Holmes
A Benchmark to Assess the Linguistic Competence of Language Models

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Abstract

We introduce Holmes, a new benchmark designed to assess language models' (LMs') *linguistic competence*—their unconscious understanding of linguistic phenomena. Specifically, we use classifier-based probing to examine LMs' internal representations regarding distinct linguistic phenomena (e.g., part-of-speech tagging). As a result, we meet recent calls to disentangle LMs' linguistic competence from other cognitive abilities, such as following instructions in prompting-based evaluations. Composing Holmes, we review over 270 probing studies and include more than 200 datasets to assess *syntax, morphology, semantics, reasoning,* and *discourse* phenomena. Analyzing over 50 LMs reveals that, aligned with known trends, their linguistic competence correlates with model size. However, surprisingly, model architecture and instruction tuning also significantly influence performance, particularly in *morphology* and *syntax*. Finally, we propose FlashHolmes, a streamlined version that reduces the computation load while maintaining high-ranking precision.

1 Introduction

Linguistic competence is the unconscious understanding of language (Chomsky, 1965), like the syntactic structure of a sentence. As language models (LMs) are trained on simple tasks such as next word prediction (Brown et al., 2020), one might naturally wonder: *What is the linguistic competence of LMs, and how do they differ?* To answer such questions, contemporary benchmarks estimate cognitive abilities, as done for mathematical reasoning (Cobbe et al., 2021) or factual knowledge (Petroni et al., 2019b, 2020). However, such benchmarks rely on LMs' *use of language* (textual responses), known as linguistic performance (Matthews, 2014). As a result, they conflate abilities tested with specific instructions, as done for syntactic phenomena in Blevins et al. (2023), with latent abilities like producing coherent text or following instructions. As this entanglement makes it infeasible to draw definitive conclusions (Hu and Levy, 2023; Liang et al., 2023; Perlitz et al., 2024), recent studies call to assess LMs' linguistic competence comprehensively and isolated (Lu et al., 2023; Mahowald et al., 2024).

In this work, we introduce Holmes (Figure 2), a benchmark to assess the linguistic competence of LMs (Figure 7) regarding numerous linguistic phenomena. To disentangle LMs' understanding of these phenomena from their linguistic performance, we assess the LMs' internals using classifier-based probing (Tenney et al., 2019a; Hewitt and Manning, 2019; Belinkov, 2022). As illustrated in Figure 1 for probing the part-of-speech (POS) tags for words, we first train linear models (probes) using the internal representations of text inputs from the last model layer to predict the specific phenomena aspects. We then approximate the LMs' grasp of these phenomena using the probes' performance, rigorously verified using control tasks (Hewitt and Liang, 2019) and from an information theory perspective (Voita and Titov, 2020). With this particular and comprehensive scope, we thoroughly address the initially raised questions as follows:

Meta-Study (§ 3) The review of over 270 probing studies reveals a gap in comprehensively

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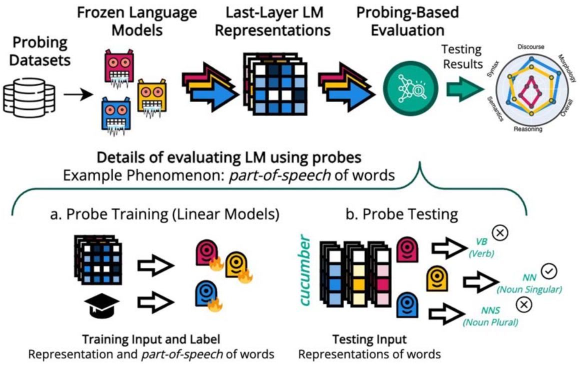


Figure 1: In Holmes, we encode examples of probing datasets using frozen LMs. Then, we train probes (linear models) with labels representing the specific linguistic phenomenon under test. Finally, we use the results of testing the probes to approximate the LMs' linguistic competence regarding the tested phenomena.

evaluating linguistic competence. Despite covering over 200 probing tasks and 150 LMs, individual studies focus on particular tasks and LMs. As a result, only three LMs were probed on over 20% of the tasks, and only one task (POS) was evaluated for more than 20% of the LMs. Notably, recent large LMs are significantly underrepresented.

Benchmark (§ 4) Addressing these identified deficiencies, Holmes offers a structured way to assess LMs' English linguistic competence comprehensively. It features 208 distinct datasets covering *morphology*, *syntax*, *semantics*, *reasoning*, and *discourse* phenomena, including previously underrepresented ones like negation or rhetoric.

Results and Analysis (§ 5) From assessing 59 LMs, we find that no LM consistently excels over the others. Further, linguistic competence is more pronounced for *morphology* and *syntax* than the other types of phenomena, and LMs' linguistic competence is fundamentally affected by **model size**, **model architecture**, and **instruction tuning**.

First, we generalize previous findings (Tenney et al., 2019b; Zhang et al., 2021) and show that LMs' linguistic competence, particularly *morphology* and *syntax*, scales beyond 350 million parameters. Second, contrary to the prompting evaluations (Lu et al., 2023) and aligned with Waldis et al. (2024a) and Gautam et al. (2024), **model architecture** is critical. The linguistic competence of decoder-only LMs lags behind encoder-only ones. Not even 70 billion decoders produce representations for words with the same stability as encoders with 110 million parameters. Third, while **instruction tuning** (Ouyang et al., 2022; Touvron et al., 2023; Zhou et al., 2023) aims to align LMs with human interactions, we focus for the first time on its effect on linguistic competence. We found that instruction tuning improves *morphology* and *syntax* but has mixed effects on other phenomena types, hinting at a superficial alignment. Lastly, we compare Holmes with other benchmarks. While LM rankings of reasoning-intense downstream tasks (Beeching et al., 2023) correlate with reasoning phenomena, explicitly prompting for linguistic phenomena (Liang et al., 2023) leads to unreliable results. As these results show that Holmes aligns with other benchmarks, its probing-based evaluation is indispensable for explicitly testing LMs' linguistic competence disentangled from their linguistic performance.

Efficiency (§ 6) Finally, to mitigate the heavy computational burden of evaluating a new LM on Holmes, we form the streamlined version FlashHolmes by selectively excluding samples not significantly influencing overall rankings (Perlitz et al., 2023). Specifically, FlashHolmes approximates Holmes rankings with high precision while requiring only ∼3% of the computation.

Contributions With Holmes, we introduce a comprehensive and thorough benchmark to assess LMs' linguistic competence, providing ground to evaluate them more holistically. Extensive experiments on Holmes reveal that LMs' linguistic competence is manifold and more pronounced for phenomena targeting words and syntactic structure than semantic, reasoning, or discourse. LMs properties like size or architecture crucially account for differences among LMs. Fostering further research, we provide interactive tools to explore Holmes and straightforward evaluation code for upcoming LMs with efficiency in mind.

2 Preliminaries

Language Models (LMs) Language models compute probabilities for word sequences i, enabling tasks such as classifying i, textual comparisons between i and another sequence i', and text generation based on i. We consider LMs as any model producing representations

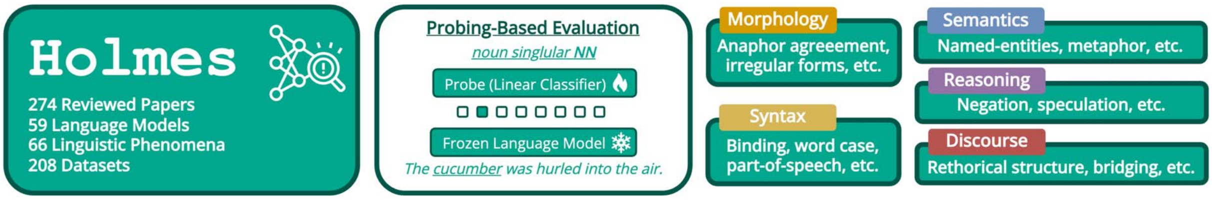

Holmes
274 Reviewed Papers
59 Language Models
66 Linguistic Phenomena
208 Datasets
Probing-Based Evaluation
noun singlular NN
Probe (Linear Classifier)
Frozen Language Model
The cucumber was hurled into the air.
Morphology
Anaphor agreeement, irregular forms, etc.
Syntax
Binding, word case, part-of-speech, etc.
Semantics
Named-entities, metaphor, etc.
Reasoning
Negation, speculation, etc.
Discourse
Rethorical structure, bridging, etc.

Figure 2: Overview of Holmes (left) with the five phenomena types (right) and an example of probing-based evaluations for part-of-speech: encoding the input tokens and predicting the POS tag for *cucumber*, here *NN*.

of i, regardless of their specific type: **sparse** like bag-of-words (Harris, 1954); **static** such as GloVe (Pennington et al., 2014); or **contextualized** transformers (Devlin et al., 2019; Raffel et al., 2020).

Linguistic Competence and Performance For centuries (Robins, 2013), linguists have been fascinated by the processes of language learning, usage, and evolution. One specific discussion is the differentiation between knowing and using a language. de Saussure (1916) distinguished between language with specific rules and words (*langue*) as an ongoing negotiated fulfillment of the societal need for communication and its usage (*parole*). Similarly, Chomsky (1965) uses the term *linguistic competence* for the unconscious understanding of language and *linguistic performance* for using languages in any utterance. In this work, we follow Chomsky's terminology and treat LMs as static artifacts of a certain time, omitting ongoing processes of the society considered by de Saussure. Specifically, we focus on assessing the linguistic competence of LMs, including specific linguistic phenomena like word dependencies and their distinct POSs. Opposed, contemporary benchmarks (Cobbe et al., 2021; Petroni et al., 2019b, 2020) assess linguistic performance by providing textual instructions and verifying LMs' textual responses. Note that this evaluation protocol can also verify an understanding of specific linguistic phenomena, as done in Blevins et al. (2023) or Liang et al. (2023) for syntactic structure. However, such evaluation protocols conflate LMs' linguistic competence with latent abilities (like following instructions). Thus, Holmes unique evaluation perspective is indispensable to assess linguistic phenomena isolated to assess LMs comprehensively.

Linguistic Phenomena We define the linguistic competence of LMs as their ability to understand a diversity of linguistic phenomena. Specifically, we focus on five phenomena types: *morphology*, the structure of words; *syntax*, the structure of sentences; *semantics*, the meaning of words; *reasoning*, the use of words in logical deduction and other related phenomena like negation or speculation; *discourse*, the context in text like rhetorical structure. Following Mahowald et al. (2024), we categorize these phenomena types into two groups: *morphology* and *syntax* are **formal** phenomena, which include understanding grammatical rules and statistical patterns, while **functional** ones (*semantics*, *reasoning*, and *discourse*) focus on practical abilities like interpreting text sentiment or detecting the existence of speculation.

Datasets We define a dataset as text examples and labels covering a specific aspect of a linguistic phenomenon, like words and their POS tags. Typically, these labels are unambiguous, enabling us to assess the specific aspect under test in isolation.

Probes Using probes, we empirically assess the linguistic competence of LMs regarding the featured linguistic phenomena in Holmes. We design probing tasks using the widely recognized classifier-based probing method (Tenney et al., 2019a; Hewitt and Manning, 2019; Belinkov, 2022) also known as diagnostic classifiers (Veldhoen et al., 2016; Giulianelli et al., 2018). Running such a probing task involves training a probe (linear model) using the specific dataset to test a distinct aspect of a linguistic phenomenon in isolation. To do this, we encode the text examples of a dataset with a given LM and use them to train the probe regarding the specific labels representing the tested linguistic phenomenon. The probe's performance is then used to approximate the LM's understanding of the specific phenomenon. A higher score indicates that LMs capture patterns relevant to this phenomenon internally, which in turn enhances the accuracy (Tenney et al., 2019b).

3 Meta-Study

This section summarizes our survey of 274 studies (§ 3.1) probing LMs' linguistic competence. We analyze them regarding their evolution, probing tasks and LMs addressed (§ 3.2), and identify the need to consolidate existing resources (§ 3.3).

3.1 Scope

We analyze 28k papers (P) from 2015 to August 2023 of major NLP conferences (TACL, ACL, AACL, COLING, EACL, EMNLP, NAACL, and the corresponding workshops) expanded with selected work from other venues such as ICLR. To identify relevant work, we employ a semi-automatic approach. First, we use automated filtering based on paper metadata and full text,[1] grounded in the occurrence of established terminology related to the specific focus of `Holmes`, namely, disentangling the linguistic competence of LMs by studying their internal representations. This terminology, including *probing* and *probe*, is commonly found in influential literature surveys (Rogers et al., 2020; Belinkov, 2022) and diverse investigation settings, such as analyzing internal representations using linear classifiers (Tenney et al., 2019b; Conneau et al., 2018; Elazar et al., 2021) or masked-based approaches focusing on lexical knowledge of LMs (Petroni et al., 2019a; Talmor et al., 2020a; Kassner et al., 2021; Peng et al., 2022). Specifically, we define three criteria to identify relevant papers: $P' = \{\forall p \in P | p \in P_1 \cup p \in P_2 \ \cup p \in P_3\}$, where:

$\mathbf{P_1}$: papers with *probing* or *probe* in the title.

$\mathbf{P_2}$: papers with *probing* or *probe* in the abstract and at least five occurrences in the main content.

$\mathbf{P_3}$: papers with *probing* or *probe* occurring at least ten times in the main content.

We identified 493 matching papers (P') by applying these criteria. We then manually review the automatically generated candidate list (P') and select studies that examined LMs with one or more specific linguistic phenomena as part of their analysis or as a primary contribution. This process involves filtering out papers using the term *probing* in other senses, such as *probing hash tables* in Bogoychev and Lopez (2016). Moreover, we supplement the candidates with a curated selection of highly relevant studies that do not meet the above criteria. For example, seminal works published before 2019 which employ terms like ‘‘*diagnostic classifier*’’ (Giulianelli et al., 2018; Hupkes and Zuidema, 2018), as well as other notable studies (Gupta et al., 2015; Shi et al., 2016). This comprehensive approach yields 274 relevant papers (P_r), which we further analyze subsequently.

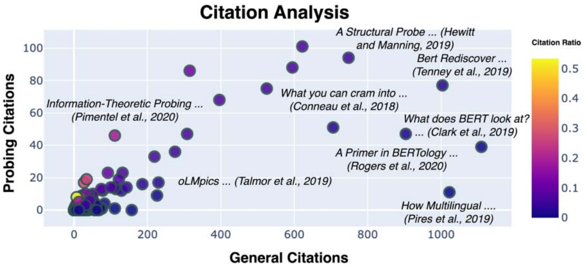


Figure 3: Citation analysis considering *probing citations* originating from the set of relevant work and every other citation (*general citations*). The color scale indicates the ratio (α) between them.

