# Accelerating Whisper Speech Recognition with Speculative Decoding: Cross-Version Token Remapping for Incompatible Architectures

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**Abstract**

Autoregressive speech recognition models like OpenAI's Whisper achieve state-of-the-art accuracy but suffer from slow inference due to sequential token generation.Implementation of speculative decoding to accelerate Whisper inference by using smaller draft models to predict tokens in parallel, which are then verified by the main model. Results achieve a **1.92× speedup** with Whisper Large-V2 using a Tiny draft model, with WER maintained at 2.4%. Furthermore, a novel **cross-version speculative decoding** approach is introduced that enables Large-V3 to leverage architecturally incompatible draft models through token remapping and dual feature extraction, achieving a 1.24× speedup despite tokenizer and feature extractor differences. The result provide comprehensive benchmarks on LibriSpeech and demonstrate practical deployment strategies for production speech recognition systems.

## Contents

# 1 Introduction

## 1.1 Background and Motivation

OpenAI's Whisper is a transformer-based speech recognition model trained on 680,000 hours of multilingual data, achieving state-of-the-art performance across diverse domains. However, Whisper's autoregressive decoding generates tokens sequentially, creating a significant computational bottleneck during inference. For real-time applications such as live transcription, voice assistants, and video captioning, this latency is prohibitive.

Speculative decoding addresses this bottleneck by using a smaller, faster "draft" model to predict multiple tokens in parallel. The main model then verifies these predictions in a single forward pass, accepting correct tokens and rejecting incorrect ones. This approach maintains output quality while reducing latency, as the draft model "speculates" about future tokens without compromising the final accuracy.

## 1.2 Challenges

Applying speculative decoding to Whisper presents several unique challenges:

1. **Version incompatibility**: Whisper Large-V3 introduced architectural changes (128 vs. 80 Mel frequency bins, updated tokenizer) that prevent direct use of existing draft models trained on earlier versions.
2. **Draft model selection**: Trade-offs between draft model size, inference speed, and token acceptance rates require empirical evaluation.
3. **Quality preservation**: Ensuring Word Error Rate (WER) remains unchanged during speculative generation is critical for production deployment.

## 1.3 Contributions

This work makes the following contributions:

- Implementation of speculative decoding for Whisper Large-V2 with multiple draft models (Tiny, Base, Distil-Large-V2), achieving up to 1.92× speedup.
- Novel cross-version speculative decoding enabling Large-V3 to use incompatible draft models via text-based token remapping and dual feature extraction.
- Comprehensive benchmarking on LibriSpeech showing zero WER degradation across all configurations.
- Analysis of speculative decoding vs. beam search trade-offs for different deployment scenarios.
- Open-source implementation with production-ready code and detailed documentation.

# 2 Related Work

**Speculative Decoding.** Leviathan et al. introduced speculative decoding for large language models, demonstrating 2-3× speedups without quality loss. Chen et al. extended this with speculative sampling, which maintains the same output distribution as autoregressive decoding.

**Whisper Optimization.** Prior work on accelerating Whisper includes model distillation, quantization, and architecture modifications. However, these approaches typically trade accuracy for speed, whereas speculative decoding maintains identical outputs.

**Speech Recognition Efficiency.** Streaming transformers and CTC-based models offer low-latency alternatives but sacrifice Whisper's robustness to diverse acoustic conditions.

The work is the first to apply speculative decoding to speech recognition and to address cross-version compatibility through token remapping.

## 3 Methodology

### 3.1 Speculative Decoding Algorithm

Speculative decoding operates in three phases:

**Phase 1: Draft Generation.** Given input features $x$ and lookahead parameter $K$, the draft model $M_d$ generates $K$ candidate tokens:

$$t_d^{1:K} = \arg\max_t M_d(x, t_{<i}) \quad \text{for } i = 1, \ldots, K \tag{1}$$

**Phase 2: Parallel Verification.** The main model $M_m$ processes all draft tokens simultaneously:

$$p_m = M_m(x, [t_{<n}, t_d^{1:K}]) \tag{2}$$

where $t_{<n}$ are previously generated tokens.

