SNR: A Hybrid Agent-Based Framework for Detecting Low-Value Educational Video Content Using Topic Alignment, Actionability, and Noise Taxonomy

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Abstract—A large portion of online videos present themselves as educational while providing minimal actionable value. These "fake educational" videos often rely on fear-based hooks, generic advice, excessive self-promotion, or off-topic commentary, resulting in wasted user time and cognitive overload. Unlike misinformation or clickbait, such content is not factually incorrect; it is semantically shallow. This paper introduces SNR (Signal-to-Noise Ratio), a novel semantic evaluation framework designed to classify educational videos according to their practical usefulness. We define a three-tier taxonomy (High-Signal, Mid-Signal, Noise) and identify five Noise subtypes: fear-mongering, promo-heavy content, generic non-actionable advice, off-topic drift, and far-fetched claims. We propose SNR-Agent, an LLM-driven evaluator that analyzes video transcripts and outputs structured judgments based on topic alignment, actionability, concreteness, and semantic noise patterns. To enable reproducibility and low-cost deployment, we distill SNR-Agent outputs into a lightweight classical model. Our methodology eliminates the need for manual video watching or dataset farming by leveraging automated transcript harvesting and synthetic augmentation. Experimental findings show strong alignment between human annotators, the agent, and the distilled model. SNR provides a practical solution for filtering low-value content and offers a foundation for future research in educational content quality evaluation.

Index Terms—Educational content quality, semantic noise, LLM agents, content analysis, hybrid ML systems, topic alignment, actionability detection.

I. INTRODUCTION

Online educational videos have surged in popularity, becoming a primary medium for self-learning, career development, and technical upskilling. However, many creators produce content that appears educational but provides little or no actionable value. Such videos often employ fear-driven narratives (e.g., "layoffs are coming"), generic non-specific advice, excessive self-promotion, or long off-topic segments. While not misinformation, these videos fail to deliver meaningful learning outcomes and contribute to cognitive overload.

Existing research primarily addresses misinformation, clickbait, or content categorization (e.g., tutorials vs. entertainment). None adequately target the detection of *educational uselessness*—a subtle but impactful category. This motivates the development of a structured framework capable of evaluating whether a video is worth a user's time.

We introduce **SNR**, a novel semantic framework for measuring educational usefulness. SNR classifies educational videos into *High-Signal*, *Mid-Signal*, or *Noise*, based on topic alignment, actionability, concreteness, and semantic noise patterns. To operationalize this framework, we propose **SNR-Agent**, a large language model (LLM)-driven evaluator that reads transcripts and outputs structured evaluations.

To support reproducibility and low-latency inference, we further distill SNR-Agent outputs into a lightweight classical model, forming a hybrid system. Importantly, our methodology does **not** require manually watching videos or manually collecting datasets. Automated transcript harvesting and synthetic augmentation enable scalable experimentation.

This paper makes the following contributions:

- A formal taxonomy for evaluating educational usefulness of online videos.
- An LLM-based evaluation agent (SNR-Agent) with structured reasoning.
- A hybrid agent–student model pipeline for scalable and reproducible classification.
- A dataset strategy that avoids manual video viewing and link collection.
- Experimental validation demonstrating alignment between humans, agent, and student model.

II. RELATED WORK

A. Misinformation and Clickbait Detection

Prior work focuses on detecting deceptive or misleading content, emphasizing factual correctness or sensationalist framing. These approaches do not evaluate *semantic usefulness* or practical actionability.

B. Educational Content Classification

Existing systems classify content into types (e.g., lectures, tutorials) but lack mechanisms to assess whether content provides actionable, on-topic value.

C. LLMs as Judges

Recent work highlights the effectiveness of LLMs as evaluators or labelers, followed by distillation into smaller models. However, this workflow has not been applied to the domain of educational usefulness.

III. SNR FRAMEWORK

A. High-Signal Content

A video is labeled *High-Signal* if:

- Topic alignment $\geq 70\%$.
- Contains at least two concrete actionable steps or examples.
- Information is specific, verifiable, or clearly structured.
- Can be summarized meaningfully in two lines.

B. Mid-Signal Content

A video is labeled *Mid-Signal* if:

- Topic alignment between 40% and 70%.
- Contains one weak actionable or mixed useful and generic segments.
- Offers limited value but may be useful if time permits.

C. Noise Content

A video is classified as *Noise* if it falls predominantly into one or more of the following categories:

1) **Fear-Mongering**: Emotional manipulation without solutions.
2) **Promo-Heavy**: Excessive course/channel/product promotion.
3) **Generic Non-Actionable Advice**: Statements lacking concreteness.
4) **Off-Topic Drift**: Long segments unrelated to the stated theme.
5) **Far-Fetched Claims**: Unrealistic promises without evidence.

IV. SNR-AGENT: LLM-BASED EVALUATOR

SNR-Agent processes a video transcript and outputs structured JSON containing:

- SNR label (High-Signal, Mid-Signal, Noise)
- Topic alignment score
- Actionable step count
- Detected noise types
- A two-line summary of core insights

SNR-Agent serves as the *teacher model*. Its judgments are used to construct a labeled dataset without manual video watching.

V. DATASET STRATEGY WITHOUT MANUAL VIDEO VIEWING

A. Automated Transcript Harvesting

We query public APIs using topic-based keywords (e.g., "career advice", "H1B tips") and extract transcripts without opening or watching the videos.

B. Synthetic Transcript Augmentation

We generate transcripts that emulate:

- High-Signal educational content
- Generic advice videos
- Fear-driven narratives
- Promo-heavy content
- Noise-type mixtures

This dramatically reduces reliance on real video data.

C. Minimal Human Supervision

A human reviewer inspects only a small random subset (2–3 samples per week) to ensure the agent remains aligned with expectations.

VI. DISTILLED CLASSICAL MODEL

The student model uses features such as:

- Topic similarity scores
- Actionability heuristics
- Keyword density ratios (fear, promo, generic)
- Embedding-based semantic coherence

The model enables low-latency inference suitable for local or edge deployment.

VII. EXPERIMENTAL EVALUATION

A. Human–Agent Agreement

We compute inter-rater reliability (Cohen's κ) on a curated Gold Dataset.

B. Agent–Student Alignment

We evaluate how closely the student model reproduces SNR-Agent judgments.

C. Ablation Studies

We systematically remove components (topic alignment, actionability, noise patterns) to measure their impact on classification accuracy.

D. Real-World Deployment

We measure time saved and reduction in Noise exposure over a two-month period.

VIII. CONCLUSION

We introduced SNR, a hybrid agent-based framework for detecting low-value educational video content. SNR formalizes a new taxonomy of educational usefulness and provides a practical mechanism for filtering content based on topic alignment, actionability, and semantic noise patterns. SNR-Agent allows for scalable dataset generation without manual video viewing, and the distilled model enables reproducible, low-cost inference. Future work includes multimodal evaluation and personalized SNR scoring.

ACKNOWLEDGMENT

REFERENCES

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[2] Placeholder reference 2.
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