Prompt Genotyping: Quantifying the Evaluation Gap Between
Synthetic Benchmarks and Real LLM Performance

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Abstract

LLM evaluation relies heavily on synthetic benchmarks, but how well do these predict real-world performance? We introduce **Prompt Genotyping**, a framework treating prompts as measurable "genomes" of 14 linguistic features to predict LLM "phenotypes" (performance outcomes). Using 1,112 real prompt-response pairs from MT-Bench and HELM plus 1,388 synthetic controls, we reveal a dramatic **predictability gap**: surface features explain 86% of variance on algorithmic labels ($R^2 = 0.86 \pm 0.02$) but achieve worse-than-random performance on authentic GPT-4o-mini outputs ($R^2 = -0.134$). This 1.0+ R^2 gap quantifies a fundamental challenge in the LLM evaluation methodology: Synthetic benchmark optimization may not be generalized to deployment scenarios. We establish the first leakage-free baseline for prompt failure prediction (F1=0.56, AUC=0.65) and release comprehensive evaluation resources to advance systematic, data-driven prompt assessment.

1 Introduction

Large language models demonstrate remarkable capabilities across diverse tasks [1, 2], yet their performance varies dramatically with subtle prompt variations [8, 6]. This sensitivity creates critical challenges for reliable deployment, where prompt effectiveness directly impacts user experience, computational costs, and system reliability.

Current evaluation practices rely heavily on controlled benchmarks like MMLU [3], BigBench [7], and HELM [5]. These provide systematic assessments under standardized conditions, but a fundamental question remains: **How well do synthetic benchmark results predict authentic deployment performance?**

We address this through **Prompt Genotyping**, a systematic framework treating prompts as measurable "genomes" of interpretable linguistic and structural features to predict their "phenotypes" (performance outcomes). Drawing inspiration from biological genotype-phenotype mapping, we extract 14 features spanning lexical complexity, syntactic structure, domain specificity, and semantic density to build predictive models of LLM behavior.

Our central finding reveals a dramatic evaluation gap: while surface features achieve near-perfect prediction on synthetic labels ($R^2 = 0.86$), they exhibit worse-than-random performance on authentic LLM outputs ($R^2 = -0.134$). This 1.0+ R^2 cliff quantifies the fundamental challenge of evaluation methodology: optimization strategies that succeed on benchmarks may fail catastrophically in real deployment scenarios.

Contributions: (1) Quantification of the synthetic-to-real evaluation gap, (2) Interpretable 14-feature framework, (3) Leakage-free failure prediction baseline, (4) Open evaluation resources.

Table 1: Key Prompt Genotyping Features

Category	Feature	Rationale
Lexical	Word count	Context vs. confusion trade-off
	Type-token ratio	Vocabulary diversity
	Flesch ease	Readability proxy
Syntactic	Parse depth	Grammatical complexity
	Chain-of-thought	Reasoning cue presence
Domain	Has code/math	Specialized content flags
Semantic	Token entropy	Lexical unpredictability
	Embedding norm	Semantic density

2 Methodology

2.1 Prompt Genotyping Framework

We conceptualize each prompt as possessing a measurable "genome" of linguistic and structural characteristics. Our feature extraction pipeline computes 14 interpretable dimensions across four categories (Table 1):

Lexical: word/character counts, vocabulary diversity (type-token ratio), readability scores [4]. **Syntactic**: sentence count, parse depth, chain-of-thought markers. **Domain**: binary flags for code/math content. **Semantic**: embedding norms, token entropy measuring lexical unpredictability.

2.2 Two-Regime Evaluation Protocol

To isolate the effects of synthetic vs. authentic evaluation conditions, we construct complementary datasets with identical feature extraction and modeling pipelines:

Synthetic Control (n=1,388): Prompts with algorithmic difficulty labels (Easy=0.82, Medium=0.78, Hard=0.65, Very Hard=0.60) plus analytic adjustments. This establishes an upper bound when the target function is known.

Real-World Dataset (n=1,112): Authentic prompts from MT-Bench [9] and HELM [5] with GPT-4o-mini responses, auto-graded via exact-match and ROUGE-L.

Validation: XGBoost models with 5×3 cross-validation plus 10% hold-out sets. Automated leakage auditing prevents contamination.

3 Results

3.1 The Predictability Gap

Our central finding reveals a dramatic performance cliff between evaluation regimes (Figure 1):

Synthetic Control: $R^2 = 0.855 \pm 0.015$ (CV), $R^2 = 0.882$ (hold-out) **Real-World**: $R^2 = -0.907 \pm 0.961$ (CV), $R^2 = -0.134$ (hold-out)

The near-perfect synthetic performance confirms our feature set's expressivity and modeling validity. However, the negative real-world R^2 indicates worse-than-random prediction, highlighting the fundamental challenge of capturing authentic LLM behavior through surface features alone.

