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Paralinguistics-Aware Speech-Empowered Large Language Models for Natural Conversation_분석

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HyorinJung

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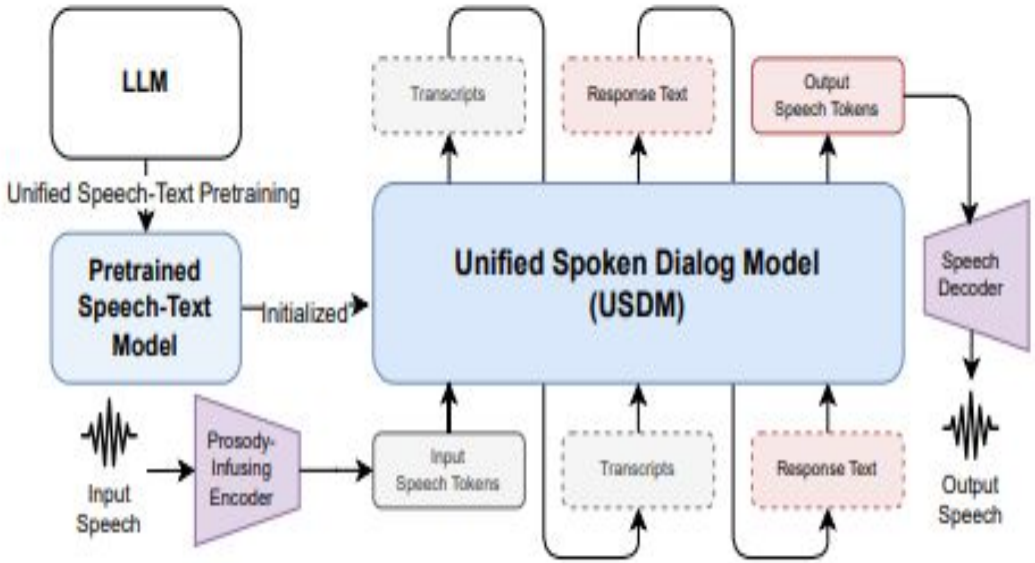
Review



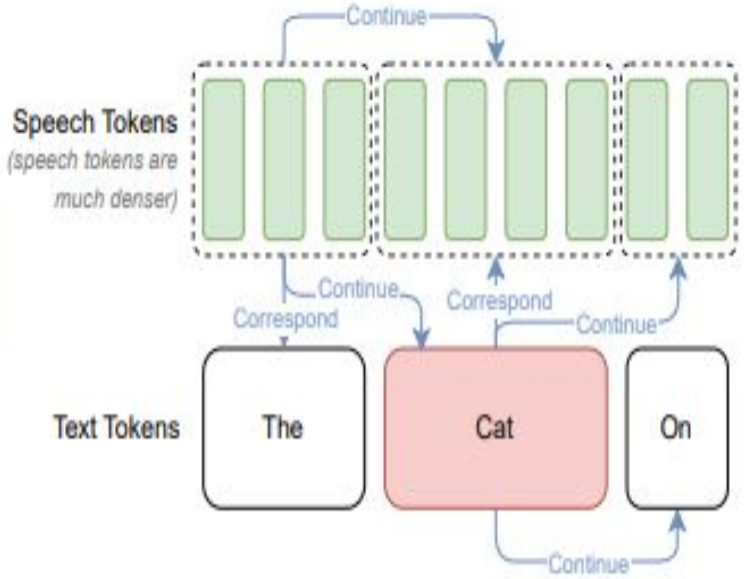


Figure 1: Overview of our spoken dialog modeling approach (Left). All possible self-supervised learning objectives from our speech-text pretraining scheme. (Right)

