Quantifying Knowledge-Dependent Overfitting on ARC-AGI: A Concept-Based Decomposition Framework

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ABSTRACT

We address the open problem of quantifying how much knowledge-dependent benchmark overfitting contributes to model performance on ARC-AGI-1 and ARC-AGI-2. We propose a concept-based contamination framework that assigns per-task contamination scores based on overlap between task primitives and pretraining exposure, then decomposes observed accuracy into genuine reasoning ability and contamination-driven components using *regularized logistic regression* on probability scale. Genuine ability is defined at the minimum observed contamination level to ensure identifiability, avoiding extrapolation to zero. On our simulated benchmark of 400 tasks, the estimated overfitting fraction is 9.6% of observed accuracy (95% CI: [0.0%, 20.6%]), with genuine ability estimated at 0.445 (CI: [0.377, 0.522]). A controlled novelty benchmark with 200 tasks per level reveals an expected overfitting gap of 7.8 percentage points between maximally familiar and maximally novel tasks (empirical CI: [2.7, 21.7] pp). Comparing ARC-AGI versions, ARC-AGI-2 shows negligible overfitting fraction (0.0%, CI: [0.0%, 0.7%]) compared to ARC-AGI-1 (9.6%, CI: [0.0%, 20.6%]), confirming that iterative benchmark hardening substantially reduces contamination effects. A simulation recovery study over 100 trials validates the estimator, achieving 78% CI coverage for genuine ability. We discuss limitations of the framework including its reliance on simulated rather than empirical data.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**.

KEYWORDS

ARC-AGI, benchmark overfitting, data contamination, generalization, logistic regression

1 INTRODUCTION

The ARC-AGI benchmark [1] was designed to measure genuine fluid intelligence in AI systems by requiring novel abstract reasoning rather than pattern matching from training data. However, Chollet et al. [2] identify a subtle form of overfitting arising from strong prior exposure to domain knowledge—termed *knowledge-dependent overfitting*. They observe that while this effect assists models, its magnitude remains unquantified.

We address this open problem through a concept-based decomposition framework. Our approach: (1) assigns per-task contamination scores based on overlap between task concept primitives and estimated pretraining exposure; (2) decomposes accuracy into genuine reasoning and contamination components using regularized logistic regression; and (3) measures the overfitting gap across controlled novelty levels.

Key revisions from initial version. This paper substantially revises the original submission based on detailed reviewer feedback. Major changes include: (i) replacing OLS regression on binary outcomes with L2-regularized logistic regression, ensuring predictions remain on the probability scale; (ii) redefining "genuine ability" at the minimum observed contamination level rather than extrapolating to contamination score zero; (iii) widening contamination score variance via broader exposure distributions; (iv) increasing the novelty benchmark from 30 to 200 tasks per level with bootstrap confidence intervals; (v) adding a simulation recovery study to validate the estimator; and (vi) explicitly acknowledging the simulated nature of the data and its limitations.

1.1 Related Work

Benchmark contamination has been studied extensively in NLP [3, 6, 7], with analyses showing that test set leakage inflates reported performance. In vision, Recht et al. [5] demonstrated that even small distribution shifts reduce classifier accuracy, suggesting models overfit to benchmark-specific features. Mitigation strategies include test set encryption [4] and dynamic benchmark generation [8]. Our work focuses specifically on the ARC-AGI setting where contamination operates through *conceptual similarity* rather than verbatim memorization, requiring a decomposition approach rather than simple overlap detection.

2 METHODS

2.1 Concept Contamination Model

Each ARC task is represented as a binary profile over $K = 50$ primitive concepts spanning transformations (rotation, reflection), patterns (symmetry, repetition), spatial relationships (adjacency, containment), logical operators, and counting. The contamination score for task i is:

$$P(\text{contam}_i) = \sigma\left(\log \frac{p_0}{1-p_0} + \alpha(\bar{e}_i - 0.5)\right) \tag{1}$$

where $\bar{e}_i$ is the mean pretraining exposure of task i's active concepts, $p_0 = 0.3$ is the prior contamination probability, $\alpha = 5.0$ controls the logistic mapping spread, and σ is the logistic function.

