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YourBench: Easy Custom Evaluation Sets for Everyone

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Abstract

Evaluating large language models (LLMs) effectively remains a critical bottleneck, as traditional static benchmarks suffer from saturation and contamination, while human evaluations are costly and slow. This hinders timely or domain-specific assessment, crucial for real-world applications. We introduce **YourBench**, a novel, open-source framework that addresses these limitations by enabling dynamic, automated generation of reliable, up-to-date, and domain-tailored benchmarks cheaply and without manual annotation, directly from user-provided documents. We demonstrate its efficacy by replicating 7 diverse MMLU subsets using minimal source text, achieving this for under $15 in total inference costs while perfectly preserving the relative model performance rankings (Spearman Rho = 1) observed on the original benchmark. To ensure that YourBench generates data grounded in provided input instead of relying on posterior parametric knowledge in models, we also introduce TEMPORA-0325, a novel dataset of over 7K diverse documents, published exclusively after March 2025. Our comprehensive analysis spans 26 SoTA models from 7 major families across varying scales (3 - 671B parameters) to validate the quality of generated evaluations through rigorous algorithmic checks (e.g., citation grounding) and human assessments. We release the YourBench library, the TEMPORA-0325 dataset, 150k+ question answer pairs based on Tempora and all evaluation/inference traces to facilitate reproducible research and empower the community to generate bespoke benchmarks on demand, fostering more relevant and trustworthy LLM evaluation.

1 Introduction

The rapid evolution of large language models (LLMs) continually outpaces traditional evaluation methodologies. Static benchmarks, foundational to earlier progress, now face critical issues: they quickly saturate, are susceptible to training data contamination, become temporally irrelevant as knowledge evolves, and often fail to capture model capabilities in specialized domains (Kiela et al., 2021; Dominguez-Olmedo et al., 2024; Zhang et al., 2024; Zhu et al., 2023; Ruder, 2023). While direct human assessment provides valuable insights, its cost and scalability limitations render it impractical for the continuous, diverse evaluation needs of the field. This creates a pressing need for evaluation generation frameworks that are automatic, while dynamic, reliable, domain-specific, and accessible.

We therefore introduce **YourBench**: an open-source framework that enables automated generation of bespoke evaluation sets directly from any collection of documents. YourBench empowers users to systematically create fresh, relevant benchmarks tailored to specific topics, achieving high reliability at low cost and without manual annotation. Central to our framework is the principle of Document-to-Evaluation Generation (D2EG), where LLMs are leveraged to produce diverse, contextually-grounded question-answer pairs with verifiable citations, optimizing for coverage, diversity, and answerability (details in §2.2, Appendix C).

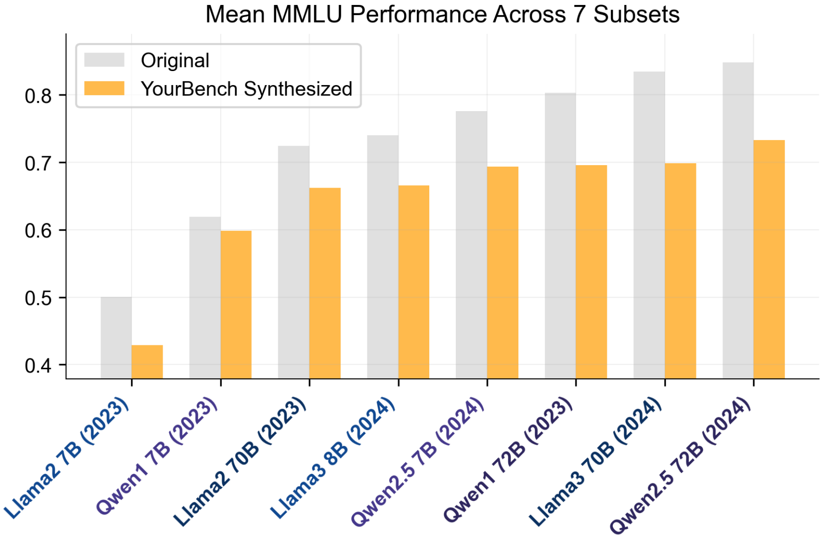

Figure 1: **YourBench Automatically Generates Challenging MMLU Replicas.** We evaluated YourBench's ability to replicate subsets of the MMLU benchmark across 7 diverse domains (Astronomy, Anatomy, etc.). Using only a few relevant Wikipedia pages per domain as input documents, YourBench automatically generated new multiple-choice question sets in the MMLU style. This process took <5 minutes and <$2 of inference cost per domain, requiring no human annotation. The resulting benchmarks (orange bars) demonstrate two key findings: (1) They perfectly preserve the relative performance rankings of various LLMs compared to the original MMLU (grey bars), confirming evaluation validity (Spearman ρ=1.00). (2) They consistently produce harder questions (lower absolute scores), yielding a more challenging, contamination-resistant evaluation derived directly from source material.

We rigorously assessed YourBench's capability at each step, then through benchmark replication, comparing to the widely-used MMLU dataset (Hendrycks et al., 2021a). As observed in Figure 1 and detailed in Section 3.3, the synthetic MMLU-style evaluation automatically generated by YourBench from minimal source text preserves the relative performance ranking of diverse LLMs, while being harder than the initial dataset.

The framework integrates a robust pipeline (§2, Appendix A) featuring multi-format document ingestion, semantic chunking, diverse LLM ensembles for question generation, and stringent automated quality controls based on citation grounding and semantic novelty. Extensive validation (§3.2) confirms the high quality of the generated evaluations: human assessments show approximately 85% question validity (Appendix E.1), and models demonstrate strong, efficiently achievable citation grounding (Appendix E.2, E.4). To further support robust evaluation, particularly concerning temporal knowledge, we release TEMPORA-0325 (§3.1.1), a dataset comprising documents published exclusively after March 2025, designed to mitigate contamination.

Our primary contributions are:

- **YourBench:** An open-source framework[1] enabling dynamic, automated generation of reliable, domain-specific evaluation sets from documents.
- **TEMPORA-0325:** A large-scale dataset[2] of recent documents (post-March 2025) to facilitate temporal evaluation and reduce benchmark contamination.

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[1] GitHub
[2] Dataset

- **Comprehensive Validation:** Empirical demonstration of YourBench's effectiveness via benchmark replication (Figure 1), high generation quality (validity, grounding), and efficiency across numerous state-of-the-art LLMs.

By providing a scalable, automated, and document-grounded approach, YourBench facilitates a move towards more timely, specific, and trustworthy LLM evaluation, enabling the research community and practitioners alike to better understand and track the true capabilities of these rapidly advancing models.

2 YourBench: Multistep Framework for Dynamic Evaluation Generation

2.1 Document Preprocessing

To effectively process diverse real-world documents (including various formats and multimodal content) using Large Language Models (LLMs), YourBench employs a multi-stage preprocessing pipeline. The primary goal is to standardize heterogeneous inputs into a unified, analyzable format while preserving crucial semantic and structural information. This involves three key stages: (1) **Document Ingestion**, which normalizes formats like PDF, Word, and HTML into markdown and incorporates descriptions for visual content; (2) **Semantic Chunking**, which partitions documents into coherent segments to manage context length limitations and improve attention focus; and (3) **Document Summarization**, which generates a global overview to retain broader context often lost during chunking. The detailed methodology, specific tools, models employed, and motivations for each stage are elaborated in Appendix B.

2.2 Question and Answer Generation Process

2.2.1 Overview

The process of generating evaluation questions from source documents, termed *Document-to-Evaluation Generation* (D2EG), aims to produce a question set satisfying three core criteria:

1. **Coverage:** Address a broad range of information within the document.
2. **Diversity:** Vary questions across difficulty, style, and reasoning type.
3. **Answerability & Quality:** Ensure each question is unambiguously answerable from the source document.

While this can be framed as a formal optimization problem (see Appendix C for the formulation using Eq. (5)), YourBench adopts a practical, greedy generation framework leveraging LLMs, following four main steps:

1. **Context Provision:** Combine individual document segments c_i (or multi-hop groups) with the document summary s to provide both local detail and global perspective.
2. **Guided Generation:** Seed LLMs with desired question types (e.g., factual, multi-hop, numeric) and difficulty levels (e.g., basic, advanced) to target diverse outputs.
3. **Ensemble Approach:** Utilize a diverse collection of LLMs (varied families, sizes) to generate questions, harnessing different model biases to improve coverage and diversity.
4. **Quality Filtering:** Automatically filter the generated questions for clarity, consistency, and verifiable answerability using the source text, with optional human refinement.

This ensemble-based, segment-parallelized approach efficiently generates a large pool of raw questions offering strong coverage, diversity, and textual grounding.

2.2.2 *Approach*

The transformation of preprocessed document segments into evaluation artifacts (QA pairs) is orchestrated via LLMs, guided by the D2EG principles (Section 2.2). Given a document d with global summary S and semantic chunks $C = \{c_1, ..., c_m\}$ (including potential multi-hop chunks $M = \{m_1, ..., m_p\}$, detailed in Appendix B.2), the core task is generating a QA pair (q, a) with supporting citations cit based on the context. We model this as sampling:

$$(q, a, \text{cit}) \sim p(\cdot|\text{prompt}_{\text{gen}}, S, c) \quad (1)$$

where $c \in C \cup M$ is the local context chunk(s) and $\text{prompt}_{\text{gen}}$ contains detailed instructions (see Appendix H).

Providing both global summary S and local chunk(s) c is crucial. The local context c focuses the LLM on specific details, mitigating attention diffusion issues (Liu et al., 2023; Ye et al., 2024), while the global summary S provides overarching context for accurate interpretation and relevant question formulation, especially when c alone (e.g., a table) lacks context.

Within $\text{prompt}_{\text{gen}}$, we instruct the LLM to dynamically adjust the quantity and variety of questions based on the perceived richness of the context (S, c), rather than imposing rigid constraints, to promote naturalness and satisfy D2EG criteria. We guide the model towards the target JSON format using explicit instructions within the prompt, avoiding reliance on specialized structured output mechanisms for broader compatibility.

A key instruction in $\text{prompt}_{\text{gen}}$ is groundedness: the model must provide citations cit (exact spans from c) substantiating the answer a, directly enforcing the D2EG 'Answerability & Quality' constraint.

To enhance robustness and diversity, we employ an LLM ensemble $\mathcal{M} = \{M_1, ..., M_N\}$. For a given context (S, c), candidate QA sets Q_l are generated from multiple models $M_l \in \mathcal{M}$. The final raw pool $Q_{\text{raw}} = \bigcup_{l=1}^{N} Q_l$ aggregates these candidates, mitigating individual model biases and yielding a more comprehensive and diverse question set. The output consists of structured candidate QA pairs (question, answer, citations), typically in JSON format.

2.3 Quality Filtering and Deduplication

The raw QA set Q_{raw} from ensemble generation (Section 2.2.2) requires refinement for fidelity and non-redundancy. We employ a two-stage process: citation validation and semantic deduplication.

2.3.1 *Citation Validation*

Ensuring QA pairs are grounded in the source context c is vital. While prompts request citations $\text{cit} = \{c_1, ..., c_{N_c}\}$, LLM stochasticity necessitates verification. We use an algorithmic approach based on fuzzy string matching (partial ratio derived from Levenshtein distance (Levenshtein, 1966)) to quantify the correspondence between each citation c_i and the source chunk c. See Appendix D.1 for the detailed 'PartialRatio' definition.

We assign a grounding score to each QA pair (q, a, cit) by averaging the partial ratios across its citations:

$$\text{Score}_{\text{QA}}(q, a, \text{cit}) = \frac{1}{N_c} \sum_{i=1}^{N_c} \text{PartialRatio}(c_i, c) \quad (2)$$

assuming $N_c > 0$ (score is 0 if $N_c = 0$). We filter Q_{raw}, retaining pairs exceeding a threshold θ_{cit}:

$$Q_{\text{cit}} = \{(q, a, \text{cit}) \in Q_{\text{raw}} \mid \text{Score}_{\text{QA}}(q, a, \text{cit}) > \theta_{\text{cit}}\} \quad (3)$$

Empirically, $\theta_{\text{cit}} = 0.85$ balances rigorous filtering of ungrounded pairs with preservation of valid items. See Appendix D.1 for the model-level scoring metric used in evaluations.

2.3.2 *Semantic Deduplication and Reweighting*

Ensemble generation and chunk overlap can lead to semantic redundancy in Q_{cit}. To manage this, we perform semantic deduplication. We obtain dense embeddings $e(q)$ for questions in Q_{cit} using a sentence embedding model (e.g., Sentence-BERT (Reimers & Gurevych, 2019)).

We apply DBSCAN (Ester et al., 1996), a density-based clustering algorithm, to the embeddings $\{e(q)\}$. DBSCAN groups semantically similar QA pairs (cosine similarity $> \tau_{\text{sim}} = 0.9$) into clusters $\mathcal{C} = \{C_1, ..., C_K\}$ and identifies outliers N.

From each cluster C_k, we select one representative QA pair $(q_k^*, a_k^*, \text{cit}_k^*)$ (e.g., the medoid). The deduplicated set is:

$$Q_{\text{dedup}} = \{(q_k^*, a_k^*, \text{cit}_k^*) \mid C_k \in \mathcal{C}\} \cup N' \tag{4}$$

where N' are the unique noise points.

To retain information about concept salience (indicated by cluster size $|C_k|$), we assign weights w_k to each representative $(q_k^*, a_k^*, \text{cit}_k^*)$ proportional to its original cluster size (e.g., $w_k = |C_k|$), with $w = 1$ for noise points. These weights are used in the final evaluation scoring (Section 3), allowing frequently questioned concepts to contribute more significantly, approximating the evaluation of the full set Q_{cit} efficiently.

2.4 Suggested Evaluator

Given the curated, weighted QA set $Q_{\text{final}} = Q_{\text{dedup}}$ (Sections 2.2.2, 2.3), we generally evaluate free form LLMs outputs using a pairwise comparative assessment strategy (as is done in model arenas). Our suggested evaluator is composed of a judge LLMs ensemble to enhance reliability and mitigate self-preference bias (Zheng et al., 2023), and an bias-corrected scoring aggregation to mitigate positional bias (the tendency of LLMs-judges to prefer an answer presented in one position compared to the other). We expand on this in Appendix D.2. It's also possible to use YourBench to generate questions with multiple choice answers through prompt modifications, in which case it becomes possible to evaluate models through a simple exact match score, as we do in Section 3.3.

3 Validating YourBench

3.1 Experimental Setup

3.1.1 *Dataset:* TEMPORA-0325

A key challenge in LLM evaluation is disentangling performance derived from provided context versus memorized pretraining data. To specifically assess grounding on novel information and mitigate potential contamination from training on benchmark data, we introduce TEMPORA-0325, a dataset comprising documents published exclusively after March 1, 2025. Evaluating models on TEMPORA-0325 forces reliance on the provided document context, revealing tendencies towards outdated parametric knowledge if inconsistencies arise.