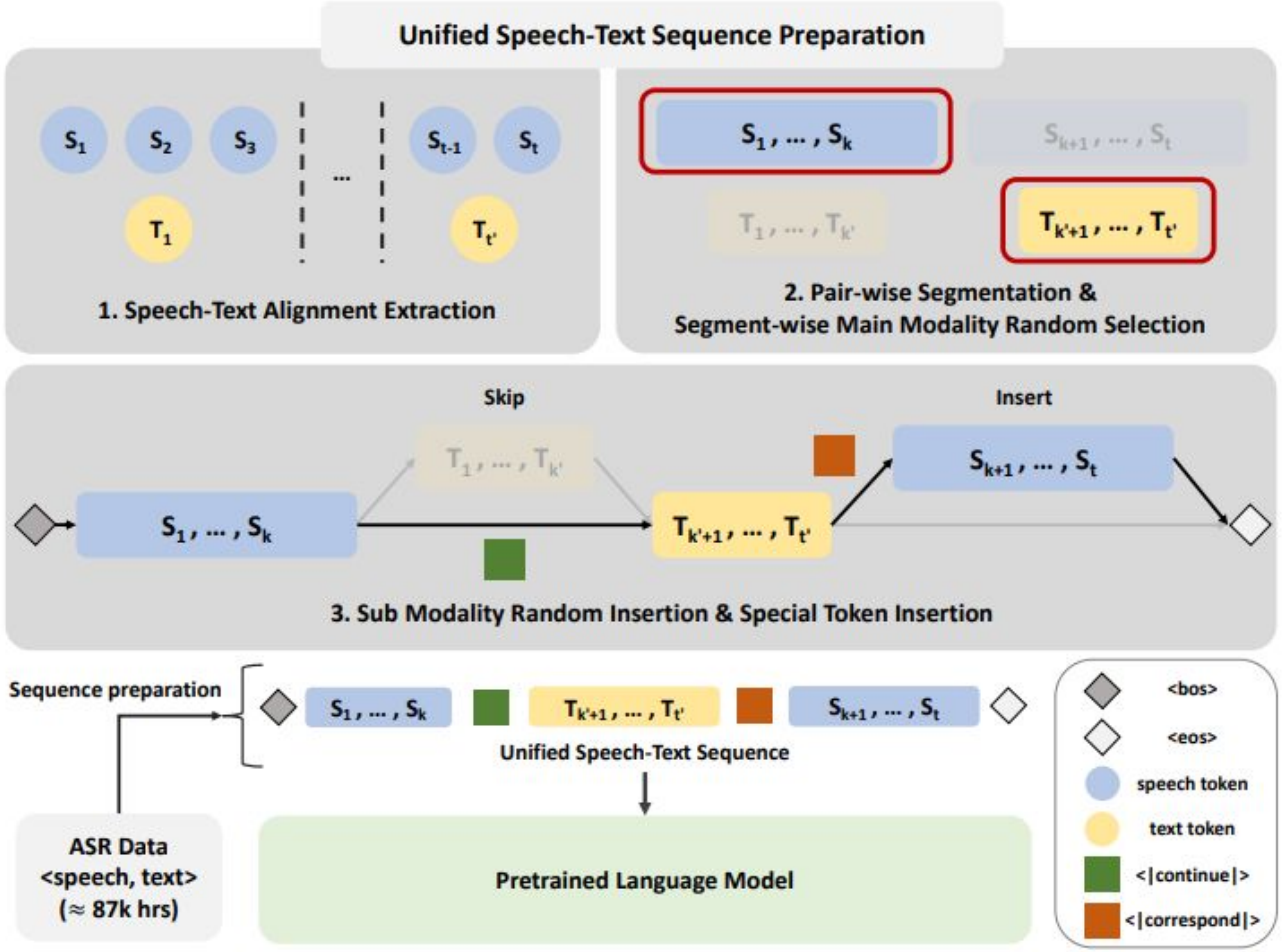


Figure 3: The overall speech-text pretraining scheme.