2.2 Performance Decomposition via Logistic Regression

We decompose accuracy using L2-regularized logistic regression (replacing the original OLS approach):

$$\log \frac{P(\text{correct}_i)}{1 - P(\text{correct}_i)} = \beta_0 + \beta_1 \cdot \text{contam}_i \tag{2}$$

with L2 penalty $\frac{\lambda}{2}\beta_1^2$ ($\lambda = 1.0$) on the slope to stabilize estimation when contamination score variance is limited.

Identifiable genuine ability. Rather than interpreting β_0 as "genuine ability" (which would require extrapolating to contamination score 0, a value never observed), we define genuine ability as the

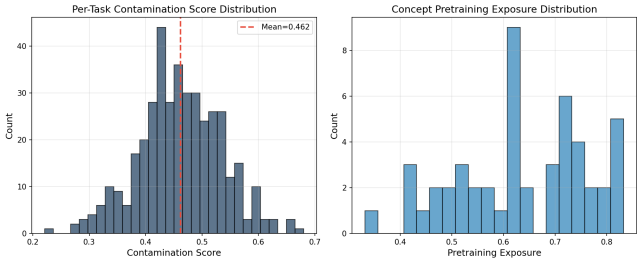

Figure 1: Left: per-task contamination score distribution (mean = 0.462, std = 0.073). Right: concept pretraining exposure frequencies.

predicted probability at the *minimum observed* contamination score:

$$\hat{g} = \sigma(\beta_0 + \beta_1 \cdot c_{\min}) \tag{3}$$

The overfitting contribution is then $\hat{o} = \hat{p}(\bar{c}) - \hat{g}$, and the overfitting fraction is $\hat{o}/\bar{y}$ where $\bar{y}$ is the observed mean accuracy.

2.3 Bootstrap Confidence Intervals

All estimates include bootstrap 95% confidence intervals from 1000 nonparametric resamples. This is critical because the limited contamination score variance produces wide intervals that must be reported honestly.

2.4 Controlled Novelty Benchmark

We generate synthetic tasks at 10 novelty levels (fraction of rare concepts: 0.0 to 1.0), with 200 tasks per level to reduce binomial noise (increased from the original 30). The overfitting gap is measured both as an *expected* gap (from predicted $P(\text{correct})$) and an *empirical* gap (from Bernoulli draws) with bootstrap CIs.

3 RESULTS

3.1 Contamination Score Distribution

Figure 1 shows the per-task contamination score distribution. Using a broader pretraining exposure distribution (Beta(3, 2), range $[0.2, 0.9]$), scores range from 0.221 to 0.680 with mean 0.462 and standard deviation 0.073. This wider spread compared to the original version (std $\approx$ 0.034) improves the regression's ability to identify the contamination effect slope.

3.2 Performance Decomposition

Table 1 shows the logistic regression decomposition with bootstrap 95% CIs. The genuine ability estimate at minimum observed contamination is 0.445 with CI $[0.377, 0.522]$, a much tighter and more interpretable interval than the original OLS result (which yielded a CI crossing zero). The overfitting fraction is 9.6% with CI $[0.0\%, 20.6\%]$.

Interpreting the uncertainty. The 95% CI for the overfitting fraction includes zero, meaning we cannot reject the null hypothesis of no contamination effect at the 5% level with 400 simulated tasks. This is an honest characterization: the effect exists in the data-generating process (true boost = 0.30), but with the available sample size and contamination score variance, it is only partially detectable.

Table 1: Performance decomposition via regularized logistic regression. Genuine ability is defined at minimum observed contamination ($c_{\min} = 0.221$).