3.2 Analysis

i) Scattered Evolution Calls for Consolidation. We begin by examining the evolution of relevant studies in the field, illustrated in Figure 3. We analyze the citation patterns among these studies, distinguishing between **probing citations** (C_p), which represent citations between them, and **general citations** (C_g), which encompass all other citations. The colorized ratio $\alpha = \frac{|C_p|+1}{|C_g|+1}$ visually relates these two measures. This analysis reveals that only a small fraction of the works have garnered broad recognition, with 16 papers exceeding 200 general citations. Furthermore, probing works cite each other relatively infrequently, with an average probing citation ratio of $\alpha = 0.1$. This suggests that other fields have paid limited attention to LMs' linguistic competence. The scattered citation patterns and lack of engagement with this topic underscore the need to consolidate existing resources and establish a solid foundation to bootstrap research in this area.

ii) Probing Work Prioritizes Tasks and Analytics over Methods. We categorize the selected work according to their probing focus into three categories: **methodological**, which introduces new methods, such as control tasks (Hewitt and Liang, 2019) or minimum description length

[1] We use PyPDF2 v3.0.0, DBLP and semanticscholar API.

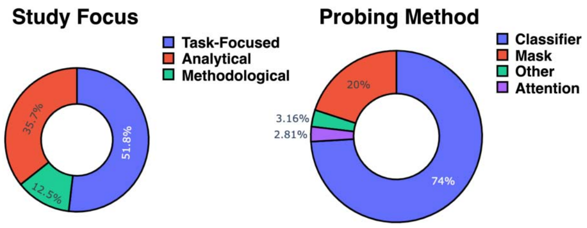


Figure 4: Categorization of the selected studies by their focus and their conducted probing method.

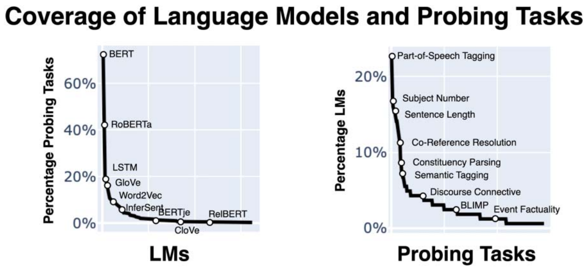


Figure 5: Overview of how many tasks single LMs cover and vice versa. Single examples are highlighted.

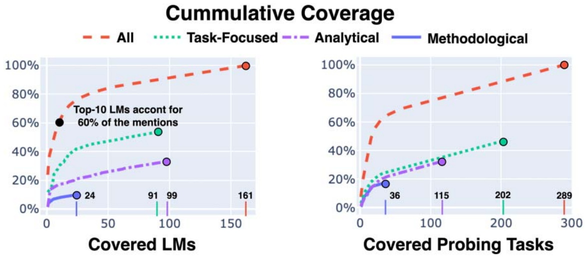


Figure 6: Cumulative coverage of LMs and tasks, considering all relevant studies and their focus.

(Voita and Titov, 2020); **task-focused**, which assesses specific linguistic phenomena as main contributions, such as discourse relations in text (Koto et al., 2021); and **analytical**, which uses probing tasks to analyze LMs, such as the impact of pre-training data (Zhang et al., 2021). As shown in Figure 4, the majority of studies (51.8%) focus on specific probing tasks, such as numeric scales (Zhang et al., 2020), or morphosyntactic analysis (Shapiro et al., 2021). A significant proportion (35.7%) use probing as a supplementary analytical tool, for example, to analyze the effect of fine-tuning (Mosbach et al., 2020a; Zhu et al., 2022a). The remaining 12.5% address methodological problems related to probing (Wu et al., 2020; Immer et al., 2022; Zhu et al., 2022b).

iii) The Dominance of Classifier-based Probing. Next, we analyze the specific employed probing method regarding four categories: (1) **classifier-based probing**, which uses linear or shallow models to probe internal representations of LMs; (2) **mask-based probing**, where LMs fill gaps to verify linguistic phenomena; (3) **attention-based probing**, which relies on attention patterns; and (4) **other methods** that do not fit into the previous three categories. Our analysis indicates that most studies (74%) utilize the classifier-based probing method, as exemplified in Tenney et al. (2019a). Additionally, 20% of studies conduct mask-based probing, as shown in Talmor et al. (2020b). In contrast, only a small portion of work ($\sim$ 3%) considers attention patterns or other approaches, such as bridging (Pandit and Hou, 2021) or dimension selection (Torroba Hennigen et al., 2020).

iv) Tasks and LMs Are Barely Broadly Evaluated. Finally, we examine the tasks and LMs investigated by the relevant studies. For example, Tenney et al. (2019b) explore BERT on various tasks, including POS tagging, semantic-role labeling (SRL), and others. Our analysis reveals that, collectively, these studies cover a remarkable 289 unique tasks and 161 distinct LMs, demonstrating a broad scope of investigation. Below, we delve into the details and highlight noteworthy findings.

We analyze how LMs and tasks are considered jointly in Figure 5. Despite the broad coverage, single studies, including fundamental ones, maintain a particular focus and consider only a fraction of LMs and tasks. For example, while most tasks (72%) were assessed on BERT, RoBERTa's coverage has already declined to 42%. Conversely, POS tagging, the most probed task, was only evaluated on 23% of the LMs, excluding prominent examples like BART (Lewis et al., 2020). In particular, more recently released larger and powerful LMs, like Pythia (Biderman et al., 2023), UL2 (Tay et al., 2023), or LLAMA-2 (Touvron et al., 2023), as well as instruction-tuned LMs like FLAN-T5 (Chung et al., 2022) or LLAMA-2-Chat (Touvron et al., 2023), are missing almost entirely, with only a few recent exceptions (Hu and Levy, 2023; Waldis et al., 2024a). Again, these insights underscore the need to consolidate existing resources for more comprehensive coverage.

Figure 6 further highlights this point by sorting LMs and tasks according to their frequency of mention in relevant works and plotting their cumulative coverage. For example, considering

Type	Phenomena	Example	Label
Morphology	Subject-Verb Agreement	*And then, the cucumber was hurled into the air.*	`Correct`
		And then, the cucumber were hurled into the air.	`Wrong`
Syntax	Part-of-Speech	*And then, the cucumber was hurled into the air.*	`NN (Noun Singular)`
Semantic	Semantic Roles	*And then, the cucumber was hurled into the air.*	`Direction`
Reasoning	Negation	*And then, the cucumber was hurled into the air.*	`No Negation`
Discourse	Node Type in Rhetorical Tree	*And then, the cucumber was hurled into the air.*	`Satellite`

Table 1: Example instance of `Holmes` datasets for every type of linguistic phenomena. The relevant part of the example for the specific label is underlined.

all studies (red line), the top-10 most mentioned LMs account for 80% of all LMs mentions (black dot), while the remaining 151 unique LMs account for only 40%. A comparison of the paper's focus reveals that methodological studies rely only on a limited set of 24 LMs and 36 tasks. In contrast, task-focused and analytical work cover a similar number of LMs (91 and 99, respectively). However, due to their distinct focus, task-focused studies cover a significantly larger number of tasks (202) than analytical ones (115).

3.3 Summary

Our meta-study emphasizes the need to consolidate existing resources for a comprehensive assessment of the linguistic competence of LMs —a manifold but rather a blind spot in evaluation research. Apart from more thorough evaluations, such a stimulus can significantly boost future research, as happened in computer vision with ImageNet (Deng et al., 2009) or in NLP with GLUE and SuperGLUE (Wang et al., 2019a,b).

4 Holmes Benchmark

With `Holmes`, we provide an extensive ground to tackle these identified deficiencies in the existing literature and comprehensively investigate the English linguistic competence of LMs. Specifically, `Holmes` features 208 datasets addressing distinct aspects of 66 phenomena covering *morphology*, *syntax*, *semantic*, *reasoning*, and *discourse*.

4.1 Datasets

We provide a comprehensive coverage of linguistic phenomena by covering 208 unique datasets. We leverage existing and established resources like OntoNotes (Weischedel et al., 2013), English Web Treebank (Silveira et al., 2014), or BLiMP (Warstadt et al., 2020) to create datasets addressing phenomena like the POS of words, their dependencies or the linguistic acceptability of sentences. Further, we include a range of less employed data, addressing contextualization of words (Klafka and Ettinger, 2020), reasoning (Talmor et al., 2020b), semantic decomposition (White et al., 2016; Rudinger et al., 2018a,b; Govindarajan et al., 2019; Vashishtha et al., 2019), grammatical knowledge (Huebner et al., 2021), bridging (Pandit and Hou, 2021), and rhetorical (Carlson et al., 2001) and discourse (Webber et al., 2019) structure in text. Finally, we cover rarely probed phenomena like negation (Szarvas et al., 2008; Konstantinova et al., 2012; Vahtola et al., 2022), or word complexity (Paetzold and Specia, 2016).

4.2 Structure

Apart from the comprehensive scope, `Holmes` provides a clear structure for specific evaluations on different levels of aggregation. We first group the datasets according to the linguistic phenomena addressed. Next we categorize these phenomena into their previously defined five phenomena types (see § 2): *morphology*, like the agreement of subject and verb; *syntax*, such as the part-of-speech of words; *semantics*, like semantic roles of words; *reasoning*, such as detecting a negated sentence; and *discourse*, like selecting the correct following sentence. Table 1 provides examples for every type of phenomenon. Note that we rely on the categorization provided by the specific studies whenever given (more details in the Appendix § A.3). For example, Conneau et al. (2018) categorized the tense of the main clause as *semantic*. This phenomenon could also be categorized as *syntax* if we test the detection of incorrect formulations given a specific tense. However, we follow the authors' suggestion and test the detection of the tense on a sentence level, which represents semantic aspects.

4.3 Experimental Setup

Holmes evaluation follows the primarily used classifier-based probing paradigm, as described in § 2, to analyze the internal representations of the last layer of LMs.[2] Thereby, we maximally disentangle the understanding of distinct linguistic phenomena from each other and from other cognitive abilities, such as following textual instructions. Further, this method allows us to assess any LM type, including sparse, static, or contextualized ones. Based on the specific dataset, we either select the embeddings of the specific input tokens (like single words for POS tagging) or average embeddings across a span or the whole sentence. We define a probing task as training a probe f_p (linear model without intermediate layers) using these embeddings as inputs and the dataset labels as training signals. If not defined in the original data, we divide the dataset samples into train/dev/test split following a ratio of 70/10/20. We repeat this procedure five times using different random seeds for a robust measurement.

4.4 Evaluations

We approximate how well an LM encodes specific linguistic phenomena using the absolute prediction performance of the probes. In addition, we rigorously evaluate the reliability of probing results using control tasks and from an information theory perspective (Voita and Titov, 2020; Hewitt and Liang, 2019). Different from commonly used prompting assessments, this particular evaluation protocol refrains from known fallacies in which the results and conclusions are sensible with specific instructions (Mizrahi et al., 2024; Min et al., 2022) or few-shot examples (Lu et al., 2023).

Task Score Metric Based on a dataset's specific task type, we use a corresponding performance measure, macro F_1 for classification or Pearson correlation for regression. In addition, we calculate the standard deviation σ of the probe across multiple seeds. A lower σ indicates a better encoding of a given linguistic phenomenon since the measurement is robust to noise. Further, we use the task score for ranking-based evaluation of all evaluated LMs $L = \{l_1, \ldots, l_m\}$ within Holmes. We calculate the mean winning rate mwr (in percentage), telling us how many times one LM l_1 wins against others (Liang et al., 2023). With a higher mwr, we assume an LM encodes tested linguistic phenomena better than others.

Compression Next, we evaluate the probes' reliability from an information-theoretic perspective. Following Voita and Titov (2020), we use the compression I. It is the ratio between the minimum description length mdl of encoding n instances with a label space of K compared to applying a uniform encoding $I = \frac{u}{mdl}$. A higher I means fewer bits are needed to encode the instance and their labels, indicating that the given linguistic phenomenon is more clearly encoded in the internal representation of LMs.

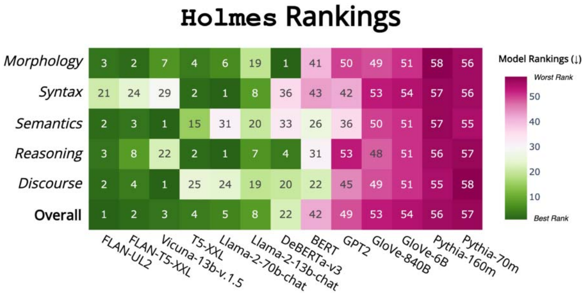
Selectivity A reliable probe should grasp patterns relevant to the tested phenomena in the internal representations of LMs but should not be able to learn anything else. Therefore, we expect high performance when evaluating the specific dataset but low performance when we randomize training signals. We check this using control tasks introduced in Hewitt and Liang (2019). Specifically, we calculate the selectivity $S = F_1(y, \hat{y}) - F_1(y', \hat{y'})$ as the difference between the probe trained with the original labels y and the control task where we train the probe with randomly assigned labels y'. With a higher S, we assume the detected patterns are relevant for the specific phenomena under test, as random patterns do not lead to similar performance.

5 Holmes Results

Using Holmes, we evaluate a diverse collection of 59 LMs.[3] Using the results of these extensive experiments, we first answer the research question: *What is the linguistic competence of LMs?* In doing so, we discuss the reliability of results (i) and the linguistic competence of LMs concerning the unique structure of Holmes (ii). Subsequently, we examine *how linguistic competence varies among LMs*, as we find LMs prevailing for different types of linguistic phenomena (Figure 7) and delve into the effects of model architecture (iii), size (iv), and instruction tuning (v). Finally, we show how Holmes' results relate to the *linguistic performance* of LMs by comparing them with the OpenLLM benchmark (vi) and further experiments with the HELM benchmark (vii).

[2] Please refer to Appendix § A.4 and Figure 14 for more details about the composition of the internal representations.

[3] Please refer to Appendix § A.2 for a complete list.



	FLAN-UL2	FLAN-T5-XXL	Vicuna-13b-v.1.5	T5-XXL	Llama-2-70b-chat	Llama-2-13b-chat	DeBERTa-v3	BERT	GPT2	GloVe-840B	GloVe-6B	Pythia-160m	Pythia-70m
Morphology	3	2	7	4	6	19	1	41	50	49	51	58	56
Syntax	21	24	29	2	1	8	36	43	42	53	54	57	56
Semantics	2	3	1	15	31	20	33	26	36	50	51	57	55
Reasoning	3	8	22	2	1	7	4	31	53	48	51	56	57
Discourse	2	4	1	25	24	19	20	22	45	49	51	55	58
Overall	1	2	3	4	5	8	22	42	49	53	54	56	57

Figure 7: A subset of `Holmes` rankings (↓) for various evaluated LMs. FLAN-UL2 outperforms the others *overall*, while different LMs prevail for the five distinct types of linguistic phenomena.