Points

Acoustic unit

Acoustic unit > 모델 > 감정분류	Acoustic Unit > 모델 > 텍스트 생성

생성 방식 점검

USDM → **USDM**
Scratch
Casacade
SpeechGPT

Human Evaluation	Gpt Evaluation

Points

Acoustic unit 생성 (코드 -preporcessing stage1)

XLS-R = self-supervised speech encoder >> 음성 특징을 추출

- 50Hz intermediate representations로 변환(이산값)
- 이것을 clustering하여 acoustic unit으로 생성(연속값)
- 음향 단위 토큰 어휘(vocab) = 10000개

https://anwarvic.github.io/speech-recognition/XLS-R?utm_source

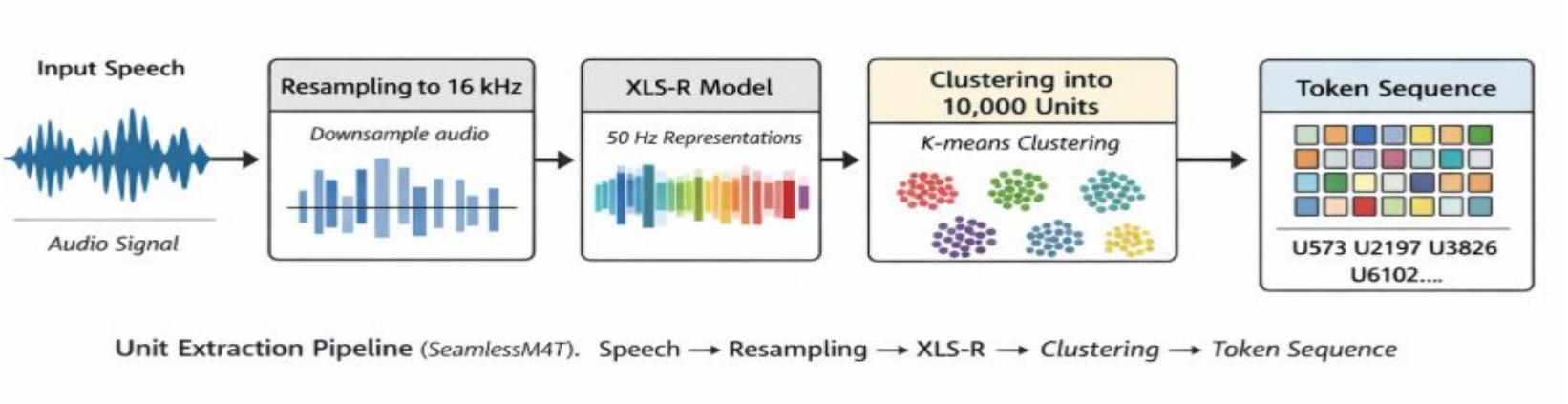
Methods： Speech-to-Unit Encoder

Unit Extraction Pipeline (SeamlessM4T)

speech ➡ resampled to 16 kHz ➡ XLS-R

➡ 50Hz intermediate representations

➡ clustered into 10,000 unit



Unit Extraction Pipeline (*SeamlessM4T*). Speech → Resampling → XLS-R → *Clustering* → *Token Sequence*

Experiment

Unit Emotion Recognition Experiment

- 3-layer transformer emotion classifier trained on **CREMA-D**
- Six emotion categories
- Random guess accuracy: **16.6%** Observed accuracy: **60.8%**