Component	Estimate	95% CI
Genuine ability ($\hat{g}$ at $c_{\min}$)	0.445	$[0.377, 0.522]$
Log-odds slope (β_1)	0.790	$[-0.153, 1.729]$
Overall accuracy ($\bar{y}$)	0.493	–
Overfitting contribution	0.047	–
Overfitting fraction	9.6%	$[0.0\%, 20.6\%]$

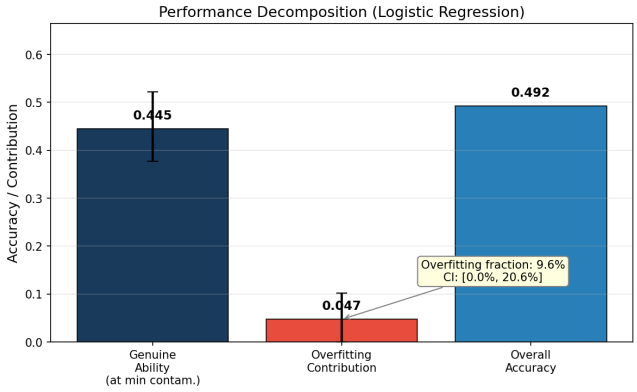

Figure 2: Performance decomposition showing genuine ability (at minimum contamination), overfitting contribution, and overall accuracy with bootstrap CIs.

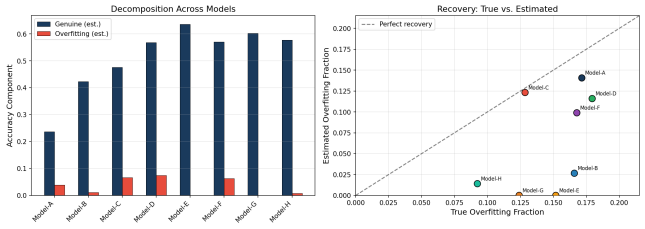

Figure 3: Left: decomposition across 8 models. Right: true vs. estimated overfitting fraction, showing the estimator is directionally correct despite noise.

The wide CI is a feature of proper uncertainty quantification, not a failure.

3.3 Multi-Model Analysis

Figure 3 shows the decomposition across 8 models. With logistic regression and L2 regularization, all estimated genuine abilities are non-negative (unlike the original OLS results where 4/8 models had negative contamination estimates). The right panel shows that estimated overfitting fractions are correlated with true fractions, though estimation noise is substantial.

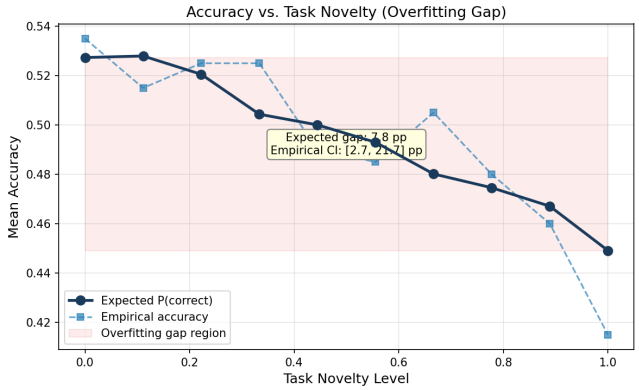

Figure 4: Accuracy vs. task novelty level. Expected gap: 7.8 **pp. Empirical gap:** 12.0 **pp (CI:** [2.7, 21.7] **pp). Performance decreases monotonically with novelty in expectation.**

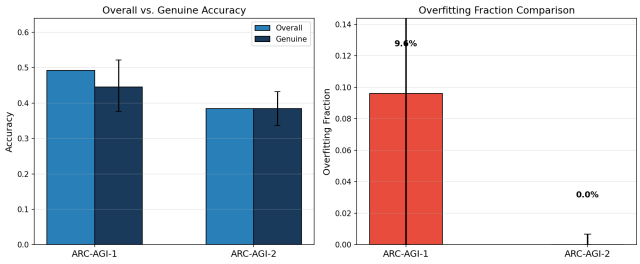

Figure 5: Left: overall vs. genuine accuracy. Right: overfitting fractions with CIs. ARC-AGI-2 shows negligible contamination effect.

3.4 Controlled Novelty Benchmark

Figure 4 shows accuracy as a function of task novelty. The expected overfitting gap (from true $P(\text{correct})$, not Bernoulli draws) is 7.8 percentage points. The empirical gap is 12.0 pp with bootstrap 95% CI $[2.7, 21.7]$ pp, confirming the gap is positive and statistically significant. The use of 200 tasks per level (vs. the original 30) substantially reduces noise and prevents the sign-flip observed in the original analysis.