**Phase 3: Token Acceptance.** Draft tokens are accepted if they match the main model's predictions:

$$n_{\text{accepted}} = \max\{i : \arg\max p_m^{(j)} = t_d^j \text{ for all } j \leq i\} \tag{3}$$

If all $K$ tokens match, the effective speedup is $K$. If none match, gain one token from $M_m$'s prediction.

### 3.2 Draft Model Selection for Large-V2

Three draft model candidates compatible with Whisper Large-V2 are evaluated:

- **Whisper-Tiny**: 39M parameters, 32× smaller than Large (1.5B params)
- **Whisper-Base**: 74M parameters, 17× smaller than Large
- **Distil-Whisper-Large-V2**: Distilled from Large-V2, optimized for speed while maintaining accuracy

All share the same tokenizer (51,864 tokens) and feature extractor (80 Mel bins), enabling direct compatibility.

# 4 Cross-Version Speculative Decoding

## 4.1 Problem Statement

Whisper Large-V3 introduced significant architectural changes that break compatibility with existing draft models:

- **Feature Extractor**: 128 Mel frequency bins (vs. 80 in V2)
- **Tokenizer**: Updated vocabulary with 51,865 tokens (vs. 51,864 in V2)
- **Positional Encodings**: Modified encoder architecture

Existing draft models (Tiny, Base) were trained with 80 Mel bins and V2's tokenizer. Direct application would fail due to:

1. Dimension mismatch in encoder inputs (80 vs. 128 channels)
2. Token ID incompatibilities between vocabularies
3. Different special token semantics

## 4.2 Solution Architecture

The approach consists of three key components:

### 4.2.1 Dual Feature Extraction Pipeline

Audio is processed separately for each model to ensure correct input dimensions:

**Algorithm 1** Dual Feature Extraction

```
1: Input: Raw audio $a$
2: Output: Main features $x_m$, Draft features $x_d$
3: $x_m \leftarrow \text{FeatureExtractor}_{\text{V3}}(a)$ {128 Mel bins}
4: $x_d \leftarrow \text{FeatureExtractor}_{\text{Tiny}}(a)$ {80 Mel bins}
5: return $x_m, x_d$
```

This ensures each model receives features in its expected format, avoiding encoder dimension mismatches.

### 4.2.2 Text-Based Token Remapping

A mapping is constructed $\phi : V_d \to V_m$ from draft vocabulary to main vocabulary based on decoded text:

**Algorithm 2** Token Remapping Construction

```
1: **Input:** Draft tokenizer $T_d$, Main tokenizer $T_m$
2: **Output:** Token mapping $\phi$
3: for each token $t_d \in V_d$ do
4:     text $\leftarrow T_d$.decode($t_d$)
5:     tokens$_m \leftarrow T_m$.encode(text)
6:     if $|\text{tokens}_m| > 0$ then
7:         $\phi[t_d] \leftarrow$ tokens$_m$[0] {Use first token}
8:     else
9:         $\phi[t_d] \leftarrow$ UNK$_m$ {Fallback to unknown}
10:    end if
11: end for
12: return $\phi$
```

**Rationale:** Most tokens represent the same text across versions (e.g., "hello", "the", special tokens like `<|en|>`). By decoding draft tokens to text and re-encoding with the main tokenizer, a semantic preservation is achieved even when token IDs differ.

**Coverage:** The implementation achieves 100% mapping coverage (51,865/51,865 tokens), with:

- 99.2% exact text matches (common words, special tokens)
- 0.8% multi-token approximations (rare compound words)

### 4.2.3 Modified Speculative Generation

The complete cross-version algorithm integrates dual feature extraction and token remapping:

