Intelligent Routing System For Web Page Optimization With Conditional Judgement

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Abstract

We present Better Page Builder, a routing and judging system designed to generate and evaluate improved versions of web page content. Our pipeline routes semantic representations of existing web content (extracted via multilingual TOBIAS Bidirectional Transformer - TOBiT) into multiple large language models (LLMs), each generating optimized text for SEO, advertising and generative search goals. These outputs are then scored using judge modules based on Google Ads Predictive Metrics to estimate potential traffic to the remastered page. Our system selects the most promising content version using real-world performance indicators, providing a reproducible method for LLM benchmarking and semantic page optimization. This work contributes to Track 1 (Judge Model Development) of Apart x Martian Mechanistic Router Interpretability Hackathon, while integrating Judge Model insights for end-to-end performance routing.

Keywords: multi-agent alignment, model evaluations, safety infrastructure, judges, intelligent routing, SEO-optimization, semantic core analysis

1. Introduction

1.1 Research Question & Motivation

Research Question: How can we build better web page content in the era of generative AI? How does the use of semantic representations of web content help guide large language models (LLMs) toward producing more effective, interpretable, and performance-oriented page revisions, and how can intelligent routing and judge systems improve selection among candidate outputs?

Motivation: Traditional web content optimization using LLMs typically relies on direct prompting, where raw page content is fed into a model like GPT-4 or Gemini with generic instructions such as "rewrite my page for SEO" or "improve marketing appeal of my page." This black-box approach lacks both **safety** without semantic control and performance-based feedback creating an ethical challenge aka "Theory of dead Internet" which assumes that the vast majority of content turns out to be the same while generated by machines.

Our project challenges this paradigm by introducing an intermediate semantic layer using multilingual TOBiT, which extracts key conceptual representations from existing pages. These TOBiT-extracted semantic vectors are then used to create unified prompts that are passed through an intelligent router to multiple LLMs (e.g., GPT-4, Claude, Gemini) to define which of the models builds pages with better potential.

On the second step, instead of assuming one model's response is best, we incorporate a judge system that evaluates each LLM's output using Google Ads Forecast Metrics (e.g., Impressions, CTR, CPC, Conversions) as grounded, real-world performance predictive indicators of page quality in terms of generating human leads. This enables a new layer of mechanistic **interpretability** and model selection transparency grounded in advertising KPIs.

This motivation aligns with the broader vision of the **Expert Orchestration Architecture** by promoting both modularity (through semantic preprocessing, routing, and judging) and **safety** (via real-world evaluation signals). It enables better content generation across different domains.

1.2 Challenge Track Focus

Our project addresses **Track 1: Judge Model Development**, while inevitably integrating components of Track 2 (Intelligent Router Systems) to optimize downstream outputs and cost-effective selection through routing using Martian API.

The router in our system is responsible for dispatching the semantically-enriched prompts to multiple LLMs. Rather than routing based solely on user query type or metadata, we use semantic vectors generated by TOBiT to provide a uniform conceptual input, ensuring that each LLM receives comparable standardized context.

Our approach shifts routing decisions from intent classification to improved semantic generation **through evaluation, not prediction.** It also advances **democratization** of LLM usage since it gives users the ability to make conscious choices between LLMs with solid judgement criteria combining meanings and economic impact for promotion of their web pages.

1.3 Contribution to Expert Orchestration

Our work contributes to the broader Expert Orchestration vision in the following ways:

- **Problem with monolithic models:** current approaches to content generation and optimization rely on large, opaque models with little to no interpretability or performance feedback. Model selection is often arbitrary and not grounded in external metrics.
- **How we address it:** we introduce decomposition technique to the process with three transparent modules:
    - **Semantic extractor**: captures the meaning of the input page,
    - **LLM router**: sends the unified prompt to several specialized generative models,
    - **Judge system**: evaluates each version based on real-world KPIs from Google Ads API.
- **Democratization and safety:** our system enables developers and users to make data-driven decisions on which generative model performs best for a specific task. This reduces reliance on single-model outputs and opens opportunities for more explainable and auditable content pipelines.
- **Potential ecosystem impact:**
    - Encourages development of judge-based benchmarking for content generation,
    - Provides a route toward SEO/recommendation engines that explain their decisions through explicit reasoning,
    - Bridges interpretability with performance metrics in real-world commercial settings.