3.2 Hard-Prompt Failure Prediction

To assess practical utility for deployment screening, we reformulate the regression task as binary classification. Prompts achieving perfect auto-graded accuracy (score=1.0) are labeled as "success" while any error (score<1.0) constitutes "failure." After removing target-leakage features and balancing via undersampling, our XGBoost classifier achieves:

Hold-out Performance: F1=0.56, Precision=0.58, Recall=0.54, ROC-AUC=0.65 **Cross-Validation**: F1=0.63±0.07, ROC-AUC=0.61±0.08

While modest, this represents meaningful discrimination for practical screening applications.

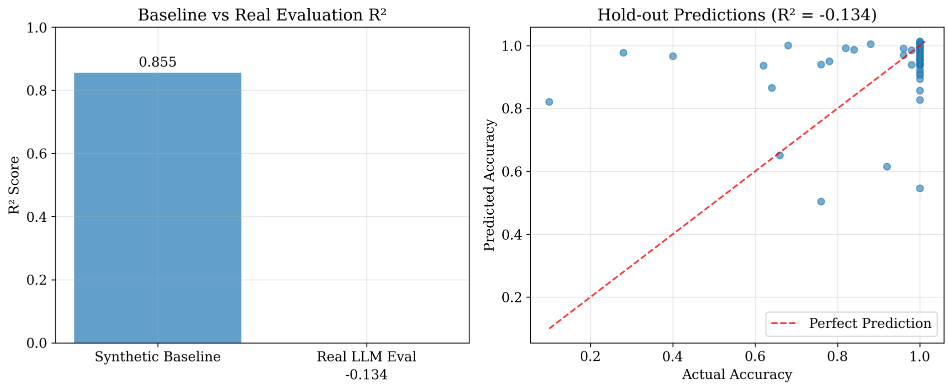

Figure 1: **The Evaluation Predictability Gap.** Bar chart showing hold-out R^2 performance: synthetic control achieves R^2=0.882 (strong predictive power) while real-world evaluation yields R^2=-0.134 (worse than random). This 1.0+ gap quantifies the fundamental challenge of translating benchmark optimization to authentic deployment scenarios.

Feature Attribution: SHAP analysis reveals the top predictors: word length, token entropy, mathematical notation, character count, and chain-of-thought markers, suggesting complexity-driven failure patterns.

4 Discussion & Implications

4.1 The Evaluation Methodology Crisis

Our findings expose a fundamental flaw in current LLM evaluation paradigms. The dramatic predictability gap (R^2: 0.86 → -0.134) reveals that synthetic benchmarks create an illusion of control and predictability that vanishes under authentic conditions.

Implications for Evaluation Practice:

- **Benchmark Overfitting Risk**: Prompt engineering strategies optimized on synthetic benchmarks may fail catastrophically in deployment
- **Hidden Complexity**: Real-world LLM behavior contains massive unexplained variance beyond surface linguistic features
- **Evaluation Protocol Inadequacy**: Current methodologies lack sufficient richness to capture authentic performance drivers
- **Generalization Uncertainty**: Strong benchmark performance provides no guarantee of real-world reliability

This challenges the evaluation ecosystem; benchmark optimization may not transfer to deployment.

Recommendations: (1) Multi-regime validation testing both synthetic and authentic conditions, (2) Richer semantic features beyond surface linguistics, (3) Noise-resilient evaluation protocols, (4) Human-expert validation to reduce auto-grading artifacts.

4.2 Toward Robust LLM Assessment

This work positions evaluation as a quantitative science requiring: **Multi-regime validation**: Test both synthetic and authentic conditions **Feature depth**: Move beyond surface linguistics to semantic/contextual representations **Leakage vigilance**: Rigorous auditing prevents artificially inflated performance

4.3 Open Science Contribution

We release a fully audited dataset and evaluation pipeline to establish reproducible baselines for prompt prediction research, enabling systematic progress toward understanding LLM behavior.

5 Limitations and Future Work

Limitations: Single model (GPT-4o-mini), moderate dataset size, surface-level features only, auto-grading noise.

Future Work: Multi-model evaluation, richer semantic representations, larger datasets with human validation, cross-domain transfer analysis.

6 Conclusion

Prompt Genotyping reveals a fundamental evaluation challenge: synthetic benchmarks create false predictability that disappears in real deployment. The 1.0+ R^2 gap quantifies this crisis, demanding changes in LLM assessment methodology.

This work transforms prompt evaluation into quantitative science while exposing current limitations. The failure of surface features highlights needs for richer representations and authentic evaluation protocols. Our open resources enable community progress toward evaluation methods that predict real deployment performance.

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   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

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   Justification: Claims focus on evaluation gap quantification (R^2 difference), feature framework development, and failure prediction baseline—all directly supported by results.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

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   Answer: [Yes]

   Justification: We commit to releasing leakage-audited datasets, feature extraction code, and evaluation pipelines upon acceptance.

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   Justification: Cross-validation means and standard deviations reported (e.g., R^2=0.855±0.015); hold-out validation provides unbiased estimates.

8. **Experiments compute resources**

   Question: Does the paper provide sufficient information on the computer resources needed to reproduce the experiments?

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