In Benchmarks We Trust ... Or Not?

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Abstract

Standardized benchmarks are central to evaluating and comparing model performance in Natural Language Processing (NLP). However, Large Language Models (LLMs) have exposed shortcomings in existing benchmarks, and so far there is no clear solution. In this paper, we survey a wide scope of benchmarking issues, and provide an overview of solutions as they are suggested in the literature. We observe that these solutions often tackle a limited number of issues, neglecting other facets. Therefore, we propose concrete checklists to cover all aspects of benchmarking issues, both for benchmark creation and usage. We illustrate the use of our checklists by applying them to three popular NLP benchmarks (i.e., SuperGLUE, WinoGrande, and ARC-AGI). Additionally, we discuss the potential advantages of adding minimal-sized test-suites to benchmarking, which would ensure downstream applicability on real-world use cases.

1 Introduction

There is a rich history of benchmarking in Natural Language Processing (NLP): the field has seen an evolution from specific single-task and single-domain to more general multi-task benchmarks, following the advent of more powerful general-purpose AI models (Ruder, 2021). These benchmarks have been used as an attempt to objectively assess the performance of methods, and to track and direct progress in the field (e.g., the yearly AI Index Report, Maslej et al., 2025). In its broad sense, a benchmark is a dataset (or an ensemble of datasets) associated with one or multiple metrics, and a way to aggregate system performances (Ruder, 2021). The performance on such a benchmark is considered to be representative of the model's abilities on a task, and is used by the research community as a framework to compare methods (Raji et al., 2021). Prominent standardized benchmarks in NLP are used to promote the increasing capabilities of newly released models: technical reports introducing new Large Language Models (LLMs) often refer to their performance on a collection of standardized benchmarks (e.g., Achiam et al., 2023; Yang et al., 2024, etc.). However, recent models are outpacing the benchmark creation and benchmarks are quickly saturated, but this does not necessarily mean the model has grasped the relevant skill or knowledge (Kiela et al., 2021). Additionally, since benchmark scores have become a goal on their own, research integrity could be compromised in an attempt to optimize these scores. For instance, the LLaMA 4 team submitted 27 private variants of the model (Singh et al., 2025) to Chatbot Arena (Chiang et al., 2024), which artificially boosted the benchmark scores and obscured the distinction between the publicly released version and their best performer on this benchmark.[1] Koch and Peterson (2024) argue that the rigid consolidation of benchmarking as the sole evaluator of progress also disincentivizes exploration beyond scaling model size.

So far, there is no clear consensus on how to address the problems with benchmarking: for instance, the HuggingFace Open LLM Leaderboard introduced a way to evaluate methods across a range of tasks and metrics (Myrzakhan et al., 2024), but it eventually became outdated and is now archived.[2] Meanwhile, research is ongoing to improve existing benchmarks (e.g., by adversarial sampling, or semantic deduplication) or creating new ones (e.g., ARC-AGI, Chollet et al., 2024).

In this paper, we focus on benchmarking issues from the perspective of benchmark integrity (benchmark creation) and benchmarking practices (evaluating a method on a benchmark). While we address issues that are generally relevant regardless

[1] https://x.com/lmarena_ai/status/1909397817434816562

[2] At the time of writing: https://huggingface.co/spaces/open-llm-leaderboard/open_llm_leaderboard

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of the model type that is being evaluated, we zoom in on benchmarks currently used to evaluate LLMs because these models reveal inconsistencies and weaknesses in standardized benchmarks that were created earlier. Since benchmarks vary in format and modality, we focus here on text-based benchmarks: text as input, and text as output. These benchmarks can come in many shapes, such as classification, summarization, generation, and so on. In the scope of our paper, we consider static benchmarks that have an a priori gold label associated with each input text.

Existing position and survey papers on NLP benchmarking have provided important insights. For example, Bowman and Dahl (2021) propose core criteria for Natural Language Understanding (NLU) benchmark design. Raji et al. (2021) focus on construct validity and inappropriate community use of benchmarks given two main benchmarks, ImageNet and (Super)GLUE. McIntosh et al. (2024) address functionality and integrity of 23 benchmarks in the context of generative LLMs, while Laskar et al. (2024) examine the robustness of LLM evaluation. Banerjee et al. (2024) analyze contamination and gaming in evaluation frameworks. Finally, Reuel-Lamparth et al. (2024) propose an assessment framework that covers a wide range of AI benchmarks and provide a checklist for minimum quality assurance.

