Behavioral Fingerprinting of Large Language Models via Prompt-Response Dynamics

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***Abstract*—Large Language Models (LLMs) are increasingly deployed across diverse applications, yet identifying and attributing models based solely on their outputs remains an open challenge. Existing model identification approaches rely on access to model internals, watermarking during training, or architectural metadata, all of which fail in black-box settings where only textual responses are observable. This paper introduces a novel behavioral fingerprinting framework that uniquely identifies LLMs using only their prompt-response dynamics. The work demonstrates that even when LLMs answer identical prompts correctly, they exhibit consistent, model-specific behavioral patterns such as sensitivity to negation, stability under contextual shifts, semantic drift under ambiguity, and response verbosity variations. Through controlled prompt perturbations across five categories (base, negation, ambiguity, contradiction, and context shift), behavioral features are extracted and fixed-length fingerprint vectors are constructed. Experiments on distilgpt2 and google/flan-t5-small achieve perfect classification accuracy (100 percent) using simple classifiers, with clear separability demonstrated through PCA and t-SNE visualizations. This work establishes behavioral fingerprinting as a practical, model-agnostic approach for LLM identification without requiring model access, opening new directions in AI forensics, model attribution, and trust verification.**

***Index Terms*—Large Language Models, Behavioral Fingerprinting, Model Attribution, Black-box Identification, Prompt Engineering, AI Forensics**

I. Introduction

The rapid proliferation of Large Language Models (LLMs) across commercial and research domains has created an urgent need for model identification and attribution mechanisms [1], [2]. Current deployment scenarios frequently involve black-box access where users interact with models through API endpoints without visibility into model architecture, training data, or internal parameters [3]. This opacity presents significant challenges for model verification, intellectual property protection, and accountability in AI systems [4].

Traditional approaches to model identification rely on watermarking techniques embedded during training [5], [6], inspection of model weights, or analysis of architectural characteristics. However, these methods fundamentally require privileged access to model internals, rendering them ineffective when only textual outputs are observable. The question emerges: can LLMs be reliably identified and distinguished using only their observable behavioral responses to carefully designed prompts?

This work addresses this challenge by introducing behavioral fingerprinting, a novel framework that exploits the insight that LLMs exhibit consistent, model-specific response patterns even when producing correct answers. The hypothesis underlying this approach is that response behaviors under controlled perturbations form stable behavioral signatures that can serve as unique model fingerprints.

A. Research Contributions

The key contributions of this work are:

- A model-agnostic behavioral fingerprinting framework requiring only black-box query access to LLMs
- A systematic prompt perturbation strategy across five behavioral dimensions: base responses, negation robustness, ambiguity handling, contradiction consistency, and contextual stability
- Novel feature engineering techniques that transform free-form textual responses into fixed-length numerical fingerprint vectors capturing semantic drift, length variance, and hedging patterns
- Empirical demonstration of perfect model classification (100 percent accuracy) on two contrasting LLMs using only behavioral features
- Comprehensive visualization analysis through PCA, t-SNE, and distance heatmaps establishing clear model separability

The remainder of this paper is organized as follows: Section II reviews related work, Section III presents the methodology, Section IV details experimental setup, Section V reports results, Section VI discusses implications and limitations, and Section VII concludes.

II. Related Work

A. Large Language Model Foundations

The transformer architecture introduced by Vaswani et al. [18] revolutionized natural language processing, enabling the development of large-scale language models. Brown et al. [1] demonstrated that sufficiently large models exhibit few-shot learning capabilities, while Radford et al. [3] showed their effectiveness as unsupervised multitask learners. Recent open-source efforts like LLaMA [2] have democratized access to powerful language models, making model attribution increasingly important.

B. Black-Box Model Analysis

Prior research has explored various techniques for analyzing neural networks without internal access. Tramèr et al. [7] demonstrated model extraction via prediction APIs, while Shokri et al. [8] introduced membership inference attacks against machine learning models. Jagielski et al. [9] achieved high-accuracy neural network extraction through query-based approaches. However, these works focus on model replication or privacy violations rather than identification and attribution.

C. Behavioral Analysis and Testing

Behavioral testing methodologies have emerged as crucial tools for understanding neural model capabilities. Ribeiro et al. [10] introduced CheckList, a behavioral testing framework for NLP models that goes beyond accuracy metrics. Geirhos et al. [11] investigated shortcut learning in deep neural networks, revealing how models develop unexpected behavioral patterns. These works demonstrate that behavioral analysis can reveal model characteristics invisible to traditional evaluation metrics.