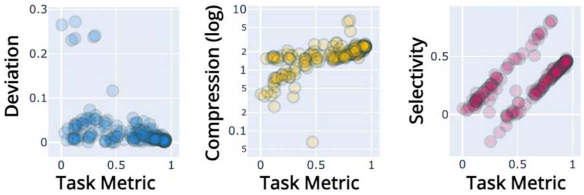


Figure 8: Reliability evaluation `Holmes` results to ensure low *deviation* across random seeds, high information *compression* (log), and high *selectivity*. Every dot represents the averaged results of one probing dataset across LMs. The x-axis represents the task metrics (either person correlation or macro F_1).

i) `Holmes` Results Are Reliable. Figure 8 shows the reliability of probing-based evaluations using averaged results across random seeds and LMs. Single outliers are datasets that are too hard for all LMs, either because the sample size is too small or the linguistic phenomena under test are too complex. First, a low average *deviation* ($\sigma = 0.02$) across five seeds underscores the reliability of probing-based measures. These results also highlight the stability of probing results over prompting-based evaluations, where prompt paraphrasing leads to deviations of $\sigma = 0.07$ reported in Mizrahi et al. (2024). Next, substantial *compression* (average $I = 1.9$) and *selectivity* (average $S = 0.31$) further confirm the probes' reliability. Note, for *selectivity*, we consider only base-sized model (10m–200m parameters) for computational efficiency. Interestingly, two parallel trends emerge. More challenging datasets with many labels, like POS tagging, are arranged around a selectivity of 0.1 to 0.4 and a task metric of 0.3. In contrast, for easier binary classification tasks (such as linguistic applicability), we observe selectivity around 0.2 to 0.5 and a task metric of 0.6 to 0.9. Furthermore, our analysis reveals a statistically significant positive correlation ($p < 0.05$) between the task metrics and both compression ($\tau = 0.64$) and selectivity ($\tau = 0.65$). This finding provides strong evidence for the reliability of our task metric, thereby justifying its use as the primary evaluation measure in our study.

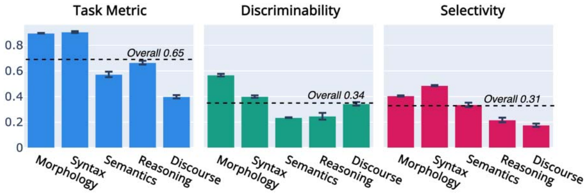


Figure 9: Average *task metric*, *difficulty*, and *discriminability* for each phenomena type. The dashed lines show the average measure over all datasets.

ii) LMs' Linguistic Competence is Manifold. We focus on what `Holmes` tells us in general and regarding formal and functional phenomena, as defined in § 2. We report in Figure 9 the *task metric*, *discriminability*, and *selectivity*, averaged for every phenomena type. Note, discriminability (Rodriguez et al., 2021) quantifies the alignment of LMs ranking of one specific dataset compared to the overall rankings using the Kendall Tau correlation. Considering these three metrics, all tested LMs strongly encode formal phenomena (*morphology* and *syntax*), which often depend on the local neighborhood of words. Therefore, we assume that LMs approximate these co-occurrences during pre-training with high precision. For example, the specific POS tag of a word, like *man* (*noun*), primarily depends on its surroundings, such as the frequent predecessor *the*. In contrast, LMs encode less information about functional phenomena (*semantics*, *reasoning*, and *discourse*) since they show a relatively low performance regarding the task metric. For these functional phenomena, we assume more complex co-occurrences are required to capture the broad context in language, such as the rhetorical relation of two distant text spans. Despite these differences between formal and functional phenomena types, they contribute to the benchmark in a balanced way. A low to medium discriminability indicates that none of these linguistic phenomenon types dominates the overall LM rankings.

This balanced influence of the five phenomena types is further visible when considering their ranking correlations (Figure 10, left). A high average correlation of 68.4 ± 7.5 with the overall results

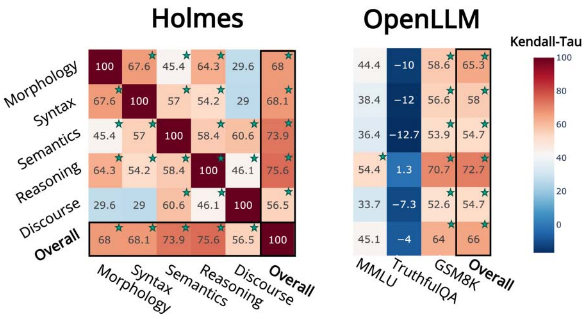


Figure 10: Kendall-tau correlation within Holmes (left) and compared to OpenLLM (right). Green stars indicate significant correlations ($p < 0.05$).

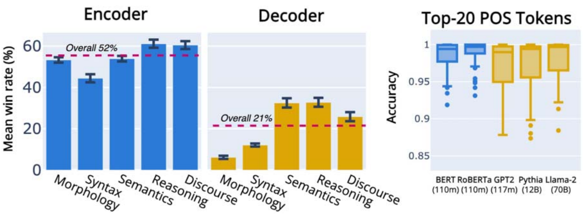


Figure 11: Comparison of the phenomenon types for encoder and decoder LMs (left) and on the right, the accuracy of the top-20 most common tokens of the three part-of-speech probing datasets for BERT, RoBERTa, GPT2, Pythia, and Llama-2.

(last column/row) hints that they are facets of a broader occurrence but share common characteristics. Still, breaking into categories is meaningful, as the phenomena types (first five columns/rows) are medium correlated (average of 54.7 ± 13.9). Analyzing the results of phenomena types further highlights the value of this distinction. While results of *semantics* and *reasoning* are similarly correlated with the overall results (73.9 and 75.6), their direct correlation (58.4) indicates their supplementary nature. Further, *discourse* results show the lowest correlation with others (44.4 ± 14.7), indicating a particular scope.

iii) Encoder Architecture Equips LMs with High Linguistic Competence. Next, we discuss the impact of model architecture on the linguistic competence of LMs. In Figure 11 (left), we compare encoder and decoder LMs. Due to the absence of big encoder LMs, we consider five *encoder* and six *decoder* LMs with up to 220m parameters. Encoder LMs show a higher mwr of 52% than decoder LMs (21%). This observation is the most saturated for *morphology* or *syntax*, encompassing a variety of token-level phenomena, like part-of-speech. We assume that the missing bi-directional encoding of decoder LMs causes this lower performance because the available context of one token heavily depends on its position. Thus, even common tokens, like *the*, have different potential representations—at the beginning or middle of a sentence. These instabilities are further evident when considering Figure 11 (right), which reports the accuracy for the top-20 most common POS tokens (such as *the*) based on the *pos*, *xpos*, *upos* dataset. Given their high frequency, one expects stable prediction performance. Surprisingly, encoder LMs (BERT and RoBERTa) show higher median accuracy and lower deviations compared to the same-size decoder counterpart (GPT2). While scaling model size to 12B (Pythia) and 70B (Llama-2) allows for improved accuracy and lower deviations, decoder LMs do not match the encoder performance, even up to **700 times bigger**.

iv) More Parameters Improve LMs' Linguistic Competence. We discuss how the number of parameters influences the linguistic competence of LMs. Given the variety of LMs of different sizes, we focus on the Pythia (decoder-only) and T5 (encoder-decoder) families. From Figure 12, we observe for both Pythia and T5 that the linguistic competence scales with model size, and it is particularly pronounced after exceeding 0.5B (Pythia) and 1.0B (T5) parameters. Again, model architecture is crucial, as T5 LMs (encoder-decoder) exhibit a clearly higher mean winning rate of 40–70% than Pythia (decoder-only) ones with mwr of 20–60%. Further, we found formal phenomena evolving differently with increased model size than functional ones. Specifically, *morphology* and *syntax* start at a lower level, with an apparent performance jump after 0.5B (Pythia) and 1.0B (T5) parameters, followed by slow but steady growth. Differently, *semantics*, *reasoning*, and *discourse* start at a higher mwr, followed by a continuous improvement as the model size grows. From these results, we assume that **more parameters enable language models to better approximate simple word co-occurrences** in nearby contexts. While handling formal phenomena like word dependencies, they struggle with more distant and complex co-occurrences, such as rhetorical relations.

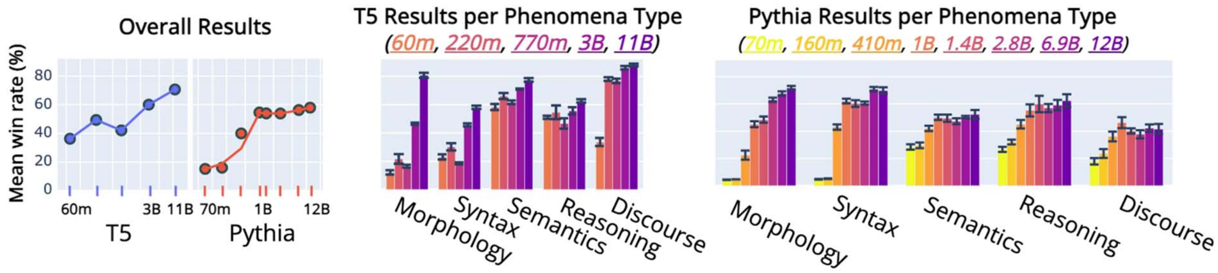


Figure 12: Effect of scaling LM parameters considering the T5 and Pythia model families providing eight and five different sizes. We address the overall scope (left) and the different types of linguistic phenomena (right).

Model	**Morphology**	**Syntax**	**Semantics**	**Reasoning**	**Discourse**	**Overall**
Comparison against Llama-2 with 7 billion parameters						
Llama-2-Chat	−8%	+5%	−6%	−8%	−2%	−2%
Comparison against T5 with 11 billion parameters						
FLAN-T5	+9%	+1%	−3%	+6%	0%	+1%
Comparison against Pythia with 12 billion parameters						
Dolly-v2	+4%	−1%	−9%	−2%	+2%	−3%
Comparison against Llama-2 with 13 billion parameters						
Tülu-2	+6%	+3%	−13%	+1%	−13%	−4%
Orca-2	0%	−4%	−6%	+3%	−2%	−3%
Llama-2-chat	+9%	+6%	0%	+7%	+1%	+4%
Vicuna-v1.5	+26%	+9%	0%	+8%	+2%	+7%
Comparison against UL2 with 20 billion parameters						
FLAN-UL2	**+41%**	**+15%**	**+6%**	**+11%**	−1%	**+12%**
Comparison against Mixtral with ∼47 billion parameters						
Mixtral-Instruct	+6%	+4%	+1%	+9%	+3%	+4%
Comparison against Llama-2 with 70 billion parameters						
Tülu-2	+14%	0%	−9%	−4%	+1%	−2%
Llama-2-Chat	+24%	+13%	+3%	+3%	**+13%**	+10%
Average	*+10%*	*+5%*	*−3%*	*+4%*	*−1%*	*+2%*

Table 2: The mixed effect of instruction tuning on the mean winning rate compared to the pre-trained LMs.

v) Instruction-tuned LMs Get Better at Mimicking Language than Understanding it. We focus on how instruction tuning affects LMs' linguistic competence and compare tuned and pre-trained LMs, for example, FLAN-UL2 vs. UL2. Table 2 shows less saturated effects for the overall scope while being more pronounced for the five phenomenon types - again emphasizing the structured and comprehensive evaluation of linguistic competence. On average, we found instruction tuning has the highest effect on *morphology* (+10%) followed by *syntax* (+5%), *reasoning* (+4%), and a negative effect for *semantics* −3% and *discourse* −1%. These results confirm previous assumptions that **instruction tuning updates are often superficial** (Yadav et al., 2023; Hershcovitch et al., 2024; Sharma et al., 2023) and that LMs get better at mimicking language (formal phenomena) than understanding it, measured with functional phenomena (Mahowald et al., 2024). Further, larger models benefit more from instruction tuning. Llama-2-70b-Chat and FLAN-UL2 gain up to +24% and +41% for *morphology* and +10% and +12% on average. When comparing LMs based on Llama-2-13B, we see that specific fine-tuning methods shape the LMs differently. The top-ranked 13B LM for Holmes and OpenLLM, Vicuna, was trained on fewer instructions than others (125k) but of higher quality. This high quality seems important as LMs with more instructions but lower quality (Tülu with approx. 330k instructions) lose performance, the same for 70B versions. Further and aligned with the previous comparison with OpenLLM results, reasoning specialization (Orca-2) is reflected in the corresponding phenomena. These insights show again that while providing a particular perspective, Holmes shows apparent differences between LMs and allows us to map them to methodological decisions.

vi) Internals of LMs are Partly Aligned with their Linguistic Performance. We analyze the alignment of the probing-based LM rankings of Holmes with prompting-based ones when evaluating downstream using the LMs responses (linguistic performance). Specifically, we compare against OpenLLM (Beeching et al., 2023).[4] Figure 10 (right) shows Holmes and OpenLLM rankings of jointly evaluated LMs are medium correlated, hinting that LMs' linguistic competence is partly reflected in their language utterances when solving concrete tasks. While *syntax*, *semantics*, and *discourse* show similar correlation (54.7 to 58.0), *morphology* and *reasoning* exhibit a substantially higher one of 65.3 and 77.5. These results suggest that **LMs' reasoning abilities are**

[4] Unlike other benchmarks like HELM (Liang et al., 2023), OpenLLM covers many open LMs' leading to high overlap with Holmes.

reflected in their internal representations when evaluating related phenomena like identifying the cause of negations. These correlation patterns are consistent across the three most meaningful Open-LLM datasets (*MMLU*, *TruthfulQA*, and *GSM8K*). As *TruthfulQA* shows lower correlations with the linguistic phenomena and other datasets within OpenLLM, we presume this dataset captures distinctly different skills (possibly knowledge).

vii) Prompting is not a Substitute for Probing When Evaluating LMs' Linguistic Competence. Finally, we compare probing- and prompting-based LM rankings on the jointly evaluated BLiMP tasks (Warstadt et al., 2020) of Holmes and HELM (Liang et al., 2023). Results (Appendix, Figure 15) show apparent discrepancies (rank correlation $\tau = 0.05$) when evaluating LMs' internal representations or their responses (linguistic performance) to HELM instructions. As most prompting-based results from HELM fall below the random baseline, only **probing-based evaluation can effectively isolate the assessment of linguistic phenomena**. In contrast, prompting-based methods mix this assessment with other abilities, such as instruction following. Similar to Hu and Levy (2023), these insights show the need for a more comprehensive comparison of different evaluation protocols like probing, prompting, or log-probabilities (used in HELM in Figure 33 on page 58 as a workaround for BLiMP). Nevertheless, probing provides a unified evaluation protocol assessing the diversity of linguistic phenomena using representations of tokens, spans, or whole texts beyond minimal pair tasks testing whether correct or wrong sentences are preferred.

6 Efficiency

Seamless, easy, cost-effective integration of new LMs is crucial to adopting benchmarks widely. As Holmes covers many datasets and examples, it is computationally heavy in encoding text and training the probes. It takes $\sim$ 6 GPU days to encode the 70 million tokens ($\sim$230k pages) and two days to run the 208 probes for a 70b model. To account for this issue, we introduce Flash-Holmes, a streamlined version of Holmes, to evaluate new LMs with a fraction of the compute while maintaining evaluation integrity.