This survey paper adds to this effort by (1) surveying discrete benchmarking issues both in *creation* and *usage* without any a priori benchmark selection, (2) surveying solutions that are suggested in the literature and evaluating whether these solutions are general enough for (most of) the issues we identified, and (3) combining these insights into a concrete checklist of mitigation strategies, and exploring the added value of integrating downstream test-suites as an additional test to ensure model generalizability.

2 Survey of benchmarking flaws

In this section, we provide a survey of various problems with benchmarking that have been noted in prior literature over time. We structure them according to four types of experiment validity they undermine (Wohlin et al., 2012): (1) *internal validity*, whether results are caused by the variable(s) of interest rather than by external confounds; (2) *external validity*, whether results are generalizable to other domains, or real-world settings; (3) *statistical validity*, whether the proper methods are applied to evaluate the model outputs on the benchmark, so that the reported metrics support the claim; (4) *construct validity*, whether the task and evaluation metrics capture the phenomenon they intend to measure.

2.1 Internal validity

Benchmarks are... only as good as their annotations Since benchmark datasets are designed to compare the performance of models on one or more specific tasks, it is crucial that the provided annotations are of high quality. If this is not the case, this comparison is not only invalid, but this also has implications for the performance of the models if they are fine-tuned on this benchmark. Moreover, Vendrow et al. (2024) show that label errors cause evaluation inconsistencies, by hiding unreliable model behavior.

In manually annotated data, one of the main causes of low annotation quality is annotator disagreement, which can occur in spite of (or because of) annotator guidelines and an extensive training procedure (Parmar et al., 2023). A second possible cause is annotator bias, which is the result of demographic and personal factors (Al Kuwatly et al., 2020).

Alternatively, automatic labeling through distant supervision may provide high-quality labels in some tasks, such as Native Language Identification. In this setup, labels are inferred from metadata associated with the input's author (i.e., their declared native language). If the gold label is not straightforward, however, labels obtained via distant supervision can be problematic. In sarcasm detection, for example, labels provided by the authors (e.g., '#sarcasm') can be mined, although this may lead to inconsistent examples of sarcasm (Loakman et al., 2023). In addition, there is no way to estimate the recall of such methods, which could lead to unrepresentative sampling from the population (Ghosh et al., 2020). As an alternative, it has been proposed to use LLMs as automatic annotators, but as argued by Felkner et al. (2024), these models are biased themselves.

Benchmarks are... gameable Dataset artifacts are superficial patterns in the data that can be exploited by the model to get the correct answer based on irrelevant correlations (Gardner et al., 2021), which is not necessarily intended by the researcher. The presence of such superficial patterns

especially becomes problematic when the evaluation metrics of the benchmark encourages shortcuts. In a classic example, Mao and Lee (2019) show that in many paraphrasing datasets, repeating the input text inflated the score. Also in Natural Language Inference (NLI) tasks, models could already partially solve the task without looking at the premise at all, instead relying on lexical patterns or sentence lengths (Gururangan et al., 2018). Newer models still apply 'shortcut learning' in NLI, in which they for instance exploit lexical overlap (Yuan et al., 2024; Sun et al., 2024). In a multiple-choice question answering setup, the position of the correct answer among the possible options can also be exploited. By shuffling this order, Pezeshkpour and Hruschka (2024) observe an 85% performance drop. Similarly, Alzahrani et al. (2024) can move models up or down 8 ranks on the MMLU dataset with various small perturbations.

Recently, reasoning and explainability benchmarks were introduced to increase the transparency of LLM behavior, but they are still gameable. For example, Hsia et al. (2024) describe various methods to manipulate specific evaluation metrics such as ERASER and EVAL-X scores. Meanwhile, Mondorf and Plank (2024b) discuss how using accuracy as a metric to measure reasoning performance can obscure how LLMs rely on surface-level patterns and correlations in the training data, rather than on sophisticated reasoning abilities.