Collection Scope & Diversity. We collected 7,368 publicly available documents published after March 1, 2025, spanning diverse domains (government, corporate, legal, medical, sports, news, blogs, miscellaneous), prioritizing factually verifiable sources. The dataset includes an *unbalanced full corpus* reflecting real-world distributions and a *balanced subset*, TEMPORA-0325B (used in our main experiments), offering uniform coverage across eight source categories for controlled analysis.

Both TEMPORA-0325 and TEMPORA-0325B are publicly available. Details on domain sources, data provenance, licensing, and verification are in Appendix B.4.

3.1.2 Model Choice

To evaluate YourBench's question generation framework (Section 2.2), we selected a diverse set of 26 state-of-the-art LLMs, prioritizing variety across (1) model families (diverse pre-training data/methods), (2) parameter scales (ranging from 7B to 671B parameters), and (3) reasoning specialization (including models explicitly optimized for multi-step reasoning). Our selection includes both open-weight and closed-source API-based models (e.g., from DeepSeek, Qwen, Mistral, Llama, Google, OpenAI, Anthropic families). For fair comparison, all models used identical inputs, sampling hyperparameters, and temperature settings during inference, with reasoning-specialized models configured to use maximum computation. This allows isolating the impact of architecture and scale on generation quality.

- **DeepSeek** (DeepSeek-AI et al., 2025b;a): DeepSeek V3 (671B), DeepSeek R1 (671B), DeepSeek R1-Distill-Llama (70B), and DeepSeek R1-Distill-Qwen (32B, 14B, 7B).
- **Qwen** (Qwen et al., 2025): Qwen2.5 models at various scales (72B, 32B, 14B, 7B) and the reasoning model Qwen QwQ (32B).
- **Mistral** (Jiang et al., 2023): Mistral Large 2411 (132B) and Mistral 3.1 Small (24B).
- **Llama** (Dubey et al., 2024): Llama 3.1 (405B, 8B) and Llama 3.3 (70B).
- **Google** (Team et al., 2024): Gemini 2.0 Flash, Gemini 2.0 Flash Lite (?B) and Gemma 3 (27B)
- **OpenAI** (OpenAI et al., 2024): GPT-4o, GPT-4o mini, and o3 mini (?B)
- **Anthropic** (Anthropic, 2024): Claude 3.7 Sonnet, Claude 3.5 Haiku (?B)

To facilitate reproducibility and further research, we open-source all inference traces for each evaluated model on the Tempora-0325B dataset (Section 3.1.1). This comprehensive collection captures the generation process across models spanning three orders of magnitude in parameter count, offering insights into how different architectures approach document-grounded question formulation.

3.2 Generated Evaluation Quality

The practical utility of `YourBench` depends fundamentally on the quality, reliability, and characteristics of the evaluation sets it generates. While the introduction highlighted the framework's success in replicating the MMLU benchmark (Figure 1), here we delve deeper into the intrinsic properties of the generated questions, examining two crucial dimensions: **Question Validity** (the intrinsic correctness and answerability of a question) and **Semantic Diversity** (the breadth of topics and concepts covered). Analyzing these facets reveals not only the robustness of the generated benchmarks but also offers insights into the distinct generative capabilities and "personalities" of different large language models.

3.2.1 The Validity-Diversity Spectrum

Evaluating the quality of generated questions requires understanding both their individual soundness and their collective variety. To assess these aspects rigorously, we employed distinct methodologies.

Assessing Question Validity. A core requirement for any useful evaluation question is its intrinsic quality: it must be clear, sensible, and definitively answerable using *only* the provided source material. To quantify this, we conducted a meticulous human evaluation process. We stratified sampled 2k unique questions generated across our suite of models from the TEMPORA-0325B dataset. Twenty trained annotators assessed each question against the source context based on criteria of clarity, contextual answerability, logical sensibility and citation answerability. Each question received three independent ratings, and the high inter-annotator agreement (Gwet's AC1 = 0.71) confirmed the reliability of this process. A question was deemed "Valid" only if it met all criteria affirmatively by majority vote. Further details on the human evaluation setup and criteria are provided in Appendix E.1.

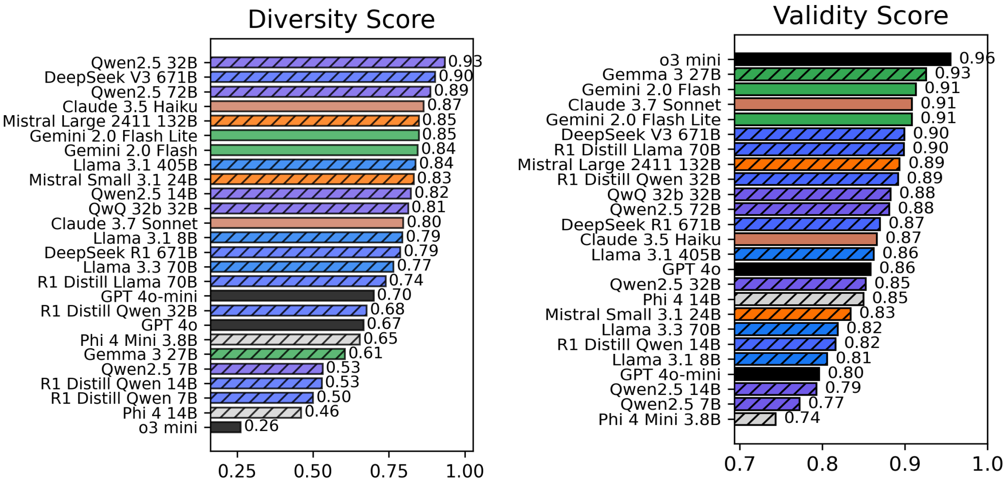


Figure 2: **The Validity-Diversity Spectrum of Language Models.** Comparing semantic diversity scores (left) and human-annotated validity scores (right) for questions generated by various models reveals an intriguing trade-off. Models like o3 mini excel in validity (generating consistently answerable, clear questions) but exhibit low diversity, often focusing on routine or algorithmic queries - when models like Qwen2.5 32B achieve high diversity but may do so at the cost of slightly lower average validity. Some rare models, like DeepSeek V3, demonstrate a strong balance, scoring well on both dimensions.

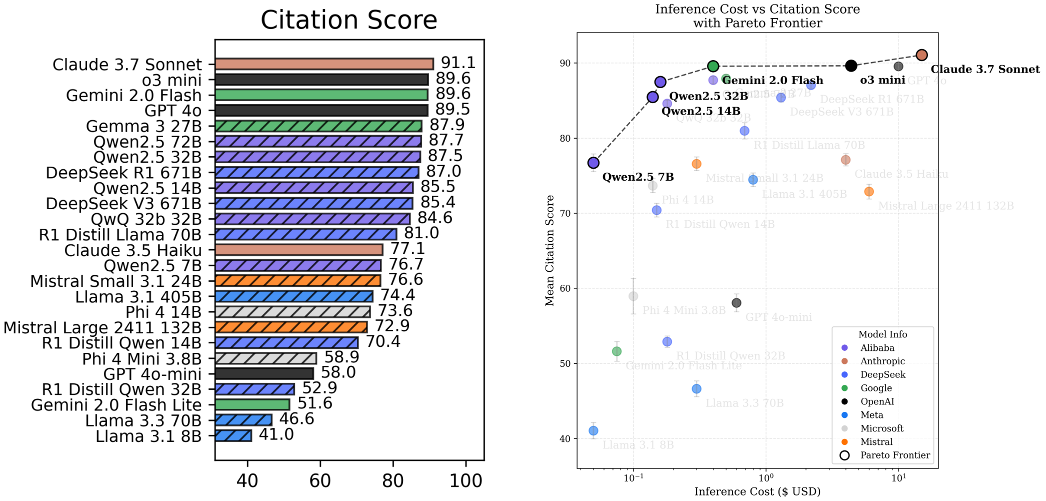
Measuring Semantic Diversity. Beyond individual question quality, the value of an evaluation set also lies in its breadth. A diverse set probes a wider range of knowledge and reasoning facets present in the source documents. We measured the semantic diversity of the question set generated by each model using embedding-based techniques. Questions were embedded into a vector space, and we computed metrics capturing both the average distance between question embeddings (dispersion) and the uniformity of their distribution across semantic clusters (entropy). A combined score, normalized across models, represents the overall semantic diversity. The detailed methodology is described in Appendix E.3.

Our analysis, summarized in Figure 2, reveals an interplay between question validity and semantic diversity across different generator models. On average, the human evaluation confirmed that contemporary models integrated within YourBench can generate questions with high intrinsic validity, averaging approximately 85% post-filtering across all models. However, performance varies significantly. Models like o3 mini (0.96 validity), Gemma 3 27B (0.93), and Gemini 2.0 Flash (0.91) demonstrate exceptional ability to produce questions that are clear, contextually grounded, and sensible according to human judgment. Simultaneously, examining semantic diversity shows a different ranking. Models such as Qwen2.5 32B (0.93 diversity), DeepSeek V3 671B (0.90), and Qwen2.5 72B (0.89) excel at generating questions that span a wide range of topics and concepts extracted from the documents. Further analysis exploring the relationship between generation cost, model size, and validity is available in Appendix E.4.

3.2.2 *Citation Grounding*

Faithful attribution to source material via citations is crucial for verifying the grounding of generated answers. YourBench incorporates automated citation validation using fuzzy string matching (detailed in §2.3 and Appendix E.2). To assess different models' proficiency in this, we computed an aggregate citation score reflecting the average grounding quality across their generated QA pairs.

Figure 3 presents the results. Panel (a) shows that leading models like Claude 3.7 Sonnet and several competitive open-weight models (e.g., from Qwen, Gemma families) demonstrate



(a) Model citation scores.

(b) Inference cost vs. Citation score.

Figure 3: Evaluation of citation grounding performance. (a) Compares aggregate citation scores across various models. (b) Illustrates the Pareto frontier for inference cost (log scale) versus citation score, highlighting efficiency trade-offs. Full model list in Appendix D.3.

strong citation generation capabilities. Panel (b), plotting inference cost against citation score, reveals significant efficiency trade-offs. Models like Qwen2.5 32B achieve high citation validity at a fraction of the cost of the top performers, indicating that reliable grounding is attainable efficiently within the `YourBench` framework. This suggests citation quality can serve as a valuable and cost-effective evaluation signal. Detailed scores and cost analysis methodology are in Appendix E.2.

3.3 End to end validation: MMLU Replication

As introduced in §1 and illustrated in Figure 1, we aimed to validate the `YourBench` framework by automatically replicating subsets of the MMLU benchmark (Hendrycks et al., 2021a). To do so, we evaluated a suite of 8 LLMs (see Table 1 in Appendix) on 7 original MMLU subject subsets and their corresponding YourBench-generated counterparts, created from sampled Wikipedia documents of relevant topics for each subset. We provide some side by side examples in Fig 4.

We then analyzed the correlation between the performance scores (accuracy) obtained on the original versus the synthetic benchmarks. The correlation analysis between original MMLU subject subsets and their YourBench counterparts revealed two key findings: (1) At the individual subject-model level (56 pairs), correlation was positive but moderate (Pearson r=0.3833, p=0.0035; Spearman ρ=0.2982, p=0.0256), suggesting some variance in specific subject measurements. (2) When examining mean model performance (7 data points), the correlation became remarkably strong (Pearson r=0.9646, p<0.0001; Spearman ρ=1.0000, p<0.0001), demonstrating that while **YourBench questions appear more challenging, they preserve the relative ranking of models perfectly**. This key finding demonstrates that YourBench reliably captures the relative capabilities of different LLMs, mirroring the discriminative power of the original MMLU, while generating fresh, potentially contamination-resistant questions. Comprehensive correlation statistics and detailed per-subject performance tables generated from our evaluation suite are provided in Appendix F.

4 Related Work

Evaluating large language models (LLMs) presents significant challenges that motivate YourBench. Traditional static benchmarks (Deng, 2012) face issues of **saturation**, as models quickly reach performance ceilings (Ruder, 2023; Wei, 2023), and **contamination**, where test data leaks into training sets, inflating scores (Kiela et al., 2021; Zhang et al., 2024). Their fixed nature also leads to **temporal irrelevance** due to evolving world knowledge (Zhu et al., 2023; Deng et al., 2024) and poor suitability for assessing **domain-specific** capabilities. These limitations underscore the need for dynamic, robust evaluation methods reflecting real-world data.

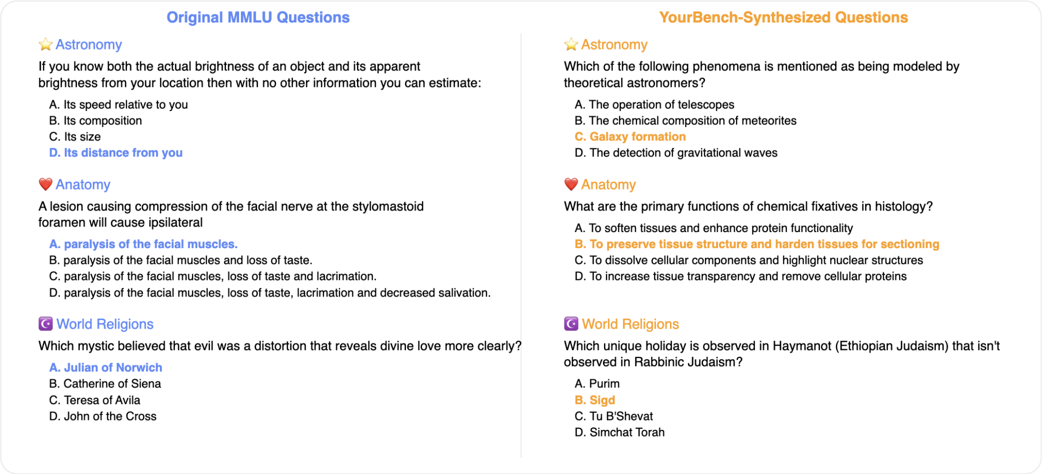
Responses include **dynamic benchmark generation**, like Dynabench (Kiela et al., 2021), which faces scaling issues, and **synthetic generation** using LLMs (Wei, 2023; Krishna et al., 2024; Ruder, 2023), which struggles with quality control and grounding (Zhou et al., 2025). **Domain-specific benchmarks** (Hung et al., 2023a; Nori et al., 2023; Holzenkamp et al., 2023) improve relevance but are often costly, static, and lack continuous updates (Zhang et al., 2024). Persistent gaps remain in creating scalable, reliable, diverse, and temporally-aware evaluations grounded in specific document sources. YourBench addresses these by providing an adaptive, document-driven framework for generating fresh, domain-specific, and contamination-resistant evaluation sets on demand. We only provided the high level view of the related works here, but a more extensive and comprehensive discussion of the literature is detailed in Appendix G.