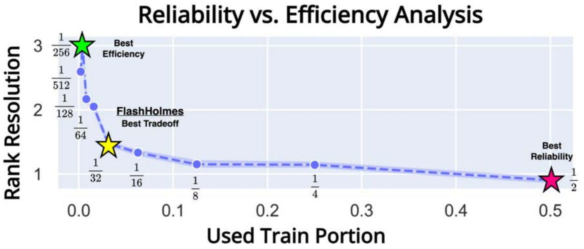


Figure 13: Analysis of the reliability vs. efficiency trade-off when reducing the number of training data.

Besides excluding licensed data (18 probing datasets), we analyze the effect of discarding training instances. As a result, we reduce the computation for encoding and the actual probing simultaneously. We follow Perlitz et al. (2023) and calculate the *rank resolution*, 95% CI of model rank difference. This measure indicates the maximum expected rank deviation from evaluating an LM on FlashHolmes compared to Holmes. For example, a rank resolution of one means that an LM evaluated on FlashHolmes and Holmes has the same rank or switch place with its neighbors with a probability of 95%. Figure 13 shows the resulting rank resolution when training only on a fraction of the instances, from $1/2$ to $1/512$. Solely focusing on efficiency ($1/512$) still provides a decent rank resolution of $\sim$2.6. In contrast, considering $1/2$ of the training data results in the best reliability of $\sim$0.9. To balance benchmark reliability and efficiency, we compose FlashHolmes using $1/32$ of the training instances. Precisely, it reduces the computation expenses of evaluating LMs to $\sim$3% of what Holmes would have required while preserving a high rank-correlation of $\sim$1.5.

7 Related Work

Benchmarking LMs Benchmarks approximate LMs abilities like general language understanding (Wang et al., 2019a,b), out-of-distribution generalization (Yang et al., 2023; Waldis et al., 2024b), real-world knowledge contradiction (Hou et al., 2024), adversarial scenarios (Nie et al., 2020; Wang et al., 2021), or retrieval (Thakur et al., 2021; Muennighoff et al., 2023). With the recent advent of large LMs, the predominant method has shifted to evaluate the obtained linguistic performance of LMs when providing textual instructions (Brown et al., 2020; Hendrycks et al., 2021; Srivastava et al., 2022). While LMs show substantial performance on application-oriented tasks (Liang et al., 2023) or mathematical reasoning

(Cobbe et al., 2021), such evaluations are sensible to specific formulations (Mizrahi et al., 2024) or metrics (Schaeffer et al., 2023) employed. Thus, results of different benchmarks were found to disagree substantially (Yuan et al., 2024; Perlitz et al., 2024).

Assessing the Linguistic Competence of LMs Analyzing LMs' linguistic competence started with static word vectors (Köhn, 2015), sentence embeddings (Conneau et al., 2018; Adi et al., 2017), the internals of translation models (Shi et al., 2016; Bau et al., 2019), or contextualized LMs (Tenney et al., 2019b,a; Hewitt and Manning, 2019). Other methodological work addressed the validity of obtained results with control tasks (Hewitt and Liang, 2019) or from an information theory perspective (Voita and Titov, 2020; Pimentel et al., 2020), or studied causal effects (Elazar et al., 2021). While further studies focus on whether LMs follow human understanding of linguistic competence when solving downstream tasks (Belinkov, 2022; Aw et al., 2023; Mahowald et al., 2024), Mosbach et al. (2020b) and Waldis et al. (2024a) found that downstream task fine-tuning hurts the understanding of linguistic phenomena.

In contrast to prior studies, Holmes assesses the linguistic competence of an extensive set of contemporary LMs covering a comprehensive collection of linguistic phenomena. Unlike other work evaluating linguistic phenomena (Blevins et al., 2023; Amouyal et al., 2024) using prompting leading to unreliable results (Liang et al., 2023), probing allows Holmes to reliably and comprehensively compare LMs regardless of architecture or pre-training. As a result, Holmes can address recent calls to thoroughly and explicitly evaluate linguistic phenomena (Hu and Levy, 2023; Lu et al., 2023; Mahowald et al., 2024).

8 Conclusion

Holmes marks the most up-to-date and extensive consolidation of existing resources addressing the need to assess the linguistic competence of LMs in isolation. Our experiments demonstrate that LMs' linguistic competence is pronounced regarding formal phenomena but lacks functional ones when information about broader textual contexts, such as rhetorical structure, is required. Simultaneously, size, architecture, and instruction tuning are crucial factors for differences among LMs. As LM and resources in linguistics constantly grow, we will actively extend Holmes with new datasets and upcoming LMs.

Ethical Considerations and Limitations

Language Holmes as well as FlashHolmes solely assess linguistic phenomena for the English language. As we plan to expand the benchmark and scope of multilingual data, we focus at the moment on English because of the widespread availability of resources, including curated corpora and the diversity of available LMs.

Last Layer Internal Representation Given the extensive scope of the analysis presented in this work, we focus on examining the internal representation of LMs through the output of their last layer. While this analysis provides valuable insights, it only partially captures the complexity inherent in LMs across all their layers. To facilitate further research into the comprehensive analysis of LMs, we see Holmes providing groundwork, including the release of the specific tasks in a unifying format and corresponding evaluation code, which can be easily adapted to investigate specific layers of LMs.

Coverage We agree with Liang et al. (2023) and see one fundamental aspect in composing a benchmark in acknowledging its incompleteness. Linguistic phenomena, LMs, and underlying meta-studies are a subset of the variety of available resources. We consolidated them carefully to provide a comprehensive scope of the linguistic competence and various LMs. However, as benchmarks evolve as tools to assess LMs, we will further expand Holmes both with the existing and upcoming LMs and data resources.

Data Availability Linguistic annotations, in particular more complex ones targeting phenomena like *discourse*, are money and time-wise expensive. Out of 208 datasets included in Holmes, 18 probing datasets are based on licensed resources and are not freely available. However, with FlashHolmes, we provide an effective and efficient alternative based on open-access resources. Furthermore, upon confirming the granted access, we are happy to share our probing datasets, including those based on the licensed resources.

Bias As Holmes relies on existing resources, it inherits the bias embodied in these datasets. Examples of such bias are gender equality or gender fairness, like the use of neo pronouns such as *em* in Lauscher et al. (2023).

Dataset Contamination Holmes encompasses a large collection of established datasets, like OntoNotes (Weischedel et al., 2013). While we solely rely on LMs with open-sourced weights, the training or instruction-tuning data is not known for all of them, as for the Llama-2 (Touvron et al., 2023), Mixtral (Jiang et al., 2024), or Wizard (Xu et al., 2023) LMs. Therefore, we need to expect that some texts were part of the LMs' pre-training corpora and that specific tasks, such as named-entity recognition (NER), were used during instruction tuning. However, instruction-tuning aligns LMs' linguistic performance to produce coherent text responding to specific textual instruction provided and does not align LMs' internal representations explicitly (Brown et al., 2020; Touvron et al., 2023; Jiang et al., 2024). As Holmes evaluates the linguistic competence using LMs' internal representations, it retains its validity even under potential data contamination (Balloccu et al., 2024). Building upon our results, showing that downstream abilities are partly reflected in LMs' internal representations, one could examine whether instruction-tuning injects task-specific information into LMs' internal representations, thereby detecting task contamination.

References

Yossi Adi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. 2017. Fine-grained analysis of sentence embeddings using auxiliary prediction tasks. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24–26, 2017, Conference Track Proceedings*. OpenReview.net.

Ehsan Aghazadeh, Mohsen Fayyaz, and Yadollah Yaghoobzadeh. 2022. Metaphors in pre-trained language models: Probing and generalization across datasets and languages. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2037–2050, Dublin, Ireland. Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.acl-long.144

Samuel Amouyal, Aya Meltzer-Asscher, and Jonathan Berant. 2024. Large language models for psycholinguistic plausibility pretesting. In *Findings of the Association for Computational Linguistics: EACL 2024*, pages 166–181, St. Julian's, Malta. Association for Computational Linguistics.

Khai Loong Aw, Syrielle Montariol, Badr AlKhamissi, Martin Schrimpf, and Antoine Bosselut. 2023. Instruction-tuning aligns llms to the human brain. *CoRR*, abs/2312.00575.

Simone Balloccu, Patrícia Schmidtová, Mateusz Lango, and Ondrej Dusek. 2024. Leak, cheat, repeat: Data contamination and evaluation malpractices in closed-source LLMs. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 67–93, St. Julian's, Malta. Association for Computational Linguistics.

Anthony Bau, Yonatan Belinkov, Hassan Sajjad, Nadir Durrani, Fahim Dalvi, and James R. Glass. 2019. Identifying and controlling important neurons in neural machine translation. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6–9, 2019*. OpenReview.net.

Edward Beeching, Clémentine Fourrier, Nathan Habib, Sheon Han, Nathan Lambert, Nazneen Rajani, Omar Sanseviero, Lewis Tunstall, and Thomas Wolf. 2023. Open llm leaderboard. https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard

Yonatan Belinkov. 2022. Probing classifiers: Promises, shortcomings, and advances. *Computational Linguistics*, 48(1):207–219. https://doi.org/10.1162/coli_a_00422

Yonatan Belinkov, Nadir Durrani, Fahim Dalvi, Hassan Sajjad, and James Glass. 2017. What do neural machine translation models learn about morphology? In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 861–872, Vancouver, Canada. Association for Computational Linguistics. https://doi.org/10.18653/v1/P17-1080

Stella Biderman, Hailey Schoelkopf, Quentin Gregory Anthony, Herbie Bradley, Kyle O'Brien, Eric Hallahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, Aviya Skowron, Lintang Sutawika, and Oskar van der Wal. 2023. Pythia: A suite for analyzing large language models across training and scaling. In *International Conference on Machine Learning, ICML 2023, 23–29 July 2023, Honolulu, Hawaii, USA*, volume 202 of *Proceedings of Machine Learning Research*, pages 2397–2430. PMLR.

Julia Birke and Anoop Sarkar. 2006. A clustering approach for nearly unsupervised recognition of nonliteral language. In *11th Conference of the European Chapter of the Association for Computational Linguistics*, pages 329–336, Trento, Italy. Association for Computational Linguistics.

Terra Blevins, Hila Gonen, and Luke Zettlemoyer. 2023. Prompting language models for linguistic structure. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6649–6663, Toronto, Canada. Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.acl-long.367

Nikolay Bogoychev and Adam Lopez. 2016. N-gram language models for massively parallel devices. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1944–1953, Berlin, Germany. Association for Computational Linguistics. https://doi.org/10.18653/v1/P16-1183

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6–12, 2020, virtual*.

Lynn Carlson, Daniel Marcu, and Mary Ellen Okurovsky. 2001. Building a discourse-tagged corpus in the framework of rhetorical structure theory. In *Proceedings of the SIGDIAL 2001 Workshop, The 2nd Annual Meeting of the Special Interest Group on Discourse and Dialogue, Saturday, September 1, 2001 to Sunday, September 2, 2001, Aalborg, Denmark*. The Association for Computer Linguistics. https://doi.org/10.3115/1118078.1118083

Noam Chomsky. 1965. *Aspects of the Theory of Syntax*. The MIT Press, Cambridge. https://doi.org/10.21236/AD0616323

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Y. Zhao, Yanping Huang, Andrew M. Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022. Scaling instruction-finetuned language models. *CoRR*, abs/2210.11416.

Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. ELECTRA: pre-training text encoders as discriminators rather than generators. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26–30, 2020*. OpenReview.net.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. 2021. Training verifiers to solve math word problems. *CoRR*, abs/2110.14168.

Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. 2018. What you can cram into a single $&!#* vector: Probing sentence embeddings for linguistic properties. In *Proceedings of the 56th*

Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2126–2136, Melbourne, Australia. Association for Computational Linguistics. https://doi.org/10.18653/v1/P18-1198

Mike Conover, Matt Hayes, Ankit Mathur, Jianwei Xie, Jun Wan, Sam Shah, Ali Ghodsi, Patrick Wendell, Matei Zaharia, and Reynold Xin. 2023. Free dolly: Introducing the world's first truly open instruction-tuned LLM.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, K. Li, and Li Fei-Fei. 2009. ImageNet: A large-scale hierarchical image database. *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 248–255. https://doi.org/10.1109/CVPR.2009.5206848

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Yanai Elazar, Shauli Ravfogel, Alon Jacovi, and Yoav Goldberg. 2021. Amnesic probing: Behavioral explanation with amnesic counterfactuals. *Transactions of the Association for Computational Linguistics*, 9:160–175. https://doi.org/10.1162/tacl_a_00359

Rudolf Franz Flesch. 1948. A new readability yardstick. *The Journal of Applied Psychology*, 32(3):221–233. https://doi.org/10.1037/h0057532, PubMed: 18867058

William Gantt, Lelia Glass, and Aaron Steven White. 2022. Decomposing and recomposing event structure. *Transactions of the Association for Computational Linguistics*, 10:17–34. https://doi.org/10.1162/tacl_a_00445

Vagrant Gautam, Eileen Bingert, D. Zhu, Anne Lauscher, and Dietrich Klakow. 2024. Robust pronoun use fidelity with english llms: Are they reasoning, repeating, or just biased? *CoRR*, abs/2404.03134.

Mario Giulianelli, Jack Harding, Florian Mohnert, Dieuwke Hupkes, and Willem Zuidema. 2018. Under the hood: Using diagnostic classifiers to investigate and improve how language models track agreement information. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 240–248, Brussels, Belgium. Association for Computational Linguistics. https://doi.org/10.18653/v1/W18-5426

Venkata Govindarajan, Benjamin Van Durme, and Aaron Steven White. 2019. Decomposing generalization: Models of generic, habitual, and episodic statements. *Transactions of the Association for Computational Linguistics*, 7:501–517. https://doi.org/10.1162/tacl_a_00285

Abhijeet Gupta, Gemma Boleda, Marco Baroni, and Sebastian Padó. 2015. Distributional vectors encode referential attributes. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 12–21, Lisbon, Portugal. Association for Computational Linguistics. https://doi.org/10.18653/v1/D15-1002

Zellig S. Harris. 1954. Distributional structure. *Word*, 10(2–3):146–162. https://doi.org/10.1080/00437956.1954.11659520

Pengcheng He, Jianfeng Gao, and Weizhu Chen. 2023. Debertav3: Improving deberta using electra-style pre-training with gradient-disentangled embedding sharing. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1–5, 2023*. OpenReview.net.

Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2021. Deberta: Decoding-enhanced bert with disentangled attention. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3–7, 2021*. OpenReview.net.