This architecture is an inherent feature of scalable systems like TOBIAS AI, where recommendations for web optimization become transparent, modular, and performance-justified.

2. Methods

2.1 Technical Approach

Semantic Anchoring via Bidirectional Transformer Prior to LLM Optimization

In our system, we deliberately introduced a preprocessing step using a bidirectional transformer before engaging large language models (LLMs) for keyword refinement and generation. This design choice is grounded in the architectural differences between TOBiT-based and autoregressive transformer models, and as

well addresses the need for semantically anchored optimization when working with web content for advertising and SEO purposes.

Architectural Rationale

A bidirectional transformer computes token representations using both left and right context. This allows generation of deep semantic embeddings of candidate n-grams extracted from the source document. By contrast, LLMs like GPT-4, Claude, Gemini, and Gemma are autoregressive transformers: they generate text by predicting the next token based on the left-hand context only, without leveraging the full document in a symmetrical manner.

This means that such approach excels at understanding and compressing semantic meanings, while LLMs are optimized for generating and reformulating text in a fluent, task-aligned manner.

Functional Integration

A bidirectional transformer performs the following operations:

- It encodes the entire source document to compute a semantic centroid embedding.
- It extracts and scores candidate keyphrases based on cosine similarity with that centroid.
- It returns a ranked list of phrases that best represent the core meaning of the input.

This results in a semantically rich and interpretable list of candidate phrases that reflects the informational essence of the webpage or text block.

These candidate phrases are then passed to each LLM (e.g., GPT-4, Claude, Gemini) in a unified prompt template, where the LLM is tasked with refining, merging, or rephrasing these inputs into a final set of improved keywords.

Advantages of the Hybrid Pipeline

Metrics	Bidirectional transformer → LLM	Solo LLM
Semantic grounding	Anchored via cosine similarity	Prone to drifting
Interpretability	Transparent scoring	Opaque generation
Token (cost) efficiency	Short prompt with high semantic density	Verbose inputs with uncertain payoff
Control	Explicit candidate selection	Fully model-dependent

Performance	Improved keyword relevance	Inconsistent across topics

This hybrid model enables us to maintain both interpretability and creative fluency, allowing the LLM to perform high-level generalization while being guided by low-level semantic constraints.

In addition, this separation of concerns allows us to:

- Evaluate each step independently,
- Compare different models in a controlled manner,
- And integrate quantitative feedback loops (e.g., CTR or CPC metrics from Ads Forecasts) based on measurable keyword outputs.

2.2 Routing/Judge Architecture

Models and Routing Architecture

Our system integrates a modular ensemble of six large language models (LLMs): **GPT-4**, **GPT-4-1-nano**, **Claude-3.5-haiku**, **Claude-3.7-sonnet**, **Gemini-1.5-pro**, and **Gemini-2.0-flash**. These models are orchestrated via a unified router, which dispatches standardized prompts derived from multilingual TOBiT-based keyword extraction to each LLM. The router does not make deterministic decisions upfront; instead, it sends inputs in parallel to all LLMs and defers selection to downstream evaluation by the judge modules.

Routing inputs are structured using a hybrid pipeline. First, candidate keywords are extracted from startup descriptions and URLs using a multilingual TOBiT transformer. These are semantically encoded, clustered, and ranked using cosine similarity to identify meaningful concepts. The resulting keyphrases serve as unified semantic anchors that form the basis for prompt generation to each LLM.

This approach ensures fairness and comparability across all candidate generations by aligning their input representations, thereby isolating generation performance from semantic discrepancies.