5 Conclusion and Initial Applications

We introduced **YourBench**, an open-source framework for the automated generation of document-grounded evaluation sets, addressing key limitations of static benchmarks and manual evaluation in assessing LLMs. Our validation demonstrated YourBench's ability to efficiently produce reliable, challenging, and domain-specific benchmarks—capable of replicating established evaluation results like MMLU rankings—without manual annotation required in the process (§3, Appendix F).

The framework's potential extends beyond benchmark replication and is already being explored in several research initiatives:

- **Domain-Specific Knowledge Assessment (Agriculture):** YourBench is being utilized to systematically evaluate LLMs on specialized, proprietary knowledge. This involves generating questions assessing factual recall, applied reasoning, and



Original MMLU Questions

⭐ Astronomy

If you know both the actual brightness of an object and its apparent brightness from your location then with no other information you can estimate:

A. Its speed relative to you
B. Its composition
C. Its size
D. Its distance from you

❤️ Anatomy

A lesion causing compression of the facial nerve at the stylomastoid foramen will cause ipsilateral

A. paralysis of the facial muscles.
B. paralysis of the facial muscles and loss of taste.
C. paralysis of the facial muscles, loss of taste and lacrimation.
D. paralysis of the facial muscles, loss of taste, lacrimation and decreased salivation.

☪ World Religions

Which mystic believed that evil was a distortion that reveals divine love more clearly?

A. Julian of Norwich
B. Catherine of Siena
C. Teresa of Avila
D. John of the Cross

YourBench-Synthesized Questions

⭐ Astronomy

Which of the following phenomena is mentioned as being modeled by theoretical astronomers?

A. The operation of telescopes
B. The chemical composition of meteorites
C. Galaxy formation
D. The detection of gravitational waves

❤️ Anatomy

What are the primary functions of chemical fixatives in histology?

A. To soften tissues and enhance protein functionality
B. To preserve tissue structure and harden tissues for sectioning
C. To dissolve cellular components and highlight nuclear structures
D. To increase tissue transparency and remove cellular proteins

☪ World Religions

Which unique holiday is observed in Haymanot (Ethiopian Judaism) that isn't observed in Rabbinic Judaism?

A. Purim
B. Sigd
C. Tu B'Shevat
D. Simchat Torah

Figure 4: Comparison of generated MMLU style questions in various domains.

retrieval-augmented generation capabilities based on diverse agricultural documents, effectively measuring a model's domain intelligence

- **Personalized Education:** In educational research, the framework is being adapted to assist teachers and generate tailored assessment questions based on individual student learning profiles derived from textual inputs, exploring pathways towards automated, personalized learning tools.
- **Advanced RAG Training Data:** YourBench's capacity for multi-hop question generation is being employed to construct challenging training corpora for retrieval-augmented generation systems. By synthesizing complex questions requiring information integration across multiple document chunks and incorporating human feedback loops, this effort aims to push the boundaries of RAG model capabilities.

By providing a robust, scalable and fast automated approach, YourBench facilitates more nuanced, timely, and targeted assessments of LLM capabilities, at a low cost (which makes the process accessible to most). We believe such tools will help drive deeper understanding and fostering continued, responsible progress in language model development and application across diverse fields.

Reproducibility

We are committed to ensuring the reproducibility of our research and facilitating further investigation by the community. To this end, we make several key resources publicly available. The complete source code for the **YourBench** framework is released under an open-source license and can be accessed at https://github.com/huggingface/yourbench. This repository includes the implementation of the document processing pipeline (Section 2.1), the question generation framework (Section 2.2), and associated evaluation scripts.

Furthermore, the TEMPORA-0325 dataset introduced in Section 3.1.1, comprising documents published after March 1, 2025, is available on the Hugging Face Hub at this datasets link. Alongside the dataset, we provide the code used for document collection, preprocessing, semantic chunking (Section B.2), and subsequent analysis within the main framework repository.

To enable detailed verification of our experimental findings, we release the complete inference traces for critical experiments, including the MMLU replication study (Section 3.3) and the citation validity analysis (Figure 3). These traces cover the diverse set of 26 large language models detailed in Section 3, spanning both open-weight models (e.g., Llama, Qwen, DeepSeek families) and closed-source API-based models (e.g., GPT, Claude, Gemini families). Our inclusion of both model types is a deliberate choice to enhance long-term reproducibility; by providing results for open models, we ensure that future researchers can replicate or extend our core findings even if commercial APIs become deprecated or change significantly over time. All code and experimental artifacts are designed to support transparency and allow the community to build upon our work effectively.

Ethical Considerations

The development of powerful AI systems necessitates equally robust and trustworthy methods for their evaluation. Frameworks like YourBench, which automate the generation of evaluation benchmarks, represent a step towards more dynamic and potentially less contaminated assessment. However, like any technology, its introduction warrants careful consideration of the ethical dimensions and potential societal impacts.

One important area relates to the human element in data creation. Traditionally, benchmark creation involves significant human labor, often in the form of detailed annotation or question writing. This labor, while essential, can sometimes be repetitive and subject to economic pressures, including concerns about fair compensation, particularly in globally distributed workforces. YourBench introduces a potential shift in this dynamic. By automating the generation of question-answer pairs, the burden on humans might transition from primarily generative tasks to ones involving oversight, validation, and curation. Instead of authoring questions from scratch, the focus could shift towards assessing the quality, relevance, and safety of machine-generated content, or guiding the generation process towards specific evaluation goals. It's uncertain as of now whether such a shift would rather elevate the nature of the work, (demanding more critical judgment rather than repetitive production), or simply remove large-scale, low-wage annotators from the equation by replacing them with skilled annotators. It requires careful consideration and proactive effort to ensure that individuals involved are equipped with the necessary skills for these evolving roles and that the economic benefits of automation are shared equitably. The potential for deskilling or displacement in certain areas must also be acknowledged and addressed thoughtfully by the community and organizations deploying such systems. We must remain mindful of the human collaborators whose insights remain crucial, even as the tools evolve.

Furthermore, the integrity of the evaluation process itself relies heavily on the quality and characteristics of the LLMs used within the YourBench framework. The models employed for generating questions, summaries, and even judging responses inevitably embed their own biases, limitations, and potential failure modes, learned from their own training data. If not carefully managed, YourBench could inadvertently propagate or even amplify these biases within the generated benchmarks. This underscores the critical importance of transparency regarding the models used in the generation process and the need for robust, ongoing validation of the generated datasets – not just for correctness, but also for fairness, representation, and potential hidden biases. Automated checks, like the citation grounding implemented, are valuable, but **human oversight remains essential for identifying more subtle issues**.

The increased accessibility offered by YourBench, allowing for rapid generation of domain-specific benchmarks, is a significant advantage. It empowers researchers and practitioners to create evaluations tailored to their specific needs, moving beyond generic, potentially saturated benchmarks. However, this ease of creation also carries a potential for misuse. Benchmarks could conceivably be generated to specifically highlight the strengths or weaknesses of particular models, potentially leading to misleading comparisons if not used responsibly and transparently.

Finally, the computational resources required to run ensembles of large models for generation and evaluation contribute to the environmental footprint of AI development. While YourBench might offer efficiencies compared to certain manual processes or continuous large-scale human evaluations, the aggregate energy consumption remains a factor worthy of consideration as such automated systems become more widespread.

In conclusion, while YourBench offers a promising direction for advancing LLM evaluation, its development and deployment must proceed with a deep sense of responsibility. Continuous monitoring of its impacts, particularly on human labor dynamics and the integrity of evaluation results, is essential. The goal should not merely be automation, but the creation of evaluation methodologies that are not only more efficient and relevant but also fundamentally fair, trustworthy, and aligned with the broader goal of developing beneficial AI.

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A YourBench Pipeline Overview

Figure 5 provides a high-level schematic of the end-to-end YourBench framework. The process begins with ingesting diverse source documents, which are then preprocessed through steps like semantic chunking and summarization (§2.1, Appendix B). An ensemble of LLMs generates raw question-answer pairs grounded in the document chunks, guided by principles aiming for coverage, diversity, and answerability (§2.2, Appendix C). These raw outputs undergo rigorous quality filtering, including citation validation and semantic deduplication, to produce a high-fidelity evaluation set (§2.3). Finally, this curated set is used within an automated evaluation framework, typically employing an ensemble of LLM judges to rank the performance of target models (§3). This modular pipeline allows for flexibility and robust, automated benchmark creation from arbitrary document inputs.

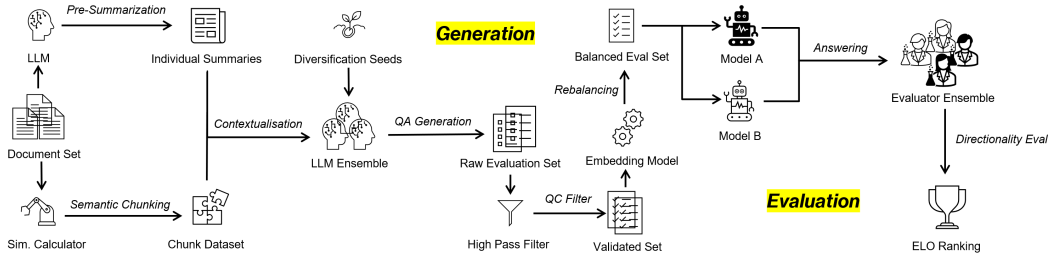

Figure 5: Overview of the YourBench Framework: A dynamic pipeline starting from diverse documents, through preprocessing (ingestion, chunking, summarization - §2.1), LLM-driven question generation (following D2EG principles - §2.2), quality filtering (citation validation, deduplication - §2.3), to automated evaluation using an LLM judge ensemble (§3).

B Detailed Document Preprocessing

This appendix details the multi-stage preprocessing pipeline used in YourBench, designed to convert diverse, real-world documents into a standardized format suitable for LLM-based question generation, as summarized in Section 2.1. The pipeline addresses challenges posed by heterogeneous formats and multimodal content.

B.1 Document Ingestion

We implement a unified ingestion pipeline using ReaderLM-v2 (Wang et al., 2025) (stripping known HTML content) and Markitdown[3] (converting various document types like PDF and Word into markdown). This approach retains key structural elements (headings, lists, tables, math) while simplifying complex layouts into a standard text-based markdown syntax, ensuring consistency across sources.

When visual content (e.g., images) is present, we generate high-level descriptions using `Qwen2.5-72B-VL` (Team, 2025) for captioning. These descriptions are incorporated into the markdown representation, allowing question generation modules to reference both textual and visual information uniformly. An example of a multimodal document input is shown in Appendix B.4 (Figure 6).

B.2 Semantic Chunking

Processing full documents directly with LLMs presents challenges, including attention dispersion potentially overlooking content (Ye et al., 2024), and performance degradation with longer contexts (Liu et al., 2023).

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[3] https://github.com/microsoft/markitdown

We address these through semantic chunking, which partitions documents into coherent segments. This process involves decomposing the document into sentences, computing embeddings, and then splitting the text into chunks based on semantic similarity and token length constraints, preserving coherence within and across segments. Multi-hop chunking is also implemented by combining multiple non-contiguous chunks to facilitate questions requiring information synthesis across different document parts.

Given a document d, we first decompose it into sentences $S = \{s_1, ..., s_n\}$ and compute their embeddings $E = \{e_1, ..., e_n\}$ using a sentence transformer model (Reimers & Gurevych, 2019), where $e_i \in \mathbb{R}^k$. The chunking process is governed by three parameters: l_{min}: minimum chunk length in tokens, l_{max}: maximum chunk length in tokens, and τ: similarity threshold for chunk boundaries. For consecutive sentences s_i and s_{i+1}, we compute their semantic similarity using cosine similarity:

$$sim(s_i, s_{i+1}) = \frac{e_i \cdot e_{i+1}}{\|e_i\| \|e_{i+1}\|}$$

A chunk **boundary** is established at position i when the current chunk's token length exceeds l_{min} AND either $sim(s_i, s_{i+1}) < \tau$ OR appending s_{i+1} would cause the accumulated chunk length to exceed l_{max}. This process yields a set of text chunks $C = \{c_1, ..., c_m\}$ where each chunk c_j is a contiguous sequence of sentences from S.

Multihop Chunking: To enable the generation of questions requiring synthesis across multiple document segments, we implement multihop chunking. Given parameters h_{min} and h_{max} (minimum and maximum number of hops), we generate composite chunks. For each multihop chunk, we sample $k \sim \mathcal{U}(h_{min}, h_{max})$ original chunks uniformly without replacement from C and concatenate their text content. This produces a set of multihop chunks $M = \{m_1, ..., m_p\}$ where each m_i consists of k potentially non-contiguous original chunks. These multihop chunks are used alongside the original chunks C during question generation (Section 2.2.2). appendix context

B.3 Document Summarization

While chunking manages context length, it can lead to a loss of global document perspective during question generation. To mitigate this, we generate a document-wide summary using an LLM (`DeepSeek-V3` (DeepSeek-AI et al., 2025b) with zero temperature). For extremely long documents exceeding context limits, techniques like those in (Chang et al., 2024) can be employed. Our summarization uses chain-of-thought prompting (Wei et al., 2023) with structured XML tags[4] for quality and consistency. This concise summary is provided alongside individual chunks (Section 2.2.2) to give the question generation LLM both local detail and global context. The full summarization prompt is available in Appendix H.

B.4 Sample Document

Figure 6 shows an example document typical of those included in the dataset, featuring a mix of text and visual elements handled by our preprocessing pipeline (Appendix B).