Iris Hendrickx, Su Nam Kim, Zornitsa Kozareva, Preslav Nakov, Diarmuid Ó. Séaghdha, Sebastian Padó, Marco Pennacchiotti, Lorenza Romano, and Stan Szpakowicz. 2010. SemEval-2010 task 8: Multi-way classification of semantic relations between pairs of nominals.

In *Proceedings of the 5th International Workshop on Semantic Evaluation*, pages 33–38, Uppsala, Sweden. Association for Computational Linguistics. https://doi.org/10.1080/00437956.1954.11659520

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2021. Measuring massive multitask language understanding. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3–7, 2021*. OpenReview.net.

Moshik Hershcovitch, Leshem Choshen, Andrew Wood, Ilias Enmouri, Peter Chin, Swaminathan Sundararaman, and Danny Harnik. 2024. Lossless and near-lossless compression for foundation models. *CoRR*, abs/2404.15198.

John Hewitt and Percy Liang. 2019. Designing and interpreting probes with control tasks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2733–2743, Hong Kong, China. Association for Computational Linguistics. https://doi.org/10.18653/v1/D19-1275

John Hewitt and Christopher D. Manning. 2019. A structural probe for finding syntax in word representations. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4129–4138, Minneapolis, Minnesota. Association for Computational Linguistics.

Yufang Hou. 2018. Enhanced word representations for bridging anaphora resolution. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 1–7, New Orleans, Louisiana. Association for Computational Linguistics. https://doi.org/10.18653/v1/N18-2001

Yufang Hou. 2020. Bridging anaphora resolution as question answering. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1428–1438, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.132

Yufang Hou, Alessandra Pascale, Javier Carnerero-Cano, Tigran Tchrakian, Radu Marinescu, Elizabeth Daly, Inkit Padhi, and Prasanna Sattigeri. 2024. Wikicontradict: A benchmark for evaluating llms on real-world knowledge conflicts from wikipedia. *arXiv preprint arXiv:2406.13805*.

Jennifer Hu and Roger Levy. 2023. Prompting is not a substitute for probability measurements in large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 5040–5060, Singapore. Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.emnlp-main.306

Philip A. Huebner, Elior Sulem, Fisher Cynthia, and Dan Roth. 2021. BabyBERTa: Learning more grammar with small-scale child-directed language. In *Proceedings of the 25th Conference on Computational Natural Language Learning*, pages 624–646, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.conll-1.49

Dieuwke Hupkes and Willem Zuidema. 2018. Visualisation and 'diagnostic classifiers' reveal how recurrent and recursive neural networks process hierarchical structure (extended abstract). In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*, pages 5617–5621, International Joint Conferences on Artificial Intelligence Organization. https://doi.org/10.24963/ijcai.2018/796

Alexander Immer, Lucas Torroba Hennigen, Vincent Fortuin, and Ryan Cotterell. 2022. Probing as quantifying inductive bias. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1839–1851, Dublin, Ireland. Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.acl-long.129

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile

Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b. *CoRR*, abs/2310.06825.

Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Emma Bou Hanna, Florian Bressand, Gianna Lengyel, Guillaume Bour, Guillaume Lample, Lélio Renard Lavaud, Lucile Saulnier, Marie-Anne Lachaux, Pierre Stock, Sandeep Subramanian, Sophia Yang, Szymon Antoniak, Teven Le Scao, Théophile Gervet, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2024. Mixtral of experts. *CoRR*, abs/2401.04088.

Nora Kassner, Philipp Dufter, and Hinrich Schütze. 2021. Multilingual LAMA: Investigating knowledge in multilingual pretrained language models. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 3250–3258, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.eacl-main.284

Josef Klafka and Allyson Ettinger. 2020. Spying on your neighbors: Fine-grained probing of contextual embeddings for information about surrounding words. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4801–4811, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.434

Arne Köhn. 2015. What's in an embedding? Analyzing word embeddings through multilingual evaluation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 2067–2073, Lisbon, Portugal. Association for Computational Linguistics. https://doi.org/10.18653/v1/D15-1246

Natalia Konstantinova, Sheila C. M. de Sousa, Noa P. Cruz, Manuel J. Maña, Maite Taboada, and Ruslan Mitkov. 2012. A review corpus annotated for negation, speculation and their scope. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12)*, pages 3190–3195, Istanbul, Turkey. European Language Resources Association (ELRA).

Fajri Koto, Jey Han Lau, and Timothy Baldwin. 2021. Discourse probing of pretrained language models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3849–3864, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.naacl-main.301

Katarzyna Krasnowska-Kieraś and Alina Wróblewska. 2019. Empirical linguistic study of sentence embeddings. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5729–5739, Florence, Italy. Association for Computational Linguistics. https://doi.org/10.18653/v1/P19-1573

Murathan Kurfalı and Robert Östling. 2021. Probing multilingual language models for discourse. In *Proceedings of the 6th Workshop on Representation Learning for NLP (RepL4NLP-2021)*, pages 8–19, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.repl4nlp-1.2

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A lite BERT for self-supervised learning of language representations. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26–30, 2020*. OpenReview.net.

Anne Lauscher, Debora Nozza, Ehm Miltersen, Archie Crowley, and Dirk Hovy. 2023. What about ''em''? How commercial machine translation fails to handle (neo-)pronouns. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 377–392, Toronto, Canada. Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.acl-long.23

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.703

Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, Benjamin Newman, Binhang Yuan, Bobby Yan, Ce Zhang, Christian Alexander Cosgrove, Christopher D. Manning, Christopher Re, Diana Acosta-Navas, Drew Arad Hudson, Eric Zelikman, Esin Durmus, Faisal Ladhak, Frieda Rong, Hongyu Ren, Huaxiu Yao, Jue WANG, Keshav Santhanam, Laurel Orr, Lucia Zheng, Mert Yuksekgonul, Mirac Suzgun, Nathan Kim, Neel Guha, Niladri S. Chatterji, Omar Khattab, Peter Henderson, Qian Huang, Ryan Andrew Chi, Sang Michael Xie, Shibani Santurkar, Surya Ganguli, Tatsunori Hashimoto, Thomas Icard, Tianyi Zhang, Vishrav Chaudhary, William Wang, Xuechen Li, Yifan Mai, Yuhui Zhang, and Yuta Koreeda. 2023. Holistic evaluation of language models. *Transactions on Machine Learning Research*. Featured Certification, Expert Certification.

Tal Linzen, Emmanuel Dupoux, and Yoav Goldberg. 2016. Assessing the ability of LSTMs to learn syntax-sensitive dependencies. *Transactions of the Association for Computational Linguistics*, 4:521–535. https://doi.org/10.1162/tacl_a_00115

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6–9, 2019*. OpenReview.net.

Sheng Lu, Irina Bigoulaeva, Rachneet Sachdeva, Harish Tayyar Madabushi, and Iryna Gurevych. 2023. Are emergent abilities in large language models just in-context learning? *CoRR*, abs/2309.01809.

Kyle Mahowald, Anna A. Ivanova, Idan A. Blank, Nancy Kanwisher, Joshua B. Tenenbaum, and Evelina Fedorenko. 2024. Dissociating language and thought in large language models. *Trends in Cognitive Sciences*. https://doi.org/10.1016/j.tics.2024.01.011, PubMed: 38508911

Peter Hugoe Matthews. 2014. *The Concise Oxford Dictionary of Linguistics*. Oxford University Press, USA.

George A. Miller. 1995. Wordnet: A lexical database for English. *Communications of the ACM*, 38(11):39–41. https://doi.org/10.1145/219717.219748

Sewon Min, Xinxi Lyu, Ari Holtzman, Mikel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2022. Rethinking the role of demonstrations: What makes in-context learning work? In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11048–11064, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.emnlp-main.759

Arindam Mitra, Luciano Del Corro, Shweti Mahajan, Andrés Codas, Clarisse Simões, Sahaj Agrawal, Xuxi Chen, Anastasia Razdaibiedina, Erik Jones, Kriti Aggarwal, Hamid Palangi, Guoqing Zheng, Corby Rosset, Hamed Khanpour, and Ahmed Awadallah. 2023. Orca 2: Teaching small language models how to reason. *CoRR*, abs/2311.11045.

Moran Mizrahi, Guy Kaplan, Dan Malkin, Rotem Dror, Dafna Shahaf, and Gabriel Stanovsky. 2024. State of what art? A call for multi-prompt LLM evaluation. *CoRR*, abs/2401.00595. https://doi.org/10.1162/tacl_a_00681

Michael Mohler, Mary Brunson, Bryan Rink, and Marc Tomlinson. 2016. Introducing the LCC metaphor datasets. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*, pages 4221–4227, Portorož, Slovenia. European Language Resources Association (ELRA).

Roser Morante and Eduardo Blanco. 2012. *SEM 2012 shared task: Resolving the scope and focus of negation. In **SEM 2012: The First Joint Conference on Lexical and Computational Semantics – Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation (SemEval 2012)*, pages 265–274, Montréal, Canada. Association for Computational Linguistics.

Marius Mosbach, Anna Khokhlova, Michael A. Hedderich, and Dietrich Klakow. 2020a. On the interplay between fine-tuning and sentence-level probing for linguistic knowledge in pre-trained transformers. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 68–82, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2020.blackboxnlp-1.7`

Marius Mosbach, Anna Khokhlova, Michael A. Hedderich, and Dietrich Klakow. 2020b. On the interplay between fine-tuning and sentence-level probing for linguistic knowledge in pre-trained transformers. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2502–2516, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2020.findings-emnlp.227`

Niklas Muennighoff, Nouamane Tazi, Loic Magne, and Nils Reimers. 2023. MTEB: Massive text embedding benchmark. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pages 2014–2037, Dubrovnik, Croatia. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2023.eacl-main.148`

Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018. Don't give me the details, just the summary! Topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807, Brussels, Belgium. Association for Computational Linguistics. `https://doi.org/10.18653/v1/D18-1206`

Allen Nie, Erin Bennett, and Noah Goodman. 2019. DisSent: Learning sentence representations from explicit discourse relations. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4497–4510, Florence, Italy. Association for Computational Linguistics. `https://doi.org/10.18653/v1/P19-1442`

Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial NLI: A new benchmark for natural language understanding. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4885–4901, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2020.acl-main.441`

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. In *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 – December 9, 2022.*

Gustavo Paetzold and Lucia Specia. 2016. SemEval 2016 task 11: Complex word identification. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 560–569, San Diego, California. Association for Computational Linguistics.

Onkar Pandit and Yufang Hou. 2021. Probing for bridging inference in transformer language models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4153–4163, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2021.naacl-main.327`

Hao Peng, Xiaozhi Wang, Shengding Hu, Hailong Jin, Lei Hou, Juanzi Li, Zhiyuan Liu, and Qun Liu. 2022. COPEN: Probing conceptual knowledge in pre-trained language models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5015–5035, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2022.emnlp-main.335`

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. GloVe: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543, Doha, Qatar. Association for Computational Linguistics. `https://doi.org/10.3115/v1/D14-1162`

Yotam Perlitz, Elron Bandel, Ariel Gera, Ofir Arviv, Liat Ein-Dor, Eyal Shnarch, Noam Slonim, Michal Shmueli-Scheuer, and Leshem Choshen. 2023. Efficient benchmarking (of language models). *CoRR*, abs/2308.11696.

Yotam Perlitz, Ariel Gera, Ofir Arviv, Asaf Yehudai, Elron Bandel, Eyal Shnarch, Michal Shmueli-Scheuer, and Leshem Choshen. 2024. Benchmark agreement testing done right: A guide for llm benchmark evaluation. *CoRR*, abs/2407.13696.

Fabio Petroni, Patrick S. H. Lewis, Aleksandra Piktus, Tim Rocktäschel, Yuxiang Wu, Alexander H. Miller, and Sebastian Riedel. 2020. How context affects language models' factual predictions. In *Conference on Automated Knowledge Base Construction, AKBC 2020, Virtual, June 22–24, 2020.*

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. 2019a. Language models as knowledge bases? In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2463–2473, Hong Kong, China. Association for Computational Linguistics. `https://doi.org/10.18653/v1/D19-1250`

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick S. H. Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander H. Miller. 2019b. Language models as knowledge bases? In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3–7, 2019*, pages 2463–2473. Association for Computational Linguistics. `https://doi.org/10.18653/v1/D19-1250`

Tiago Pimentel, Josef Valvoda, Rowan Hall Maudslay, Ran Zmigrod, Adina Williams, and Ryan Cotterell. 2020. Information-theoretic probing for linguistic structure. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4609–4622, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2020.acl-main.420`

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Robert Henry Robins. 2013. *A Short History of Linguistics*. Routledge. `https://doi.org/10.4324/9781315843186`

Pedro Rodriguez, Joe Barrow, Alexander Miserlis Hoyle, John P. Lalor, Robin Jia, and Jordan Boyd-Graber. 2021. Evaluation examples are not equally informative: How should that change NLP leaderboards? In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4486–4503, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2021.acl-long.346`

Anna Rogers, Olga Kovaleva, and Anna Rumshisky. 2020. A primer in BERTology: What we know about how BERT works. *Transactions of the Association for Computational Linguistics*, 8:842–866. `https://doi.org/10.1162/tacl_a_00349`

Rachel Rudinger, Adam Teichert, Ryan Culkin, Sheng Zhang, and Benjamin Van Durme.

2018a. Neural-Davidsonian semantic proto-role labeling. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 944–955, Brussels, Belgium. Association for Computational Linguistics. https://doi.org/10.18653/v1/D18-1114

Rachel Rudinger, Aaron Steven White, and Benjamin Van Durme. 2018b. Neural models of factuality. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 731–744, New Orleans, Louisiana. Association for Computational Linguistics. https://doi.org/10.18653/v1/N18-1067

Ferdinand de Saussure. 1916. *Cours de linguistique générale*. Payot, Paris.

Rylan Schaeffer, Brando Miranda, and Sanmi Koyejo. 2023. Are emergent abilities of large language models a mirage? In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 – 16, 2023*.

Naomi Shapiro, Amandalynne Paullada, and Shane Steinert-Threlkeld. 2021. A multilabel approach to morphosyntactic probing. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 4486–4524, Punta Cana, Dominican Republic. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.findings-emnlp.382

Pratyusha Sharma, Jordan T. Ash, and Dipendra Misra. 2023. The truth is in there: Improving reasoning in language models with layer-selective rank reduction. *CoRR*, abs/2312.13558.

Xing Shi, Inkit Padhi, and Kevin Knight. 2016. Does string-based neural MT learn source syntax? In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1526–1534, Austin, Texas. Association for Computational Linguistics. https://doi.org/10.18653/v1/D16-1159

Natalia Silveira, Timothy Dozat, Marie-Catherine de Marneffe, Samuel Bowman, Miriam Connor, John Bauer, and Chris Manning. 2014. A gold standard dependency corpus for English. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, pages 2897–2904, Reykjavik, Iceland. European Language Resources Association (ELRA).

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642, Seattle, Washington, USA. Association for Computational Linguistics.

