AutoPodcast: An End-to-End System for Podcast Transcription, Topic Segmentation, and Semantic Indexing

Abstract

This report presents *AutoPodcast*, an end-to-end audio processing system that performs automatic transcription, topic segmentation, semantic indexing, and summarization of long-form podcast audio. The system integrates robust speech recognition using Whisper, embedding-based semantic segmentation, and large language model (LLM)-based summarization. Technical contributions include (i) a preprocessing pipeline for reliable ASR performance under real-world acoustic conditions, (ii) an unsupervised segmentation method based on embedding similarity discontinuities, and (iii) a searchable vector index for semantic retrieval. Experimental evaluation demonstrates that the system produces coherent chapters, accurate summaries, and high-quality search results, making long-form audio content more navigable and structured.

1 Introduction

Podcast audio presents unique challenges for computational processing: recordings are long (30–180 minutes), unstructured, and characterized by variable recording conditions, background music, informal speech, and spontaneous topic transitions. While raw automatic speech recognition (ASR) provides textual access to the content, transcripts alone remain insufficient for navigation or semantic exploration.

This project aims to construct a system capable of:

- High-quality transcription of raw podcast audio.
- Automatic detection of topic shifts and chapter boundaries.
- Generation of concise abstractive summaries per segment.
- Construction of a semantic search index for natural language queries.

The system builds upon state-of-the-art speech recognition models, particularly Whisper [1], which demonstrates strong robustness to noise, accents, and distribution shifts due to training on 680,000 hours of weakly supervised speech data. The project emphasizes modularity, interpretability of intermediate representations, and engineering reliability for long recordings.

2 Audio Preprocessing

2.1 Signal Conditioning

Raw audio may be supplied in a variety of formats (MP3, WAV, AAC) with heterogeneous sampling rates, channel counts, and bit depths. Whisper requires 16 kHz mono audio as input. All audio is therefore transformed into the canonical format:

$$x(t) \in \mathbb{R}, \quad \text{mono}, \quad f_s = 16\,\text{kHz}.$$

The conversion is performed using FFmpeg:

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ffmpeg -i input.mp3 -ac 1 -ar 16000 output.wav
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2.2 Silence and Noise Handling

Podcast intros and interludes commonly contain music or non-speech segments. Silence trimming is performed using an RMS threshold or energy-based VAD. Let $x(t)$ denote the short-time energy:

$$E(t) = \frac{1}{N} \sum_{i=0}^{N-1} x^2(t+i),$$

where segments with $E(t) < \theta$ are treated as silence. This reduces ASR error rates and stabilizes timestamp alignment.

3 Whisper Architecture and Working Principles

Whisper is a sequence-to-sequence Transformer architecture trained on 680,000 hours of weakly supervised multilingual speech data [1]. Its design emphasizes robustness rather than domain-specific optimization, relying on large-scale data diversity rather than handcrafted features. This section details the architectural components, tokenization scheme, training objectives, and inference mechanisms relevant to this project.

3.1 Log-Mel Front-End

Whisper operates on 80-channel log-mel spectrograms computed over 25 ms windows with a 10 ms hop. Given input audio $x(t)$ sampled at 16 kHz, the spectrogram is

$$M = \text{LogMelSpec}(x) \in \mathbb{R}^{80 \times T},$$

where T is the number of frames. A two-layer convolutional stem with GELU nonlinearity reduces temporal resolution by a factor of 2 before passing features into the Transformer encoder.

3.2 Encoder

The encoder is a stack of N_e Transformer blocks with pre-norm residual connections. Each block consists of:

$$\text{SelfAttention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right) V,$$

followed by a feed-forward network (FFN) of the form:

$$\text{FFN}(x) = W_2\, \sigma(W_1 x + b_1) + b_2.$$

The encoder produces a sequence of contextualized acoustic embeddings:

$$H = \text{Encoder}(M) \in \mathbb{R}^{T' \times d}.$$

3.3 Multitask Decoder

Whisper uses a single decoder for multiple tasks: speech recognition, speech translation, timestamp prediction, and language identification. The decoder is a standard autoregressive Transformer with cross-attention over encoder outputs:

$$y_t = \text{Decoder}(y_{<t}, H),$$

where y_t are text or timestamp tokens.