**Algorithm 3** Cross-Version Speculative Generation

```
1: Input: Audio $a$, Main model $M_m$, Draft model $M_d$, Lookahead $K$, Mapping $\phi$
2: Output: Transcript tokens
3: $x_m, x_d \leftarrow$ DualFeatureExtraction($a$)
4: $h_m \leftarrow \text{Encoder}_m(x_m)$, $h_d \leftarrow \text{Encoder}_d(x_d)$
5: output $\leftarrow$ [BOS]
6: while not EOS and |output| < max_length do
7:     {Draft phase}
8:     $t_d^{1:K} \leftarrow \text{Generate}_d(h_d, \text{output})$ {K tokens from draft}
9:     {Remap tokens}
10:    $t_m^{1:K} \leftarrow [\phi[t] \text{ for } t \in t_d^{1:K}]$
11:    {Verify with main model}
12:    $p_m \leftarrow M_m(h_m, \text{output} \oplus t_m^{1:K})$
13:    $\text{pred}_m \leftarrow \arg\max p_m$
14:    {Accept matching tokens}
15:    $n \leftarrow \text{CountMatches}(\text{pred}_m, t_m^{1:K})$
16:    if $n > 0$ then
17:        output $\leftarrow$ output $\oplus\, t_m^{1:n}$
18:    else
19:        output $\leftarrow$ output $\oplus\, [\text{pred}_m[0]]$
20:    end if
21: end while
22: return output
```

## 4.3 Design Rationale

**Why text-based mapping?** Alternative approaches include:

1. *Embedding alignment*: Train a mapping between token embeddings. However, this requires additional training data and may not preserve semantic meaning.
2. *Vocabulary intersection*: Only use tokens present in both vocabularies. This severely limits coverage (<60%).
3. *Byte-pair encoding (BPE) merge alignment*: Map based on BPE operations. This fails when merge orders differ between versions.

Text-based mapping is simple, requires no training, and achieves near-perfect coverage by leveraging the fact that both tokenizers encode the same language.

**Handling multi-token cases.** When a draft token decodes to multiple main tokens (e.g., compound words), the architecture use the first token as an approximation. The main model's verification phase corrects this in the next iteration, maintaining output quality.

## 4.4 Thinking Behind the Logic

The key insight is that **tokenizers are lossy compression schemes**. While token IDs may differ between versions, the underlying text representation is preserved. By going through the text domain (decode $\rightarrow$ encode), the ID mismatch problem is entirely removed.

This approach works because:

- Whisper tokenizers are deterministic (same text always maps to same tokens)
- Special tokens (`<|en|>`, `<|transcribe|>`, etc.) have identical text representations
- Common words ("hello", "the", "is") map 1:1 across versions
- Rare multi-token cases are corrected by main model verification

The trade-off is a lower acceptance rate ( 40% vs. 60% for same-version) because the draft model's token distribution doesn't perfectly align with the main model's expectations after remapping. However, this is acceptable because the architecture still maintain correctness (100% WER preservation) while gaining speedup.

## 5 Experimental Setup

### 5.1 Dataset

**LibriSpeech ASR**:

- **Split**: Clean validation set
- **Samples**: 8 utterances for Large-V2 benchmarks, 10 for Large-V3, 20 for beam search analysis
- **Domain**: Read English speech from public domain audiobooks
- **Characteristics**: High audio quality, clear pronunciation, standard American English

### 5.2 Evaluation Metrics

- **Word Error Rate (WER)**: WER = $\frac{\mathrm{S+I+D}}{\mathrm{N}}$, where S = substitutions, I = insertions, D = deletions, N = total words
- **Character Error Rate (CER)**: Fine-grained accuracy at character level
- **Latency**: Total inference time in seconds, measured with GPU synchronization
- **Speedup**: $\frac{\text{Baseline Latency}}{\text{Speculative Latency}}$

### 5.3 Implementation Details

- **Hardware**: NVIDIA T4 GPU (16GB VRAM)
- **Precision**: FP16 for GPU inference, FP32 for CPU
- **Framework**: PyTorch 2.0, Transformers 4.35
- **Hyperparameters**:
  - Lookahead $K = 5$ for Large-V2, $K = 3$ for Large-V3 (tuned empirically)

  - Batch size = 1 (sequential processing for fair comparison)
  - Max tokens = 400 (to avoid context length errors)

- **Code**: Available at `https://github.com/prathamc25/whisper-speculative-decoding`

## 6 Results

### 6.1 Large-V2 Speculative Decoding

Table 1 shows results for Whisper Large-V2 with different draft models on 8 LibriSpeech samples.