👉 This is strong evidence that acoustic units **contain clear emotional cue**

실험 구성

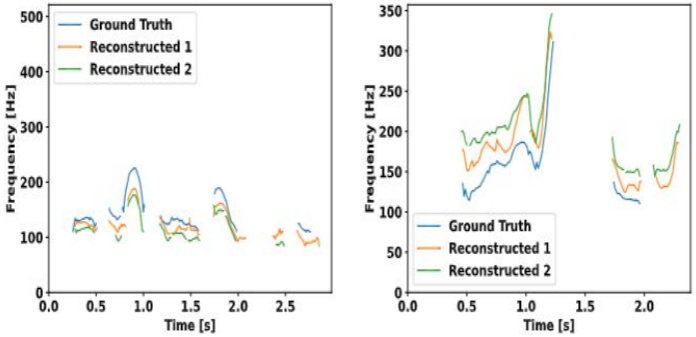
- 모델 구성 : 3-layer Transformer-based emotion classifier
- 손실 함수 : Cross-entropy loss
- 데이터셋 : CREMA-D
  - 총 7,442개 오디오
  - 91명 배우
  - 6개 감정 범주
  - Anger / Disgust / Fear / Happy / Neutral / Sad
- 데이터 분할 : Train / Validation / Test = 70% / 15% / 15%

Methods： Speech-to-Unit Encoder

Unit-to-Speech Reconstruction Experiment

- Train a unit-to-speech reconstruction model
- Uses Voicebox architecture
- Trained on 54,000 hours of speech

>>> Generates speech solely from unit sequences



Results.

- Timbre(음색) and absolute pitch(음높이) differ from original speech
- BUT Pitch variation(억양 변화 패턴) shows a similar trend

👉 This indicates preservation of **non-verbal characteristics**

Unit-to-Speech Reconstruction Experiment

Model	**Training Data**
• Voicebox: Flow-Matching 기반 zero-shot TTS • 출력: Mel-spectrogram • Vocoder: BigVGAN (22,050 Hz)	• Multilingual LibriSpeech (EN subset) • GigaSpeech • 총 54K hours ASR data
Alignment & Duration	**Inference Configuration**
• Montreal Forced Aligner (MFA) 사용 • 음소-멜 스펙트로그램 alignment 추출 • 음소별 duration 계산 • 학습 시: 음소 시퀀스를 멜 길이에 맞게 확장(ex) 안안안녕녕녕녕) • 추론 시: Duration Predictor 사용	• 50 timesteps(50번) • Classifier-free guidance scale = 1(억지로 생성 x, 자연스럽게) • Mel-spectrogram resolution: ~86 Hz • BigVGAN 공식 22,050 Hz 설정과 동일

Unit-to-Speech Reconstruction Experiment

Core Voicebox(기본)

- Flow-Matching 기반 zero-shot TTS 모델
- 입력: 텍스트 + 기준 음성 (reference speech)
- 출력: Mel-spectrogram → BigVGAN으로 음성 변환
- MFA로 음소-음성 정렬
- Duration predictor로 발음 길이 예측

Unit-Voicebox for USDM

- 역할: Speech decoder
  - 모델이 만든 unit sequence → 음성 복원
- 특징:
  - Reference speech 사용 (학습 & 추론) → Zero-shot 음성 복원 가능
- 멀티턴 대화:
  - 이전 턴 음성을 다음 턴의 기준 음성으로 사용 → 화자 음성 일관성 유지
- Duration predictor 불필요 (unit자체가 이미 시간순으로 배열)