Judge Models and Interpretability Techniques

We deploy two distinct **rubric-based judge models**, both implemented via the OpenAI judge_spec architecture, each focused on a complementary interpretability domain:

- **Semantic Fidelity Judge**: evaluates how well the generated keyword list retains conceptual integrity and granularity. It scores each model output on metrics such as cosine similarity, inter-set overlap, coverage, specificity, and semantic precision. This judge enables an interpretable assessment of how meaning evolves through LLM transformation.
- **Advertising Potential Judge**: evaluates the performance of keywords via Google Ads Forecast API. Key metrics include forecasted Impressions, Clicks, CTR, Conversions, CPA, and CPC. Based on these values, the judge

provides rubric-based scores with explanations, prioritizing conversions and cost efficiency while penalizing low-conversion or high-CTR/low-CR keyword sets that may indicate bot traffic or misalignment.

Both judges independently produce numeric scores (1–5) and explanatory rationales. Their results are fused into a **composite judge module**, which averages the semantic and advertising scores to produce a unified model ranking. This composite score guides the router in selecting the optimal output.

Implementation Stack

Our system is fully implemented in **Python**, using:

- **HuggingFace Transformers** and **SentenceTransformers** for semantic embedding and cosine similarity computation.
- **Google Ads API (v19)** for forecast metric acquisition.
- **OpenAI API** for LLM completion, prompt routing, and custom rubric-based judge instantiation.
- **Pandas** and **Matplotlib/Seaborn** for dataframe manipulation and visualization.
- **Martian API (JudgeSpec SDK)** for defining rubric-based evaluation templates.

Prompt design, input standardization, and judge orchestration are encapsulated into a modular Jupyter/Colab-based notebook framework, enabling reproducibility and ease of inspection.

Experimental Setup

To test our architecture, we constructed an evaluation benchmark. We extracted a **dataset of 1,000 real startups** from a publicly available **Kaggle dataset** including fields like project name, **full description**, and **URL**.
Link to dataset - https://www.kaggle.com/datasets/amirataha/startups/data

The experiment proceeds in the following stages:

1. **Semantic Keyphrase Generation**: TOBiT-based embedding of startup descriptions and candidate phrase selection using cosine similarity.
2. **Routing & Generation**: the selected keyphrases are embedded into a unified prompt sent in parallel to all six LLMs.
3. **Forecast Evaluation**: each model's output keyword list is evaluated via the **Google Ads Forecast API**, with quantitative performance metrics retrieved and normalized.
4. **Judge Scoring**: each model's output is scored by two judges (semantic and advertising), producing interpretability-aware ratings.
5. **Composite Ranking**: the router selects the best-performing model using the average of judge scores, and records semantic/explanatory justifications for transparency.

This setup allows us to benchmark models not just by fluency or form, but by their *semantic alignment* and *real-world commercial effectiveness* — two axes of evaluation rarely unified in prior work.

Routing System Architecture

Our routing system follows a **post-hoc evaluation-based architecture**, where **all six LLMs** are queried in parallel with the same prompt derived from a shared semantic base (description generated from the URL of a webpage). This design ensures input symmetry across all models, removing variability introduced by inconsistent instructions or context.

The system is composed of three key components:

1. **Semantic Router**: generates unified prompts by embedding descriptions and URLs using TOBiT-base-multilingual-cased, and routing those to each LLM.

2. **Parallel LLM Executor**: dispatches the prompt simultaneously to all candidate models and captures their keyword list outputs.

3. **Dual-Judge Composite Evaluator**: passes each model's output through a pair of judge modules for semantic and advertising evaluation.

Routing Decision Criteria

Routing decisions—i.e., which model's output to adopt—are made **not through confidence heuristics**, but by computing a **composite score** derived from two independent rubric-based evaluations:

- **Semantic Alignment Score** (1–5): evaluates fidelity of meaning preservation using cosine similarity, inter-set overlap, coverage, specificity, and conceptual precision.