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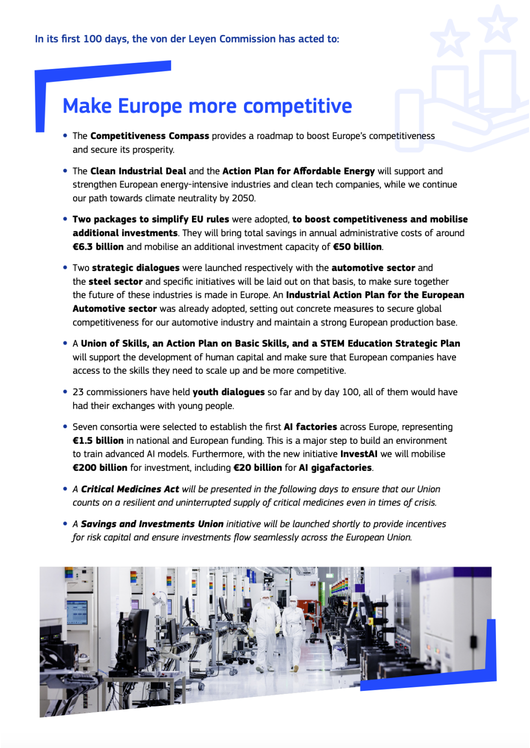
[4] https://docs.anthropic.com/en/docs/build-with-claude/prompt-engineering/use-xml-tags



In its first 100 days, the von der Leyen Commission has acted to:

Make Europe more competitive

- The **Competitiveness Compass** provides a roadmap to boost Europe's competitiveness and secure its prosperity.
- The **Clean Industrial Deal** and the **Action Plan for Affordable Energy** will support and strengthen European energy-intensive industries and clean tech companies, while we continue our path towards climate neutrality by 2050.
- **Two packages to simplify EU rules** were adopted, **to boost competitiveness and mobilise additional investments**. They will bring total savings in annual administrative costs of around **€6.3 billion** and mobilise an additional investment capacity of **€50 billion**.
- Two **strategic dialogues** were launched respectively with the **automotive sector** and the **steel sector** and specific initiatives will be laid out on that basis, to make sure together the future of these industries is made in Europe. An **Industrial Action Plan for the European Automotive sector** was already adopted, setting out concrete measures to secure global competitiveness for our automotive industry and maintain a strong European production base.
- A **Union of Skills, an Action Plan on Basic Skills, and a STEM Education Strategic Plan** will support the development of human capital and make sure that European companies have access to the skills they need to scale up and be more competitive.
- 23 commissioners have held **youth dialogues** so far and by day 100, all of them would have had their exchanges with young people.
- Seven consortia were selected to establish the first **AI factories** across Europe, representing **€1.5 billion** in national and European funding. This is a major step to build an environment to train advanced AI models. Furthermore, with the new initiative **InvestAI** we will mobilise **€200 billion** for investment, including **€20 billion** for **AI gigafactories**.
- *A **Critical Medicines Act** will be presented in the following days to ensure that our Union counts on a resilient and uninterrupted supply of critical medicines even in times of crisis.*
- *A **Savings and Investments Union** initiative will be launched shortly to provide incentives for risk capital and ensure investments flow seamlessly across the European Union.*

Figure 6: Example of a contemporary multimodal document included in Tempora-0325

C Theoretical framework underlying the data generation work

This appendix outlines the theoretical foundation for automated benchmark generation from source documents within the YourBench framework, termed *Document-to-Evaluation Generation* (D2EG), as introduced conceptually in Section 2.2. The goal is to produce a representative question set Q derived from a source document (partitioned into segments $\{c_1, \ldots, c_m\}$ and optionally summarized by s) that satisfies key desiderata.

Let $\mathcal{Q}$ be the universe of all possible questions derivable from the document segments. We seek a subset $Q \subseteq \mathcal{Q}$ that optimizes the trade-off between:

1. **Minimality:** Penalizing the total number of questions $|Q|$ for efficiency.
2. **Coverage:** Maximizing the extent to which Q addresses the source material.
3. **Diversity:** Ensuring variety in question type, difficulty, and targeted reasoning skills.
4. **Answerability & Quality:** A hard constraint ensuring every $q \in Q$ is valid and verifiably answerable from the source.

This can be formalized conceptually as a constrained optimization problem:

$$\min_{Q \subseteq \mathcal{Q}} \mathcal{L}(Q) = \alpha \left|Q\right| + \beta \mathcal{L}_{\text{uncov}}(Q) + \gamma \mathcal{L}_{\text{unif}}(Q), \tag{5}$$

subject to the constraint that every question in Q is verifiably answerable from the source document. Here, $\mathcal{L}_{\text{uncov}}(Q)$ penalizes the amount of source material left uncovered by Q, while $\mathcal{L}_{\text{unif}}(Q)$ penalizes lack of diversity (e.g., high semantic overlap) within Q. The non-negative coefficients α, β, γ balance these competing objectives.

Finding an exact solution to (5) is generally intractable due to the combinatorial nature of selecting Q from $\mathcal{Q}$. Therefore, as described in Section 2.2, YourBench employs a practical, greedy generation framework using LLMs, guided by prompts and context, to approximate a desirable question set Q that adheres to the D2EG principles.

D Framework Theoretical Complements

D.1 Citation validity

To validate the grounding of a generated answer a with citations $\text{cit} = \{c_1, ..., c_{N_c}\}$ to a source text chunk c, we use fuzzy string matching. For a given citation string c_i and the source chunk text c, we compute the partial ratio score using the Levenshtein distance concept:

$$\text{PartialRatio}(c_i, c) = \max_{s_j \subseteq c} \frac{2 \cdot \text{LCS}(c_i, s_j)}{|c_i| + |s_j|} \times 100$$

where $\text{LCS}(c_i, s_j)$ is the length of the longest common subsequence between the citation c_i and a substring s_j of the source text c. The maximum is taken over all possible substrings s_j of c. This score ranges from 0 to 100.

The overall grounding score for a single QA pair (q, a, cit) is calculated as described in Section 2.3 (Eq. (2)).

To calculate an overall citation performance score for a specific *generation model* (as reported in Section D.1), we average the QA grounding scores across all questions generated by that model:

$$\text{ModelCitationScore} = \frac{1}{N_{q,\text{model}}} \sum_{q=1}^{N_{q,\text{model}}} \text{Score}_{\text{QA}}(q, a_q, \text{cit}_q)$$

where $N_{q,\text{model}}$ is the total number of valid questions generated by the model after initial filtering, and $\text{Score}_{\text{QA}}(q, a_q, \text{cit}_q)$ is the grounding score for question q as defined in Eq. (2).

D.2 Evaluation Framework

Given the curated, weighted QA set $Q_{\text{final}} = Q_{\text{dedup}}$ (Sections 2.2.2, 2.3), we evaluate LLMs $\mathcal{M} = \{M_1, ..., M_N\}$ using a pairwise comparative assessment strategy with an ensemble of judge LLMs $\mathcal{J} = \{J_1, ..., J_K\}$ to enhance reliability (Zheng et al., 2023).

For each question $(q_j, a_j^*, \text{cit}_j^*) \in Q_{\text{final}}$ (weight w_j) and model pair (M_A, M_B), we elicit responses R_A^j, R_B^j. Each judge $J_l \in \mathcal{J}$ receives the context tuple:

$$\xi_{j,l,A,B} = (q_j, R_A^j, R_B^j, S, c_j) \tag{6}$$

including the question q_j, responses R_A^j, R_B^j, global summary S, and source chunk(s) c_j for grounded evaluation.

The judge J_l produces a continuous score $v_{lj}(A, B) \in [-1, 1]$ reflecting the relative quality of R_A^j vs R_B^j, often guided by a prompted chain-of-thought process (see Appendix for prompt details):

$$v_{lj}(A, B) = J_l(\xi_{j,l,A,B}) \tag{7}$$

Scores are averaged across judges for consensus $\bar{v}_j(A, B) = \frac{1}{K} \sum_{l=1}^{K} v_{lj}(A, B)$ and weighted by question salience w_j:

$$V_j(A, B) = w_j \cdot \bar{v}_j(A, B) \tag{8}$$

To counteract positional bias, we evaluate both (A, B) and (B, A) pairings and compute a bias-corrected score:

$$V_j'(A, B) = \frac{1}{2} \left(V_j(A, B) - V_j(B, A) \right) \tag{9}$$

The overall comparative score $S(A, B)$ between M_A and M_B is the sum over all questions:

$$S(A, B) = \sum_{j=1}^{|Q_{\text{final}}|} V'_j(A, B) \tag{10}$$

The sign indicates preference; magnitude indicates difference strength. These pairwise scores $\{S(A, B)\}$ form the basis for global ranking using methods like Bradley-Terry (Bradley & Terry, 1952) or Elo (Elo, 1978).

D.3 Evaluated Models

The following 26 models from 7 families were used in the generation and evaluation experiments described in Section 3:

- **DeepSeek** (DeepSeek-AI et al., 2025b;a): DeepSeek V3 (671B), DeepSeek R1 (671B), DeepSeek R1-Distill-Llama (70B), and DeepSeek R1-Distill-Qwen (32B, 14B, 7B).
- **Qwen** (Qwen et al., 2025): Qwen2.5 models at various scales (72B, 32B, 14B, 7B) and the reasoning model Qwen QwQ (32B).
- **Mistral** (Jiang et al., 2023): Mistral Large 2411 (132B) and Mistral 3.1 Small (24B).
- **Llama** (Dubey et al., 2024): Llama 3.1 (405B, 8B) and Llama 3.3 (70B).
- **Google** (Team et al., 2024): Gemini 2.0 Flash, Gemini 2.0 Flash Lite (?B) and Gemma 3 (27B).
- **OpenAI** (OpenAI et al., 2024): GPT-4o, GPT-4o mini, and o3 mini (?B).
- **Anthropic** (Anthropic, 2024): Claude 3.7 Sonnet, Claude 3.5 Haiku (?B).

E Evaluation Quality Details

This appendix provides detailed methodologies and supplementary results for the validation of generated evaluation quality presented in Section 3.2.

E.1 Question Validity Methodology and Detailed Results

Human Evaluation Setup. As introduced in Section 3.2.1, we conducted a manual evaluation to assess the intrinsic quality of generated questions. We sampled 2,000 unique questions generated from the TEMPORA-0325B dataset (Section 3.1.1) using the models listed in Appendix D.3. The sampling was stratified to ensure representation across models, document domains, targeted difficulty levels (basic, advanced), and question types (e.g., factual, multi-hop, numeric) specified during generation (Section 2.2.2).

Twenty trained annotators participated. Each annotator was presented with the source document chunk(s), the global document summary, the generated question, and the model-generated answer with its citations. Annotators were asked to assign a binary validity label (Valid/Invalid) based on the following criteria:

- **Clarity:** Is the question grammatically correct and unambiguous?
- **Contextual Answerability:** Can the question be definitively answered using *only* the provided document chunk(s) and summary? Does it require external knowledge or unwarranted assumptions?
- **Sensibility:** Is the question reasonable and logically coherent in the context of the document? (e.g., not nonsensical or self-contradictory).

A question was marked "Valid" only if it met all three criteria positively. Any ambiguity, reliance on external knowledge, or nonsensical phrasing resulted in an "Invalid" rating.

Inter-Annotator Agreement. Each question was evaluated independently by 3 randomly assigned annotators. To measure the consistency of their judgments, we calculated Gwet's AC1 coefficient (Gwet, 2008), a robust statistic for assessing inter-rater reliability, especially suitable for binary ratings with potential prevalence issues. The formula for Gwet's AC1 for two raters is:

$$AC1 = \frac{P_a - P_e(\gamma)}{1 - P_e(\gamma)}$$

where P_a is the observed percent agreement, and $P_e(\gamma)$ is the chance agreement probability, calculated as $P_e(\gamma) = 2\pi(1-\pi)$, with π being the overall proportion of "Valid" ratings (averaged across raters). For multiple raters (3 in our case), we used a multi-rater extension of the formula. The resulting overall AC1 score was 0.71, typically interpreted as substantial agreement (Landis & Koch, 1977), confirming the reliability of our human validity labels.

Detailed Results and Examples. The average validity rate reported in the main text ($\approx$85%) represents the mean percentage of questions rated "Valid" (by majority vote across the 3 annotators) across all models and question types post-filtering. The per-model validity scores are visualized in Figure 2 (right panel). Further breakdowns (e.g., validity per question type) can be derived from the released annotations accompanying our dataset. Examples of questions marked "Valid" and "Invalid" during this process, illustrating common failure modes like ambiguity or requiring external knowledge, are provided in Appendix I.

Juxtaposing these results highlights a prevalent, though not absolute, trade-off. The model achieving the highest validity, o3 mini, scores lowest in diversity (0.26). This suggests a generative posture focused on precision and safety, perhaps by asking more routine or algorithmically verifiable questions based directly on easily identifiable facts, leading to high validity but low exploration of the document's semantic space. Conversely, the top diversity model, Qwen2.5 32B, while still generating reasonably valid questions (0.81 validity, rank #11), sacrifices some peak validity in favor of broader conceptual coverage. This might indicate a more exploratory or creative generation strategy.

This validity-diversity spectrum is not a strict dichotomy. Notably, models like DeepSeek V3 671B manage to achieve impressive scores on both metrics (0.90 diversity, rank #2; 0.90 validity, rank #6), suggesting that balancing breadth and correctness is achievable. Similarly, models like Claude 3.7 Sonnet (0.80 diversity, 0.91 validity) also perform well across both dimensions.

This observed tension between generating highly valid, focused questions versus diverse, exploratory questions is an intriguing phenomenon. It reflects the different latent capabilities and perhaps inherent strategies employed by various LLMs when tasked with abstracting knowledge into evaluative queries. Rather than a limitation, this presents a valuable characteristic of the YourBench framework: it allows practitioners to select generator models or ensembles that align with their specific evaluation goals—be it rigorous testing of factual recall with high-validity generators, or broad assessment of understanding across topics using high-diversity generators, or seeking a balanced perspective with models adept at both. Understanding this trade-off provides deeper insight into the nature of LLM-driven generation and empowers more informed benchmark creation.

Length Metrics vs. Validity. We also analyzed the relationship between question/answer/citation length and the observed validity rate from human evaluation. Figure 7 plots the validity rate (averaged across all models) against different length metrics binned appropriately. While there isn't a perfectly monotonic trend, we observe a general tendency for validity to decrease slightly for very long questions, answers, or unified text lengths, potentially reflecting the increased difficulty in maintaining coherence and contextual grounding over longer generations. Citation length shows less variation. The black line represents the average validity rate across bins, while faint lines show individual model trends, highlighting variability. These plots reinforce the finding that generating complex (often longer) valid questions remains challenging.

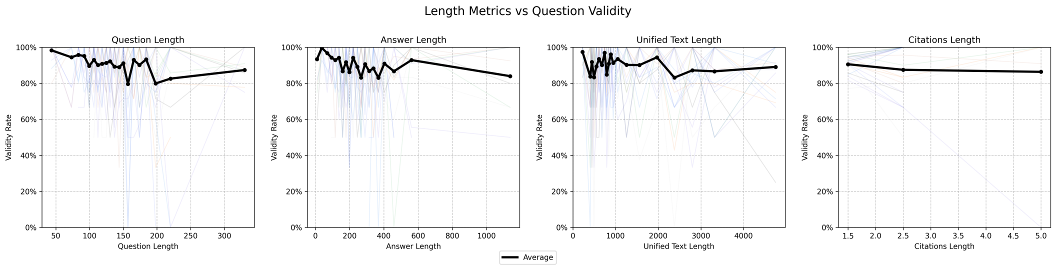


Figure 7: Relationship between generation length metrics and average question validity rate (across all models). Validity tends to decrease slightly for very long generations. Faint lines represent individual model trends.