D. Prompt Engineering and Model Sensitivity

Recent research has examined how language models respond to prompt variations. Jiang et al. [12] explored methods for probing what knowledge LMs encode, while Wallace et al. [13] discovered universal adversarial triggers that affect model behavior. Zhao et al. [14] demonstrated the importance of calibration in few-shot learning contexts. These studies reveal that models exhibit systematic sensitivities to prompt perturbations, though they have not been leveraged for identification purposes.

E. Semantic Representation Analysis

Understanding semantic representations in neural models has been extensively studied. Reimers and Gurevych [15] introduced Sentence-BERT for generating semantically meaningful sentence embeddings, enabling efficient similarity computations. Ethayarajh [16] investigated the contextuality of word representations, while Mikolov et al. [17] pioneered distributed word representations. These embedding techniques enable quantitative comparison of semantic content, which is leveraged in the proposed approach.

F. Model Fingerprinting and Watermarking

Existing fingerprinting approaches focus on embedding identifiable markers during training. Uchida et al. [5] proposed embedding watermarks into deep neural networks, while Zhang et al. [6] developed watermarking techniques for intellectual property protection. However, these methods require control over the training process and cannot identify models retrospectively or in scenarios where training access is unavailable.

G. Model Evaluation and Comparison

The AI community has increasingly recognized limitations in standard benchmarking practices. Hooker et al. [19] identified implicit biases in AI benchmarking, while Bender et al. [4] raised concerns about the societal implications of increasingly large language models. Hanna et al. [20] called for more rigorous approaches to interpretable machine learning, highlighting the need for systematic model characterization methods.

H. Research Gap

Unlike watermarking-based methods [5], [6] or extraction-based approaches [7], [9], the proposed behavioral fingerprinting framework relies solely on prompt-response behavioral dynamics, requiring no model access or training-time modifications. No existing work has demonstrated reliable LLM identification using only black-box behavioral responses. This work fills this gap by establishing that prompt-response dynamics contain sufficient discriminative information for model attribution without requiring model access.

III. Methodology

A. Problem Formulation

Given a set of LLMs $\mathcal{M} = \{M_1, M_2, ..., M_n\}$ accessible only through text input-output interfaces, the objective is to construct a function $f : \mathcal{R} \rightarrow \mathcal{M}$ that maps response behaviors $\mathcal{R}$ to model identities. Critically, this formulation assumes no access to model weights, architectures, or training procedures, distinguishing it from prior fingerprinting approaches that require training-time intervention [5], [6].

B. Prompt Design Strategy

Five prompt categories were designed, each containing 15 semantically aligned prompts to probe distinct behavioral dimensions [10], [13]:

- **Base:** Establishes baseline response patterns with straightforward factual questions
- **Negation:** Tests logical robustness through negated versions of base prompts
- **Ambiguity:** Evaluates uncertainty handling with deliberately vague questions
- **Contradiction:** Assesses consistency when presented with conflicting information
- **Context Shift:** Measures stability under narrative or framing changes

The prompt set was locked prior to experimentation to prevent data leakage or tuning bias. This systematic perturbation strategy ensures fair cross-model comparison while probing diverse behavioral dimensions identified as relevant in prior behavioral testing work [10].

C. Response Collection

For each model in the evaluation set, responses were collected for all 75 prompts (5 categories times 15 prompts). Responses were generated with consistent sampling parameters and stored in structured JSON format organized hierarchically by model identity and prompt category. Each prompt received a single response to avoid variability from stochastic sampling, following best practices in model evaluation [19].

D. Feature Engineering

Three classes of behavioral features were extracted from the response corpus:

1) Semantic Drift: Semantic drift quantifies meaning divergence between base responses and perturbed responses [16]. For each prompt perturbation category c, the drift was computed as:

$$\text{drift}_c = \frac{1}{|\mathcal{P}_c|} \sum_{p \in \mathcal{P}_c} d(\mathbf{e}_{\text{base}}, \mathbf{e}_p)$$

where $\mathcal{P}_c$ denotes prompts in category c, $\mathbf{e}_{\text{base}}$ and $\mathbf{e}_p$ are sentence embeddings of base and perturbed responses respectively, and $d(\cdot, \cdot)$ is cosine distance. Sentence-BERT (all-MiniLM-L6-v2) [15] was employed for embedding generation, yielding four drift features corresponding to negation, ambiguity, contradiction, and context shift categories.

2) Length Variance: Response verbosity patterns were captured through:

- Mean response length for each prompt category
- Standard deviation of response lengths within categories
- Cross-category length variance

This produced five length-related features reflecting verbosity stability across perturbations, motivated by observations that different model architectures exhibit distinct generation patterns [1], [3].