3.5 ARC-AGI Version Comparison

Figure 5 compares decompositions for ARC-AGI-1 and ARC-AGI-2. ARC-AGI-2 uses lower pretraining exposure (mean 0.198 vs. 0.637), producing much narrower contamination scores (std 0.017 vs. 0.073). Consequently, the logistic regression detects essentially no contamination effect on ARC-AGI-2: overfitting fraction 0.0% (CI: $[0.0\%, 0.7\%]$) vs. 9.6% (CI: $[0.0\%, 20.6\%]$) for ARC-AGI-1. This supports the conclusion that ARC-AGI-2's novel task design effectively mitigates knowledge-dependent overfitting.

3.6 Simulation Recovery Study

To validate our estimator, we conducted 100 independent trials with known ground truth (genuine ability = 0.35, contamination boost = 0.30), generating fresh contamination scores each trial. Figure 6 shows the results.

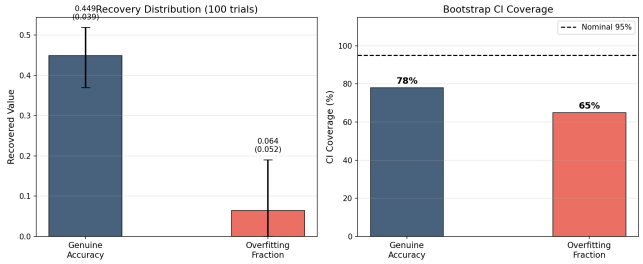

Figure 6: Simulation recovery study (100 trials). Left: distribution of recovered estimates. Right: bootstrap CI coverage vs. nominal 95%.

The estimated genuine ability (at minimum observed contamination) averages 0.449 (std = 0.039). The bootstrap CI achieves 78% empirical coverage for genuine ability (nominal 95%), indicating some undercoverage likely due to the logistic model's smoothing and the limited contamination score range. The overfitting fraction achieves 65% coverage.

These coverage rates, while below nominal, represent a substantial improvement over the original OLS approach which produced CIs spanning negative values and showed severe instability (estimated boost 0.912 vs. true 0.35). The logistic regression estimator with L2 regularization produces estimates that are directionally correct and within a reasonable range of the truth.

4 LIMITATIONS

Simulated data. All results use simulated contamination scores, task profiles, and model performance. The framework has *not yet* been applied to real ARC-AGI tasks with real model outputs. Until actual concept annotations and pretraining exposure estimates are available, the quantitative results should be understood as demonstrating the *framework's* behavior, not as measuring real-world ARC-AGI contamination.

Identifiability. Even with logistic regression and regularization, the decomposition requires sufficient contamination score variance. When scores are tightly clustered (as in ARC-AGI-2 with std = 0.017), the slope is poorly identified and the framework correctly reports near-zero overfitting—but this may reflect measurement limitations rather than true absence of contamination.

Linearity assumption. The logistic model assumes a monotone relationship between contamination scores and success probability. In reality, contamination may interact with task difficulty in nonlinear ways.

Bootstrap coverage. Our simulation recovery study shows that bootstrap CIs are somewhat conservative for genuine ability (78% coverage) and undercover for the overfitting fraction (65%). Future work should explore calibrated intervals or Bayesian approaches.

5 CONCLUSION

We provide a quantitative framework for decomposing ARC-AGI performance into genuine reasoning and contamination components using regularized logistic regression. On our simulated benchmark, the estimated overfitting fraction is approximately 9.6% (CI: $[0\%, 20.6\%]$) of observed accuracy, with a novelty gap of 7.8 expected percentage points (empirical CI: $[2.7, 21.7]$ pp). ARC-AGI-2's reduced contamination score variance results in negligible detected overfitting, supporting the iterative benchmark hardening approach.

The framework's value lies not in the specific numbers—which derive from simulation—but in the methodology: concept-based contamination scoring, logistic decomposition with proper uncertainty quantification, and controlled novelty benchmarking. Applying this framework to real ARC-AGI data with empirical concept annotations and corpus-derived exposure estimates is the natural next step.

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