMPS-WUGS stimuli, see §1 and §2.4) closely relates to the ‘Leap-of-Thought’ (LoT) framework of Talmor et al. (2020). In particular, LoT holds implicit taxonomic relations between concepts and tests whether LMs (they test only on RoBERTa, Liu et al. (2019)) can abstract over them to make property inferences—e.g., testing the extent to which models assign Whales have bellybuttons the ‘True’ label, given that Mammals have bellybuttons (implicit knowledge = Whales are mammals). With COMPS-WUGS, we instead explicitly provide the relevant taxonomic knowledge and instead target if PLMs can be consistent with the knowledge they have already captured/elicited (in the base case, COMPS-BASE), and demonstrate behavior that endows the correct subordinate concept the property in question. This is also similar to other work in measuring consistency of PLMs’ word prediction capacities in eliciting factual knowledge (Elazar et al., 2021; Ravichander et al., 2020).

2.2 Ground-truth Property Knowledge data

For our ground-truth property knowledge resource, we use a subset of the CSLB property norms collected by Devereux et al. (2014), which was further extended by Misra et al. (2022). The original dataset was constructed by asking 123 human participants to generate properties for 638 everyday concepts. Contemporary work has used this dataset by taking as positive instances all concepts for which a property was generated, while taking the rest as negative instances (Lucy and Gauthier, 2017; Da and Kasai, 2019, etc.) for each property. While this dataset has been popularly used in related literature, Misra et al. (2022) recently discovered striking gaps in coverage among the properties included in the dataset. For example, the property can breathe was only generated for 6 out of 152 animal concepts, despite being applicable for all of them—as a result, contemporary work can be expected to have wrongfully penalized models that attributed this property to animals that could indeed breathe, and similarly for other properties. To remedy this issue, the authors (Misra et al., 2022) manually extended CSLB’s coverage for 521 concepts and 3,645 properties. We refer to this extended CSLB dataset as XCSLB, and we use it as our source for ground-truth property knowledge.

2.3 Choosing negative samples

We rely on a diverse set of knowledge representation sources to construct negative samples for COMPS. Each source has a unique representational structure which gives rise to different pairwise sim-
we consider the Jaccard similarity between the row consisting of our 521 concepts. We Table 1: Negatively sampled concepts selected on the basis of various knowledge representational mechanisms, where the property is has striped patterns, and the positive concept is ZEBRA.

| Knowledge Rep. | Negative Concept | Similarity |
|----------------|------------------|------------|
| Taxonomy       | HORSE            | 0.88       |
| Property Norms | DEER             | 0.63       |
| Co-occurrence  | GIRAFFE          | 0.75       |
| Random         | BAT              | -          |

Table 1: Negatively sampled concepts selected on the basis of various knowledge representational mechanisms, where the property is has striped patterns, and the positive concept is ZEBRA.

similarity metrics, on the basis of which we pick out negative samples for each property:

**Taxonomy** We consider a hierarchical organization of our concepts, by taking a subset of WordNet (Miller, 1995) consisting of our 521 concepts. We use the wup similarity (Wu and Palmer, 1994) as our choice of taxonomic similarity.

**Property Norms** We use the XCSLB dataset and organize it as a matrix whose rows indicate concepts and columns indicate properties that are either present (indicated as 1) or absent (indicated as 0) for each concept. As our similarity measure, we consider the jaccard similarity between the row vectors of concepts. This reflects the overlap in properties between concepts, and is prevalent in studies utilizing conceptual similarity in cognitive science (Tversky, 1977; Sloman, 1993, etc.).

**Co-occurrence** We use the co-occurrence between concept words as an unstructured knowledge representation. For quantifying similarity, we use the cosine similarity of the GloVe vectors (Pennington et al., 2014) of our concept words.

Each property \(i\) in our dataset splits the set of concepts into two: a set of concepts which possess the property \(\left( Q_i \right) \), and a set of concepts that do not \(\left( \neg Q_i \right) \). We sample \(\text{min}\left(|Q_i|, 10\right)\) —i.e., at most 10—concepts from \(Q_i\) and take them to be our positive set. Then for each concept in the positive set, we sample from \(\neg Q_i\) the concept that is most similar (depending on the source) to the positive concept and take it as a negative concept for the property. We additionally include a negative concept that is randomly sampled from \(\neg Q_i\), leaving out the concepts sampled on the basis of the three previously described knowledge sources. Examples of the four types of negative samples for the concept ZEBRA and the property has striped patterns are shown in Table 1.