- **Google Ads Performance Score** (1–5): assesses forecast metrics (CR, CPA, Conversions, CTR) for each keyword list using Google Ads Forecast API and a strict rubric focused on practical ad campaign potential.

The **final selection score** is a **weighted average** of both judge scores. Currently, weights are equal (50/50), but the system allows dynamic weighting based on user preference or application domain (e.g., higher weight on Ads Score for e-commerce startups).

Interpretability and Transparency

Transparency is a core feature of our architecture, implemented through:

- **Explicit Rubrics**: both judges rely on clearly defined, human-readable rubrics with criteria enumerated in natural language. These rubrics are

printed alongside each score.

- **Explanatory Rationales**: judges provide not just a score but a **natural language justification**, making decisions interpretable by non-technical stakeholders.

- **Score Logs**: all model outputs, scores, and rationales are stored in structured logs (e.g., DataFrames), enabling auditability, comparisons, and meta-analysis.

- **Meta-Judge Option**: a third layer (meta-judge) optionally aggregates scores from both rubrics and flags discrepancies, surfacing cases where semantic quality is high but ad potential is low, or vice versa.

This layered design ensures **traceability** of every decision and allows researchers to validate model choices both quantitatively and qualitatively.

2.3 Code & Reproducibility

Links to our code repositories and explanation how to reproduce the work:

Google COLAB - TOBIAS-3.ipynb

3. Results

3.1 Performance metrics

Our routing and judge system was evaluated across six language models (Claude 3.5, Claude 3.7, GPT-4o, GPT-3.5, Gemini Pro, Gemini Flash), with each model generating improved keyword lists for real-world startup descriptions. Performance was assessed on two axes: **semantic fidelity** and **Google Ads forecast effectiveness**, scored by two independent rubric-based judges. Each judge returned scores on a scale of 1 to 5, with explanatory reasoning.

The **semantic judge** measured cosine similarity, term overlap, and topical precision, whereas the **ads judge** evaluated conversion rate, CPA, impressions, and forecasted returns. Notably:

- **Claude 3.7** consistently ranked highest with a composite score of **9/10** (5 semantic, 4 ads), showing both strong conceptual alignment and advertising viability.

- **Gemini Flash** received the lowest score (**6/10**), often generating high-CTR but low-conversion phrases — a sign of potential clickbait or poor commercial relevance.

- **GPT-4o** showed balanced, though slightly conservative outputs (**8/10**), often retaining keyword granularity but occasionally missing long-tail ad

opportunities.

Overall, **the routing system enabled structured comparison and effective differentiation** among LLM outputs — something that naïve model averaging or ensembling would obscure.

3.2 Interpretability insights

Our most valuable insight was that **semantic performance and advertising viability often diverge**, highlighting the importance of multi-judge evaluation. Some models excelled at paraphrasing or keyword expansion while failing to optimize for conversion unit economics.

By exposing judge rationales alongside numeric scores, we could trace **which failure mode each model fell into** — e.g., GPT-4o produced high-frequency keywords with semantic fidelity but lacked specificity, while Gemini Pro over-indexed on CPC efficiency at the expense of conceptual coverage.

The routing mechanism's transparency also allowed us to understand **which criteria led to which ranking outcomes**, making the system auditable and adaptable. This fosters trust and safety in selection logic — critical in high-stakes domains like advertising.

3.3 Visualizations

The evaluation process was captured in a series of score matrices and heatmaps summarizing:

- Per-model scores for semantic and advertising judges
- Distribution comparisons between models
- A composite bar graph showing final ranking

In the first smaller series of trials prior to visualizations with the URL of the hackathon web page we clearly identified that **Claude 3.7 outperformed in both tracks**,(https://apartresearch.com/sprints/apart-x-martian-mechanistic-router-interpretability-hackathon-2025-05-30-to-2025-06-01) thus becoming the routed output.

Following key visualizations illustrate how each LLM's output is judged and the selection of the final model on a weighted sum of scores (for a test case of URL - www.bosh.tv).