E.2 Citation Grounding Methodology and Detailed Results

Citation Scoring Metric. As described in Section 2.3, we quantify the grounding of an answer a with citations $\mathrm{cit} = \{c_1, ..., c_{N_c}\}$ to a source chunk c using fuzzy string matching. The core metric is 'PartialRatio', based on Levenshtein distance (Levenshtein, 1966), computed for each citation c_i against the source c:

$$\mathrm{PartialRatio}(c_i, c) = \max_{s_j \subseteq c, |s_j| \geq |c_i|} \frac{2 \cdot \mathrm{Match}(c_i, s_j)}{|c_i| + |s_j|} \times 100$$

where $\mathrm{Match}(c_i, s_j)$ finds the length of the best matching contiguous block between c_i and substrings s_j of c (typically using sequence matching algorithms). The maximum is taken over substrings s_j of c that are at least as long as the citation c_i. This score ranges from 0 (no match) to 100 (perfect match of c_i within c).

The QA grounding score $\mathrm{Score}_{\mathrm{QA}}(q, a, \mathrm{cit})$ is the average of these partial ratios across all N_c citations, as given in Eq. (2). If $N_c = 0$, the score is 0.

Model-Level Citation Score. The overall citation score for a generation model M, as reported in Figure 3, is the average of the QA grounding scores across all valid QA pairs generated by that model:

$$\mathrm{ModelCitationScore}_M = \frac{1}{|Q_{\mathrm{valid},M}|} \sum_{(q,a,\mathrm{cit}) \in Q_{\mathrm{valid},M}} \mathrm{Score}_{\mathrm{QA}}(q, a, \mathrm{cit})$$

where $Q_{\mathrm{valid},M}$ is the set of QA pairs generated by model M that passed initial quality filters (e.g., parseable format, non-empty question/answer). This provides a single metric to compare the average citation reliability of different models. Detailed scores for all evaluated models are implicitly represented in Figure 3.

Inference Cost Calculation. The inference costs used in Figure 3b were estimated based on the per-token pricing for output tokens (as generation is output-heavy) published on OpenRouter (`https://openrouter.ai/docs/models`) as of the time of experiments, using the lowest available price tier for each model. For models not on OpenRouter or without public pricing (indicated by "?B" parameters), relative cost estimates were made based on known parameter counts or comparable models where possible, or they were excluded from the cost analysis. This provides a practical estimate of the economic efficiency of using different models for generation within the `YourBench` framework.

E.3 Semantic Diversity Methodology and Detailed Results

Diversity Metrics. As discussed in Section 3.2.1, we quantified the semantic diversity of the set of questions Q_M generated by a model M using two embedding-based metrics:

1. **Embedding Dispersion:** We first compute sentence embeddings $e(q)$ for each question $q \in Q_M$ using a standard sentence transformer model (e.g., 'all-mpnet-base-v2' (Reimers & Gurevych, 2019)). The dispersion is the average pairwise cosine distance:

$$\text{Dispersion}(Q_M) = \frac{1}{|Q_M|(|Q_M|-1)} \sum_{q_i \in Q_M} \sum_{q_j \in Q_M, i \neq j} \left(1 - \frac{e(q_i) \cdot e(q_j)}{\|e(q_i)\| \|e(q_j)\|}\right)$$

A higher dispersion value indicates that the question embeddings are, on average, further apart in the embedding space, suggesting greater semantic variety.

2. **Semantic Entropy:** We apply K-Means clustering (with K chosen based on heuristics like the elbow method or a fixed moderate number, e.g., $K = 50$) to the question embeddings $\{e(q) \mid q \in Q_M\}$. Let N_k be the number of questions assigned to cluster k, and $N = |Q_M| = \sum_k N_k$. The proportion of questions in cluster k is $p_k = N_k/N$. The semantic entropy is the Shannon entropy of the cluster distribution:

$$\text{Entropy}(Q_M) = -\sum_{k=1}^{K} p_k \log_2(p_k)$$

Higher entropy indicates that the questions are distributed more evenly across different semantic clusters, implying broader coverage of different conceptual areas. Lower entropy suggests concentration in a few dominant semantic themes.

The final "Diversity Score" reported in Figure 2 (left panel) is a normalized combination or average of these two metrics (e.g., scaled to [0, 1] based on observed ranges across models). This composite score aims to capture both the spread and the evenness of the semantic distribution.

Detailed Scores. Figure 2 provides the final composite diversity scores for the evaluated models. The underlying dispersion and entropy values, along with the specific normalization method, are available with the project's source code and results data. The variation observed confirms that model choice significantly impacts the semantic breadth of the generated evaluation set.

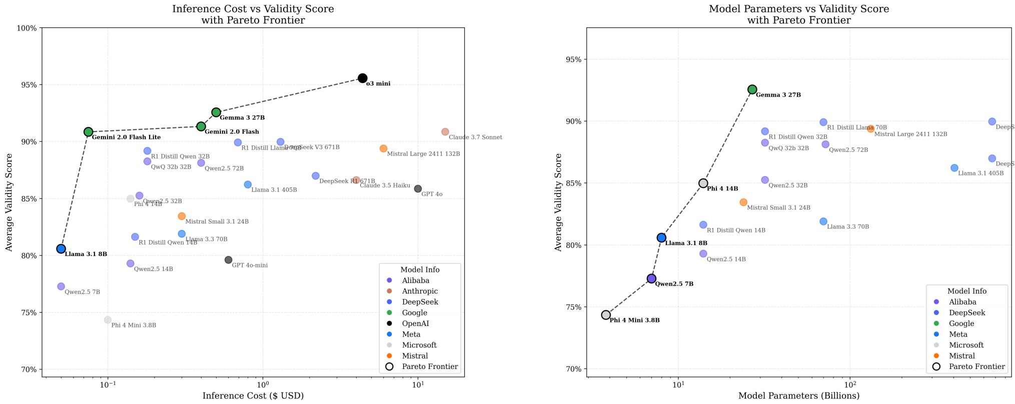
E.4 Cost and Parameter Efficiency Analysis

Beyond citation grounding (Figure 3b), we analyzed the relationship between model cost/size and overall question quality, approximated by the average validity score (Section 3.2.1). Figures 8a and 8b show Pareto frontiers for average validity score versus inference cost and model parameters, respectively.

These plots further illustrate favorable scaling trends and efficiency possibilities.

- **Cost Efficiency (Fig. 8a):** Models like Llama 3.1 8B, Gemini 2.0 Flash Lite, and Gemma 3 27B appear on or near the Pareto frontier, achieving relatively high validity scores (80-90%+) at substantially lower costs compared to the largest or most expensive models. This demonstrates that high question validity is attainable without exorbitant inference budgets.
- **Parameter Efficiency (Fig. 8b):** Smaller models, including Phi 4 Mini 3.8B, Qwen2.5 7B, Llama 3.1 8B, and Phi 4 14B, form part of the Pareto frontier. This indicates that smaller parameter counts do not necessarily preclude high validity generation. Phi 4 14B, for instance, reaches approximately 85% validity, competitive with much larger models, showcasing significant parameter efficiency. Gemma 3 27B also stands out, achieving over 90

Together, these analyses suggest that while larger models sometimes offer peak performance, carefully selected smaller or more cost-effective models can generate high-quality evaluation sets efficiently within the `YourBench` framework, democratizing access to customized benchmarking.



(a) Inference Cost vs. Average Validity Score.

(b) Model Parameters vs. Average Validity Score.

Figure 8: Pareto frontiers illustrating trade-offs between average question validity and (a) inference cost (log scale) and (b) model parameters (log scale). Smaller/cheaper models like Llama 3.1 8B, Gemini 2.0 Flash Lite, and Phi 4 14B can achieve high validity scores efficiently. Full model list in Appendix D.3.

F MMLU Replication: Detailed Analysis and Results

This appendix provides a detailed breakdown of the MMLU replication experiment discussed in §3.3 and introduced in Figure 1. We aimed to validate whether `YourBench` could automatically generate MMLU-style benchmarks from source documents that reliably reflect the relative performance of different LLMs compared to the original MMLU benchmark.

F.1 Correlation Analysis

We evaluated a suite of 8 LLMs (see Table 1) on 7 original MMLU subject subsets and their corresponding YourBench-generated counterparts ("new"). We then analyzed the correlation between the performance scores (accuracy) obtained on the original versus the "new" benchmarks.

- **Overall Correlation (All Subject-Model Pairs):** When analyzing all individual data points (8 models × 7 subjects = 56 pairs), the correlation is positive but moderate, suggesting some variance at the specific subject level or potential noise in individual measurements.
  - Pearson r: 0.3833 (p = 0.0035)
  - Spearman ρ: 0.2982 (p = 0.0256)
- **Model Mean Performance Correlation:** When analyzing the average performance of each model across all 7 subjects (8 data points), the correlation becomes extremely strong, particularly in terms of rank order. This indicates that while absolute scores differ (YourBench questions are harder), the relative ranking of models is preserved.
  - Pearson r: 0.9646 ($p < 0.0001$)
  - Spearman ρ: 1.0000 ($p < 0.0001$)

The perfect Spearman correlation for mean model performance strongly supports the validity of YourBench for generating discriminative evaluations that align with established benchmarks in terms of relative model capability assessment.

F.2 Per-Subject Performance Plots

The following figures visualize the performance comparison for each individual MMLU subject included in the study. Each plot compares the performance of the evaluated LLMs on the original MMLU subset (grey bars) versus the YourBench-generated subset (orange bars). These plots visually complement the aggregated data in Figure 1 and the comprehensive data in Table 1.