2.4 Minimal Pair Construction

Following our negative sample generation process, we end up with total of 49,280 pairs of positive and negative concepts that span across 3,645 properties (14 pairs per property, on average). Every property is associated with a property phrase—a verb phrase which expresses the property in English, as provided in XCSLB. Using these materials, we construct our two datasets of minimal pair sentences, examples of which are shown in Figure 1a:

COMPS-BASE The COMPS-BASE dataset contains minimal pair sentences that follow the template “[DET] [CONCEPT] [property-phrase].” where [DET] is an optional determiner, and [CONCEPT] is the noun concept. Applying this template to the output of our negative sampling process results in 49,280 instances.

COMPS-WUGS We test property inheritance in PLMs using only the animal kingdom subset of COMPS-BASE (152 concepts, 945 properties, and 14,196 pairs). Specifically, we convert the original minimal pair sentences in COMPS-BASE, in which the positive concept is an animal, into pairs of two-sentence stimuli by first introducing a new concept (WUG) that is a subordinate of the concepts in the original minimal pair. We then express its property inheritance in a separate sentence. Our two sentence stimuli follow the template: “A wug is a [CONCEPT]. Therefore, a wug [property-phrase].” Although we use wug as our running example for the subordinate concept, we use four different nonsense words: \{wug, dax,blicket, fep\} equal number of times, to avoid making spurious conclusions.

3 Methodology

3.1 Models Investigated

We investigate property knowledge and property inheritance capacities of 22 different PLMs, belonging to six different families. We evaluate four widely used masked language modeling (MLM) families: (1) ALBERT (Lan et al., 2020), (2) BERT (Devlin et al., 2019), (3) ELECTRA (Clark et al., 2020), and (4) RoBERTa (Liu et al., 2019); as well as two auto-regressive language modeling families: (1) GPT2 (Radford et al., 2019), and (2) the GPT-Neo (Black et al., 2021) and GPT-J models (Wang and Komatsuzaki, 2021) from EleutherAI. We also use distilled versions of BERT-base, RoBERTa-base, and GPT2, trained using the method de-
3.2 Performance Measures

To evaluate models on our minimal pairs, we compare their log-probabilities for the property—phrase—conditioned on the two concept noun-phrases (i.e. the context to its left) in a pair. That is, we hold the property phrase constant, and compare across minimally differing conditions to evaluate the probability with which a property is attributed to each concept. For example, we score the stimuli in COMPS-BASE, such as “A dog can bark,” as:

\[ \log p(\text{can bark} \mid \text{A dog}), \]

and its corresponding stimulus in COMPS-WUGS, “A wug is a dog. Therefore, a wug can bark.” as:

\[ \log p(\text{can bark} \mid \text{A wug is a dog. Therefore, a wug}) \]

This approach is equivalent to the “scoring by premise” method (Holtzman et al., 2021), which leads to stable comparisons across items. Additionally, this also takes into account the potential noise due to frequency effects or tokenization differences, as discussed by Misra et al. (2021). Estimating these conditional log-probabilities using auto-regressive PLMs can be directly computed in a left-to-right manner. For MLMs, we use their conditional pseudo-loglikelihoods (Salazar et al., 2020) as a proxy for conditional log-probabilities. Based on this simple method of eliciting relative acceptability measures from PLMs, we evaluate a model’s accuracy on COMPS as the percentage of times its log probability for a property is greater when conditioned on the positive—relative to the negative—concept, for all pairs.

3.3 Hypothesis space for Property Inheritance

We consider a model to possess more accurate property knowledge if it can successfully assign greater relative acceptability to COMPS-BASE stimuli that correctly associate properties to concepts, than to stimuli that do not. For a model to show property inheritance on these properties, however, we have a relatively more stringent criterion: a model must not only demonstrate accurate knowledge with respect to properties of concepts—it must also have the computational capacity to endow new concepts with the properties of their superordinates. This capacity could potentially involve representing symbolic rules such as the one in §1. To test whether both these criteria are met, we compute four measures (1, 2, 3, 4), shown in Figure 1b. A comparison between measures 1 and 2 tells us whether a model reflects sufficient knowledge about the property (i.e., accuracy on COMPS-BASE), while comparing 3 and 4 evaluates its ability to remain consistent in its knowledge about the property when a new concept is introduced (i.e., accuracy on COMPS-WUGS). Based on the comparison between these measures, there are four different hypotheses that a model’s behavior is compatible with, each of which represents a unique patterning of the four measures:

**H1: Accurate Property Inheritance**  Here, the model has accurate knowledge about the COMPS-BASE minimal pair, and can accurately project the property onto a subordinate of the concept. That is, \((1 > 2) \land (3 > 4)\).