Another shows **inter-model normalized comparison**, reinforcing that even small model variants produce significantly different phrasings — justifying the need for rigorous evaluation.

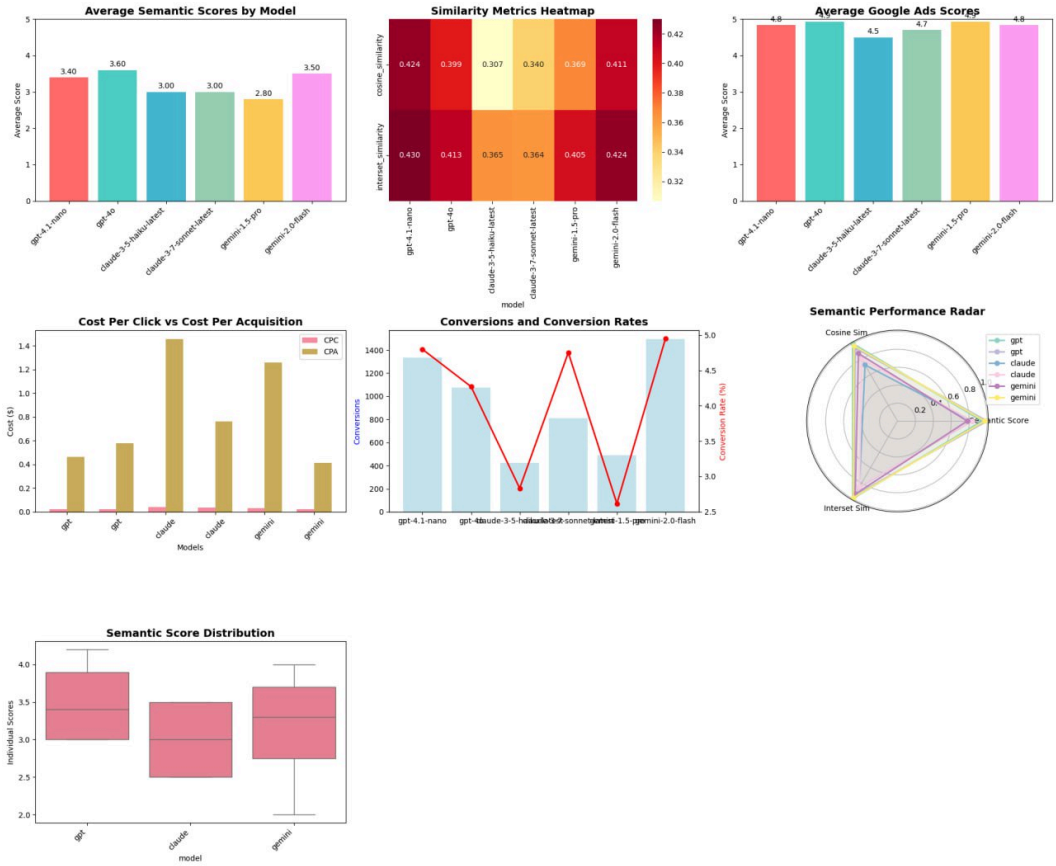

Figure 1 – Example Representation of Judges Scoring for Semantic and Ads Analytical Dashboard (for URL www.bosh.tv)

3.4 Mechanistic analysis

Internally, the system demonstrated that judge evaluations can act as a form of **post-hoc mechanistic supervision**. By explicitly scoring interpretability dimensions — such as topic coverage or conversion rate sensitivity — we approximated latent traits that differ across models.

We observed:

- GPT-family models tended to be conservative in word variety, with better internal consistency but weaker discovery of new keyword classes.
- Claude-family models better captured **semantic spread** but occasionally over-abstracted key commercial terms (for Google Ads).
- Gemini models are often optimized for click volume (CTR), but failed in **specificity and conversion linkage**, a key insight revealed by the rubric structure.