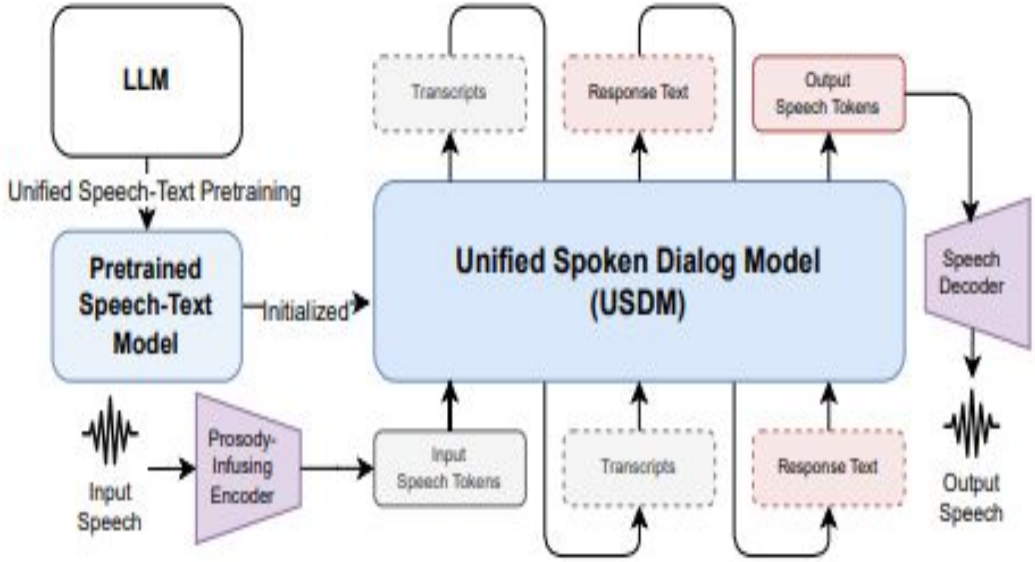
Voicebox for Cascaded Baseline

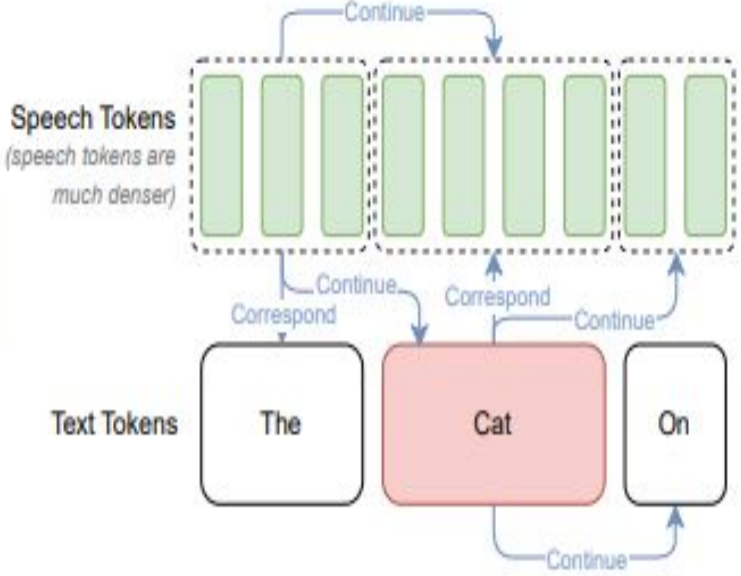
- 목적: 비교용 베이스라인 TTS
- 설정: Unit-Voicebox와 동일한 데이터·학습 방식 → 공정한 비교
- 차이점:
  - 입력: 텍스트
  - 별도의 duration predictor 학습 필요

Methods : Unified Speech-Text Pretraining

Models

- Backbone: Mistral-7B as the pretrained LLM
- Add 10,000 acoustic unit tokens + 2 special tokens(corresponse+continue) Only the embedding weights of newly added tokens are reinitialized
- Pretraining data: ~87,000 hours of English ASR data