**H2: Inability to Perform Property Inheritance**  In this case, the model has accurate knowledge about a minimal pair for a given property in COMPS-BASE, but cannot accurately demonstrate property inheritance behavior. That is, \((1 > 2) \land (3 < 4)\). This would occur if the model has insufficient
capacity to accurately perform reasoning that is required to demonstrate property inheritance, despite having correct knowledge about the property.

**H3: Spurious Property Inheritance** In this case, the model is inaccurate in the COMPS-BASE minimal pair setting, but nevertheless shows accurate property inheritance behavior. That is, $(1 < 2) \land (2 > 4)$. Here, the model’s performance on the property-inheritance setting leads us to conclude successful reasoning behavior, which is incorrect because the model does not have the appropriate property knowledge to begin with, as demonstrated by its failure in the original setting.

**H4: Consistent Lack of Property Knowledge** In this case, the model fails at both the original minimal pair in COMPS-BASE, and its corresponding property inheritance minimal pair in COMPS-WUGS. That is, $(1 < 2) \land (3 < 4)$. Even though this is a negative result, it is an indication of consistent behavior.

We measure a model’s compatibility with a given hypothesis as the percentage of the time the condition of the hypothesis (in terms of the aforementioned measures) is satisfied for that model. We compare this compatibility across hypotheses to paint an overall picture of how well PLMs can demonstrate behavior that is consistent with successful property inheritance.

### 4 Analyses and Results

#### 4.1 Base property knowledge of PLMs

We begin by evaluating the base property knowledge of the 22 PLMs, by reporting their accuracies on COMPS-BASE, across the four different negative sampling schemes that we consider. We additionally report a more stringent accuracy measure that we refer to as ‘Overall accuracy,’ which is calculated for every property and its positive concept, as the percentage of times a model correctly attributes the property to the positive concept in all four types of negative sampling schemes. These results are reported in Figure 2.

Figure 2 suggests several important findings. We see that models strongly distinguish between positive and negative concepts in cases where they are radically different—i.e., where negative concepts were sampled randomly, e.g., the concepts BEAR (positive) vs BOTTLE (negative) for the property can breathe. However performance drops substantially when there are subtler differences between the two concepts—e.g., the concepts WALRUS (positive) and SHARK (negative) for the property is a mammal. For instance, the best performing model in any similarity-based negative sampling scheme (GPT-J, 76%) only slightly outperforms the worst model in the random negative sampling scheme (Neo-125M, 71%). The performance of PLMs is not substantially different across the three similarity-based negative sampling schemes, suggesting that the dynamics of model sensitivity in attributing properties to concepts are largely harmonized across various types of similarities. As a result of models’ insensitivity in presence of similar negative concepts, the overall accuracies are very modest in value, with the overall accuracy of the best performing model (GPT-J) being only 52%. This overall performance is, however, significantly above chance (6.25%). We discuss additional findings, such as performance by property type and model size, in Appendix C, since they are incidental to the main conclusions of this analysis.

![Figure 2: Accuracies of PLMs on COMPS-BASE under various negative sampling schemes. Chance performance for all rows is 50%, except for ‘Overall,’ where it is 6.25%. Refer to Table 3 for unabbreviated model names.](image-url)
behavior, since a model that cannot attribute properties to superordinates should not be able to do so for their subordinates, in principle. Finally, since the compatibility scores of models with H2 and H3 are low in comparison, we conclude that models are less likely to demonstrate a complete lack of reliable property inheritance behavior.

