Public Report - Model Collapse on NLP Datasets

Introduction

Building on prior work that combined augmentation techniques with rigorous evaluation metrics and reinforcement learning, this phase addresses model collapse, the tendency of language models to produce near-identical paraphrases over successive generations (ZHANG; LIU, 2021).

To prevent this, the research began with a detailed project plan defining objectives, methodological phases, and computational resources tailored to Portuguese NLP contexts .

Central to the solution is a generator–critic architecture: the Generator issues few-shot prompts to produce multiple paraphrase candidates, and the Critic immediately applies dynamic metrics such as Jaccard similarity, novel-term ratio, embedding cosine distance, and Unique Trigram Ratio to filter out overly similar outputs in real time (JAYAWARDENA; YAPA, 2024).

Prompt engineering was refined through system-level reminders, expert framing, and controlled synonym variations, techniques drawn from jailbreak-resistance studies that steer both models without altering their weights (MADAAN; LEE; SINGH, 2023; BROWN; SMITH, 2022).

This framework was prototyped via the HuggingFace Pro Inference API, resolving challenges such as chain-of-thought leakage and ensuring reproducible metric extraction (YANG et al., 2023).

The final pipeline introduces warm-up threshold calibration, exponential smoothing, minimal negative constraints, and periodic re-anchoring to maintain both semantic fidelity and genuine lexical innovation across iterations (ROGERS; FLORIAN, 2022; ZHANG; LIU, 2021). The remainder of this report details the architecture, prompt strategies, prototype implementation, pipeline enhancements, empirical results, and recommendations for further collapse mitigation.

Generator–Critic Architecture

Initial Framework

The initial framework paired a paraphrase generator with an immediate evaluator to prevent repetitive outputs. The generator received few-shot prompts containing demonstration examples and controlled decoding parameters to produce multiple candidates. Each candidate was then evaluated by the critic through four quantitative measures: a fixed windowed Jaccard similarity check to limit token overlap, a ratio of new vocabulary to encourage variation, cosine distance between sentence embeddings to preserve semantics, and a Unique Trigram Ratio analysis to detect local repetition (JAYAWARDENA; YAPA, 2024).

Advancements

Prompt-engineering insights led to re-anchoring demonstration examples in every iteration and replacing the percentage-based novelty threshold with an absolute count of new words, improving performance on shorter inputs (MADAAN; LEE; SINGH, 2023). Controlled synonym perturbations in prompts exposed trivial substitutions and hardened the critic against superficial changes (BROWN; SMITH, 2022). Prototyping via the HuggingFace Pro Inference API revealed instability in overlap measurements and parsing challenges, leading to the introduction of a zero-overlap gate and a fixed minimum of six novel terms (ROGERS; FLORIAN, 2022). A warm-up calibration phase was added to derive initial Jaccard and trigram-uniqueness thresholds from candidate statistics, and exponential smoothing was applied to both bounds to stabilize critic verdicts under production-like conditions (YANG et al., 2023).

Final Implementation

In production, the system begins with a warm-up phase that generates initial paraphrase statistics to establish threshold values for token overlap and trigram uniqueness (YANG et al., 2023). These thresholds are updated each iteration via exponential smoothing (YANG et al., 2023). Candidates with zero token overlap or fewer than six novel terms are rejected immediately (ROGERS; FLORIAN, 2022). Passing candidates then undergo cosine-similarity checks on sentence embeddings to ensure semantic fidelity (JAYAWARDENA; YAPA, 2024). Dynamic trigram-uniqueness bounds exclude locally repetitive outputs (YANG et al., 2023), while negative constraints blacklist only the immediately prior paraphrase (ROGERS; FLORIAN, 2022). The original sentence is reinserted after a fixed number of generations to prevent collapse attractors (ZHANG; LIU, 2021).

Model Usage

Early prototyping occurred in Jupyter notebooks running on Google Colab, where local invocations of transformer models via the HuggingFace Transformers library enabled rapid iteration on prompt designs and metric integrations. However, this setup suffered from session timeouts, fluctuating GPU availability, and dependency drift, which undermined reproducibility and introduced variability in paraphrase outputs .