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W. Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ameet Rahane, Anantharaman S. Iyer, Anders Andreassen, Andrea Santilli, Andreas Stuhlmüller, Andrew M. Dai, Andrew La, Andrew K. Lampinen, Andy Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Aykut Erdem, Ayla Karakas, and et al. 2022. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *CoRR*, abs/2206.04615.

Gerard J. Steen, Aletta G. Dorst, J. Berenike Herrmann, Anna A. Kaal, Tina Krennmayr, Tryntje Pasma, et al. 2010. *A method for linguistic metaphor identification*. Converging evidence in language and communication research. John Benjamins Publishing Company Amsterdam. https://doi.org/10.1075/celcr.14

Shivchander Sudalairaj, Abhishek Bhandwaldar, Aldo Pareja, Kai Xu, David D. Cox, and Akash

Srivastava. 2024. LAB: large-scale alignment for chatbots. *CoRR*, abs/2403.01081.

György Szarvas, Veronika Vincze, Richárd Farkas, and János Csirik. 2008. The BioScope corpus: Annotation for negation, uncertainty and their scope in biomedical texts. In *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing*, pages 38–45, Columbus, Ohio. Association for Computational Linguistics. `https://doi.org/10.3115/1572306.1572314`

Alon Talmor, Yanai Elazar, Yoav Goldberg, and Jonathan Berant. 2020a. oLMpics-on what language model pre-training captures. *Transactions of the Association for Computational Linguistics*, 8:743–758. `https://doi.org/10.1162/tacl_a_00342`

Alon Talmor, Yanai Elazar, Yoav Goldberg, and Jonathan Berant. 2020b. oLMpics-On what language model pre-training captures. *Transactions of the Association for Computational Linguistics*, 8:743–758. `https://doi.org/10.1162/tacl_a_00342`

Yi Tay, Mostafa Dehghani, Vinh Q. Tran, Xavier Garcia, Jason Wei, Xuezhi Wang, Hyung Won Chung, Dara Bahri, Tal Schuster, Huaixiu Steven Zheng, Denny Zhou, Neil Houlsby, and Donald Metzler. 2023. UL2: Unifying language learning paradigms. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1–5, 2023*. OpenReview.net.

Ian Tenney, Dipanjan Das, and Ellie Pavlick. 2019a. BERT rediscovers the classical NLP pipeline. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4593–4601, Florence, Italy. Association for Computational Linguistics. `https://doi.org/10.18653/v1/P19-1452`

Ian Tenney, Patrick Xia, Berlin Chen, Alex Wang, Adam Poliak, R. Thomas McCoy, Najoung Kim, Benjamin Van Durme, Samuel R. Bowman, Dipanjan Das, and Ellie Pavlick. 2019b. What do you learn from context? Probing for sentence structure in contextualized word representations. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6–9, 2019*. OpenReview.net.

Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2021. BEIR: A heterogeneous benchmark for zero-shot evaluation of information retrieval models. In *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual*.

Lucas Torroba Hennigen, Adina Williams, and Ryan Cotterell. 2020. Intrinsic probing through dimension selection. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 197–216, Online. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2020.emnlp-main.15`

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288.

Teemu Vahtola, Mathias Creutz, and Jörg Tiedemann. 2022. It is not easy to detect paraphrases: Analysing semantic similarity with antonyms and negation using the new SemAntoNeg benchmark. In *Proceedings of the Fifth BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 249–262, Abu Dhabi, United Arab

Emirates (Hybrid). Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.blackboxnlp-1.20

Siddharth Vashishtha, Benjamin Van Durme, and Aaron Steven White. 2019. Fine-grained temporal relation extraction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2906–2919, Florence, Italy. Association for Computational Linguistics. https://doi.org/10.18653/v1/P19-1280

Sara Veldhoen, Dieuwke Hupkes, and Willem H. Zuidema. 2016. Diagnostic classifiers revealing how neural networks process hierarchical structure. In *Proceedings of the Workshop on Cognitive Computation: Integrating neural and symbolic approaches 2016 co-located with the 30th Annual Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain, December 9, 2016*, volume 1773 of *CEUR Workshop Proceedings*. CEUR-WS.org.

Elena Voita and Ivan Titov. 2020. Information-theoretic probing with minimum description length. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 183–196, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.emnlp-main.14

Andreas Waldis, Yufang Hou, and Iryna Gurevych. 2024a. Dive into the chasm: Probing the gap between in- and cross-topic generalization. In *Findings of the Association for Computational Linguistics: EACL 2024*, pages 2197–2214, St. Julian's, Malta. Association for Computational Linguistics.

Andreas Waldis, Yufang Hou, and Iryna Gurevych. 2024b. How to handle different types of out-of-distribution scenarios in computational argumentation? A comprehensive and fine-grained field study. *CoRR*, abs/2309.08316. https://doi.org/10.18653/v1/2024.acl-long.795

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019a. Superglue: A stickier benchmark for general-purpose language understanding systems. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019b. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6–9, 2019*. OpenReview.net.

Boxin Wang, Chejian Xu, Shuohang Wang, Zhe Gan, Yu Cheng, Jianfeng Gao, Ahmed Hassan Awadallah, and Bo Li. 2021. Adversarial GLUE: A multi-task benchmark for robustness evaluation of language models. In *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual*.

Yizhong Wang, Hamish Ivison, Pradeep Dasigi, Jack Hessel, Tushar Khot, Khyathi Chandu, David Wadden, Kelsey MacMillan, Noah A. Smith, Iz Beltagy, and Hannaneh Hajishirzi. 2023. How far can camels go? Exploring the state of instruction tuning on open resources. In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 – 16, 2023*.

Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Atharva Naik, Arjun Ashok, Arut Selvan Dhanasekaran, Anjana Arunkumar, David Stap, Eshaan Pathak, Giannis Karamanolakis, Haizhi Lai, Ishan Purohit, Ishani Mondal, Jacob Anderson, Kirby Kuznia, Krima Doshi, Kuntal Kumar Pal, Maitreya Patel, Mehrad Moradshahi, Mihir Parmar, Mirali Purohit, Neeraj Varshney, Phani Rohitha Kaza, Pulkit Verma, Ravsehaj Singh Puri, Rushang Karia, Savan Doshi, Shailaja Keyur Sampat, Siddhartha Mishra, Sujan Reddy A., Sumanta Patro, Tanay Dixit, and Xudong Shen. 2022. Super-NaturalInstructions: Generalization via declarative instructions on 1600+ NLP tasks. In *Proceedings of the 2022 Conference on Empirical Methods in Natural*

Language Processing, pages 5085–5109, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.emnlp-main.340

Alex Warstadt, Alicia Parrish, Haokun Liu, Anhad Mohananey, Wei Peng, Sheng-Fu Wang, and Samuel R. Bowman. 2020. BLiMP: The benchmark of linguistic minimal pairs for English. *Transactions of the Association for Computational Linguistics*, 8:377–392. https://doi.org/10.1162/tacl_a_00321

Bonnie Webber, Rashmi Prasad, Alan Lee, and Aravind Joshi. 2019. The Penn discourse treebank 3.0 annotation manual. *Philadelphia, University of Pennsylvania*.

Ralph Weischedel, Martha Palmer, Mitchell Marcus, Eduard Hovy, Sameer Pradhan, Lance Ramshaw, Nianwen Xue, Ann Taylor, Jeff Kaufman, Michelle Franchini, et al. 2013. Ontonotes release 5.0. *Linguistic Data Consortium, Philadelphia, PA*, 23:170.

Aaron Steven White, Drew Reisinger, Keisuke Sakaguchi, Tim Vieira, Sheng Zhang, Rachel Rudinger, Kyle Rawlins, and Benjamin Van Durme. 2016. Universal decompositional semantics on Universal Dependencies. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1713–1723, Austin, Texas. Association for Computational Linguistics. https://doi.org/10.18653/v1/D16-1177

Zhiyong Wu, Yun Chen, Ben Kao, and Qun Liu. 2020. Perturbed masking: Parameter-free probing for analyzing and interpreting BERT. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4166–4176, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.383

Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. 2023. Wizardlm: Empowering large language models to follow complex instructions. *CoRR*, abs/2304.12244.

Prateek Yadav, Leshem Choshen, Colin Raffel, and Mohit Bansal. 2023. Compeft: Compression for communicating parameter efficient updates via sparsification and quantization. *CoRR*, abs/2311.13171.

Linyi Yang, Shuibai Zhang, Libo Qin, Yafu Li, Yidong Wang, Hanmeng Liu, Jindong Wang, Xing Xie, and Yue Zhang. 2023. GLUE-X: Evaluating natural language understanding models from an out-of-distribution generalization perspective. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 12731–12750, Toronto, Canada. Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.findings-acl.806

Zhangdie Yuan, Chenxi Whitehouse, Eric Chamoun, Rami Aly, and Andreas Vlachos. 2024. Probelm: Plausibility ranking evaluation for language models. *CoRR*, abs/2404.03818.

Amir Zeldes. 2017. The GUM corpus: Creating multilayer resources in the classroom. *Language Resources and Evaluation*, 51(3):581–612. https://doi.org/10.1007/s10579-016-9343-x

Xikun Zhang, Deepak Ramachandran, Ian Tenney, Yanai Elazar, and Dan Roth. 2020. Do language embeddings capture scales? In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 292–299, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.blackboxnlp-1.27

Yian Zhang, Alex Warstadt, Xiaocheng Li, and Samuel R. Bowman. 2021. When do you need billions of words of pretraining data? In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1112–1125, Online. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.acl-long.90

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. 2023. Judging llm-as-a-judge with mt-bench and chatbot arena. In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 – 16, 2023*.

Chunting Zhou, Pengfei Liu, Puxin Xu, Srinivasan Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, Susan Zhang, Gargi Ghosh, Mike Lewis, Luke Zettlemoyer, and Omer Levy. 2023. LIMA: Less is more for alignment. In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 – 16, 2023*.

Zining Zhu, Soroosh Shahtalebi, and Frank Rudzicz. 2022a. Predicting fine-tuning performance with probing. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11534–11547, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2022.emnlp-main.793`

Zining Zhu, Jixuan Wang, Bai Li, and Frank Rudzicz. 2022b. On the data requirements of probing. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 4132–4147, Dublin, Ireland. Association for Computational Linguistics. `https://doi.org/10.18653/v1/2022.findings-acl.326`

A Additional Details of `Holmes`

A.1 Additional Details on the Evolution of Probing Literature

We analyze publication trends by year and venue as shown in Table 3. Less work was published between 2015-2018 (*earlier*) focusing on LSTM-based (Linzen et al., 2016; Conneau et al., 2018) and static LMs (Köhn, 2015; Linzen et al., 2016; Belinkov et al., 2017; Conneau et al., 2018). With the release of BERT (Devlin et al., 2019) in 2019, we note increasing attention to analyzing linguistic abilities within LMs, with a peak of 90 papers in 2022. Considering the venue, more than half of the relevant work (149 papers) was published at major conferences (ACL and EMNLP), and 68 papers were published at AACL, EACL, NAACL, and COLING.[5] In addition, we observe a constant contribution of TACL, various workshops, such as Analyzing and Interpreting Neural Networks for NLP or Representation Learning for NLP.

	earlier	*2019*	*2020*	*2021*	*2022*	*2023*	Total
`ACL`	2	10	12	9	34	25	92
`AACL`	–	–	–	–	1	–	1
`COLING`	–	–	10	–	9	–	19
`EACL`	–	–	–	7	–	15	22
`EMNLP`	2	4	13	17	21	–	57
`NAACL`	–	3	–	9	14	–	26
`TACL`	1	1	2	3	3	1	11
`Workshops`	4	4	10	10	7	1	36
`Other`	1	2	1	1	1	4	10
`Probing`	10	24	48	56	90	46	274
`All Papers`	8,056	3,111	3,822	4,294	5,133	3,647	28,063

Table 3: Evolution of probing studies. Note that EMNLP-23 and AACL-23 proceedings were not published when conducting this meta-study.

A.2 Experimental Details

Probing Hyperparameters Following previous work (Hewitt and Liang, 2019; Voita and Titov, 2020), we use fixed hyperparameters for training the probes: 20 epochs, where we find the best one using dev instances; AdamW (Loshchilov and Hutter, 2019) as optimizer; a batch size of 64; a learning rate of 0.0005; a dropout rate of 0.2; a warmup rate of 10% of the steps; random seeds: $[0, 1, 2, 3, 4]$

Hardware We run all of our experiments using 12 Nvidia RTX A6000 GPUs. Every GPU provides 48GB of memory and 10752 CUDA Cores.

Considered LMs Table 9 outlines the details of the LMs we evaluate on `Holmes` in this work.

A.3 Probing Datasets Categorization

We show in Table 4, Table 5, Table 8, Table 6, and Table 7 which resources `Holmes` use to cover *morphology*, *syntax*, *semantics*, *reasoning*, and *discourse* phenomena. Further, we provide illustrative examples of the phenomena. We rely on 33 works providing the data, the specific linguistic phenomena, or both. For example, for *readability*, we use the data of Weischedel et al. (2013) and calculated the Flesch score (Flesch, 1948).

Morphology First, we feature 19 tasks verifying *morphology* phenomena: *Anaphor agreement*,

[5] Note that EMNLP-23 and AACL-23 proceedings were not published when conducting this meta-study.

determiner noun agreement, *subject-verb agreement* and *irregular forms* (Warstadt et al., 2020; Huebner et al., 2021).

Syntax The second group of 75 tasks verifies the following *syntax* phenomena: *Part-of-speech* and *constituent labeling* (Weischedel et al., 2013); *dependency labeling* (Silveira et al., 2014); *bigram-shift* (whether two words were shifted), *tree-depth* (the depth of a sentence constituency tree), *top-constituent-task* (top constituency tag), and *sentence-length* (Conneau et al., 2018); *subject-* & *object-number* (singular/plural), and *deoncausative-inchoative alternation* (interaction of a verb with its context) based on Klafka and Ettinger (2020); *binding*, *control/raising*, *negative polarity item licensing*, *island-effects*, *argument-structure*, *ellipsis*, and *filler-gap* (Warstadt et al., 2020; Huebner et al., 2021).

Semantics Third, consider 67 datasets covering *semantics* phenomena: *Named-entity labeling* and *semantic-role labeling* (Weischedel et al., 2013); *tense*, *semantic odd man out*, *word content*, and *coordination inversion* (Conneau et al., 2018); *semantic relation classification* (Hendrickx et al., 2010); *semantic proto-roles* (Rudinger et al., 2018a); *factuality* (if a span is factual or not) (Rudinger et al., 2018b); *genericity* (whether a span is generic or not) (Govindarajan et al., 2019); *event structure* (Gantt et al., 2022); *time* (time dimension of a span) (Vashishtha et al., 2019); *word sense* (White et al., 2016); *sentiment analysis* (Socher et al., 2013); *object-* and *subject-animacy* (whether a entity is animate, like human, or not, such as cars), *object-* and *subject-gender* (male/female), *verb-tense*, and *verb-dynamic* Klafka and Ettinger (2020); *metaphor* (Mohler et al., 2016; Birke and Sarkar, 2006; Steen et al., 2010); *complex word identification* (whether the word is complex or not) (Paetzold and Specia, 2016); and *passive* (Krasnowska-Kieraś and Wróblewska, 2019). In addition, we derive an *synonym-/antonym-detection* dataset using WordNet (Miller, 1995) and the texts from OntoNotes v5 Weischedel et al. (2013).