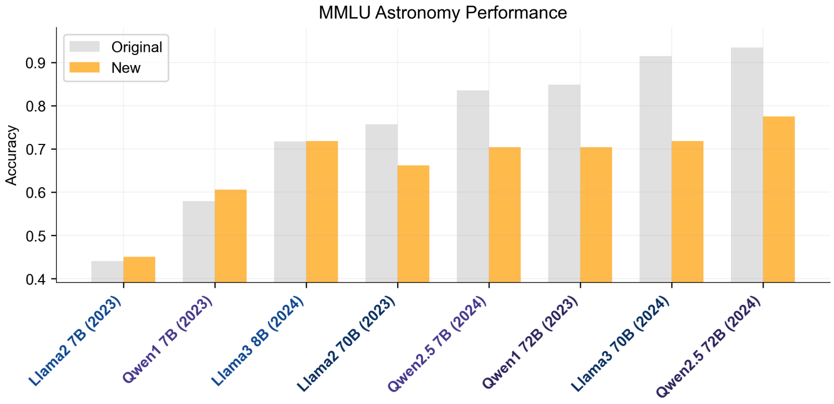


Figure 9: MMLU Replication Performance: Astronomy

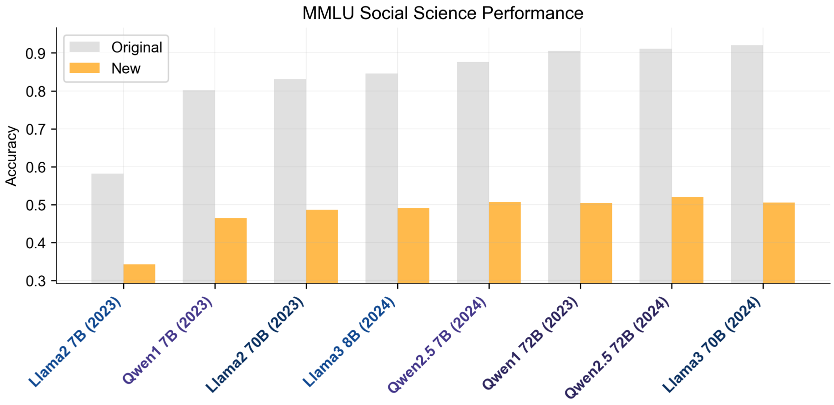


Figure 10: MMLU Replication Performance: Social Science

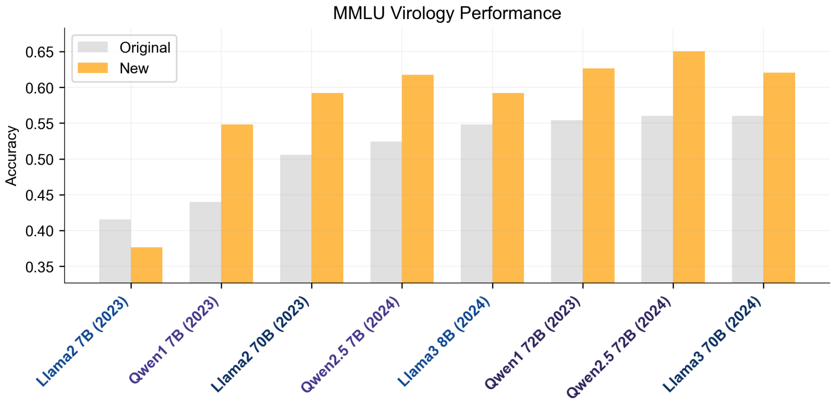


Figure 11: MMLU Replication Performance: Virology

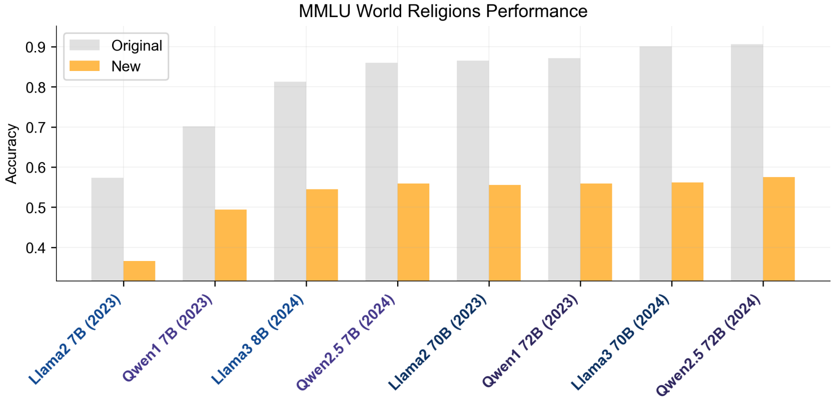


Figure 12: MMLU Replication Performance: World Religions

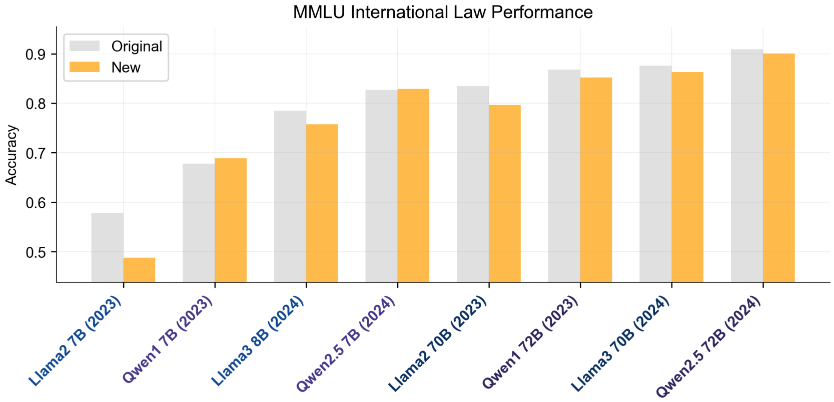


Figure 13: MMLU Replication Performance: International Law

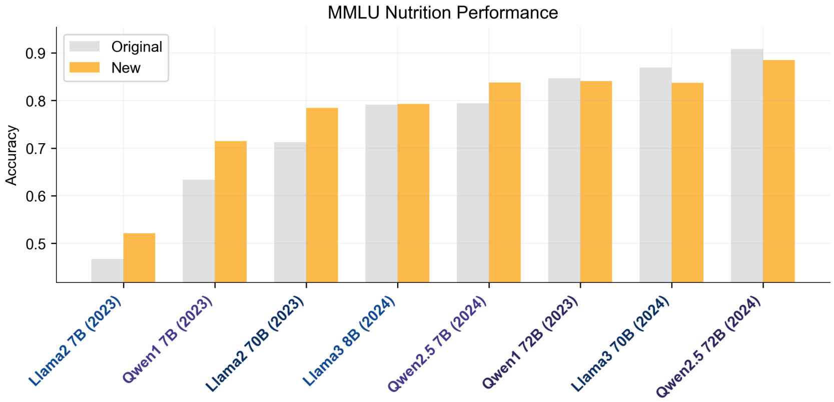


Figure 14: MMLU Replication Performance: Nutrition

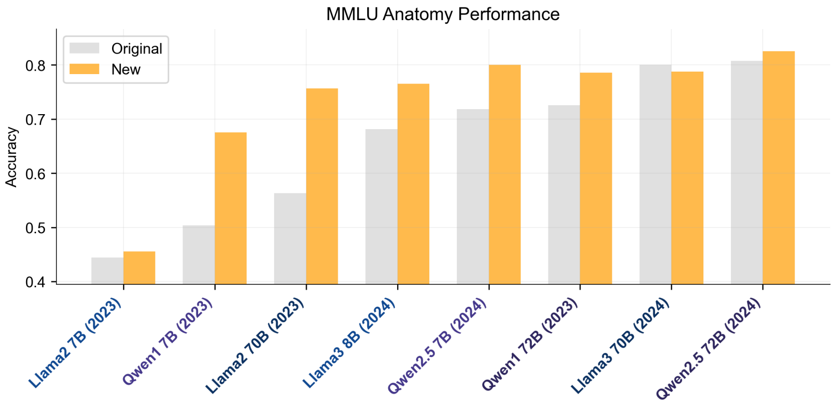


Figure 15: MMLU Replication Performance: Anatomy

F.3 Comprehensive Performance Table

Table 1 provides the complete numerical results, detailing the accuracy and standard error[5] for each model on both the original ("orig") and YourBench-generated ("new") MMLU subsets across the seven evaluated domains.

Table 1: Comprehensive MMLU Replication Results: Accuracy (Std Err) across Models and Subjects. "New" refers to YourBench-generated benchmarks, "Orig" refers to original MMLU subsets.

	Astronomy		Social Science		Virology		World Religions	
Model	New	Orig	New	Orig	New	Orig	New	Orig
Qwen1 7B (2023)	60.56% (5.84%)	57.89% (4.02%)	46.37% (1.67%)	80.10% (2.82%)	54.82% (1.93%)	43.98% (3.86%)	49.43% (1.16%)	70.18% (3.51%)
Qwen2.5 7B (2024)	70.42% (5.45%)	83.55% (3.02%)	50.61% (1.67%)	87.56% (2.33%)	61.75% (1.89%)	52.41% (3.89%)	55.93% (1.16%)	85.96% (2.66%)
Llama3 8B (2024)	71.83% (5.38%)	71.71% (3.67%)	49.05% (1.67%)	84.58% (2.55%)	59.19% (1.91%)	54.82% (3.87%)	54.47% (1.16%)	81.29% (2.99%)
Llama2 7B (2023)	45.07% (5.95%)	44.08% (4.04%)	34.19% (1.59%)	58.21% (3.49%)	37.65% (1.88%)	41.57% (3.84%)	36.60% (1.12%)	57.31% (3.79%)
Llama2 70B (2023)	66.20% (5.65%)	75.66% (3.49%)	48.60% (1.67%)	83.08% (2.65%)	59.19% (1.91%)	50.60% (3.89%)	55.55% (1.16%)	86.55% (2.62%)
Qwen1 72B (2023)	70.42% (5.45%)	84.87% (2.92%)	50.39% (1.67%)	90.55% (2.07%)	62.65% (1.88%)	55.42% (3.87%)	55.87% (1.16%)	87.13% (2.57%)
Qwen2.5 72B (2024)	77.46% (4.99%)	93.42% (2.02%)	52.07% (1.67%)	91.04% (2.02%)	65.06% (1.85%)	56.02% (3.86%)	57.55% (1.15%)	90.64% (2.23%)
Llama3 70B (2024)	71.83% (5.38%)	91.45% (2.28%)	50.50% (1.67%)	92.04% (1.91%)	62.05% (1.88%)	56.02% (3.86%)	56.15% (1.15%)	90.06% (2.29%)

	International Law		Nutrition		Anatomy		**Average**	
Model	New	Orig	New	Orig	New	Orig	**New Avg**	**Orig Avg**
Qwen1 7B (2023)	68.87% (1.70%)	67.77% (4.27%)	71.45% (1.54%)	63.40% (2.76%)	67.57% (2.14%)	50.37% (4.32%)	59.87%	64.80%
Qwen2.5 7B (2024)	82.88% (1.38%)	82.64% (3.46%)	83.80% (1.26%)	79.41% (2.32%)	80.04% (1.82%)	71.85% (3.89%)	70.78%	78.84%
Llama3 8B (2024)	75.74% (1.57%)	78.51% (3.75%)	79.25% (1.39%)	79.08% (2.33%)	76.51% (1.94%)	68.15% (4.02%)	67.99%	73.45%
Llama2 7B (2023)	48.79% (1.84%)	57.85% (4.51%)	52.10% (1.71%)	46.73% (2.86%)	45.53% (2.27%)	44.44% (4.29%)	41.41%	50.03%
Llama2 70B (2023)	79.65% (1.48%)	83.47% (3.39%)	78.44% (1.40%)	71.24% (2.59%)	75.68% (1.96%)	56.30% (4.28%)	67.61%	72.81%
Qwen1 72B (2023)	85.18% (1.31%)	86.78% (3.09%)	84.03% (1.25%)	84.64% (2.06%)	78.59% (1.87%)	72.59% (3.85%)	69.89%	79.84%
Qwen2.5 72B (2024)	90.03% (1.10%)	90.91% (2.62%)	88.46% (1.09%)	90.85% (1.65%)	82.54% (1.73%)	80.74% (3.41%)	73.31%	84.89%
Llama3 70B (2024)	86.25% (1.26%)	87.60% (3.01%)	83.68% (1.26%)	86.93% (1.93%)	78.79% (1.87%)	80.00% (3.46%)	70.61%	82.01%

G Detailed Related Work and Literature Review

This appendix provides a comprehensive discussion of the related work surveyed in Section 4, detailing the challenges in large language model (LLM) evaluation and prior approaches that motivate the development of YourBench. As models have grown in size and sophistication, traditional evaluation approaches have struggled to keep pace. We survey four key directions in LLM benchmarking—(1) the challenges of static, human-curated benchmarks, (2) synthetic and dynamic benchmark generation, (3) temporal validity concerns, and (4) domain-specific evaluations—and highlight how **YourBench** addresses the major open problems that emerge in each.

G.1 Limitations of Static Benchmarks

Historically, static benchmarks such as MNIST (Deng, 2012), GLUE (Wang et al., 2019), and SQuAD (Rajpurkar et al., 2016) have been central to measuring progress in machine learning. Although these datasets propelled rapid innovation, modern LLMs can quickly saturate their performance ceilings, sometimes surpassing human-level scores within mere months (Ruder, 2023; Wei, 2023). This *benchmark saturation* hampers their long-term utility in discriminating genuinely more capable models. For instance, models that reached near-perfect scores on GLUE soon forced the community to adopt other, more challenging tasks (Wei, 2023).

An additional concern is *benchmark contamination*, where test data is inadvertently included in a model's training corpus. Because large-scale pretraining involves ingesting vast amounts of web content, popular benchmarks are often seen—or memorized—by the model (Kiela et al., 2021; Ruder, 2023; Zhang et al., 2024). Empirical analyses show that certain LLMs can repeat verbatim segments from question banks such as GSM8K (Cobbe et al., 2021) or MATH (Hendrycks et al., 2021b) when tested in a zero-shot setting (Wei, 2023), artificially inflating performance. Holding out an unseen test set is one partial solution, but as time passes and these datasets spread online, the likelihood of contamination grows (Gupta et al., 2024). Consequently, reliance on a single, static, and publicly available

---

[5] Standard error was derived directly from the accuracy mean, following the methodology in (Fourrier et al., 2023).

benchmark may induce narrow optimization rather than robust generalization (Hendrycks et al., 2021a).

G.2 Toward Dynamic and Synthetic Evaluation

Faced with saturation and contamination, researchers have pursued *dynamic* and *synthetic* benchmark generation. Kiela et al. (2021) introduced Dynabench to update evaluation sets interactively, challenging models with adversarially crafted queries. This iterative approach demonstrated that once a model adapts to a static test, new data can still reveal surprising failures. However, such human-in-the-loop curation remains expensive and slow to scale.

A more automated strategy is to use LLMs themselves for benchmark synthesis. Several techniques involve prompting a strong generator model to create new questions or tasks, sometimes based on existing ones (*benchmark rewriting*) (Wei, 2023; Krishna et al., 2024). Methods like Auto-Dataset (Ruder, 2023) or ITD (Wei, 2023) rephrase, expand, or mutate original items while controlling for difficulty, ensuring the new tasks remain answerable. Others adopt *multi-agent* pipelines, in which distinct LLMs generate candidate questions and validate them, filtering out ambiguous or erroneous samples (Zhou et al., 2025). Further exploring the role of LLMs in the evaluation pipeline, early work by Shashidhar et al. (2023) utilized LLMs as judges to assess model outputs, correcting for positional bias inherent in such automated evaluations. Despite promising progress, fully synthetic benchmarks introduce new challenges, including the risk of hallucinated or trivial questions. Quality control and verification remain active research topics, especially when the aim is to test advanced reasoning or domain-specific knowledge.

G.3 Temporal Validity and Knowledge Evolution

Another major challenge is *temporal validity*, reflecting the fact that knowledge and world events change continuously. Many popular benchmarks capture only static snapshots, making them less relevant when facts become outdated (Zhu et al., 2023; Deng et al., 2024). LLM performance thus appears high on older queries but may degrade sharply on newly introduced or time-sensitive questions (Zhu et al., 2023). Holding out a private test set of recent data can help, but frequent refreshes are necessary to track a model's ability to integrate new information (Ruder, 2023; Zhang et al., 2024).

Several works illustrate the severity of the problem. Zhu et al. (2023) generated *post-training* news-based questions to measure whether an LLM truly updates its internal knowledge representation. They found LLMs frequently defaulted to outdated responses, highlighting a gap between real-time information usage and parametric memory. Similarly, Deng et al. (2024) created an evolving dataset of newly coined terminology, demonstrating 20%+ accuracy drops for concepts introduced long after a model's pretraining cutoff. These findings underscore the necessity for *continually updated* benchmarks that can test a model's recency-awareness and its ability to override memorized facts.

G.4 Domain-Specific Evaluation

Moving from general-purpose benchmarks to specialized ones is increasingly essential, especially in high-stakes fields like medicine, law, and finance (Hung et al., 2023a). Benchmarks such as USMLE-based medical QA (Nori et al., 2023), or specialized legal datasets like CaseHOLD and LegalBench (Holzenkamp et al., 2023), have revealed critical blind spots in LLM reasoning (Hung et al., 2023b). For instance, LLMs might achieve near-human scores on open-domain quizzes yet commit severe factual errors or hallucinations in domain-specific contexts (Gupta et al., 2024).

Building domain-specific benchmarks demands costly expert annotations and must reflect the latest regulations, guidelines, or terminology. In medicine, for example, clinical protocols can change frequently, making a static test rapidly obsolete. Researchers have thus proposed *rolling* domain benchmarks—continuously collected or synthesized data for niche areas such as real-time medical literature or changing legal precedents (Zhang et al., 2024). So far, these dynamic domain evaluations remain nascent: they are typically narrow, small in size, and do not integrate robust automated generation pipelines or multi-modal content ingestion.

Synthesizing these research themes reveals persistent open problems in LLM benchmarking. **First**, existing static benchmarks are prone to contamination and rapid saturation. **Second**, purely human-driven dynamic approaches cannot scale indefinitely. **Third**, synthetic generation requires careful quality control and can still produce stale or trivial tasks if not refreshed in tandem with new knowledge sources. **Fourth**, few existing solutions integrate domain expertise in a flexible manner or support continuous updates for specialized fields. **Finally**, temporal drift in factual knowledge remains inadequately addressed, as most benchmarks do not systematically ensure that test data are *entirely* post-training or reflective of newly emerging concepts.