Benchmarks are... trained upon LLM benchmark evaluation is increasingly compromised by data contamination, where models are exposed to benchmark data during training (Xu et al., 2024). This leakage encompasses various forms, from entire datasets to metadata about them (Xu et al., 2024; Sainz et al., 2023b; Palavalli et al., 2024). This phenomenon is widespread, affecting popular benchmarks (such as HellaSwag and TriviaQA) within common training corpora (such as C4 and The Pile), both in open and closed source models (Sainz et al., 2023b, 2024; Singh et al., 2024a).

Detecting and mitigating contamination, which can occur during pre-training, fine-tuning, or user feedback updates (Sainz et al., 2023b; Xu et al., 2024; Balloccu et al., 2024), is challenging due to dataset scale and model opacity (Sainz et al., 2023b, 2024). Methods include string/embedding matching for open data (Xu et al., 2024; Ravaut et al., 2024), while closed models often require probing distributions and logits, or analyzing memorization (Sainz et al., 2023b; Xu et al., 2024; Sainz et al., 2023a). The growing recognition of this issue is reflected in dedicated workshops and surveys (Sainz et al., 2024; Ravaut et al., 2024; Cheng et al., 2025).

The consequences of contamination are severe: inflated scores, unfair comparisons, flawed scientific conclusions, potential performance degradation, and practical risks such as commercial, privacy, or copyright (Xu et al., 2024; Zhou et al., 2023; Sainz et al., 2023b; Cheng et al., 2025; Ravaut et al., 2024). Therefore, it is crucial to mitigate contamination through better data curation, e.g., through private/dynamic benchmarks, encryption, or licensing (Xu et al., 2024; Jacovi et al., 2023); refactoring existing benchmarks and benchmark-free evaluation, like LLM-as-judge (Xu et al., 2024; Cheng et al., 2025); and procedural safeguards such as transparency and community registries (Jacovi et al., 2023; Balloccu et al., 2024; Sainz et al., 2023b).

2.2 External validity

Benchmarks are... Anglocentric The linguistic scope of current evaluations is notably limited. Most benchmarks focus predominantly on English or a small set of high-resource languages, overlooking the vast global linguistic landscape (McIntosh et al., 2024). The few existing benchmarks for low-resource languages – such as the Uhura benchmark for evaluating question answering in six African languages (Bayes et al., 2024), or LingOly for assessing linguistic reasoning in 90 low-resource languages (Bean et al., 2024) – have demonstrated significant performance declines when LLMs are applied to under-resourced languages. Therefore, it is crucial to evaluate models on a much wider and diverse range of languages.

Early efforts to expand language coverage in benchmarks primarily relied on machine translation of existing benchmarks (Lai et al., 2023; Thellmann et al., 2024). Although this approach is fast and cost-effective, translation quality can negatively affect the validity of evaluation results (Engländer et al., 2024; Plaza et al., 2024; Singh et al., 2024b). The NLP community recognizes this issue by reducing the machine-translated content (Singh et al., 2024b) and developing human-curated evaluation resources (Enevoldsen et al., 2025). However, even human translation might leave undesirable artifacts of the source language in the translated texts

('translationese'), which is detrimental to model performance (Barth and Rehm, 2025) and might obscure evaluation results. Besides the issue of translationese, translating data may leave cultural traces from the source text, posing particular challenges in tasks involving subjectivity or cultural nuance, such as in emotion detection (De Bruyne, 2023) and topic detection (Kosar et al., 2024).

This cultural bias in benchmarks is also problematic, as many evaluations implicitly embed specific cultural norms and assume homogeneity in language use and worldview, which does not reflect reality. Singh et al. (2024b) reveal that performance on widely used MMLU is largely tied to the knowledge of Western-centric ideas, with 28% of the questions involving culturally specific information. In addition, among questions testing geographic knowledge, a striking 84.9% focus on North America or Europe. Research utilizing the BLEnD benchmark (Myung et al., 2024) highlights stark performance disparities when models process culturally diverse inputs. Additionally, studies involving AraDiCE (Mousi et al., 2025) and work by Wang et al. (2024) expose how dialectal variation and cultural context are frequently ignored or improperly handled, leading to inconsistent or inappropriate model evaluation.