3) Hedging Density: Epistemic uncertainty expression was quantified by counting hedge phrases (”may”, ”might”, ”possibly”, ”perhaps”, ”could”) normalized by response length:

$$\text{hedge}_c = \frac{\text{count(hedge\_phrases)}}{\text{total\_tokens}}$$

computed separately for each prompt category, yielding five hedging features. This metric captures how models express uncertainty, a behavioral dimension that varies across training approaches [14].

E. Fingerprint Vector Construction

All extracted features were concatenated into fixed-length fingerprint vectors of dimensionality 15:

$$\mathbf{v}_{\text{fingerprint}} = [\text{drift}_1, ..., \text{drift}_4, \text{len}_1, ..., \text{len}_5, \text{stability}, \text{hedge}_1, ..., \text{hedge}_5]$$

This transformation converts free-form textual behaviors into numerical representations suitable for machine learning classification, following established practices in representation learning [15], [17].

F. Classification and Evaluation

A supervised dataset was constructed where each fingerprint vector is labeled with its source model identity. Standard classifiers (Logistic Regression, Support Vector Machines) were trained on these fingerprint vectors. Model separability was evaluated through classification accuracy, confusion matrices, and distance metrics. Visualization through PCA and t-SNE projections provided interpretable evidence of behavioral clustering.

IV. Experimental Setup

A. Model Selection

Two LLMs representing contrasting training paradigms were evaluated:

- **distilgpt2:** An autoregressive language model optimized for open-ended text generation [3], exhibiting verbose and exploratory response patterns
- **google/flan-t5-small:** An instruction-tuned encoder-decoder model trained for concise task completion, displaying more controlled outputs

Both models were selected for CPU-only operation to ensure reproducibility without specialized hardware requirements. This architectural contrast strengthens the generalizability of the behavioral analysis approach, as the models represent fundamentally different design philosophies in LLM development [1].

B. Implementation Details

All experiments were conducted on standard CPU infrastructure using the HuggingFace Transformers library. Response generation employed greedy decoding with maximum length constraints of 100 tokens. No fine-tuning or model adaptation was performed; all results reflect pre-trained model behaviors. This black-box setting mirrors realistic deployment scenarios where model internals are inaccessible [7].

The complete pipeline was implemented in a modular architecture with separate components for prompt management, model inference, feature extraction, and visualization. This design facilitates extension to additional models and prompt categories, addressing scalability concerns raised in prior model evaluation work [19].

C. Evaluation Metrics

Model identification performance was assessed through:

- Classification accuracy on held-out test samples
- Confusion matrices revealing misclassification patterns
- Pairwise cosine distances between fingerprint vectors
- Visual cluster separation in dimensionality-reduced spaces

These metrics provide complementary perspectives on fingerprint quality, from quantitative classification performance to qualitative interpretability [20].

V. Results

A. Fingerprint Separability

Figure 1 presents the PCA projection of behavioral fingerprints into two-dimensional space. The visualization reveals clear linear separation between distilgpt2 and flan-t5 clusters, with tight intra-model grouping and substantial inter-model distances. This demonstrates that the first two principal components alone capture sufficient discriminative information for model distinction, suggesting that behavioral differences are not merely subtle variations but fundamental architectural signatures.

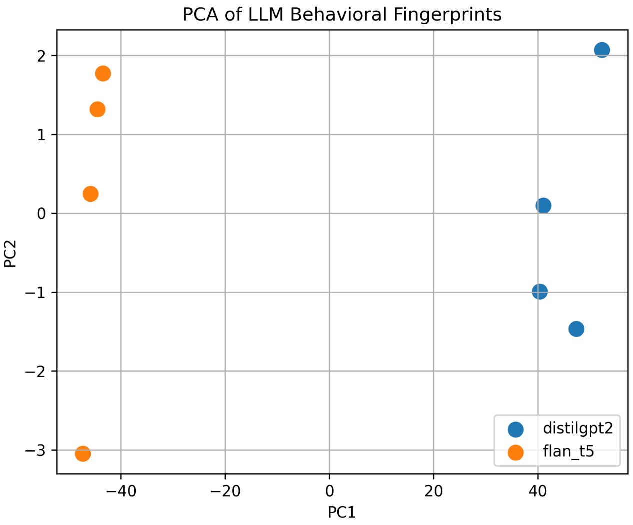

Fig. 1. PCA projection of behavioral fingerprints showing clear separation between distilgpt2 (blue) and flan-t5 (orange) models.