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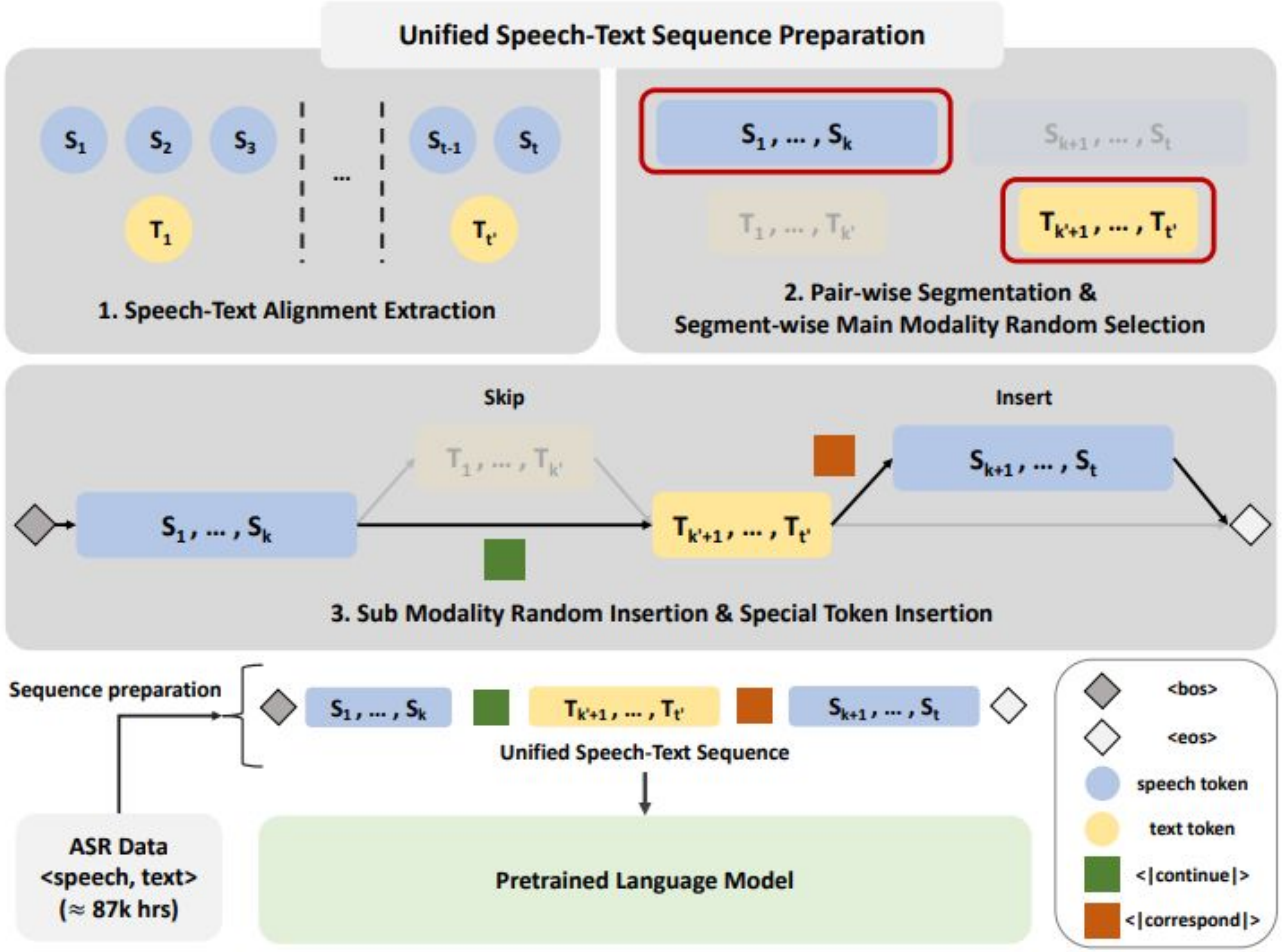

Figure 3: The overall speech-text pretraining scheme.

Methods

Speech-Text Alignment Extraction

- Extract word-level speech-text alignments; Using Montreal Forced Aligner
- Convert speech intervals into unit-index intervals at 50 Hz

Pair-wise Segmentation & Main Modality Selection

- Each speech-text pair is divided into N segments
- From each segment, only one modality is selected
- $N = \lfloor S/10 \rfloor + 1$, where S is speech length (seconds)

Methods

왜 두 곳에서 특수 토큰 추가하는 것? stage2 + train_pt

stage2에서 돌리고 저장안함 > train_pt에서 다시 호출

Sub-Modality Insertion & Special Tokens

- Non-selected modality is inserted with **50% probability**
- Two special tokens are introduced:
  - <|correspond|>
  - <|continue|>
- Special tokens are added **only when modality changes**