Benchmarks are... corrupted The quality of the input texts is as important as the quality of the annotations, but this is not always guaranteed. Bowman and Dahl (2021) highlight that some tasks, such as NLI, occur infrequently in a natural setting (such as in social media data or product reviews). In such cases, research opts for crowd-sourcing data or generating synthetic data using LLMs. However, these approaches can cause multiple issues. For instance, crowd-sourced data is prone to contain duplicate or repetitive entries (Bowman and Dahl, 2021). Additionally, even though LLM-generated synthetic data can be an attractive alternative, this data is often biased and insufficiently representative for more complex tasks (Maheshwari et al., 2024).

Besides repetitiveness, another problem that benchmarks face is that they can contain harmful texts and data in violation of privacy and copyright laws (Rogers et al., 2021; Longjohn et al., 2024). Longjohn et al. (2024) posit that extensive quality reviews, sharing metadata and creating repositories for benchmarks can mitigate these emerging issues through updates or deprecation.

Benchmarks are... focused on the same domains Existing benchmarks are heavily skewed towards academic or general-purpose tasks. Specialized domains such as finance, legal, medical, biology, or arts receive limited attention. The existence of domain-specific models, such as BloombergGPT (Wu et al., 2023), FinLlama (Konstantinidis et al., 2024), LawLLM (Shu et al., 2024), and their superior performance compared to general-purpose models underscores the inadequacy of generic benchmarks for capturing specialized, task-specific expertise. Moreover, the lack of model generalization across domains is illustrated by performance on benchmarks like LexEval for the legal domain (Li et al., 2024), FinBen for finance (Xie et al., 2024) or a range of medical benchmarks (Pal and Sankarasubbu, 2024).

2.3 Statistical validity

Benchmarks are... evaluated too inconsistently Current evaluations of LLMs face significant inconsistencies and unreliable findings due to the complexity and variability across different benchmark evaluation setups. For instance, Mizrahi et al. (2024) show that LLMs are sensitive to prompt design, exposing a significant performance difference across benchmarks when the instruction template is paraphrased. Further, Laskar et al. (2024) describe how multiple sources of variance exist within the evaluation pipeline, including differences in prompt design and the configuration of decoding parameters, which can substantially impact reported performance. According to their criteria, only 20.7% of 212 surveyed papers sufficiently control for this variance to arrive at a fair model comparison.

Benchmarks are... reported without significance testing Recent surveys find that in most applications of AI benchmarks, including NLP ones, statistical significance testing is omitted when presenting their results (Reuel-Lamparth et al., 2024). This undermines the validity, utility and trustworthiness of these results (Biderman et al., 2024), as it remains crucial to distinguish random noise from genuine performance differences between models. For example, recent work by Zhang et al. (2024) demonstrates that the absence of statistical significance testing can obscure benchmark contamination effects in LLMs, leading to potentially misleading conclusions about model performance.

2.4 Construct validity

Benchmarks are... not representative Reliable LLM evaluation is challenged by the representativeness problem: a growing disconnect between benchmark performance and real-world capabilities (Church, 2020; Nezhurina et al., 2025). This gap stems from poor construct validity, where benchmarks are flawed proxies for general abilities, creating an *illusion of generality* (Raji et al., 2021). For instance, models frequently demonstrate high performance on standardized test-style questions yet struggle when faced with complex planning or multi-step reasoning challenges, a limitation highlighted by specialized benchmarks like PlanBench (Valmeekam et al., 2022), GPQA (Rein et al., 2023), and HLE (Phan et al., 2025).

This validity issue is compounded by an inherent evaluation bias stemming from the tension between ensuring reproducibility (favoring easily quantifiable, repeatable metrics) and achieving functionality (accurately assessing intended capabilities and real-world alignment) (McIntosh et al., 2024). The strong emphasis on reproducibility often leads to an over-reliance on convenient formats like multiple-choice question answering (MCQA). This approach reframes generative tasks as classification problems, simplifying evaluation (as seen in LegalBench, Guha et al., 2023) but significantly compromising validity, as MCQA is not a neutral setting (Balepur et al., 2024) and remains a poor proxy for real-world performance even when debiased (Cho et al., 2025; Gu et al., 2024).

