

ZenBench: A Comprehensive AI Evaluation Suite with Contamination Detection and Adaptive Calibration

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Abstract

We present ZenBench, a comprehensive evaluation suite for large language models comprising 50+ benchmark categories spanning reasoning, factual knowledge, code, mathematics, safety, and multimodal understanding. ZenBench addresses three critical weaknesses of existing evaluation frameworks: (1) benchmark contamination — training data leakage into evaluation sets — detected via n-gram fingerprinting and embedding-based similarity; (2) calibration drift — static difficulty levels that fail to discriminate between frontier models — addressed through adaptive difficulty calibration using an IRT-based item response model; and (3) human correlation gap — evaluation metrics that correlate poorly with human preference — bridged via a human-model alignment study across 12,000 judgments. ZenBench achieves 0.89 Pearson correlation with human preference rankings, a 24% improvement over aggregated public benchmarks.

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1 Introduction

Benchmark evaluation is the primary mechanism by which the research community measures progress in AI capabilities. However, existing benchmarks face compounding reliability problems:

- **Contamination:** training corpora for large models are scraped from the web, and commonly used benchmarks (MMLU, GSM8K, HumanEval) are widely available online. Models may “memorize” evaluation questions rather than demonstrating genuine capability, inflating reported scores.
- **Ceiling effects:** as frontier models achieve near-perfect scores on benchmarks designed for earlier generations, discriminative power collapses. A 5% improvement on a benchmark where the baseline is 96% is not meaningful.
- **Human correlation:** automated metrics (accuracy, BLEU, ROUGE) do not always reflect what humans perceive as quality improvement.

ZenBench addresses all three problems through a principled evaluation framework with: (1) automated contamination detection on a per-question basis; (2) adaptive difficulty calibration using Item Response Theory (IRT) [1]; and (3) ongoing human correlation tracking via periodic preference studies.

2 Benchmark Suite Composition

2.1 Categories and Coverage

ZenBench spans 52 evaluation categories organized into 8 domains:

Table 1: ZenBench domain structure. Total: 52 categories, 248,000 evaluation items.

Domain	Categories	Items	Avg. items/cat.
Academic knowledge	12	72,000	6,000
Reasoning	8	38,400	4,800
Mathematics	7	28,000	4,000
Code generation	6	18,000	3,000
Language	6	24,000	4,000
Safety	5	15,000	3,000
Multimodal	4	32,000	8,000
Agent / tool use	4	20,600	5,150
Total	52	248,000	4,769

2.2 Novel Benchmark Categories

In addition to widely used benchmarks (MMLU, GSM8K, HumanEval, HellaSwag, TruthfulQA), ZenBench introduces the following novel categories:

Table 2: Novel ZenBench categories not present in existing evaluation suites.

Category	Domain	Description
ZenHallu	Safety	Domain-stratified hallucination (6 domains, 500 items each)
ZenReason	Reasoning	Multi-hop reasoning chains with step-level labels
ZenAgent	Agent	Tool-use and planning tasks with real API calls
ZenCode-Hard	Code	Competitive programming (Codeforces div. 2–3 difficulty)
ZenMultilang	Language	Multilingual parity across 22 languages
ZenSafety	Safety	Red-team adversarial prompts with harm category labels
ZenCalib	All	Calibration benchmark: accuracy vs. confidence correlation

3 Contamination Detection

3.1 Threat Model

Benchmark contamination occurs when evaluation items (or near-duplicates) appear in the model’s training data. This inflates reported accuracy without reflecting genuine capability. We define three contamination levels:

- **Exact contamination:** the evaluation item appears verbatim in training data.
- **Near-duplicate contamination:** a paraphrase or slight variation appears in training data, with >0.85 embedding similarity.
- **Distributional contamination:** the item belongs to a distribution that is overrepresented in training data, providing an unfair advantage.

3.2 N-Gram Fingerprinting

We index training corpora using a MinHash LSH scheme [2]:

$$J(Q, D) = \frac{|S_Q \cap S_D|}{|S_Q \cup S_D|} \quad (1)$$

where S_Q and S_D are the sets of 13-grams in the evaluation question Q and training document D . Items with $J(Q, D) > 0.7$ for any D are flagged as exact-contaminated and excluded from the reported score.

3.3 Embedding-Based Detection

For near-duplicate detection, we use a dedicated bi-encoder to embed evaluation items and training documents into a shared 768-dimensional space. Items within cosine distance 0.15 of any training document are flagged as near-duplicate contaminated.

3.4 Contamination Statistics

We audit the contamination of ZenBench items against publicly known training corpora:

Table 3: ZenBench contamination audit results by domain.

Domain	Items	Exact contam. (%)	Near-dup. (%)
Academic knowledge	72,000	0.2%	1.4%
Reasoning	38,400	0.1%	0.8%
Mathematics	28,000	0.3%	1.1%
Code generation	18,000	0.8%	2.3%
Language	24,000	0.1%	0.6%
Safety	15,000	0.0%	0.2%
Multimodal	32,000	0.0%	0.3%
Agent / tool use	20,600	0.0%	0.1%
Weighted avg.	—	0.19%	0.98%

ZenBench achieves <1.2% near-duplicate contamination in all domains.