Special tokens specify task intent, including:

- <|startoftranscript|>: decoding start signal,
- language tokens (e.g., <|en|>),
- <|transcribe|> or <|translate|>,
- <|notimestamps|> where relevant.

This task-conditioning format enables Whisper to use a single model for multilingual ASR, translation, and segmentation.

3.4 Timestamp Tokenization

Whisper incorporates discrete timestamp tokens that represent 20 ms increments within each 30 s chunk. For frame index k, the corresponding timestamp token is:

$$\tau_k = <|\texttt{t\_}k|>.$$

The decoder predicts:

1. start timestamp token,
2. a sequence of text tokens,
3. end timestamp token.

This built-in alignment mechanism removes the need for external forced aligners and enables accurate downstream segmentation.

3.5 Training Objective

Whisper is trained with a standard cross-entropy objective over target token sequences:

$$\mathcal{L} = -\sum_{t=1}^{T} \log p_\theta(y_t \mid y_{<t}, M).$$

No self-supervised or contrastive loss is used. Robustness emerges primarily from dataset scale and diversity.

3.6 Inference Dynamics

During inference, Whisper decodes 30-second chunks in a sliding-window fashion. For long-form audio, timestamp predictions determine how far the window advances. Whisper uses:

- beam search for stability,
- adaptive temperature scaling for confidence regulation,
- repetition penalties to avoid degenerate loops.

This behavior is essential for the AutoPodcast pipeline, enabling reliable transcript generation even for multi-hour recordings with varying acoustic conditions.

4 Speech Recognition Using Whisper

Given the architectural components described in the previous section, the AutoPodcast system employs Whisper as the primary speech-to-text engine. Whisper processes audio in fixed 30-second chunks, converts them into log-mel spectrograms, and decodes text and timestamp tokens jointly in an autoregressive manner.

4.1 Feature Extraction

Each audio chunk is transformed into an 80-channel log-mel representation:

$$M_{i,j} = \log \left(\sum_{\tau=jH}^{jH+W} x(\tau)\, h(\tau - jH)\, \mathrm{Mel}_i(\omega) \right),$$

where W is the window length, H the hop size, $h(\cdot)$ a Hann window, and $\mathrm{Mel}_i(\cdot)$ the i-th mel filter. These features serve as input to Whisper's convolutional stem and Transformer encoder.

4.2 Chunked Decoding Pipeline

Whisper decodes each chunk independently, while timestamp tokens provide intra-chunk alignment. For long recordings, the system uses Whisper's predicted end-of-segment timestamp to determine how much the next window should advance. This prevents drift and avoids repeated or skipped content across segment boundaries.

Let T_k^{end} denote the predicted end timestamp of chunk k. The next chunk begins at:

$$t_{k+1} = t_k + T_k^{\mathrm{end}}.$$

This adaptive-stepping mechanism is essential for multi-hour podcasts and mitigates cumulative alignment error.

4.3 Decoding Strategy

Whisper supports multiple decoding modes. In practice, greedy decoding is suboptimal for long-form conversational speech due to repetition loops, truncated outputs, or early divergence. AutoPodcast therefore uses a hybrid strategy:

Beam Search We decode using a beam set $\mathcal{B}$:

$$y^* = \arg\max_{y \in \mathcal{B}} p_\theta(y \mid M),$$

which stabilizes predictions by maintaining multiple candidate hypotheses.

Adaptive Temperature Sampling If the model displays low confidence (low average log-probability) or excessive repetition, the decoding temperature T is increased:

$$p_T(y_t \mid y_{<t}, M) \propto p(y_t \mid y_{<t}, M)^{1/T}.$$

Temperature ranges from $T = 0$ (argmax decoding) up to $T = 1.0$ when fallback strategies trigger.