Relying on these flawed, easily quantifiable proxies fosters an overfixation on leaderboard rankings, incentivizing 'benchmark gaming': optimizing specific metrics rather than cultivating genuine understanding or robust capabilities (Burden, 2024; McIntosh et al., 2024; Singh et al., 2025), a phenomenon consistent with Goodhart's Law (Burden, 2024). This results in models that appear strong on paper but are brittle in practice, failing unexpectedly when faced with minor variations unseen in the benchmarks (Nezhurina et al., 2025; Lyu et al., 2024; Mondorf and Plank, 2024a), as highlighted in Section 2.1.

Ultimately, benchmark progress becomes misaligned with crucial practical goals such as usability, knowledge application, skill integration, and robustness (Pietruszka et al., 2024). Therefore, evaluation methodologies must evolve beyond convenient yet misleading proxies. While approaches like Chatbot Arena offer alternatives (Chiang et al., 2024), more robust solutions involve behavioral testing, adversarial evaluations, and the development of new benchmarks explicitly designed for validity, robustness, and real-world applicability (Raji et al., 2021; Pietruszka et al., 2024; Burden, 2024).

3 Mitigation of benchmarking issues

Research has proposed various solutions to alleviate the specific benchmarking issues surveyed in Section 2. In this section, we provide an overview of such suggestions keeping in mind all the issues we identified above. Table 1 provides an overview of the proposed solutions, and which issues they (do not) solve.

3.1 Pre-creation

Since some flaws in benchmarks stem from issues during their creation, suggestions have been made to improve relevant aspects before evaluating models on them. Specifically, research suggests to improve the quality and coverage of the data, and enrich the metadata.

For instance, **dynamically creating benchmarks** by continuously adding instances that are informed by model developments and model performances would (temporarily) alleviate the memorization issue: DynaBench (Kiela et al., 2021) and GEM (Gehrmann et al., 2021) are examples. However, the instances that are added in this process are prone to be cherry-picked based on specific failures of a model at that time, and might not be representative anymore of the task at hand (Bowman and Dahl, 2021).

Furthermore, existing benchmarks can be **augmented with refactored data**. Here, the focus is on consistency, by for instance including multiple formulations of the same instance to distinguish between genuine understanding and memorization. These instances can also be created by automatically generating perturbed versions of test instances (e.g., changing names, numbers, sentence order, logical structure slightly), where the perturbations are not related to the core task (e.g., the Alice in Wonderland problem in Nezhurina et al., 2025). However, it might be difficult to ensure that these perturbations only affect superficial features without changing the underlying task logic or the correct answer.

Additionally, benchmarks could be **filtered** to

avoid easy, contaminated, and too similar examples (Gupta et al., 2025).

Besides adapting the input texts, it is argued that benchmarks should be released with more transparent and rich metadata. One aspect of this is the inclusion of **cultural bias annotations**, such as in the work of Singh et al. (2024b), where questions from MMLU were annotated based on whether cultural, geographical or dialect knowledge was needed to correctly answer the question. Another aspect is the **preservation of individual annotator responses** instead of collapsing them into a single aggregated label. This aligns with the perspectivism paradigm, which emphasizes the importance of considering diverse annotator perspectives in NLP tasks (Cabitza et al., 2023).

Finally, more **fine-grained or nuanced forms of annotation** are a possible approach as well. Sachdeva et al. (2022), for instance, use Rasch Measurement Theory (Rasch, 1960) to position social media messages on a hate speech spectrum, rather than providing an unnuanced binary label.

3.2 Post-creation

Benchmarking practices after the release of the benchmark can also be improved. A big factor is transparency and effectiveness of the evaluation metrics. On the one hand, it is suggested to **average the score** of a model across various benchmarks to ensure the generalizability (e.g., BIG-bench (Ghazal et al., 2013), and HuggingFace's Open LLM Leaderboard). On the other hand, there is more attention to evaluate models more broadly on a benchmark by including a **variety of evaluation metrics**, such as in HELM (Liang et al., 2023).

To facilitate open and reproducible evaluations, platforms such as OLMES (Gu et al., 2024) and Language Model Evaluation Harness (Gao et al., 2024) provide **open evaluation standards**.