H Prompts

H.1 Document Summarization Prompt

The following prompt is first provided into the language model. Once the model provides a response answer, we extract the content that is contained within the `final_summary` XML tags to function as our document summary.

```
You are an AI assistant tasked with analyzing and summarizing documents from various
↪  domains. Your goal is to generate a concise yet comprehensive summary of the given
↪  document. Follow these steps carefully:

1. You will be provided with a document extracted from a website. This document may
↪  contain unnecessary artifacts such as links, HTML tags, or other web-related
↪  elements.

2. Here is the document to be summarized:
<document>
{document}
</document>

3. Before generating the summary, use a mental scratchpad to take notes as you read
↪  through the document. Enclose your notes within <scratchpad> tags. For example:

<scratchpad>
- Main topic: [Note the main subject of the document]
- Key points: [List important information]
- Structure: [Note how the document is organized]
- Potential artifacts to ignore: [List any web-related elements that should be
↪  disregarded]
</scratchpad>

4. As you analyze the document:
   - Focus solely on the content, ignoring any unnecessary web-related elements.
   - Identify the main topic and key points.
   - Note any important details, facts, or arguments presented.
   - Pay attention to the overall structure and flow of the document.

5. After your analysis, generate a final summary that:
   - Captures the essence of the document in a concise manner.
   - Includes the main topic and key points.
   - Presents information in a logical and coherent order.
   - Is comprehensive yet concise, typically ranging from 3-5 sentences (unless the
   ↪  document is particularly long or complex).

6. Enclose your final summary within <final_summary> tags. For example:

<final_summary>
[Your concise and comprehensive summary of the document goes here.]
</final_summary>

Remember, your task is to provide a clear, accurate, and concise summary of the
↪  document's content, disregarding any web-related artifacts or unnecessary elements.
```

H.2 Single Shot Question Generation Prompt

```
## Your Role

You are an expert educational content creator specializing in crafting thoughtful, rich,
↪  and engaging questions based on provided textual information. Your goal is to produce
↪  meaningful, moderately challenging question-answer pairs that encourage reflection,
↪  insight, and nuanced understanding, tailored specifically according to provided
↪  instructions.

## Input Structure

Your input consists of:

<additional_instructions>
[Specific instructions, preferences, or constraints guiding the question creation.]
</additional_instructions>

<title>
[Document title]
</title>

<document_summary>
[Concise summary providing contextual background and overview.]
</document_summary>

<text_chunk>
[The single text segment to analyze.]
</text_chunk>

## Primary Objective

Your goal is to generate a thoughtful set of question-answer pairs from a single provided
↪  `<text_chunk>`. Aim for moderate complexity that encourages learners to deeply
↪  engage with the content, critically reflect on implications, and clearly demonstrate
↪  their understanding.

### Context Fields:

- `<title>`: Contextualizes the content.
- `<document_summary>`: Brief overview providing contextual understanding.
- `<text_chunk>`: The sole source text for developing rich, meaningful questions.
- `<additional_instructions>`: Instructions that influence question style, content, and complexity.

## Analysis Phase

Conduct careful analysis within `<document_analysis>` XML tags, following these steps:

1. **Thoughtful Content Examination**
   - Carefully analyze the given text_chunk, identifying central ideas, nuanced themes, and significant relationships within it.

2. **Concept Exploration**
   - Consider implicit assumptions, subtle details, underlying theories, and potential applications of the provided information.

3. **Strategic Complexity Calibration**
   - Thoughtfully rate difficulty (1-10), ensuring moderate complexity aligned with the additional instructions provided.

4. **Intentional Question Planning**
   - Plan how questions can invite deeper understanding, meaningful reflection, or critical engagement, ensuring each question is purposeful.

## Additional Instructions for Handling Irrelevant or Bogus Information

### Identification and Ignoring of Irrelevant Information:

- **Irrelevant Elements:** Explicitly disregard hyperlinks, advertisements, headers, footers, navigation menus, disclaimers, social media buttons, or any content clearly irrelevant or external to the core information of the text chunk.
- **Bogus Information:** Detect and exclude any information that appears nonsensical or disconnected from the primary subject matter.

### Decision Criteria for Question Generation:

- **Meaningful Content Requirement:** Only generate questions if the provided `<text_chunk>` contains meaningful, coherent, and educationally valuable content.
- **Complete Irrelevance:** If the entire `<text_chunk>` consists exclusively of irrelevant, promotional, web navigation, footer, header, or non-informational text, explicitly state this in your analysis and do NOT produce any question-answer pairs.

### Documentation in Analysis:

- Clearly document the rationale in the `<document_analysis>` tags when identifying irrelevant or bogus content, explaining your reasons for exclusion or inclusion decisions.
- Briefly justify any decision NOT to generate questions due to irrelevance or poor quality content.


## Question Generation Guidelines
```

~~~
### Encouraged Question Characteristics:

- **Thoughtful Engagement**: Prioritize creating questions that inspire deeper thought and nuanced consideration.
- **Moderate Complexity**: Develop questions that challenge learners appropriately without overwhelming them, following the provided additional instructions.
- **Self-contained Clarity**: Questions and answers should contain sufficient context, clearly understandable independently of external references.
- **Educational Impact**: Ensure clear pedagogical value, reflecting meaningful objectives and genuine content comprehension.
- **Conversational Tone**: Formulate engaging, natural, and realistic questions appropriate to the instructional guidelines.

### Permitted Question Types:

- Analytical
- Application-based
- Clarification
- Counterfactual
- Conceptual
- True-False
- Factual
- Open-ended
- False-premise
- Edge-case

(You do not need to use every question type, only those naturally fitting the content and instructions.)

## Output Structure

Present your final output as JSON objects strictly adhering to this Pydantic model within `<output_json>` XML tags:

```python
class QuestionAnswerPair(BaseModel):
    thought_process: str # Clear, detailed rationale for selecting question and analysis approach
    question_type: Literal["analytical", "application-based", "clarification",
                           "counterfactual", "conceptual", "true-false",
                           "factual", "open-ended", "false-premise", "edge-case"]
    question: str
    answer: str
    estimated_difficulty: int  # 1-10, calibrated according to additional instructions
    citations: List[str]  # Direct quotes from the text_chunk supporting the answer
```

## Output Format

Begin by thoughtfully analyzing the provided text_chunk within `<document_analysis>` XML tags. Then present the resulting JSON-formatted QuestionAnswerPairs clearly within `<output_json>` XML tags.

## Important Notes
~~~

```
- Strive to generate questions that inspire genuine curiosity, reflection, and
↪  thoughtful engagement.
- Maintain clear, direct, and accurate citations drawn verbatim from the provided
↪  text_chunk.
- Ensure complexity and depth reflect thoughtful moderation as guided by the additional
↪  instructions.
- Each "thought_process" should reflect careful consideration and reasoning behind your
↪  question selection.
- Ensure rigorous adherence to JSON formatting and the provided Pydantic validation
↪  model.
- When generating questions, NEVER include phrases like 'as per the text,' 'according to
↪  the document,' or any similar explicit references. Questions should inherently
↪  integrate content naturally and stand independently without explicit references to
↪  the source material
```

H.3 Multi Hop Question Generation Prompt

```
## Your Role

You are an expert educational content creator specialized in generating insightful and
↪  thoughtfully designed multi-hop questions. Your task is to craft sophisticated,
↪  moderately challenging questions that inherently require careful, integrative
↪  reasoning over multiple chunks of textual information. Aim to provoke thoughtful
↪  reflection, nuanced understanding, and synthesis, particularly when the provided
↪  text allows for it.

## Input Structure

Your input will consist of these components:

<additional_instructions>
[Specific guidelines, preferences, or constraints influencing question generation.]
</additional_instructions>

<title>
[Document title]
</title>

<document_summary>
[A concise summary providing context and thematic overview.]
</document_summary>

<text_chunks>
<text_chunk_0>
[First text segment]
</text_chunk_0>
<text_chunk_1>
[Second text segment]
</text_chunk_1>
[Additional text segments as necessary]
</text_chunks>
```

```
## Primary Objective

Generate a thoughtful, educationally meaningful set of multi-hop question-answer pairs.
↪  Questions should ideally integrate concepts across multiple text chunks, challenging
↪  learners moderately and encouraging critical thinking and deeper understanding.

### Context Fields:
- `<title>`: Document context
- `<document_summary>`: Broad contextual summary for orientation
- `<text_chunks>`: Source material to form integrative multi-hop questions
- `<additional_instructions>`: Specific instructions guiding the complexity and depth of
↪  questions

## Analysis Phase

Perform careful analysis within `<document_analysis>` XML tags:

1. **In-depth Text Analysis**
   - Thoughtfully read each text chunk.
   - Identify key themes, nuanced details, and subtle connections.
   - Highlight opportunities for insightful synthesis across multiple chunks.

2. **Reasoning Path Construction**
   - Construct potential pathways of multi-hop reasoning by connecting ideas, details, or
   ↪  implications found across text chunks.

3. **Complexity Calibration**
   - Rate difficulty thoughtfully on a scale of 1-10, moderately challenging learners
   ↪  according to provided additional instructions.

4. **Strategic Question Selection**
   - Choose questions that naturally emerge from the depth and complexity of the content
   ↪  provided, prioritizing integrative reasoning and genuine curiosity.

## Question Generation Guidelines

### Question Characteristics
- **Multi-Hop Integration**: Questions should naturally require integration across
↪  multiple chunks, demonstrating clear interconnected reasoning.
- **Thoughtfulness & Complexity**: Construct questions that stimulate critical thinking,
↪  reflection, or moderate challenge appropriate to the content.
- **Clarity & Precision**: Ensure each question and answer clearly and concisely
↪  communicates intent without ambiguity.
- **Educational Relevance**: Ensure each question has clear pedagogical purpose,
↪  enhancing understanding or critical reflection.
- **Authentic Language**: Use engaging, conversational language reflecting genuine human
↪  curiosity and inquiry.

### Suggested Question Types
(Use naturally, as fitting to the content complexity)
- Analytical
- Application-based
- Clarification
```

~~~
- Counterfactual
- Conceptual
- True-False
- Factual
- Open-ended
- False-premise
- Edge-case


## **Filtering Irrelevant Content**:
  - **Ignore completely** any irrelevant, redundant, promotional, or unrelated content, including headers, footers, navigation links, promotional materials, ads, or extraneous hyperlinks frequently found in web extracts.
  - **Disregard entirely** chunks composed solely of such irrelevant content. Do **not** generate questions from these chunks.
  - When partially relevant content is mixed with irrelevant material within the same chunk, carefully extract only the meaningful, educationally relevant portions for your integrative analysis.

- **Evaluating Chunk Quality**:
  - If, upon careful analysis, a chunk does not provide sufficient meaningful context or substantial educational relevance, explicitly note this in the `<document_analysis>` section and refrain from generating questions based on it.

- **Prioritizing Quality and Relevance**:
  - Always prioritize the quality, clarity, and educational integrity of generated questions. Do not force questions from unsuitable content.


## Output Structure

Present output as JSON objects conforming strictly to the following Pydantic model within `<output_json>` XML tags:

```python
class QuestionAnswerPair(BaseModel):
    thought_process: str # Explanation of integrative reasoning and rationale
    question_type: Literal["analytical", "application-based", "clarification",
                           "counterfactual", "conceptual", "true-false",
                           "factual", "open-ended", "false-premise", "edge-case"]
    question: str
    answer: str
    estimated_difficulty: int  # 1-10, moderately challenging as per additional instructions
    citations: List[str]  # Exact supporting quotes from text_chunks
```

## Output Format

First, thoroughly conduct your analysis within `<document_analysis>` XML tags. Then, provide your synthesized question-answer pairs as valid JSON within `<output_json>` tags.

## Important Notes
~~~

```
- Prioritize depth and thoughtfulness in your reasoning paths.
- Allow natural complexity to guide question formulation, aiming for moderate challenge.
- Precisely cite verbatim excerpts from text chunks.
- Clearly communicate your thought process for integrative reasoning.
- Adhere strictly to JSON formatting and Pydantic validation requirements.
- Generate questions that genuinely inspire deeper reflection or meaningful exploration
↪  of the provided content.
- When generating questions, NEVER include phrases like 'as per the text,' 'according to
↪  the document,' or any similar explicit references. Questions should inherently
↪  integrate content naturally and stand independently without explicit references to
↪  the source material
```

H.4 Judge System Prompt

```
You will be provided with the summary of a document, a piece of text, a question
↪  generated from that text, and the correct or "gold" answer to the question.
↪  Additionally, you will receive two answers: Answer A and Answer B. Your task is to
↪  determine which of these answers is closer to the gold answer by assessing the
↪  overlap of key points between the ground truth and the two given answers.

# Steps

1. **Document Understanding**:
   - Analyze the provided document summary to grasp the context and main themes.

2. **Chunk Understanding**:
   - Examine the provided text (chunk) to understand its content.

3. **Question Understanding**:
   - Interpret the given question to fully comprehend what is being asked.

4. **Ground Truth Answer Understanding**:
   - Understand the provided ground truth answer, identifying its key points.

5. **Answer A Understanding**:
   - Analyze Answer A, identifying key points and assessing accuracy and factuality.

6. **Answer B Understanding**:
   - Examine Answer B, identifying key points and assessing accuracy and factuality.

7. **Similarity Comparison**:
   - Compare Answer A and the ground truth answer, noting similarities in key points.
   - Compare Answer B and the ground truth answer, noting similarities in key points.

8. **Final Similarity Analysis**:
   - Evaluate both answers based on the similarities identified and determine which is
   ↪  closer to the ground truth in terms of key points and factuality.

# Output Format

- Provide your final evaluation of which answer is closer to the ground truth within
↪  `<final_answer>` XML tags.
```

~~~
- Include a detailed analysis for each part within the designated XML tags: `<document_understanding>`, `<chunk_understanding>`, `<question_understanding>`, `<ground_truth_answer_understanding>`, `<answer_a_understanding>`, `<answer_b_understanding>`, `<similarity_comparison_answer_a>`, `<similarity_comparison_answer_b>`, and `<final_similarity_analysis>`.

# Examples

**Input**:
```xml
<document_summary>
[Summary]
</document_summary>

<piece_of_text>
[Text]
</piece_of_text>

<question>
[Question]
</question>

<gold_answer>
[Gold Answer]
</gold_answer>

<answer_a>
[Answer A]
</answer_a>

<answer_b>
[Answer B]
</answer_b>
```
**Output**:
```xml

<document_understanding>
Understanding of the summary including key themes
</document_understanding>

<chunk_understanding>
Analysis of the piece of text
</chunk_understanding>

<question_understanding>
Comprehension of the question being asked
</question_understanding>

<ground_truth_answer_understanding>
Key points from the gold answer
</ground_truth_answer_understanding>

<answer_a_understanding>
~~~

~~~
Key points and accuracy of Answer A
</answer_a_understanding>

<answer_b_understanding>
Key points and accuracy of Answer B
</answer_b_understanding>

<similarity_comparison_answer_a>
Comparison notes between Answer A and the gold answer
</similarity_comparison_answer_a>

<similarity_comparison_answer_b>
Comparison notes between Answer B and the gold answer
</similarity_comparison_answer_b>

<final_similarity_analysis>
Overall analysis determining the closer answer
</final_similarity_analysis>

<final_answer>
Answer X (where X is the option you pick)
</final_answer>
```

# Notes

- Always focus on key points and factual correctness as per the ground truth.
- Avoid any biases and rely solely on the evidence presented.
- Enclose all evaluations and analyses in the specified XML tags for clarity and
↪  structure.
~~~