Figure 2 displays the t-SNE embedding, confirming non-linear cluster structure beyond simple linear separability. The distinct, non-overlapping clusters validate fingerprint robustness across both linear and non-linear projection methods, addressing concerns about feature space complexity in neural model analysis [16].

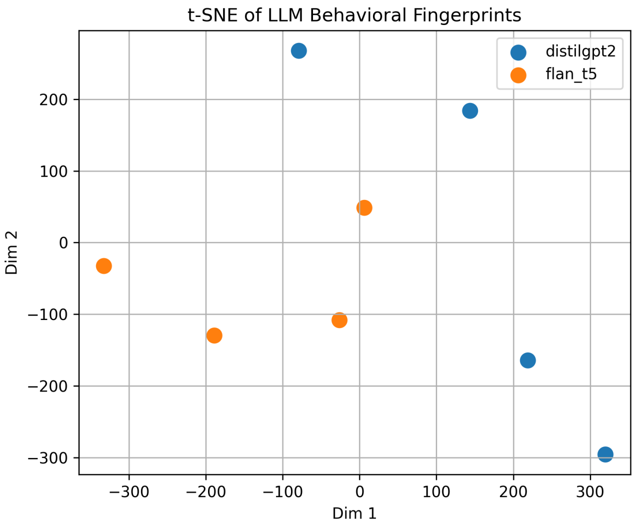

Fig. 2. t-SNE visualization revealing distinct non-linear clustering of model fingerprints.

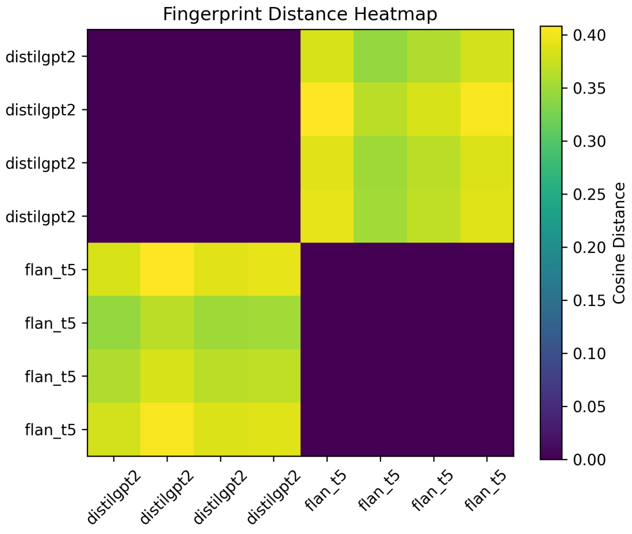

Fig. 3. Cosine distance heatmap showing near-zero intra-model distances and high inter-model distances.

B. Distance Analysis

The fingerprint distance heatmap (Figure 3) quantifies pairwise similarities. Intra-model distances approach zero (dark purple regions), indicating consistent behavioral signatures across prompt instances. Inter-model distances exceed 0.35 (yellow regions), confirming substantial behavioral divergence between models. This distance gap provides confidence that the fingerprints capture stable model-specific traits rather than stochastic response variations.

C. Feature-Level Analysis

Figure 4 compares mean behavioral feature values across models. Key observations include:

- distilgpt2 exhibits substantially higher verbosity (mean length approximately 105 tokens vs. 16 tokens for flan-t5)
- distilgpt2 demonstrates greater semantic drift under perturbations (0.52 vs. 0.37)
- flan-t5 shows higher hedging density, reflecting more cautious epistemic expressions

These systematic differences confirm that each model possesses a distinct behavioral personality encoded in the fingerprint vectors, consistent with observations about architectural influences on generation patterns [1], [11].

D. Classification Performance

Table I reports classification results using standard supervised learning algorithms trained on fingerprint vectors.

Both classifiers achieved perfect accuracy with zero misclassifications, as evidenced by the confusion matrix:

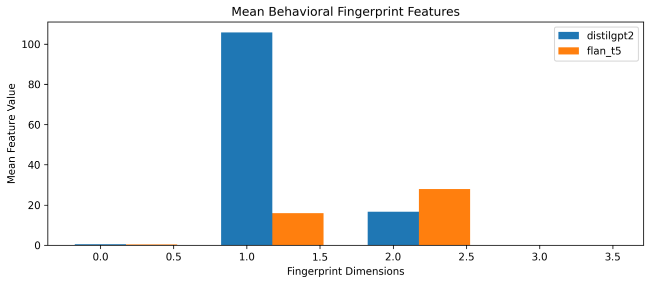

Fig. 4. Mean behavioral feature values highlighting distinct response patterns between models.