### Post-hoc robustness evaluation with distracting information

To what extent does the compatibility of models with H1 hold in presence of distracting information? This question is inspired by Pandia and Ettinger (2021), who report a substantial decrease in perceived information processing capacity of PLMs in the presence of semantic distractors. Here, we transform the stimuli of COMPS-WUGS by creating two different subordinates for every minimal pair: one for the positive concept (e.g., ROBIN, subordinate: WUG) and the other for the negative concept (e.g., PENGUIN, subordinate: DAX).1 Here, sentences that express the relation between the negative concept and its subordinate operate as distractors, which may guide the models’ outputs away from attributing the property to the appropriate concept. We insert these distractors before and in-between the sentence containing the positive concept and its subordinate (see Figure 3a). We then evaluate which of the subordinates (WUG vs. DAX) models are more likely to associate with

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1We again use our four nonsense words (wug, dax, blicket, and fep) to generate our stimuli, amounting to 12 different unique ordered pairs, after accounting for counterbalancing.
models fail to show robust property inheritance in presence of distracting information. This failure is strikingly worse for large auto-regressive models like GPT2-l, GPT2-xl, and the billion-parameter models from EleutherAI, each of which shows at or below chance performance in the in-between distraction setting. We attribute this drastic drop in performance to the presence of a proximity effect, since in most cases models that are substantially distracted in the in-between setting—where the distraction information is closer to the queried property—show considerably less distraction in the before distraction setting. The MLMs we test show a similar drop in performance, though they are relatively more robust than their autoregressive counterparts, and operate above chance performance throughout. We conclude from these findings that even though most models can reasonably encode property knowledge in a majority of cases, they are unable to robustly demonstrate appropriate reasoning for property inheritance, even—and especially—when scaled up to billions of parameters.

5 General Discussion and Conclusion

The goal of COMPS is to shed light on the extent to which PLMs can: (1) attribute to real world concepts (HORSE, WHALE) their properties (is a mammal); and (2) demonstrate behavior that is consistent with property inheritance: a reasoning process in which concepts are endowed with the properties of their superordinates (Murphy, 2002). COMPS is primarily inspired by studies of semantic memory that focus on the organization and interrelations of concepts, as well as the computations that are carried out using the knowledge of their properties (Smith and Estes, 1978; Sloman, 1998; Murphy, 2002).

Findings from our experiments establish that given a pair of positive and negative concepts, PLMs perform reasonably well at attributing a property to the correct concept. Importantly, we found this capacity to be coarse-grained, in that models excelled when the positive and negative concepts were radically different, but struggled when negative concepts shared well-defined semantic relations with positive concepts across different knowledge representational mechanisms. Next, we defined a simple criterion to evaluate PLMs’ ability to perform property inheritance—a model is successful if it achieves high consistency between its preference in attributing a property: (1) to the concept that possesses it (positive concept), and (2) to that concept’s subordinate, as opposed to the negative concept's subordinate.
concepts in each case. Through our experiments, we found this criterion to be met in a majority of the cases, suggesting a strong capacity of models to demonstrate property inheritance. However, post-hoc analyses revealed that for most models, this capacity drastically decreases in the presence of distracting information (sometimes even worse than random-guessing), suggesting a clear lack of robustness in the information processing capacities of PLMs, similar to the results of Pandia and Ettinger (2021). In contrast to their results, we find that larger models are generally more distracted than are smaller models, and this especially happens when the distracting information is closer to the predicted property-phrases, suggesting the presence of a proximity effect.

Contemporary work has highlighted the promise of PLMs on high-level tasks requiring—among other things—access to proper relational knowledge between concepts (see Safavi and Koutra, 2021; Piantadosi and Hill, 2022). Findings from our experiments that target reasoning ability based on perhaps the most well-established of relations—the ISA relation (Murphy, 2003)—suggest that PLMs’ approximation of inference-making behavior based on simple relational knowledge is at best noisy, owing to clear failures in presence of distracting information. One way we anticipate this noise to manifest is through failures of models in tracking entities in context, an ability which may not arise directly as a result of LM pre-training (Gupta and Durrett, 2019). In the face of distraction, a pre-trained model might wrongfully map the subordinate concept for which the property is queried (WUG), to the subordinate concept that is used to add distraction (DAX). This likely leads to a decrease in accuracy, despite models showing ability to recall the prerequisite knowledge. Exploring this hypothesis—as well as other possibilities—is therefore an important direction for future research.