I Question Validity

I.1 Valid Question Examples

I.1.1 Example 1

```
# Question Details
## Source Information

iraqi immigrant hailed as hero for preventing armed robbery at ypsilanti juice shop
↪  ypsilanti, mich. (wxyz) — vara juice in ypsilanti nearly became the victim of an
↪  armed robbery this past friday. caught on camera, the suspect had no clue that his
↪  attempt to make quick cash would come to a hard stop, all thanks to a hero who was
↪  next door. thirty-five-year-old ali hadma owns a hookah place called cups on a
↪  mission, located next to vara juice on washtenaw ave. **"3 years,"** said ali when
↪  asked how long he's owned the shop. ali pins the suspect against the counter. a
↪  struggle to control the firearm begins. ali disarms the suspect. and eventually takes
↪  him down. "have you got any tactical or self-defense training? " i asked. "no. i just
↪  go to the gym 6 days a week," said ali. once ali got the cash back, he let go of the
↪  suspect, who can be seen walking away in the security footage. all the girls he
↪  treats like his sisters,"** said sadam badani, the owner of the vara juice location.
↪  badani tells me mariam is doing okay, but her parents will only allow mariam to
↪  resume work if her hero, ali, is around. "i don't care about the money, about
↪  anything else. as long as nobody got hurt," said sadam. "whenever ali need me, i'll
↪  be there," said sadam.

## Question

In what ways have Ali's actions during the robbery influenced the community's perception
↪  of him and their sense of security?

## Answer

Ali's actions during the robbery have made him a local hero and gained him widespread
↪  appreciation. The community, including the juice shop owner and employees, deeply
↪  appreciates his bravery and quick thinking. This has led to a stronger sense of
↪  security, with the juice shop owner stating that Mariam can only resume work if Ali
↪  is around.

## Citations

[All the girls he treats like his sisters," said Sadam Badani, the owner of the Vara
↪  Juice location.,"Whenever Ali need me, I'll be there," said Sadam.]

# Human Evaluation

## Determination

valid

## Reasoning

-
```

```
# Generation Details

## Model

mistralai/Mistral-Large-Instruct-2411

## Question Category

open-ended

## Kind

multi_hop

## Estimated Difficulty

6/10
```

I.1.2 *Example 2*

```
# Question Details
## Source Information

(truncated)...   (pn12-36) christopher landau (cal. no. 41) (pn12-25) ordered, that
↪  following the conclusion of morning business on monday, march 24, 2025, the senate
↪  proceed to executive session and resume consideration of the nomination of john
↪  phelan, of florida, to be secretary of the navy. (mar. 14, 2025. ) michael kratsios
↪  (cal. no. 38) (pn13-8) jayanta bhattacharya (cal. no. 44) (pn12-2) martin makary
↪  (cal. no. 45) (pn12-28) james bishop (cal. no. 39) (pn12-3) aaron reitz (cal. no. 48)
↪  (pn12-37) ordered, that on tuesday, march 25, 2025, the cloture motions on the
↪  following nominations ripen: michael kratsios, of south carolina, to be director of
↪  the office of science and technology policy; jayanta bhattacharya, of california, to
↪  be director of the national institutes of health; martin makary, of virginia, to be
↪  commissioner of food and drugs, department of health and human services; james
↪  bishop, of north carolina, to be deputy director of the office of management and
↪  budget; and aaron reitz, of texas, to be an assistant attorney general. * 33 25-32
↪  jonathan mckernan, of tennessee, to be mar 06, 2025 reported by mr. director, bureau
↪  of consumer financial protection for a term of five years, vice rohit chopra. scott
↪  sc, committee on banking, housing, and urban affairs, without printed report.
↪  department of defense * 36 12-36 john phelan, of florida, to be secretary of the mar
↪  11, 2025 reported by mr. navy, vice carlos del toro, resigned. wicker, committee on
↪  armed services, without printed report. mar 12, 2025 reported by mr. risch, committee
↪  on foreign relations, without printed report. department of veterans affairs * 43
↪  13-9 paul lawrence, of virginia, to be deputy mar 12, 2025 reported by mr. secretary
↪  of veterans affairs, vice tanya j. bradsher, resigned. moran, committee on veterans'
↪  affairs, without printed report. * signifies nominee’s commitment to respond to
↪  requests to appear and testify before any duly constituted committee of the senate
   5 nominations calendar no. mar 13, 2025 reported by mr. grassley, committee on the
↪  judiciary, without printed report. mar 13, 2025 reported by mr. grassley, committee
↪  on the judiciary, without printed report. mar 13, 2025 reported by mr. grassley,
↪  committee on the judiciary, without printed report. mar 13, 2025 reported by mrs.
↪  capito, committee on environment and public works, without printed report. * 50 25-53
↪  aaron szabo, of virginia, to be an assistant mar 13, 2025 reported by mrs
```

```
## Question

On what date are cloture motions for the nominations of Michael Kratsios, Jayanta
↪  Bhattacharya, Martin Makary, James Bishop, and Aaron Reitz set to ripen, and what are
↪  their respective positions?

## Answer

The cloture motions for Michael Kratsios (Director of the Office of Science and
↪  Technology Policy), Jayanta Bhattacharya (Director of the National Institutes of
↪  Health), Martin Makary (Commissioner of Food and Drugs, Department of Health and
↪  Human Services), James Bishop (Deputy Director of the Office of Management and
↪  Budget), and Aaron Reitz (Assistant Attorney General) are set to ripen on Tuesday,
↪  March 25, 2025.

## Citations

['Mar. 14, 2025. Ordered, That on Tuesday, March 25, 2025, the cloture motions on the
↪  following nominations ripen: Michael Kratsios, of South Carolina, to be Director of
↪  the Office of Science and Technology Policy; Jayanta Bhattacharya, of California, to
↪  be Director of the National Institutes of Health; Martin Makary, of Virginia, to be
↪  Commissioner of Food and Drugs, Department of Health and Human Services; James
↪  Bishop, of North Carolina, to be Deputy Director of the Office of Management and
↪  Budget; and Aaron Reitz, of Texas, to be an Assistant Attorney General.']

# Human Evaluation

## Determination

Valid

## Reasoning

question, answer and citations are correct


# Generation Details

## Model

Qwen/Qwen2.5-14B-Instruct

## Question Category

factual

## Kind

multi-hop

## Estimated Difficulty
```

```
7/10
```

I.1.3 Example 3

```
# Question Details
## Source Information

org. following the selection process, all applications will be destroyed. questions?
↪ please send an email to: scholarships@agbell. org response time may be up to three
↪ business days, so please plan accordingly when submitting your questions. george h.
↪ nofer scholarship for law 2025 please type or print clearly and review for accuracy;
↪ illegible or incorrect information will delay review and could disqualify your
↪ application. identifying information name (first, mi, last):
↪ __________________________________________________________________ date of birth
↪ (mm/dd/yyyy) ___________ gender: male female complete mailing address:
↪ ______________________________________________________________ email address:
↪ ________________________________________________________________________
↪ communication throughout the process will be via email. if you do not provide an
↪ email address, if it is written incorrectly, or if we are not able to read it, we
↪ will not be able to communicate with you. telephone number: _______________________
↪ hearing health history age when hearing loss was diagnosed: __________ *if you do not
↪ have a cochlear implant and your pta is below 60db in your better-hearing ear, you do
↪ not qualify.
## Question

How will applicants be contacted regarding updates or decisions about their scholarship
↪ application?

## Answer

Communication throughout the process will be via email.

## Citations

['Communication throughout the process will be via email.']

# Human Evaluation

## Determination

valid

## Reasoning

-

# Generation Details

## Model

google/gemini-2.0-flash-001
```

```
## Question Category

factual

## Kind

single shot

## Estimated Difficulty

6/10
```

I.2 Invalid Question Examples

I.2.1 Example 1

```
# Question Details
## Source Information

according to the committee, out of the 40 who signed up to deliver testimony, 38 were
↪  opposed to the bill. one of the biggest points of concern was in relation to the
↪  staff-to-child ratio being lowered. as the bill is currently written, a single person
↪  would be allowed to run a large daycare facility overseeing many children. those in
↪  support of the bill believe that won't be a problem and instead, will open up more
↪  opportunities for idahoans to start daycare businesses of their own. chris cargill
↪  with mountain states policy center explained, "we believe that if the legislation is
↪  passed, we will see an increase in new and quality childcare providers in idaho. "
↪  mark kirby of soda springs, idaho, told the tragic story of how his 11-week-old
↪  nephew lost his life after being dropped off at a daycare. "later that afternoon, she
↪  got a call stating that something was very wrong. upon arriving there, she was
↪  escorted in and learned that her son had passed away from asphyxiation," said a
↪  teary-eyed kirby. kirby explained that an investigation found the death was due to
↪  overwhelming child-to-staff ratios and negligence of supervision while the baby was
↪  napping. the committee passed the bill five to four. "we are clearly disappointed
↪  with the outcome," said kirby. "i feel more disappointed about losing this bill than
↪  any other in the session. we have worked on this issue for decades to ensure that we
↪  are promoting business practices and children's safety," added senator melissa
↪  wintrow. the bill will now head to the senate floor. if a majority of state senators
↪  vote to pass the legislation, it will head to the governor's desk, where it will
↪  either be vetoed or signed into law. this is a developing story, and we will continue
↪  to update it as more information becomes available. ## more news in downtown boise we
↪  cover stories making an impact in downtown boise. this is your home to stay on top of
↪  what is changing in downtown boise and why it matters to you and your family. we want
↪  to hear from you! and tell us what we should be covering in your neighborhood.

## Question

How did the death of a child at a daycare facility through asphyxiation influence the
↪  testimony given during the committee hearing on House Bill 243?

## Answer
```

```
The tragic death caused by asphyxiation due to high child-to-staff ratios was a pivotal
↪  moment that resonated emotionally with the committee members and played a
↪  significant role in bolstering the opposition to the bill, underscoring safety
↪  concerns related to its proposed deregulation.

## Citations

[ "'Later that afternoon, she got a call stating that something was very wrong. Upon
↪  arriving there, she was escorted in and learned that her son had passed away from
↪  asphyxiation,' said a teary-eyed Kirby." ]

# Human Evaluation

## Determination

Invalid

## Reasoning

the citations don't support the answer. it is also factually inaccurate according to the
↪  text

# Generation Details

## Model

microsoft/Phi-4-mini-instruct

## Question Category

Factual

## Kind

multi_hop

## Estimated Difficulty

6
```

I.2.2 Example 2

```
# Question Details
## Source Information
```

```
(truncated)... and trustworthiness. to prepare, many are increasing their cyber budgets
↪  with a particular focus on data protection and trust. by strategically investing in
↪  these areas, companies are not only building resilience but positioning themselves
↪  positively to their customers. ### investing in what matters most: cloud and data
↪  trust go hand-in-hand over the next 12 months, organisations are prioritising data
↪  protection/trust and cloud security above other cyber investments. they understand
↪  that securing sensitive information is vital to maintaining stakeholder trust and
↪  brand integrity. g. , reducing the time to recover mission-critical data or patching
↪  a system). - - determine the business value of data protection and cloud security to
↪  gain stakeholder trust and make more informed cybersecurity investment decisions. -
↪  - collaborate with tech, security and finance executives to pinpoint the most
↪  essential data security and integrity priorities to guide the information and cloud
↪  security investment strategy. confirming data quality and readiness is necessary to
↪  increase security investments. ## is your cyber strategy and leadership driving real
↪  resilience? from lagging resilience efforts to gaps in ciso involvement in strategic
↪  decisions, there are clear areas where strategic alignment is needed. to get there,
↪  organisations should emulate the leading cybersecurity practices of their top
↪  performing peers. they should also move beyond addressing known threats and implement
↪  an agile, secure-by-design approach to business, one that strives to build trust and
↪  lasting resilience. ### partial implementation isn’t enough despite mounting
↪  concerns about cyber risk, most businesses are struggling to fully implement cyber
↪  resilience across core practices. a review of 12 resilience actions across people,
↪  processes and technology indicates that 42% or fewer of executives believe their
↪  organisations have fully implemented any one of those actions. more concerning, only
↪  2% say all 12 resilience actions have been implemented across their organisation.
↪  this leaves a glaring vulnerability — without enterprise-wide resilience, companies
↪  remain dangerously exposed to the increasing threats that could compromise the
↪  entire operation. ### elevating the ciso: aligning strategy with security many
↪  organisations miss critical opportunities by not fully involving their cisos in key
↪  initiatives. fewer than half of executives tell us that their cisos are largely
↪  involved in strategic planning for cyber investments, board reporting and overseeing
↪  tech deployments. this gap leaves organisations vulnerable to misaligned strategies
↪  and weaker security postures. ## bridging the gaps to cyber resilience: the c-suite
↪  playbook ### sign up to get the full playbook and access more of the latest findings
↪  for 2025. ### about the survey the 2025 global digital trust insights is a survey of
↪  4,042 business and technology leaders conducted in the may through july 2024 period.
↪  - a quarter of leaders are from large companies with $5 billion or more in revenues.
↪  respondents operate in a range of industries, including industrials and services
↪  (21%), tech, media, telecom (20%), financial services (19%), retail and consumer
↪  markets (17%), energy, utilities, and resources (11%), health (7%) and government
↪  and public services (4%). - respondents are based in 77 countries. the regional
↪  breakdown is western europe (30%), north america (25%), asia pacific (18%), latin
↪  america (12%), central and eastern europe (6%), africa (5%) and middle east (3%).

## Question

What are the critical factors that organizations should prioritize to achieve true cyber
↪  resilience, and how do they interconnect?

## Answer
```

```
Critical factors include CISO involvement in strategic planning, adopting a
↪  secure-by-design approach, and investing in data protection and cloud security. These
↪  elements interconnect by ensuring strategic alignment, proactive security measures,
↪  and building stakeholder trust, which collectively enhance organizational resilience.

## Citations

['While the rapid advancement of generative AI (GenAI) is ushering in new opportunities
↪  across industries, it also presents cybersecurity risks.',
'To prepare, many are increasing their cyber budgets with a particular focus on data
↪  protection and trust.',
'They should also move beyond addressing known threats and implement an agile,
↪  secure-by-design approach to business, one that strives to build trust and lasting
↪  resilience.']

# Human Evaluation

## Determination

Invalid

## Reasoning

answer looks to be correct, but the citations are wrong


# Generation Details

## Model

DeepSeek-R1-Distill-Qwen-14B

## Question Category

analytical

## Kind

multi-hop

## Estimated Difficulty

8/10
```

I.2.3 Example 3

```
# Question Details
## Source Information
```

```
"it's nice to have the memories, but i wish we could make more," said jesse collins, alexis' uncle. **investigative findings:** - **david plagmann, 36**: responsible for alexis' death. fired by the shelby county sheriff's office. - **marianne and jesse collins**: alexis' aunt and uncle. - **jake collins**: alexis' father. alexis' family describes her as having a soft and loving heart, always step up to care for others, including her four children. she was always positive and believed things would improve, even if it was hard.
## Question

How many children did Alexis Martin-Collins have?

## Answer

Four children

## Citations

[She was always positive and believed things would improve, even if it was hard.]

# Human Evaluation

## Determination

Invalid

## Reasoning

answer is correct and factual, and it makes a valid citation, but the citation points to wrong part of text


# Generation Details

## Model

claude-3-5-haiku-20241022

## Question Category

factual

## Kind

single shot

## Estimated Difficulty

2/10
```