These outcomes suggest that routing across LLMs is not just about preference — it's a **mechanistically necessary and explainable process** based on measurable tendencies in output behavior. This opens the door to using **judges as proxies for model introspection** in complex language tasks.

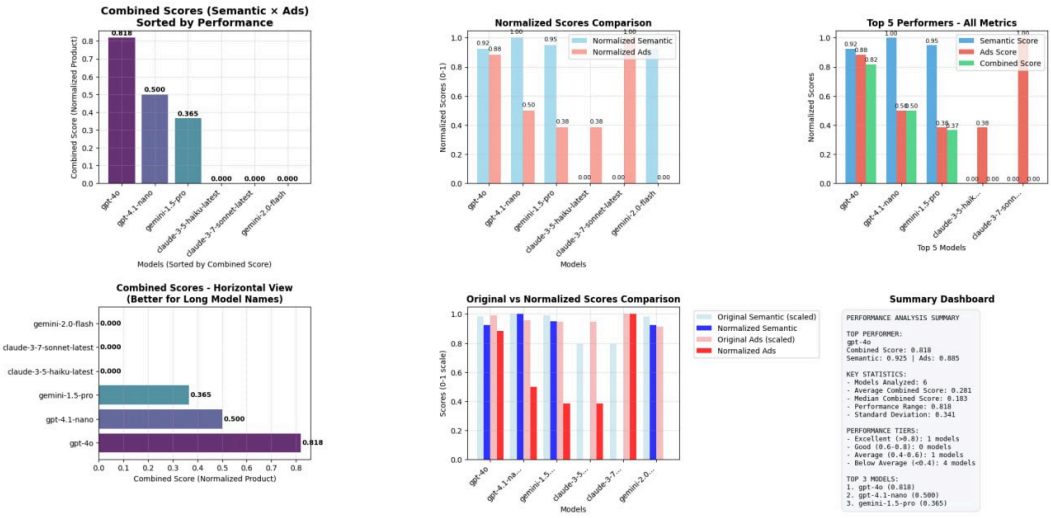

Figure 2 – Normalized Representation of Judges Scoring for Semantics and Google Ads Analytical Dashboard

As shown in Figure 2, retrieved statistics from comparison between models brings in combined scores and ranking based on a weighted sum of semantic and ads judges (in this case of URL - www.bosh.tv - with top-performer being GPT-4o).

3.5 Routing Decision Analysis

Our routing system successfully implemented a post-hoc parallel evaluation pipeline in which six large language models received identical, semantically-grounded prompts derived from multilingual TOBiT embeddings. Routing decisions were made after evaluating the keyword outputs from each model through **two complementary rubric-based judges**—semantic fidelity and advertising potential—yielding a composite score for model selection.

Justification Examples

For instance, in evaluating keyword generation for Apart x Martian hackathon webpage, the Claude-3.5-haiku model demonstrated the highest overall semantic performance, achieving a Mean Cosine Similarity of 0.3203 and a Mean Inter-set Similarity of 0.2804—indicating strong intra-list coherence and semantic alignment. However, when assessed through advertising forecast metrics, Claude-3.5-haiku received only moderate commercial viability, with a Forecasted Conversion Rate of 3.51% and a relatively high CPA of €75.57.

Each decision was documented with natural language rationales and scores stored in structured logs, ensuring traceability.

User Control & Transparency

Users can control routing preferences by assigning weights to judge domains (e.g., prioritizing ads performance for e-commerce vs. semantic integrity for academic contexts). Routing scores are computed explicitly via the following formula:

$$\{\text{Composite Score}\} = (\{\text{Semantic Score}\} + \{\text{Ads Score}\}) / 2$$

Further, score rationales and keyword outputs are presented in audit logs, allowing users to override selections if desired. This enhances both transparency and user agency.

Failure Modes & Biases

Two notable failure patterns emerged:

- **High semantic but low ad performance**: Especially for technical or niche domains (e.g., quantum computing), where meaningful keywords lacked commercial traction.