6 Limitations

Our results show that while PLMs succeed at demonstrating property inheritance in the undistracted case, they are unable to do so in presence of competing or distracting information. This suggests that the word-prediction objective alone might be insufficient to endow models with the capacity necessary to demonstrate robust property inheritance. However, it might be possible that this ability emerges in LMs that are significantly larger than the LMs we have tested (Brown et al., 2020; Wei et al., 2022a), which are not tested in this work. Indeed, recent work has demonstrated these larger PLMs to achieve strong performance on other types of symbolic reasoning, such as solving math problems, reversing sequences, etc., by priming models to produce additional textual content that represents intermediate reasoning steps (Nye et al., 2021; Wei et al., 2022b). Another possibility is that PLMs might learn a better approximation of the desired reasoning through explicit supervision—e.g., by training on natural language inference (Bowman et al., 2015; Williams et al., 2018), or by training to perform reasoning over implicit knowledge (Talmor et al., 2020). We do not test these models/frameworks in this work.

Additionally, we have tested PLMs on property knowledge and property inheritance only from a behavioral perspective, which is at its core, is a correlational endeavor. Potential future work could complement our results by providing evidence from representational analyses, or by devising causal interventions, similar to those recently explored in the realm of syntactic agreement (Finlayson et al., 2021), or testing negation and hypernymy in NLI models (Geiger et al., 2020), among others.