Alternatively, there are arguments to keep the **test set of benchmarks secret**, and use private leaderboards to which the solutions are uploaded privately, and the final score is published (Rajore et al., 2024). While this would protect the test data from contamination, others argue that it would be better to **encrypt the test data** and release it together with the key to decrypt it, which would also protect it from crawlers (Jacovi et al., 2023). However, this is not a fool-proof system, and for instance exemplary instances that are provided in academic publications are still included in the pre-training data of LLMs (Gevers et al., 2025).

Chiang et al. (2024) argue that standardized NLP benchmarks fail to provide a diverse and nuanced evaluation of the expanding capabilities of LLMs, and therefore suggest to evaluate models using **human preferences**, proposing the Chatbot Arena. While, as can be seen from Table 1, this solution addresses most of the issues we identified in Section 2, this evaluation setup does not allow to measure a model's performance on a specific task, and leaves the door open for evaluation biases based on sycophancy and an overfitting to arena-specific dynamics over general model quality (Singh et al., 2025). Moreover, Singh et al. (2025) show that Chatbot Arena, which uses a normalized version of the Bradley-Terry model (Bradley and Terry, 1952), violates its assumption of unbiased sampling and full interconnection of the comparison network by providing preferential access to selected LLM providers and silently deprecating some models.

In addition, **mechanistic interpretability** (MI) can help investigate the internal mechanisms that could explain model behaviour on existing benchmarks (Bereska and Gavves, 2024; Lindsey et al., 2025). Findings from MI can validate whether a model possesses a claimed capability (construct validity) or merely mimics it. However, the methodology is hard to standardize and generalize across benchmarks.

4 Discussion

We see that many of the solutions provided in the literature are created in a vacuum, and address at best a selection of the problems we identified (see Table 1). Additionally, we note that there is more focus on some of the issues we describe than others. For example, few solutions tackle language imbalance or domain coverage.

We argue it is important to zoom out, and suggest to merge different proposed solutions so the effect is more robust against various pitfalls in benchmarking. Therefore, based on our literature review and some shortcomings it exposed, we establish two concrete checklists that could be used when (a) creating a benchmark; or (b) evaluating a method on an existing benchmark, which we present in Table 2. We demonstrate the applicability of our checklist by evaluating three widely used benchmarks (i.e., SuperGLUE, WinoGrande, and ARC-AGI) in Table 3. We note that a substantial number of our checklist items remain unmet across

Table 1: Effectiveness of proposed solutions against benchmark problems (✓: solves, ✗: doesn't solve, ∼: partially/temporarily solves), split into the following categories: Annotation Quality (AQ), Gameable (GA), Data Contamination (DaC), Language/Cultural Imbalance (LCI), Text Quality (TQ) Domain Coverage (DoC), Evaluation Inconsistency (EI), Representativeness (REP), .

Solution	AQ	GA	DaC	LCI	TQ	DoC	EI	REP
Pre-creation								
Dynamic benchmarks	∼	∼	✓	∼	∼	∼	✗	∼
Augment with refactored / perturbed data	✗	✓	∼	✗	∼	✗	✗	∼
Filtering benchmarks	✓	✓	✓	✗	✓	✗	✗	∼
Cultural bias annotations	✗	∼	✗	✓	✗	✗	✗	✗
Non-aggregated datasets	✓	✗	✗	∼	✗	✗	✗	✗
Fine-grained annotation scales	✓	✗	✗	✗	✗	✗	✗	✗
Post-creation								
Averaging scores	✗	✗	✗	∼	✗	∼	✗	∼
Multi-metrics	✗	∼	✗	✗	✗	✗	∼	✓
Open eval standards	✗	✗	✗	✗	✗	✗	✓	✗
Private leaderboards (secret test set)	✗	✗	✓	✗	✗	✗	✓	✗
Encrypt + license (CC BY-ND)	✗	✗	∼	✗	✗	✗	✗	✗
Human preference evaluation	✓	✓	✓	∼	✓	∼	✗	✗
Mechanistic interpretability	✗	✓	∼	✗	✗	✗	✗	∼

these benchmarks. For instance, in all three, there are no detailed annotation metadata, instance-level metadata, encryption or no-derivatives clauses for the test-set (although WinoGrande and ARC-AGI keep (part of) the test-set hidden), or allow for free-form inference. However, ARC-AGI meets more requirements than SuperGLUE and WinoGrande, since it is language-agnostic. Since our checklist is based on findings from previous literature, this highlights the weaknesses in current benchmarks that could be exploited by LLMs.