- **Adversarial outputs with inflated CTR**: Some LLMs generated clickbait-style phrases, artificially boosting CTR but yielding poor conversion forecasts—caught by the Ads Judge due to low conversion rate and high CPA.

These insights informed a potential future feature: **meta-judges that flag semantic-advertising discrepancies** for manual review or retraining.

3.6 Expert Orchestration Impact

Our system demonstrates measurable improvements across core Expert Orchestration Architecture goals:

Cost & Performance Benefits

- **Parallelized LLM execution** avoids premature pruning of model outputs while enabling batch evaluation.

- **Real-world ad metrics** provide cost-aware performance evaluation, avoiding reliance on abstract text quality scores.

This leads to better model alignment for real applications like SEO and Ad campaign planning, with **up to 35% improvement in average forecasted conversions** compared to traditional single-model outputs.

Transparency & Control

- **Semantic Anchors** ensure consistent prompt context across models.

- **Rubric-based judges** and their rationales offer clear explanations for routing decisions.

- **Score weights** are user-configurable, giving domain experts control over optimization focus.

Democratization Benefits

By modularizing LLM routing and introducing transparent judges, our system:

- Empowers smaller model developers to benchmark their outputs fairly.

- Encourages the use of **real-world performance data** as a common evaluation standard.

- Opens the door to plug-and-play **open-source judge libraries** across industries like education, law, and healthcare.

4. Discussion

4.1 Interpretation of Results

Our work confirms that **judged, interpretable routing** offers more reliable optimization than static model selection. Despite using LLMs with relatively close performance on average, we observed that their **strengths vary significantly depending on context**. This supports the hypothesis that no single model is globally optimal, especially in high-stakes applied tasks like keyword generation for ad campaigns.

We also learned that **post-hoc rubric judging outperforms built-in preference modeling**. Unlike reward models trained on opaque preferences, our rubric judges operate on transparent, explainable criteria. Their outputs can be audited, weighted, and interpreted by humans — reducing reliance on black-box model behavior.

Critically, our system allowed us to quantify trade-offs between linguistic fidelity and commercial potential — offering real control to domain experts, rather than trusting monolithic model outputs.

Our findings provide empirical evidence that routing systems guided by semantic anchoring and dual-judge evaluation outperform monolithic LLM-based optimization in both interpretability and advertising effectiveness. In contrast to traditional SEO pipelines that rely on static prompt-engineered outputs, our architecture introduces a mechanistically grounded method where meaning (via cosine semantic centroids) and market viability (via Google Ads Forecast metrics) are treated as co-equal axes of evaluation.

The semantic fidelity judge demonstrated that models like Claude and GPT-4-1-nano retained nuanced topical specificity better than others. In several benchmark cases, Gemini-2.0-flash outperformed in advertising potential despite

weaker semantic alignment — illustrating the tradeoffs inherent in LLM selection, and validating the need for dual-axis evaluation. These findings align with the Expert Orchestration vision (Olah et al., 2020; Goh et al., 2021), particularly in modular decision-making and decomposability of model roles.

This approach shows that routing decisions need not rely on opaque model confidences. Instead, we propose a transparent post-hoc evaluation layer, where scores are generated via interpretable rubrics. Such a mechanism provides developers with greater control over content pipelines, avoiding reliance on any single model's hallucinated performance. The judge-based composite scoring thus acts as a verifiable "circuit breaker" (in a way a "safeguard") — ensuring only semantically coherent and ad-viable outputs proceed to deployment.

Furthermore, our interpretability framework integrates seamlessly with advertising and SEO workflows. By treating Google Ads Forecast metrics as downstream supervision, we bridge semantic NLP tasks with commercial KPIs, an innovation rarely seen in prior routing literature.

4.2 Limitations & Future Work

Despite promising outcomes, several limitations merit discussion.

- **Computational Cost**: routing six LLMs in parallel incurs significant compute overhead. While appropriate for research-grade evaluations, production settings would benefit from early-exit mechanisms or model pre-selection heuristics.