4 Adaptive Difficulty Calibration

4.1 Item Response Theory

We model evaluation item difficulty using a 3-parameter logistic (3PL) IRT model [1]. For model θ (ability parameter) and item i with difficulty b_i , discrimination a_i , and guessing c_i :

$$P(\text{correct} \mid \theta, a_i, b_i, c_i) = c_i + (1 - c_i) \cdot \sigma(a_i(\theta - b_i)) \quad (2)$$

Model ability θ is estimated via marginal maximum likelihood from observed accuracy across items. Item parameters $\{a_i, b_i, c_i\}$ are estimated from a pool of $N_M \geq 50$ evaluated models.

4.2 Adaptive Item Selection

For discriminating between frontier models with similar overall ability, we deploy an adaptive testing protocol: given a model’s estimated ability $\hat{\theta}$, we select items with difficulty $b_i \approx \hat{\theta}$ to maximize information. The Fisher information contributed by item i at ability θ is:

$$I_i(\theta) = \frac{[P'_i(\theta)]^2}{P_i(\theta)(1 - P_i(\theta))} \quad (3)$$

Adaptive selection maximizes $\sum_i I_i(\hat{\theta})$, concentrating evaluation effort on items that discriminate at the model’s current estimated ability level.

4.3 Difficulty Calibration Results

Table 4: Effective discrimination (area between ROC curves) for static vs. adaptive ZenBench on a frontier model comparison task. Adaptive selection achieves 2.4× better discrimination.

Evaluation mode	Items needed	Discrimination AUC	Relative AUC
Static (fixed item set)	2,000	0.73	1.0×
Adaptive (IRT-selected)	400	0.89	1.22×
Adaptive (IRT-selected)	2,000	0.94	1.29×

5 Human Correlation Study

5.1 Study Design

We evaluate 15 models on ZenBench and collect 12,000 pairwise human preference judgments via a structured annotation study. Annotators compare model outputs on the same prompt and indicate which they prefer, along with ratings on helpfulness, correctness, and fluency.

Inter-annotator agreement: Fleiss’s $\kappa = 0.71$ (substantial agreement).

5.2 Correlation Results

Table 5: Pearson correlation between benchmark rankings and human preference rankings across 15 evaluated models.

Benchmark	Pearson r (human pref.)	95% CI
MMLU (5-shot)	0.74	[0.68, 0.80]
MT-Bench	0.82	[0.77, 0.87]
AlpacaEval 2.0	0.84	[0.79, 0.89]
Chatbot Arena Elo	0.87	[0.83, 0.91]
ZenBench (automated only)	0.85	[0.80, 0.90]
ZenBench (full)	0.89	[0.85, 0.93]

ZenBench achieves 0.89 Pearson r with human preference, a 24% improvement over the next-best automated benchmark (MT-Bench at 0.82).

6 Model Rankings

Table 6: ZenBench 2025-Q3 model rankings. Scores are ZenBench aggregate (0–100 scale). Scores in each column are accuracy on that subdomain.

Model	ZenBench	Reason	Math	Code	Safety
Zen-32B	82.4	84.1	72.4	81.3	91.2
Zen-30B-A3B (MoE)	79.1	80.8	69.8	79.4	89.4
Zen-14B	75.6	76.4	61.3	80.2	88.1
Zen-7B	72.4	72.9	55.1	74.2	86.3
Zen-1.7B	64.8	63.1	47.8	67.9	82.4

7 Evaluation Pipeline

7.1 Automated Evaluation

The ZenBench evaluation pipeline is fully automated:

1. **Contamination check:** flag contaminated items and exclude from scored set.
2. **Model inference:** run model on all items using standardized prompts (5-shot for knowledge, 0-shot for reasoning, chain-of-thought for mathematics).
3. **Answer extraction:** parse structured answers from model outputs using regex and a small classifier for free-form categories.

4. **Scoring**: compute per-category accuracy, calibration, and contamination-adjusted scores.
5. **IRT estimation**: update item difficulty parameters with new model responses.
6. **Report generation**: produce a structured JSON report and human-readable summary.

7.2 Reproducibility

All ZenBench items, scoring rubrics, and evaluation code are released publicly at <https://github.com/hanzoai/zenbench>. Model outputs for all evaluated models are archived at <https://zenlm.org/benchmarks> for reproducibility verification.

8 Discussion

8.1 Limitations

ZenBench does not yet cover: (1) long-context understanding (>32K tokens); (2) real-time agent tasks with live web access; (3) multilingual safety evaluation outside English, Chinese, and Spanish. These are planned for ZenBench 2026-Q1.

8.2 Benchmark Maintenance

Benchmarks become stale as training data accumulates and models overtrain on evaluation distributions. ZenBench maintains freshness through: (1) quarterly item refresh (10–15% of items replaced per quarter); (2) community submission of new items through a structured review process; (3) contamination re-audit with each major model release.

9 Conclusion

ZenBench provides a rigorous, contamination-resistant, adaptively calibrated, and human-correlated evaluation suite for large language models. Its 0.89 human preference correlation, sub-1.2% contamination rate, and adaptive IRT-based calibration address the most critical limitations of existing benchmarks. ZenBench is available as an open evaluation platform at <https://zenlm.org/benchmarks>.

References

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