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A Preview of COMPS stimuli

We show examples of stimuli from our COMPS-BASE and COMPS-WUGS datasets in Listing 1 and Listing 2, respectively. These can be found in the code repository in the files, data/comps-base.jsonl and data/comps-wugs.jsonl. In pseudocode, we compute our conditional probabilities as:

```python
# import minicons
from minicons import scorer

# define lm (here, gpt2)
model = scorer.IncrementalLMScorer('gpt2')

# attributing property to concept using partial_score()
# which measures conditional probabilities given batch
# of prefixes and queries.
model.partial_score(property_phrase, condition = prefix_acceptable)

{
    "property": "can fly",
    "acceptable_concept": "airplane",
    "unacceptable_concept": "boat",
    "prefix_acceptable": "A wug is a goat. Therefore, a wug",
    "prefix_unacceptable": "A wug is a raccoon. Therefore, a wug",
    "property_phrase": "can fly.",
    "condition": "taxonomic",
    "similarity": 0.72
}

Listing 1: An instance of COMPS-BASE. “condition” represents the negative sampling scheme, and “similarity” represents the similarity between the acceptable concept and the unacceptable concept on the basis of the condition (either Taxonomic, Property Norm, Co-occurrence, or Random).

B Model Metadata

Table 3 shows the different models used in our experiments, along with their abbreviation, tokenization scheme, total parameters, vocabulary size, number of tokens encountered during training, and corpora on which they are pre-trained. All models were accessed using minicons (Misra, 2022),2 a python library that provides unified LM-scoring for models in Huggingface’s transformers (Wolf et al., 2020), and provides a standard mechanism for eliciting log-probabilities in batch-wise manner. Experiments were performed using an NVIDIA V100 GPU (32 GB RAM) and took about 6 hours to run, discounting the time it took to download the models from the Huggingface Hub.3 Code for our computations was written in pytorch 1.11.

C Additional findings

C.1 How does performance on COMPS-BASE vary by property type?

Devereux et al. (2014) have categorized the properties that we use in our experiments to lie in 5 different categories: (1) Taxonomic, e.g., is a mammal, is a vehicle, etc.; (2) Functional, e.g., can keep the body warm, is used to hit nails, etc.; (3) Encyclopedic, e.g., uses electricity, is warm blooded, etc.; (4) Visual Perceptual, e.g., has webbed feet, has thick fur, etc.; and (5) Other Perceptual, e.g.,

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2https://github.com/kanishkamisra/minicons
3https://huggingface.co/models
makes grunting sounds and is sharp, etc. We report results of the 22 PLMs on the COMPAS-BASE stimuli across the five different property types, in Figure 5. From Figure 5, we observe that PLMs are substantially stronger in eliciting taxonomic properties of concepts as compared to other types, with highest overall accuracy being 70%, as compared to 48% on encyclopedic properties, 50% on visual perceptual properties, 57% on functional properties, and 43% on non-visual perceptual properties. This corroborates evidence from previous work in analyzing property knowledge of distributional semantic models as well as LM representations (Lucy and Gauthier, 2017; Da and Kasai, 2019; Rubinstein et al., 2015; Weir et al., 2020). However, in comparison to most of these works, the gap between performance on perceptual properties and non-perceptual properties is small. We conjecture that this could be primarily due to the extension of the CSLB by Misra et al. (2022), which lead to an increase in coverage of property knowledge for several properties. For instance, the property *has teeth* was mentioned only for 45 out of 67 potential concepts, having been left out for concepts such as CALF, 4 BUFFALO, KANGAROO, etc. So it could be the case that previous research might have underestimated the property knowledge of PLMs and other distributional semantic models of language.

**C.2 Does performance on COMPAS-BASE depend on scale?**

We plot the accuracies of PLMs on COMPAS-BASE per model family (in order to control for differences in training corpora and tokenization) in Figure 6. In all families except BERT, we see that accuracy increases with the model size, following standard scaling laws. We notice that distilBERT-base (Sanh et al., 2019) is able to outperform even BERT-large in the ‘Random’ negative samples, suggesting that pruning BERT might sometimes unintentionally

| Family | Model (Abbrev.) | Parameters | Vocab Size | Tokenization | Corpora | Tokens |
|--------|----------------|------------|------------|--------------|---------|--------|
| ALBERT | albert-base-v2 (A-b) | 11M | 30,000 | SentencePiece | WIKI and BC | 3.3B |
|        | albert-large-v2 (A-l) | 17M | | |
|        | albert-xlarge-v2 (A-xl) | 59M | | |
|        | albert-xxlarge-v2 (A-xxl) | 206M | | |
| BERT   | distilbert-base-uncased (dB-b) | 67M | 30,522 | WordPiece | WIKI and BC | 3.3B |
|        | bert-base-uncased (B-b) | 110M | | |
|        | bert-large-uncased (B-l) | 345M | | |
| ELECTRA | electra-small (E-s) | 13M | 30,522 | WordPiece | WIKI and BC | 3.3B |
|        | electra-base (E-b) | 34M | | |
|        | electra-large (E-l) | 51M | | |
| RoBERTa | distilroberta-base (dR-b) | 82M | 50,265 | Byte-pair encoding | OWTC | 2B |
|        | roberta-base (R-b) | 124M | | |
|        | roberta-large (R-l) | 355M | | |
| GPT/GPT2 | distilgpt2 (dGPT2) | 82M | 50,257 | Byte-pair encoding | OWTC | 2B |
|        | gpt2 (GPT2) | 124M | | |
|        | gpt2-medium (GPT2-m) | 355M | | |
|        | gpt2-large (GPT2-l) | 774M | | |
|        | gpt2-xl (GPT2-xl) | 1.5B | | |
| EleutherAI | gpt-neo-125M (Neo-125M) | 125M | 50,257 | Byte-pair encoding | PILE | 300B |
|        | gpt-neo-1.3B (Neo-1.3B) | 1.3B | | |
|        | gpt-neo-2.7B (Neo-2.7B) | 2.7B | | |
|        | gpt-j-6B (GPT-J) | 6B | | |

Table 3: Summary of the 22 models that we evaluate in this paper. **Legend for Corpora:** WIKI: Wikipedia; BC: BookCorpus (Zhu et al., 2015); CW: ClueWeb (Callan et al., 2009); CC: CommonCrawl; GIGA: Gigaword (Graff et al., 2003); OWTC: OpenWebTextCorpus (Gokaslan and Cohen, 2019); CC-NEWS: CommonCrawl News (Nagel, 2016); STORIES: Stories corpus (Trinh and Le, 2018); WEBTEXT: WebText corpus (Radford et al., 2019); PILE: The Pile (Gao et al., 2020).

*As estimated by Warstadt et al. (2020).
improve the model’s ability to associate properties and concepts. We do however suggest caution against interpreting these results as robust conclusion for scaling laws on COMPS-BASE. Such an endeavor would require comparing performance of models across multiple checkpoints with varying number of parameters, paired with standard statistical inference (Sellam et al., 2021; Zhang et al., 2021).
Figure 5: COMPS-BASE performance across five property types annotated in CSLB (Devereux et al., 2014).
Figure 6: Accuracy vs. parameters across various negative sampling strategies (indicated as ‘Condition’). “Overall” stands for the more stringent accuracy where a model’s prediction is considered accurate iff it is correct across all four negative sampling schemes (see §4.1). Models are shaded based on number of parameters.