Table 1: Whisper Large-V2 Speculative Decoding Results (8 samples)

| **Configuration** | **Latency (s)** | **WER** | **Speedup** |
|---|---|---|---|
| Baseline (Large-V2) | 8.05 | 2.4% | 1.00× |
| + Tiny Draft | 4.19 | 2.4% | **1.92**× |
| + Base Draft | 4.62 | 2.4% | 1.74× |
| + Distil-Large Draft | 5.92 | 2.4% | 1.36× |

**Key findings:**

- **Best speedup**: Tiny draft achieves 1.92× speedup (4.19s vs. 8.05s)
- **Zero WER degradation**: All configurations maintain WER at 2.4%
- **Diminishing returns**: Larger draft models (Base, Distil) provide less speedup due to increased draft inference cost
- **Tiny is optimal**: Smallest model maximizes speed while maintaining verification quality

### 6.2 Cross-Version Speculative Decoding (Large-V3 + Tiny)

Table 2 compares Large-V3 baseline with cross-version speculative decoding using the Tiny draft model.

Table 2: Whisper Large-V3 + Tiny Cross-Version Results (10 samples)

| **Configuration** | **Latency (s)** | **WER** | **Speedup** |
|---|---|---|---|
| Baseline (Large-V3) | 10.90 | 9.09% | 1.00× |
| Speculative (V3 + Tiny) | 8.80 | 9.09% | **1.24**× |

**Analysis:**

- **Speedup achieved**: 1.24× despite architectural incompatibility
- **Performance gap**: 35% slower than same-version (1.92× vs. 1.24×) due to:
  1. Dual feature extraction overhead (∼10% latency)

2. Token remapping computation (∼5% latency)
3. Lower acceptance rate (∼40% vs. ∼60% for same-version)

- **WER preserved**: Both configurations achieve 9.09% WER (identical outputs)
- **Feasibility demonstrated**: Cross-version approach works in practice when compatible draft models are unavailable

## 6.3 Beam Search Comparison

Table 3 shows beam search trade-offs for Large-V3 on 20 samples.

Table 3: Beam Search Analysis on Large-V3 (20 samples)

| Beam Size | Latency (s) | Avg/Sample (s) | WER | CER |
|---|---|---|---|---|
| 1 (Greedy) | 16.73 | 0.837 | 14.02% | 3.34% |
| 2 | 20.94 | 1.047 | 14.02% | 3.34% |
| 3 | 23.27 | 1.163 | 14.02% | 3.34% |
| 4 | 25.36 | 1.268 | 14.02% | 3.34% |
| 5 | 28.01 | 1.400 | 14.02% | 3.34% |

**Insights:**

- **No accuracy gain**: All beam sizes achieve identical WER (14.02%) and CER (3.34%)
- **Linear slowdown**: Beam 5 is 1.67× slower than greedy (28.01s vs. 16.73s)
- **Speculative dominates**: For this dataset, speculative decoding (1.24-1.92× speedup) outperforms beam search without accuracy loss
- **Beam utility limited**: Beam search offers minimal benefit on clean LibriSpeech data; may help on noisy audio

## 6.4 Comparison with Tiny and Base Beam Search

Table 4 shows beam search results for smaller models.

Table 4: Beam Search on Tiny and Base Models (8 samples)

| Configuration | Latency (s) | WER |
|---|---|---|
| Tiny (Beam 5) | 1.59 | 2.4% |
| Base (Beam 5) | 1.77 | 2.4% |
| Large-V2 (Beam 5) | 14.78 | 2.4% |

**Takeaways:**

- Tiny/Base with beam search are extremely fast but lack Large-V2's robustness
- For production, **Large-V2 + Tiny speculative** (4.19s, 2.4% WER) offers best balance

# 7 Discussion

## 7.1 Speedup Analysis

The 1.92× speedup with Large-V2 + Tiny demonstrates the efficiency of speculative decoding when models share architectures. Contributing factors:

1. **Parallel verification**: Main model processes $K = 5$ tokens simultaneously (vs. 5 sequential forward passes)
2. **High acceptance rate**: ∼60% of draft tokens match main model predictions
3. **Minimal draft cost**: Tiny adds only 15-20ms per forward pass

Expected tokens accepted per iteration:

$$E[n] = \sum_{k=1}^{K} k \cdot P(\text{accept } k \text{ tokens}) + P(\text{accept } 0) \cdot 1 \tag{4}$$

For $K = 5$ with 60% acceptance per token: $E[n] \approx 2.8$ tokens/iteration.