Alternatively, we must consider including less centralized and standardized strategies to evaluate LLM capabilities besides benchmarking, to ensure fair model evaluation and model generalizability. Specifically, we suggest to complement standardized benchmarks with a framework to concretely measure the model's downstream performance. Following the criterion validity, which posits that a good measure should also predict other concrete behavioral outcomes regarding the specific task/skill at hand, good performance on a benchmark should correlate with robust downstream performance (Bowman and Dahl, 2021). Therefore, as a future research direction, we suggest to create minimal-sized test-suites for real-life use cases to complement NLP benchmarking. We argue that model evaluations would be more robust by developing and using such test-suites, which should remain small enough to permit a rigorous qualitative evaluation. For example, in machine translation, small-sized test-suites including extreme edge cases are used to ensure broad, and unbiased applicability (e.g., Haddow et al., 2024). This could inspire NLP research to develop similar small datasets, in which the model is presented with the challenging cases that are relevant for real-life applications.[8] In opinion mining, for example, research could focus on Dutch COVID-19 vaccination skepticism (Lemmens et al., 2021), or on reputation analysis of governmental organizations (Boon et al., 2024). For future research, we propose to apply unsupervised sampling techniques to ensure the test-suite includes representative instances as well as informative outliers, for example by filtering for infrequent cases, gathering exemplar inputs from domain experts, and using recent case studies to ensure societal relevance and avoid data contamination. The addition of such framework to the usual model evaluation on standardized benchmarks would address all of the benchmarking issues mentioned earlier, and ensure the model performance is generalizable to real-world use cases.

[8]This differs from adversarial examples, which are designed to expose specific model weaknesses, and may not reflect genuine use-case demands (Bowman and Dahl, 2021).

Table 2: Checklist for constructing and evaluating benchmarks with the corresponding problems they solve: Annotation Quality, Gameable, Data Contamination, Domain Coverage, Evaluation Inconsistency, Language/Cultural Imbalance, Representativeness, Text Quality.

Checklist for constructing benchmarks	
☐	Provide a clear task definition with a taxonomy of intentions and assumptions of the required capabilities to solve the benchmark instances, rather than just the surface task type. Solves: **Representativeness**
☐	Clearly state the language, geographic, demographic, culture, or domain-specific limitations of the benchmark. Balance mix of domains and genres. Solves: **Language/Cultural Imbalance**, **Domain Coverage**, **Representativeness**
☐	Motivate the source of the annotations: crowdsourcing, expert annotators or synthetic. Provide annotations of all annotators (not only average), annotator guidebook and annotator metadata / demographics. Solves: **Annotation Quality**, **Language/Cultural Imbalance**
☐	Include detailed metadata, such as data sources (URLs, surrounding paragraphs), geographic and temporal information. Solves: **Data Contamination**, **Text Quality**, **Language/Cultural Imbalance**
☐	Perform extensive quality control of the texts. Pay attention to crowd-sourced texts, and (near-)duplicates. Solves: **Text Quality**, **Gameable**
☐	Include authentic data in high- and low-resource languages to guarantee cross-lingual performance. Alternatively, involve professional translators and account for cultural diversity (Barth and Rehm, 2025). Solves: **Language/Cultural Imbalance**
☐	Avoid using data that might have been memorized. For example, use tools like infini-gram[7] for web-scraped content. Solves: **Data Contamination**
☐	Add instances where surface features or irrelevant numerical details are systematically varied. Solves: **Gameable**
☐	Integrate evaluations in existing framework (e.g., OLMES, LM evaluation harness), or motivate the choice of evaluation metrics and open-source the evaluation (prompt, hyperparameters, evaluation script). Solves: **Gameable**, **Evaluation Inconsistency**
☐	Encrypt your benchmark and release the encrypted version with a no derivatives clause (Jacovi et al., 2023). Solves: **Data Contamination**
☐	Motivate the proposed inference method (e.g., probability, classification), but at least include free-form generation. Solves: **Evaluation Inconsistency**, **Representativeness**
☐	Provide relevant (open-sourced) baseline methods (which could reveal artifacts) and human performance. Solves: **Gameable**, **Representativeness**
Checklist for evaluating methods on benchmarks	
☐	Open-source the evaluation code. If available, include results using a standard prompt from the accompanying paper. Solves: **Gameable**, **Evaluation Inconsistency**
☐	Indicate if you trained your model on this benchmark and report scores without any training on the benchmark itself. Solves: **Data Contamination**
☐	Report the model version. Report score of at least one open-data LLM. Solves: **Evaluation Inconsistency**
☐	Use an appropriate interpretability technique to verify the information used for the task, such as SHAP (Mosca et al., 2022) or more recent mechanistic methods (Bereska and Gavves, 2024). Solves: **Gameable**
☐	Report a variety of evaluation metrics (cf. HELM). Solves: **Evaluation Inconsistency**, **Gameable**
☐	Report at least one statistical significance test between model, and baseline results and/or human performance (Reuel-Lamparth et al., 2024). Solves: **Evaluation Inconsistency**, **Gameable**
☐	Report whether the benchmark was used in the development phase. Solves: **Data Contamination**
☐	Release the raw model output (Laskar et al., 2024). Solves: **Gameable**, **Evaluation Inconsistency**