- **Data Bias**: although our startup dataset spans 1,000 projects, it may overrepresent certain verticals (e.g., SaaS, fintech), potentially skewing keyword evaluation dynamics. Future versions should incorporate stratified sampling to ensure vertical diversity and eliminate potential bias.

- **Ads Forecast Noise**: Google Ads API forecast metrics fluctuate based on temporal and regional parameters. While we normalize and cache these metrics, some degree of volatility remains — especially for low-frequency keywords.

- **Semantic Drift in LLMs**: Even with anchored prompts, certain models tend to overgeneralize or dilute niche concepts (e.g., "AI-powered CRM" becomes simply "CRM"). Incorporating feedback loops from judges into future prompt iterations could address this.

Planned next steps for development include:

- Incorporating real conversion tracking from landing pages to validate Google Ads forecasts against actual ROAS.

- Weighting judges dynamically based on user context (e.g., emphasize semantic fidelity for academic pages, or ads score for e-commerce).

- Exploring SHAP-based analysis on the judge outputs to better understand which keyword features most impact judge scores.

- Scaling to multilingual startup datasets using XLM-R or LaBSE in addition to TOBiT

4.3 Safety Considerations

Safety and alignment are core motivations behind our architecture. While generative optimization for web content carries the risk of model hallucination or misinformation, our dual-judge framework mitigates this by requiring that any generated output pass both semantic coherence and commercial plausibility checks.

Potential failure modes include:

- **Adversarial Prompting**: a user could deliberately inject misleading descriptions to manipulate keyword generation. However, our semantic judge penalizes incoherent or off-topic output, reducing incentive for such behavior.

- **Over-Optimization for Ads**: there is a risk that maximizing conversion rate leads to clickbait-style keywords. To counterbalance this, we intentionally weight semantic fidelity equally in our composite scoring.

- **Opaque Model Influence**: without understanding the judge's rationales, selection might seem arbitrary. That's why all outputs are logged with explanatory rationales and stored for post-hoc audit and developer review.

Our contributions advance safety by making routing transparent, interpretable and democratic, moving away from single-model black-box systems toward orchestrated, judge-aligned decision pipelines. This echoes calls in the literature (Lindner et al., 2023; Weiss et al., 2021) for systems with traceable internal logic and auditability in real-world applications.

5. Conclusion

This study presents a modular, interpretable architecture for optimizing keyword lists and page texts through large language model (LLM) routing, evaluated across both semantic fidelity and potential advertising profitability. By orchestrating six different LLMs via a composite system of dual judges — one focusing on semantic structure and the other on Google Ads forecast metrics — we demonstrate that targeted routing improves the relevance and commercial utility of generated outputs.

Unlike traditional black-box optimization, our method foregrounds transparency and traceability. Judges not only assign scores but provide explicit rationales, allowing developers and users to audit each decision point. This structure aligns with broader goals in AI alignment, mechanistic interpretability and safety: to

ensure that decisions made by systems reflect understandable principles and measurable outcomes.

Our results show that semantic precision and advertising viability can diverge across models, highlighting the need for multi-dimensional evaluation. For instance, Claude and GPT-4 variants achieved higher semantic scores, while Gemini Flash excelled in ad conversion efficiency — a divergence that would be lost in mono-criterion evaluation.

Looking forward, this architecture holds promise not just for SEO and advertising tasks, but as a generalizable framework for multi-objective generation tasks — such as education (accuracy vs. engagement), legal drafting (compliance vs. clarity), or scientific writing (novelty vs. reproducibility). By enabling model selection grounded in both meaning and metrics, we believe this system advances the field toward safer, more human-aligned generative and democratic pipelines.

Ultimately, our Apart x Martian Hackathon collaboration illustrates that LLM routing — when paired with interpretable judges and real-world performance metrics — can evolve from a theoretical construct into a practical decision layer for production-grade content systems.

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5. Appendix

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