Reasoning Forth, 19 datasets cover *reasoning* phenomena: *Paraphrasticity* with negation and antonyms (Vahtola et al., 2022); *negation detection* (Szarvas et al., 2008; Konstantinova et al., 2012; Morante and Blanco, 2012); *negation-span classification* (does a span cause a negation) (Szarvas et al., 2008; Konstantinova et al., 2012); *negation-correspondence* (the target span of a negation) (Szarvas et al., 2008; Konstantinova et al., 2012); *speculation detection*, *speculation-span classification*, and *speculation-correspondence* (the target span of a sepculation) (Szarvas et al., 2008); and *always-never*, *age comparison*, *objects comparison*, *antonym negation*, *property conjunction*, *taxonomy connection*, and *multi-hop composition* (Talmor et al., 2020b).

Discourse Finally, `Holmes` embodies 28 datasets addressing *discourse* phenomena: *Co-reference resolution* Weischedel et al. (2013); *bridging* (Hou, 2018, 2020; Pandit and Hou, 2021); *discourse connective* (Nie et al., 2019); *sentence order* and *next-sentence prediction* (Narayan et al., 2018); Given discourse tree, whether two nodes correspond (*discourse correspondence*), the correct order of two nodes (*discourse order*), node-node relation (*discourse relation*), distance between two nodes (*discourse distance*), explicit node class *discourse explicit classes*, implicit node class *discourse implicit classes* (Webber et al., 2019; Kurfalı and Östling, 2021); and given a rhetorical tree with the number of child nodes (*rst-count*), the node depth (*rst-depth*), distance between two nodes *rst-distance*, node-node relation (*rst-relation*), node-node relation group (*rst-relation-group*), appear two nodes after each other (*rst-successively*), node type (*rst-type*) (Carlson et al., 2001; Koto et al., 2021; Kurfalı and Östling, 2021; Zeldes, 2017).

A.4 Details of Probing Dataset Composition

Whenever possible, we rely on established probing datasets and transform instances into a unified format: **1)** an input x which is either one or a pair of span(s) or sentence(s), including the string and an optional starting and ending index in the context c when task type is either a span or span-pair classification; **2)** an optional textual context c to encode x, for example the sentence in which a span occurs; and **3)** a corresponding label y. Figure 14 shows the composition of the specific probing input x for these four tasks using the internal representation of the last layer of LMs. Note that additional averaging operations are required if

Phenomena	Illustrative Example	Text	Text-Pair	Span	Span-Pair	Warstadt et al. (2020)	Huebner et al. (2021)
anaphor agreement	Katherine can't help herself*/himself.	3				✓	✓
determiner noun agreement	Craig explored that grocery store*/stores.	10				✓	✓
irregular forms	Edward hid*/hidden the cats.	3				✓	✓
subject-verb agreement	A sketch of lights does not*/do not appear.	10				✓	✓

Table 4: Overview of resources and linguistic phenomena mapping for *morphology*. We give an illustrative example for each phenomenon (*indicates the right option, if options are given) and the number of datasets for the phenomenon by dataset type.

Phenomena	Illustrative Example	Text	Text-Pair	Span	Span-Pair	Weischedel et al. (2013)	Silveira et al. (2014)	Conneau et al. (2018)	Flesch (1948)	Klafka and Ettinger (2020)	Warstadt et al. (2020)	Huebner et al. (2021)
argument-structure	Most cashiers are disliked*/flirted.	20									✓	✓
bigram-shift	What are you*/you are doing out there?		1						✓			
binding	Carlos said that Lori helped him*/himself.	8									✓	✓
case-subjective-pronoun	He brought the pig this suit.*/The pig brought he this suit.	1										✓
constituent parsing	sees Bill ⇒ VP	2			1	✓						
control/raising	Julia wasn't fun*/unlikely to talk to.	5									✓	✓
deoncausative-inchoative alternation	The warden melted the ice.*/The warden bought the ice.	1								✓		
dependency parsing	(into, air) ⇒ pobj				1		✓					
ellipsis	He cleans one important book and Stacey cleans a few.*/He cleans one book and Stacey cleans a few important.	3									✓	✓
filler-gap	Brett knew what many waiters find.*/Brett knew that many waiters find.	9									✓	✓
island-effects	Which bikes is John fixing?*/Which is John fixing bikes?	10									✓	✓
local attractor	Can the access work?*/ Can the access works?	1										✓
object-number	Oh gods! ⇒ Plural	2						✓			✓	
part-of-speech	cucumber ⇒ NN (Noun Singular)			3		✓	✓					
readability	Curriculums need selling points. ⇒ 50.5 (middle)	1				✓			✓			
sentence-length	Oh gods! ⇒ 3 words	1						✓				
subject-number	Things are going to be noticed. $Rightarrow$ Plural	2						✓			✓	
top-constituent	Did it all matter? $Rightarrow$ VBD NP VP	1						✓				
tree-depth	Where do you want it? ⇒ 6	1						✓				

Table 5: Overview of resources and linguistic phenomena mapping for *syntax*. We give an illustrative example for each phenomenon (*indicates the right option, if options are given) and the number of datasets for the phenomenon by dataset type.

words are tokenized into multiple tokens to get one average vector representing one word, for example, when probing for the part-of-speech tag of a rare word.

If given, we use the original train/dev/test splits. However, if this division does not exist, we use a 70/10/20 ratio to form these splits. Furthermore, we adapted the design of some data to map our dataset format. Exemplary, for the oLMmpics (Talmor et al., 2020b) dataset, we transform the mask-filling tasks into a binary classification where the *correct* label corresponds to a sentence with a correctly filled mask and *incorrect* to a sentence where the mask was filled wrongly.

OnToNotes Following Tenney et al. (2019b,a), we use the *OntoNotes* (Weischedel et al., 2013) dataset to derive *part-of-speech tagging*, *constituent labeling*, *named-entity labeling*, *semantic role*, and *co-reference resolution* probing datasets. Further, we consider with *constituent maximum depth* and *constituent node length* further properties of the constituent tree this dataset *OntoNotes*.

Dependency Corpus As in Tenney et al. (2019b,a), we use Universal Dependencies annotations of the English Web Treebank to form a *dependency labeling* datasets.

Phenomena	**Illustrative Example**	Text	Text-Pair	Span	Span-Pair	Vahtola et al. (2022)	Szarvas et al. (2008)	Konstantinova et al. (2012)	Morante and Blanco (2012)	Talmor et al. (2020b)
age comparison	21 years old is older than 35 years fold.*/21 years old is younger than 35 years fold.	1								✓
always-never	Horses have always*/never four legs.	1								✓
antonym negation	It was not*/really hot, it was cold.	1								✓
multi-hop composition	Comparing a 23, a 38 and a 31 year old, the last*/first is oldest.	1								✓
negation	I don't like bananas. ⇒ Negation		3	1	2	2	✓	✓	✓	✓
objects comparison	An airplane is bigger*/smaller than a pen.	1								✓
property conjunction	A pen*/computer is usually located at hand and used for writing.	1								✓
speculation	Just about every PC can be upgraded. ⇒ Speculation	1		1	1		✓			
taxonomy connection	Ferry and floatplane are both boats*/airplaines.	1								✓

Table 6: Overview of resources and linguistic phenomena mapping for *reasoning*. We give an illustrative example for each phenomenon (*indicates the right option, if options are given) and the number of datasets for the phenomenon by dataset type.

Phenomena	**Illustrative Example**	Text	Text-Pair	Span	Span-Pair	Weischedel et al. (2013)	Pandit and Hou (2021)	Nie et al. (2019)	Narayan et al. (2018)	Webber et al. (2019)	Carlson et al. (2001)	Zeldes (2017)
bridging	The disease and symptoms of advanced infection. ⇒ Valid Bridge	1			1		✓					
co-reference resolution	National Taiwan University opened the doors of five of its graduate schools. ⇒ Valid Co-Reference				1	✓						
discourse connective	Leaning against his hip. He reclined with his feet up on the table. ⇒ when		1					✓				
discourse representation theory	This is an old story. We're talking about years ago. ⇒ Implicit Relation			8							✓	
next-sentence prediction	Sentence A, Sentence B ⇒ Valid Next Sentence		1						✓			
rethorical structure theory	The statistics quoted by the ‘‘ new ’’ Census Bureau report ⇒ Elaboration			6	8					✓		✓
sentence order	Given Sentence B, C, and D ⇒ C is at position 2	1							✓			

Table 7: Overview of resources and linguistic phenomena mapping for *discourse*. We give an illustrative example for each phenomenon (*indicates the right option, if options are given) and the number of datasets for the phenomenon by dataset type.

Context Probes Presented in Klafka and Ettinger, (2020), we compose the nine datasets verifying LMs' knowledge about the context of words. For example, is a word animate (like animals or humans) or inanimate (like buildings or vehicles), or is a verb static or dynamic

BLiMP Dataset Using the data presented in the BLiMP benchmark (Warstadt et al., 2020), we derive 67 probing datasets verifying specific phenomena, like *island effect*, covering *morphology*, *syntax*, and *semantics*. Unlike the original version, we compose a binary classification task for every phenomenon, either accepting a valid sentence or rejecting one that violates the given linguistic phenomenon.

Zorro Dataset As for the BLiMP tasks, we convert the 21 distinct Zorro tasks into a binary classification task on whether a sentence accepts or rejects the given linguistic phenomena is violated.

SemEval-2010 Task 8 For *semantic relation classification*, we rely on the dataset of Hendrickx et al. (2010).

Decompositional Semantics Initiative The *Decompositional Semantics Initiative*[6] provides a large number of datasets to verify semantic phenomena. Apart from the common use *semantic proto-roles* (Rudinger et al., 2018a), we use their collection of works to compose probing datasets for *factuality* (Rudinger et al., 2018b), genericity (Govindarajan et al., 2019), event structure (Vashishtha et al., 2019), time (Vashishtha et al., 2019), and word sense (White et al., 2016).

[6] https://decomp.io/.

Phenomena	Illustrative Example	Text	Text-Pair	Span	Span-Pair	Weischedel et al. (2013)	Conneau et al. (2018)	Klafka and Ettinger (2020)	Warstadt et al. (2020)	Huebner et al. (2021)	Hendrickx et al. (2010)	Rudinger et al. (2018a)	Rudinger et al. (2018b)	Govindarajan et al. (2019)	Gantt et al. (2022)	Vashishtha et al. (2019)	White et al. (2016)	Socher et al. (2013)	Mohler et al. (2016)	Birke and Sarkar (2006)	Steen et al. (2010)	Paetzold and Specia (2016)	Krasnowska-Kieraś and Wróblewska (2019)	Miller (1995)
complex word identification	membrane ⇒ Complex, his ⇒ Simple			1																		✓		
coordination inversion	He knew it, and he deserved no answer. ⇒ Inversion	1					✓																	
event structure	Give them to a library or burn them. ⇒ Distributive			4	2										✓									
factuality	I ran across this item on the Internet. ⇒ Factual				1								✓											
genericity	I assume you mean the crazy horse memorial. ⇒ Not Dynamic			6										✓										
metaphor	After all, morons pay taxes, too. ⇒ Valid Metaphor			4															✓	✓	✓			
named-entity labeling	Paris ⇒ City			1		✓																		
negative polarity item licensing	Only/Even Bill would ever complain.	4							✓	✓														
object-animacy	The rhino fined the pumpkin. ⇒ Animate	1						✓																
object-gender	The princess uncovered the heiress. ⇒ Feminine	1						✓																
passive	He is considered a European poet through and through. ⇒ Passive Sentence	1																					✓	
quantifiers	There aren't many*/all lights darkening.	6								✓														
semantic relation classification	Those cancers were caused by radiation exposures. ⇒ Cause-Effect		1								✓													
semantic proto-roles	These look fine to me. ⇒ Exists as physical				20							✓												
semantic odd man out	I wanted to know if it was real or a ploy. ⇒ Original	1					✓																	
semantic-role labeling	And what effect does their return have on campus? ⇒ ARGM-ADV				1	✓																		
sentiment analysis	You 'll probably love it. ⇒ Positive	1																✓						
subject-animacy	The turtle betrayed the judge. ⇒ Animate	1						✓																
subject-gender	The waitress betrayed the judge. ⇒ Feminine	1						✓																
synonym-/antonym-detection	Is the degree really that important → unimportant to them? ⇒ Antonym Replacement	1																						✓
tense	I quietly snuck up to him and pulled at his sleeve. → Present	2					✓	✓																
time	His mother was also killed in the attack. ⇒ Minutes			1												✓								
verb-dynamic	The lawyer found the judge. ⇒ Dynamic Verb	1						✓																
word content	You mean Alice. ⇒ Contains Word *Alice*	1					✓																	
word sense	His mother was also killed in the attack. ⇒ Supersense Noun Person			1													✓							

Table 8: Overview of resources and linguistic phenomena mapping for *semantics*. We give an illustrative example for each phenomenon (*indicates the right option, if options are given) and the number of datasets for the phenomenon by dataset type.

Sentiment Analysis We use the commonly used work of Socher et al. (2013) and form a probing dataset targeting sentiment.

Metaphor As in Aghazadeh et al. (2022), we use the data from Mohler et al. (2016); Birke and Sarkar (2006); Steen et al. (2010) to form three metaphor datasets.

Complex Word Identification We consider word complexity for the first time and use the data presented in Paetzold and Specia (2016). It provides annotations for different complexity levels of words.

Passive We use data from Krasnowska-Kieraś and Wróblewska (2019) to form a probing dataset assessing knowledge about passive language.

Synonym / Antonym Replacement Using the text of the *OntoNotes* (Weischedel et al., 2013) and Wordnet (Miller, 1995), we form a probing dataset to detect synonym and antonym replacement. Specifically, the binary classification task is: given two texts (the original and an updated one), was the updated one changed by replacing a word with its synonym or antonym?

Negation With this work, we verify for the first time *negation* based on human annotated datasets (Vahtola et al., 2022; Szarvas et al., 2008; Konstantinova et al., 2012). Specifically, we form different probing datasets.