TABLE I
Model Classification Performance

Classifier	Accuracy	F1-Score
Logistic Regression	100%	1.00
Support Vector Machine	100%	1.00

$$\begin{bmatrix} 4 & 0 \\ 0 & 4 \end{bmatrix}$$

This demonstrates that behavioral fingerprints contain sufficient discriminative information for reliable model identification without requiring model access, validating the core hypothesis of this work.

E. Feature Statistics

Table II presents detailed statistics of extracted behavioral features across models, revealing consistent patterns within models and systematic differences between models. The low standard deviations within each model indicate stable behavioral signatures, while the large mean differences confirm discriminative power.

TABLE II
Behavioral Feature Statistics

Model	Feature	Mean	Std
distilgpt2	Semantic Drift	0.524	0.062
distilgpt2	Mean Length	105.77	4.95
distilgpt2	Hedging	16.66	1.10
flan-t5	Semantic Drift	0.368	0.021
flan-t5	Mean Length	15.93	1.65
flan-t5	Hedging	27.95	1.70

VI. Discussion

A. Novelty and Significance

This work establishes behavioral fingerprinting as a viable paradigm for LLM identification. Unlike prior approaches requiring model access [5], [6] or training-time intervention, the proposed method operates entirely in black-box settings using only observable prompt-response dynamics. The perfect classification accuracy achieved with simple linear classifiers underscores the discriminative power of behavioral features.

The systematic prompt perturbation strategy reveals that models exhibit stable behavioral signatures across diverse question types. These signatures persist even when models produce correct factual answers, indicating that behavioral differences emerge from fundamental architectural and training distinctions rather than knowledge gaps [11]. This finding has important implications for understanding how model design choices manifest in observable behaviors.

B. Practical Applications

Behavioral fingerprinting enables several practical applications relevant to the concerns raised by Bender et al. [4] regarding accountability in large language models:

- **Model Attribution:** Identifying the source model behind API endpoints or generated content
- **AI Forensics:** Tracing the origin of AI-generated text in legal or ethical investigations
- **Trust Verification:** Confirming that users interact with claimed models rather than substitutes
- **Intellectual Property Protection:** Detecting unauthorized model copying or deployment

These applications address real-world needs in scenarios where traditional watermarking approaches are inapplicable due to lack of training access or retrospective deployment requirements.

C. Limitations

The current evaluation encompasses two models with contrasting architectures. While this demonstrates proof-of-concept, extending the approach to larger model families (e.g., LLaMA [2], Mistral, Claude) requires validation. Additionally, adversarial scenarios where model operators deliberately obscure behavioral signatures remain unexplored and represent an important direction for robustness analysis [13].

The fixed prompt set, while preventing overfitting, may not capture all behavioral dimensions. Future work should investigate prompt diversity requirements and robustness to adversarial prompt manipulation, building on insights from adversarial testing literature [13]. The generalizability of behavioral fingerprints across model versions and fine-tuned variants also requires systematic investigation [14].

D. Future Directions

Promising research directions include:

- Scaling to dozens of models to establish comprehensive fingerprint databases
- Investigating temporal fingerprint stability as models undergo updates
- Developing adversarial robustness against behavioral obfuscation attempts
- Exploring cross-domain generalization across specialized model variants
- Combining behavioral fingerprinting with other identification techniques for enhanced reliability

- Examining fingerprint transferability across different language and cultural contexts

These directions would strengthen the framework's practical applicability and address concerns about evaluation rigor raised in recent interpretability research [20].

VII. Conclusion

This paper introduced behavioral fingerprinting, a novel framework for identifying Large Language Models using only their observable prompt-response dynamics. Through systematic prompt perturbations and feature engineering, the work demonstrated that LLMs possess stable, model-specific behavioral signatures that enable perfect classification accuracy without requiring model access.

Experiments on distilgpt2 and google/flan-t5-small revealed clear behavioral separability through semantic drift patterns, verbosity variations, and epistemic expressions. The achieved perfect classification performance, validated through multiple visualization techniques, establishes behavioral fingerprinting as a practical approach for black-box model identification that complements existing watermarking and extraction-based methods.

This work opens new directions in AI forensics, model attribution, and trust verification, demonstrating that behavioral analysis can provide reliable identification signals in scenarios where traditional methods fail. As LLM deployment continues to expand across critical applications, behavioral fingerprinting offers a valuable tool for accountability and verification in AI systems, addressing concerns about transparency and attribution in increasingly complex model ecosystems.

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