The reduced 1.24× speedup for Large-V3 + Tiny reflects:

- **Dual feature extraction**: 10% overhead from processing audio twice
- **Token remapping**: 5% overhead (amortized hash table lookups)
- **Lower acceptance rate**: ∼40% due to tokenizer mismatch reducing $E[n]$ to ∼1.8

## 7.2 When to Use Cross-Version Speculative Decoding

**Recommended when:**

- Latest model version (V3) required for accuracy on challenging domains
- No version-compatible draft models available
- 1.2-1.3× speedup justifies added implementation complexity
- WER preservation is critical (beam search not viable)

**Not recommended when:**

- Same-version draft models exist (use standard speculative for 1.5-2× speedup)
- Extreme low-latency required (<100ms; consider model distillation or streaming architectures)
- Memory-constrained devices (dual model loading requires ∼2GB extra VRAM)

## 7.3 Beam Search vs. Speculative Decoding

Table 5 summarizes trade-offs:

**Recommendation**: For most applications, Large-V2 + Tiny speculative offers the best speed/accuracy balance.

Table 5: Deployment Strategy Comparison

| **Strategy** | **Speedup** | **WER Change** | **Use Case** |
|---|---|---|---|
| Beam Search (5) | 0.60× | 0% | Maximum accuracy |
| Greedy (Baseline) | 1.00× | 0% | Standard |
| Speculative (V2) | 1.92× | 0% | Production (best) |
| Speculative (V3) | 1.24× | 0% | Latest model |

### 7.4 Future Optimizations

Several optimizations could improve cross-version performance:

**1. Learned Token Mapping.** Train a lightweight neural network to map draft embeddings to main embeddings:

$$\phi_\theta : R^{d_d} \to R^{d_m} \tag{5}$$

This could improve acceptance rates by learning semantic similarities beyond text matching.

**2. Adaptive Lookahead.** Dynamically adjust $K$ based on observed acceptance:

$$K_{t+1} = \begin{cases} \min(K_t + 1, K_{\max}) & \text{if } r_t > 0.8 \\ \max(K_t - 1, 1) & \text{if } r_t < 0.3 \\ K_t & \text{otherwise} \end{cases} \tag{6}$$

where $r_t$ is acceptance rate at step $t$.

**3. Training V3-Compatible Draft Models.** The ideal solution is training Tiny/Base models with 128 Mel bins and V3's tokenizer, eliminating remapping overhead entirely. Estimated speedup: 1.6-1.8×.

## 8 Conclusion

It was demonstrated that speculative decoding effectively accelerates Whisper speech recognition, achieving **1.92× speedup** with Large-V2 + Tiny draft model while maintaining WER at 2.4%. The novel cross-version approach enables Large-V3 to leverage architecturally incompatible draft models through text-based token remapping and dual feature extraction, achieving **1.24× speedup** with zero WER degradation.

**Key achievements:**

- First implementation of cross-version speculative decoding for speech recognition
- 100% token mapping coverage between Whisper V3 and Tiny vocabularies (51,865 tokens)
- Zero quality loss across all configurations on LibriSpeech
- Production-ready open-source implementation with comprehensive benchmarks

**Impact:** These speedups enable real-time transcription on commodity hardware, reducing cloud inference costs by $\sim$50% for Large-V2 deployments and $\sim$20% for Large-V3.

Future work includes training V3-native draft models, optimizing token remapping with learned mappings, and extending to multilingual and noisy audio scenarios.

## Code Availability

Full implementation, benchmarks, and reproduction scripts available at:
`https://github.com/prathamc25/whisper-speculative-decoding`

## References

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