To resolve these issues, the workflow transitioned to the HuggingFace Pro Inference API, which provides managed endpoints for both LLaMA and QWEN models. By outsourcing model hosting and version control, the API ensured consistent compute performance and stable library versions across all runs, allowing the team to focus entirely on refining prompts and evaluation logic .

Implementation of the API-based pipeline involved defining an `AugmentationGenerator` class that assembles few-shot prompts with explicit separator tokens, and a `CriticLLM` class that parses streamed API responses to extract each paraphrase candidate for metric evaluation . Access to usage logs and latency statistics through the Pro API also made it possible to systematically tune batch sizes and parallel request strategies, balancing throughput against cost. This API-centric approach laid the groundwork for the production-grade pipeline, uniting scalable infrastructure with the stringent, metric-driven controls of the generator–critic architecture .

Results

Early trials using fixed thresholds revealed that over 40 percent of generated candidates were rejected due to excessive lexical overlap (average Jaccard similarity above 0.80) and insufficient semantic alignment (embedding-cosine distances often below 0.50). Repeat-penalty flags occurred so frequently that only two consecutive augmentation iterations were feasible before collapse set in .

Migrating to managed inference endpoints allowed systematic comparison between two LLMs. One model averaged a Jaccard overlap of 0.62 with a novel-term ratio of 0.27, while the other achieved 0.48 overlap and 0.22 novelty. Despite consistent execution, collapse events persisted at approximately 25 percent across five generations, indicating that infrastructure stability alone did not prevent repetition and underscoring the need for adaptive thresholding .

Introducing a warm-up phase to calibrate initial threshold values, followed by exponential smoothing across iterations, produced substantial improvements. Collapse rates fell below 10 percent over five augmentation cycles. Average Jaccard similarity stabilized between 0.20 and 0.35, embedding-cosine scores consistently exceeded 0.80, and Unique Trigram Ratios remained above 0.85. Repeat-penalty occurrences dropped below 5 percent, confirming that dynamic, prompt-informed evaluation maintains both semantic fidelity and genuine lexical diversity over multiple rounds .

Improvements (Discussion)

Revisiting Static Metric-Driven Augmentation

Early metric-driven augmentation applied operations such as swap, insert, delete, and replace, then filtered outputs post-hoc using fixed thresholds on Jaccard similarity, centroid distance, BPRO, SLOR, and Unique Trigram Ratio. Although this approach improved sample variety, detailed case studies revealed that strong metric scores sometimes accompanied awkward phrasing or semantic drift, and no mechanism existed to halt repetitive attractor cycles once they formed .

Quality Checks within the Generation Loop

Embedding evaluation was moved from retrospective filtering to inline prevention. A warm-up phase gathers initial paraphrase statistics to establish dynamic bounds for token overlap and repetition, and these bounds are then updated each iteration through exponential smoothing. Candidates exhibiting zero token overlap or failing to introduce the required number of novel terms are rejected before re-entry, while continuous cosine-similarity checks on sentence embeddings ensure semantic fidelity. Dynamic Unique Trigram Ratio bounds detect local repetition in real time, interrupting emerging attractor cycles .

Sustained Diversity

To preserve exploration without permitting immediate repetition, the system enforces minimal negative constraints by blacklisting only the most recent paraphrase rather than accumulating prohibitions on all prior outputs. Multiple paraphrase variants are generated per iteration and scored by the critic; a soft-max selection among these candidates balances innovation with fidelity. Periodic re-anchoring of the original sentence after fixed intervals provides a hard reset that prevents gradual Semantic drift. Tiered acceptance zones allow candidates that narrowly miss a threshold to be retained with concise improvement hints, fostering incremental innovation without wholesale rejection .

Learned Evaluation Metrics

Complementing rule-based checks with learned evaluation functions captures subtler aspects of paraphrase quality. BLEURT provides a learned assessment of semantic fidelity, while BERTScore evaluates fluency and lexical choice through contextual embeddings. Embedding-based measures remain central to the critic’s verdicts, aligning with best practices for robust paraphrase assessment .

By uniting dynamic thresholding, inline evaluation, minimal negative constraints, multi-candidate sampling, periodic re-anchoring, tiered acceptance, and learned metrics, the generator–critic framework sustains both semantic integrity and genuine lexical innovation across successive paraphrase generations, effectively mitigating model collapse.

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