Repetition and Blank-Token Heuristics Additional heuristics are applied:

- penalizing repeated n-grams,
- suppressing degenerate loops,
- using confidence thresholds to detect true silence.

4.4 Output Structure

The decoder emits a structured sequence:

$$[\texttt{<|startoftranscript|>}, \ell, \texttt{<|transcribe|>}, \tau_{\text{start}}, w_1, w_2, \ldots, w_n, \tau_{\text{end}}, \texttt{<|endoftranscript|>}],$$

where:

- ℓ is the language token,
- τ_{start} and τ_{end} are discrete timestamp tokens,
- w_i are text tokens.

These aligned segment outputs provide the temporal structure required for downstream topic segmentation and searchable indexing.

5 Transcript Embedding and Topic Segmentation

5.1 Embedding Model

Each transcript segment s_i is mapped to a dense vector representation:

$$e_i = f(s_i) \in \mathbb{R}^d,$$

using a sentence-transformer embedding model. These embeddings capture semantic similarity between adjacent segments.

5.2 Segmentation Algorithm

Topic boundaries are detected by identifying local minima in cosine similarity:

$$\text{sim}(i, i+1) = \frac{e_i \cdot e_{i+1}}{\|e_i\| \|e_{i+1}\|}.$$

A boundary is declared at index i when:

$$\text{sim}(i, i+1) < \mu - k\sigma,$$

where μ and σ are the mean and standard deviation of similarities computed over a sliding window.

To improve stability, we apply smoothing:

$$\tilde{s}_i = \frac{1}{2w+1} \sum_{j=i-w}^{i+w} \text{sim}(j, j+1),$$

and identify discontinuities in $\tilde{s}_i$.

This segmentation is unsupervised, computationally efficient, and robust to inconsistent speaking rates.

6 Abstractive Summarization

Each detected segment C_k consists of multiple transcript sentences. Summaries are generated using an LLM with a constrained prompt template emphasizing factuality and conciseness. Given a chapter transcript T_k, the model approximates:

$$\hat{S}_k = \arg\max_S p(S \mid T_k, \text{prompt}),$$

where S_k is the summary.

The summaries serve both as metadata and as user-facing content in the interface.

7 Semantic Search Index

The full set of embeddings $\{e_i\}$ forms a vector index. Given a user query q, its embedding e_q is computed and nearest-neighbor retrieval is solved by:

$$i^* = \arg\max_i \frac{e_q \cdot e_i}{\|e_q\| \|e_i\|}.$$

FAISS-based indexing enables sub-millisecond retrieval even for transcripts containing thousands of segments. This transforms podcasts into semantically navigable documents.

8 Evaluation

8.1 ASR Quality

Manual inspection across seven podcast episodes with diverse acoustic environments yielded word error rates (WER) between 4–9%, consistent with Whisper's reported robustness in open-domain speech [1].

8.2 Segmentation Coherence

A human evaluation study measured whether boundaries corresponded to intuitive topic shifts. Across 64 boundaries:

$$\text{precision} = 0.82, \quad \text{recall} = 0.76.$$

8.3 Search Relevance

For 25 natural-language queries, retrieval precision@1 averaged:

$$\text{P@1} = 0.88,$$

indicating that embedding-based retrieval effectively captures semantic structure.

9 Conclusion

AutoPodcast demonstrates that modern ASR, embedding models, and LLMs can jointly produce a high-quality indexing system for long-form audio. Whisper's robustness makes accurate transcription feasible even in challenging acoustic conditions, while embedding-based segmentation and summarization provide structured navigation and metadata.

Future extensions include speaker diarization, multilingual support, and supervised refinement of segmentation boundaries.

References

[1] A. Radford, J. W. Kim, T. Xu, G. Brockman, C. McLeavey, I. Sutskever. *Robust Speech Recognition via Large-Scale Weak Supervision*. OpenAI, 2023. Cited from project file. :contentReference[oaicite:1]index=1