- Is a text negated or not?
- Given two text spans, does the negation within the first one correspond to the second one?
- Given a text span, is it the cue or the scope of the negation?

oLMmpics We form probing datasets addressing different lexical reasoning using the data presented in Talmor et al. (2020b). As they provide multiple choices, we form *correct* instances by filling the gap with the correct option and *wrong* ones by filling in the other options. Specifically, we form dataset for

Model	Citation	Size	Pre-Training Objective	Pre-Training Data	Huggingface Tag
Encoder-Only Language Models					
ALBERT	Lan et al. (2020)	10 million	MLM+SOP	16GB	`albert-base-v2`
BERT	Tenney et al. (2019a)	110 million	MLM+NSP	16GB	`bert-base-uncased`
DeBERTa	He et al. (2021)	100 million	MLM	80GB	`microsoft/deberta-base`
DeBERTa-v3	He et al. (2023)	86 million	MLM+DISC	160GB	`microsoft/deberta-v3-base`
ELECTRA	Clark et al. (2020)	110 million	MLM	16GB	`google/electra-base-discriminator`
RoBERTa	Liu et al. (2019)	110 million	MLM+DISC	160GB	`roberta-base`
Decoder-Only Language Models					
GPT2	Radford et al. (2019)	117 million	LM	40GB	`gpt2`
Pythia-70m	Biderman et al. (2023)	70 million	LM	300 billion tokens	`EleutherAI/pythia-70m`
Pythia-160m	Biderman et al. (2023)	160 million	LM	300 billion tokens	`EleutherAI/pythia-160m`
Pythia-410m	Biderman et al. (2023)	410 million	LM	300 billion tokens	`EleutherAI/pythia-410m`
Pythia-1b	Biderman et al. (2023)	1 billion	LM	300 billion tokens	`EleutherAI/pythia-1B`
Pythia-1.4b	Biderman et al. (2023)	1.4 billion	LM	300 billion tokens	`EleutherAI/pythia-1.4B`
Pythia-2.8b	Biderman et al. (2023)	2.8 billion	LM	300 billion tokens	`EleutherAI/pythia-2.8B`
Pythia-6.9b	Biderman et al. (2023)	6.9 billion	LM	300 billion tokens	`EleutherAI/pythia-6.9B`
Pythia-12b	Biderman et al. (2023)	12 billion	LM	300 billion tokens	`EleutherAI/pythia-12B`
Pythia-70m-dedup	Biderman et al. (2023)	70 million	LM	207 billion tokens	`EleutherAI/pythia-70m-deduped`
Pythia-160m-dedup	Biderman et al. (2023)	160 million	LM	207 billion tokens	`EleutherAI/pythia-160m-deduped`
Pythia-410m-dedup	Biderman et al. (2023)	410 million	LM	207 billion tokens	`EleutherAI/pythia-410m-deduped`
Pythia-1b-dedup	Biderman et al. (2023)	1 billion	LM	207 billion tokens	`EleutherAI/pythia-1B-deduped`
Pythia-1.4b-dedup	Biderman et al. (2023)	1.4 billion	LM	207 billion tokens	`EleutherAI/pythia-1.4B-deduped`
Pythia-2.8b-dedup	Biderman et al. (2023)	2.8 billion	LM	207 billion tokens	`EleutherAI/pythia-2.8B-deduped`
Pythia-6.9b-dedup	Biderman et al. (2023)	6.9 billion	LM	207 billion tokens	`EleutherAI/pythia-6.9B-deduped`
Pythia-12b-dedup	Biderman et al. (2023)	12 billion	LM	207 billion tokens	`EleutherAI/pythia-12B-deduped`
Dolly-v2	Conover et al. (2023)	12 billion	LM+IT	300 billion token + 15K instructions	`databricks/dolly-v2-12b`
Llama-2-7b	Touvron et al. (2023)	7 billion	LM	2.4 trillion tokens	`meta-llama/Llama-2-7b-hf`
Llama-2-13b	Touvron et al. (2023)	13 billion	LM	2.4 trillion tokens	`meta-llama/Llama-2-13b-hf`
Llama-2-70b	Touvron et al. (2023)	70 billion	LM	2.4 trillion tokens	`meta-llama/Llama-2-70b-hf`
Llama-2-7b-chat	Touvron et al. (2023)	7 billion	LM+IT	2.4 trillion tokens + 27,5K instructions	`meta-llama/Llama-2-7b-chat-hf`
Llama-2-13b-chat	Touvron et al. (2023)	13 billion	LM+IT	2.4 trillion tokens + 27,5K instructions	`meta-llama/Llama-2-13b-chat-hf`
Llama-2-70b-chat	Touvron et al. (2023)	70 billion	LM+IT	2.4 trillion tokens + 27,5K instructions	`meta-llama/Llama-2-70b-chat-hf`
IBM-Merlinite	Sudalairaj et al. (2024)	7 billion	LM+IT	2.4 trillion tokens + 1400k instructions	`ibm/merlinite-7b`
IBM-Labradorite	Sudalairaj et al. (2024)	13 billion	LM+IT	2.4 trillion tokens + 1400k instructions	`ibm/labradorite-13b`
Vicuna-13b-v1.5	Zheng et al. (2023)	13 billion	LM+IT	2.4 trillion tokens + 125k instructions	`lmsys/vicuna-13b-v1.5`
Orca-2-13b	Mitra et al. (2023)	13 billion	LM+IT	2.4 trillion tokens + 817K instructions	`microsoft/Orca-2-13b`
Wizard-13B-v1.2	Xu et al. (2023)	13 billion	LM	unknown	`WizardLM/WizardLM-13B-V1.2`
Tülu-2-13b	Wang et al. (2023)	13 billion	LM+IT	2.4 trillion tokens + 330k instructions	`allenai/tulu-2-13b`
Tülu-2-dpo-13b	Wang et al. (2023)	13 billion	LM+IT	2.4 trillion tokens + 330k instructions	`tulu-2-dpo-13b`
Tülu-2-70b	Wang et al. (2023)	70 billion	LM+IT	2.4 trillion tokens + 330k instructions	`allenai/tulu-2-70b`
Tülu-2-dpo-70b	Wang et al. (2023)	70 billion	LM+IT	2.4 trillion tokens + 330k instructions	`tulu-2-dpo-70b`
Mistral-7b	Jiang et al. (2023)	7 billion	LM	unknown	`mistralai/Mistral-7B-v0.1`
Mistral-7b-Inst	Jiang et al. (2023)	7 billion	LM	unknown	`mistralai/Mistral-7B-Instruct-v0.1`
Mixtral-8×7b	Jiang et al. (2024)	47 billion	LM	unknown	`mistralai/Mixtral-8×7B-v0.1`
Mixtral-8×7b-Inst	Jiang et al. (2024)	47 billion	LM	unknown	`mistralai/Mistral-7B-v0.1`
Encoder-Decoder Language Models					
BART	Lewis et al. (2020)	121 million	DAE	160GB	`google/facebook/bart-base`
T5-small	Raffel et al. (2020)	60 million	DAE	800GB	`google/t5-small-lm-adapt`
T5-base	Raffel et al. (2020)	220 million	DAE	800GB	`google/t5-base-lm-adapt`
T5-large	Raffel et al. (2020)	770 million	DAE	800GB	`google/t5-large-lm-adapt`
T5-xl	Raffel et al. (2020)	3 billion	DAE	800GB	`google/t5-xl-lm-adapt`
T5-xxl	Raffel et al. (2020)	11 billion	DAE	800GB	`google/t5-xxl-lm-adapt`
FLAN-T5-small	Raffel et al. (2020)	60 million	DAE+IT	800GB + 1.8k tasks	`google/t5-small-lm-adapt`
FLAN-T5-base	Raffel et al. (2020)	220 million	DAE+IT	800GB + 1.8k tasks	`google/t5-base-lm-adapt`
FLAN-T5-large	Raffel et al. (2020)	770 million	DAE+IT	800GB + 1.8k tasks	`google/t5-large-lm-adapt`
FLAN-T5-xl	Raffel et al. (2020)	3 billion	DAE+IT	800GB + 1.8k tasks	`google/t5-xl-lm-adapt`
FLAN-T5-xxl	Raffel et al. (2020)	11 billion	DAE+IT	800GB + 1.8k tasks	`google/t5-xxl-lm-adapt`
TK-Instruct	Wang et al. (2022)	11 billion	DAE+IT	800GB + 1.6k tasks	`allenai/tk-instruct-11b-def`
UL2	Tay et al. (2023)	20 billion	DAE	800GB	`google/ul2`
FLAN-UL2	Tay et al. (2023)	20 billion	DAE+IT	800GB + 100k instructions	`google/flan-ul2`
Static Language Models					
Glove-6B	Pennington et al. (2014)	–	WP	6 billion tokens	`glove.6B.300d`
Glove-840B	Pennington et al. (2014)	–	WP	840 billion tokens	`glove.840B.300d`

Table 9: Overview of the evaluated LMS covering the corresponding citation, model size, model architecture, pre-training objective & data, and the Huggingface model tag. Regarding the pre-training objective, we distinguish between masked language modeling (MLM), sentence order prediction (SOP), next sentence prediction (NSP), next word prediction (LM), instruction fine-tuning (IT), word denoising (DAE), and word probabilities from word co-occurrences (WP). For pre-training data, we report known numbers, either as the size of the corpora in gigabytes (GB), the number of pre-training tokens, the number of instructions for fine-tuning, or the number of tasks for instruction fine-tuning.

always-never, *age comparison*, *objects comparison*, *antonym-negation*, *multi-hop composition property conjunction*, *taxonomy conjunction*, and *encyclopedic composition*.

Bridging We rely on the data presented in Pandit and Hou (2021) and form two probing datasets. One is to verify whether a text is linguistically applicable, considering bridging (antecedent matches anaphora). And a second one to verify whether an antecedent and anaphora match.

Discourse Connective Using data from Nie et al. (2019), we form a probing dataset to assess whether a given connective marker matches the discourse of the given text.

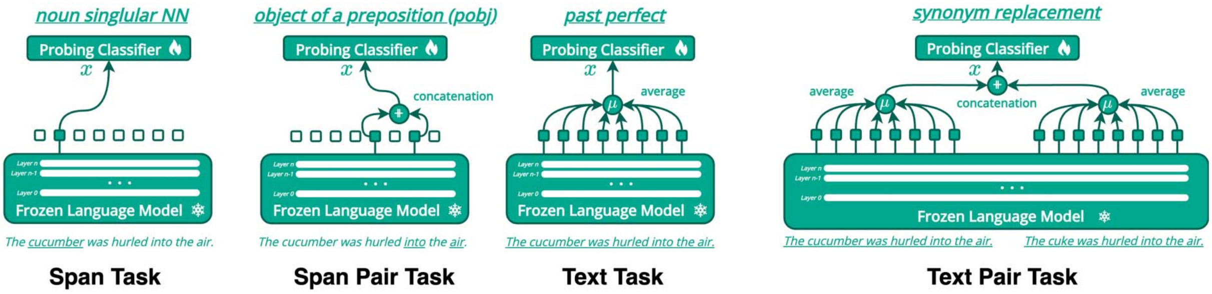


Figure 14: Overview of the composition of the probing input x based on the given text the four types of tasks using concatenating and averaging. In case a tokenizer splits one word into multiple tokens and applies additional averaging operations, such as when probing the part-of-speech phenomenon.

Sentence Order and Next Sentence Prediction Following Narayan et al. (2018), we form two datasets to verify the order of good or badness of a given sentence and whether two sentences occur after each other.

Discourse Representation Theory We use data from Webber et al. (2019) to compose eight probing datasets addressing *discourse representation theory*:

- Four probing dataset predicting the class of a given span. We distinguish between *implicit*, *explicit*, *implicit-coarse*, and *explicit-coarse*.
- The absolute distance, number of words, between two spans in the text.
- Whether the order of two spans is correct or not.
- Whether two spans have discourse relation or not.
- The specific discourse relation of two spans.

Rhetorical Structure Theory Using annotations from Carlson et al. (2001); Zeldes (2017), we compose 14 probing datasets addressing *rhetorical theory*. Specifically, we compose the following seven types of datasets for both works:

- The rhetorical type of a text span, either nucleus or satellite.
- The number of children of a text span within the rhetorical tree of the text.
- The depth of a text span within the rhetorical tree of the text.
- The number of edges between two text spans within the rhetorical tree.
- The specific rhetorical relation between two text spans like *conclusion*.
- The relation group of a specific rhetorical relation between two text spans like *evaluation* for the relation *conclusion*.
- Whether two text spans occur after each other in the rhetorical tree.

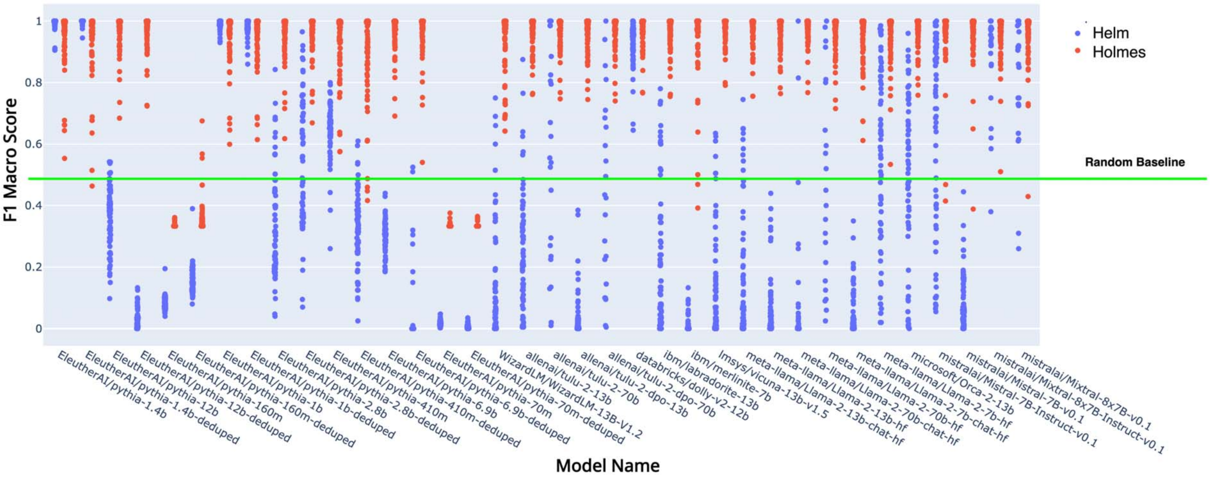


Figure 15: Detailed Holmes vs. HELM (Liang et al., 2023) comparison for 40 open decoder models and 22 Blimp datasets covering *quantifier*, *island effects*, *irregular forms*, and *binding* phenomena. We use the evaluation code of HELM and run the prompting-based adaption (*multiple joice joined*). The `Holmes` and Helm results for 40 open decoder models. These results show the advantage of disentangled evaluation (`Holmes`) over entanglement evaluations (like in HELM), which intertwine the understanding of specific linguistic phenomena and other abilities (like following instructions or answering precisely) in HELM. Most HELM results are below the random baseline, underscoring the necessity to measure linguistic phenomena directly in isolation within LMs.