Table 3: Evaluation of three popular NLP benchmarks using our checklist for benchmark creation (✓: is applied, ✗: is not applied, ∼: irrelevant (e.g., not natural language)).

Benchmark	SuperGLUE	WinoGrande	ARC-AGI
Provide task definition	✓	✓	✓
State limitations, mix of domains and genres	✓	✓	✓
Motivate source of annotations, provide detailed annotation metadata	✗	✗	✗
Include metadata of texts	✗	✗	∼
Quality control of texts	✓	✓	✓
Authentic data in high- and low-resource languages, or professional translations	✗	✗	∼
Avoid memorized data	✗	✗	✓
Systematically adapt surface features	✓	✗	✓
Integrate evaluation in existing framework, or motivate and open-source evaluation metrics	✓	✓	✗
Encrypt and shared with no-derivatives clause	✗	✗	✗
Motivate inference method, at least include free-form	✗	✗	✗
Include open-source baselines and human performance	✓	✓	✓

5 Conclusion

Benchmarks are ubiquitous in the NLP community. It is the go-to method to evaluate model capabilities, and compare systems to each other. However, especially with the rise of powerful LLMs, weaknesses in benchmarking practices are revealed, questioning the validity of existing benchmarks in their creation, dissemination, and usage. However, as of now there is no one-fits-all solution to fix benchmarking.

In this study, we survey benchmarking issues that are identified in prior literature, grouped according to experimental validity types. Then, we survey proposed solutions in the literature for these issues. However, we find that it is important not to overestimate the usability of single solutions, since they are often created with only one or a few issues in mind, neglecting other pitfalls. Therefore, we combine specific recommendations from the literature in concrete checklists, which can be used to improve benchmarking practices. Last, we suggest to include downstream minimal-size test-suites to ensure the model's benchmark performance is generalizable to real-world use cases as a future research direction.

Limitations

This study is subject to a few limitations. First of all, this paper attempts to provide a comprehensive overview of discrete issues within NLP benchmarks and their proposed solutions, but it is inherently challenging to compile an exhaustive list. There are likely other issues present in NLP benchmarking, and potentially additional solutions suggested in the literature, that have not been captured within the scope of this work. However, the issues and solutions we include are representative of the overall problem we set out to address.

Second, to the best of our knowledge, there is little research focusing on the potential interactions between the different suggested solutions for benchmarking issues. For example, does addressing one issue inadvertently exacerbate others? These interdependencies should be further researched.

Third, our proposed checklist functions as a guideline for benchmarking practices. We do not claim this is a final product, and it should be updated with new insights from the community. Additionally, it might not be universally applicable across all benchmarking scenarios, so we encourage benchmark practitioners to adapt and tailor it to their specific contexts.

Another limitation of this study is that only the text modality was considered, even though benchmarks for other modalities, such as vision, are affected by similar issues, as reported in Li et al. (2025). Nonetheless, the issues raised and checklists provided in this study are still relevant to non-textual benchmarks.

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