Resulting Interleaved Sequences

- Generate interleaved sequences {Ij}
- Enable:
  - unimodal modeling
  - comprehensive cross-modal modeling

Unit-to-Speech Decoder

- Unit-to-speech decoder based on the Voicebox architecture
- Voicebox: a zero-shot TTS model using text and reference speech
- Adapted to generate speech from acoustic unit sequences
- Reference speech enables speaker adaptation
- Paralinguistic information in units supports prosodic speech generation >> Referred to as unit-Voicebox

Unified Spoken Dialog Model (USDM)

- Fine-tune a pretrained speech–text model on spoken dialog data to leverage pretrained LLMs.
- Motivated by step-by-step reasoning and text-based speech bridging
- End-to-End Speech–Text–Speech Pipeline:
  - Instead of directly modeling speech-to-speech
  - The model performs:
    - Speech transcription
    - Response text generation
    - Response speech generation
  - All within a single end-to-end pipeline
- Text-related tasks are inserted between speech input and output
  - Enables leveraging pretrained LLM knowledge
  - Supports chained reasoning over the intermediary modality
- Each stage attends to all input and output tokens generated so far >> Joint modeling improves robustness to transcription errors
- Comparison with Cascaded Approaches:
  - More robust than independent cascaded modules
  - Avoids severe error propagation
- Supervised Fine-tuning Template
  - Loss is computed only for:
    - input transcript
    - answer text
    - answer unit tokens

Setting

- Experiments conducted on DailyTalk
- 20 hours of spoken dialog data
- Sampling rate: 22,050 Hz
- Two speakers: one male, one female
- Model comparisons with three baselines
- Compared Models:
  - USDM
  - From Scratch (Evaluate effectiveness of speech-text pretraining)
  - Cascaded (unified vs cascaded)
  - SpeechGPT(Validate advantages)

USDM Configuration	From Scratch Baseline

• Speech-to-unit: XLS-R, k = 10,000 quantizer
• Unit-to-speech: unit-Voicebox
• Vocoder: BigVGAN
• Unified speech-text pretraining:
  ○ ~87,000 hours of English ASR data
  ○ Max sequence length: 8,192
• Spoken dialog fine-tuning:
  ○ 5 epochs
  ○ Global batch size: 64
  ○ max learning rate: 2x10-5
	• Identical to USDM architecture
	• No speech-text pretraining
	• Mistral-7B fine-tuned directly on spoken dialog data

Cascaded Baseline	SpeechGPT Baseline
• Separate modules for each stage • ASR: whisper-large-v3 • Text dialog model: Mistral-7B • TTS: Voicebox • ASR → Text Dialog → TTS pipeline • Identical to USDM architecture	• Based on SpeechGPT • Pretrained speech-text model • Fine-tuned on DailyTalk for fair comparison

Table 4: Models for each component of the USDM and the baselines.

Model	ASR Model	Speech Encoder	LLM	Speech Decoder	TTS Model
USDM	–	XLS-R	Mistral-7B	unit-Voicebox + BigVGAN	–
From Scratch	–	XLS-R	Mistral-7B	unit-Voicebox + BigVGAN	–
SpeechGPT	–	mHuBERT	Llama-7B	unit-HiFi-GAN	–
Cascaded	*whisper-large-v3*	–	Mistral-7B	–	Voicebox + BigVGAN

Evaluation Sampling

- Spoken responses evaluated on naturalness, prosody, and semantic coherence
- Sampling: top-k = 40, top-p = 0.7, temperature = 0.3(SpeechGPT제외)
- All audio resampled to 16 kHz and normalized to −27 dB
- Reference speech: previous turn (Voicebox, unit-Voicebox)

Human Evaluation

- Human preference test via Amazon Mechanical Turk
- 50 randomly selected spoken dialogs
- Criteria: naturalness, prosody, semantic coherence/ 텍스트 내용은 동일
- Additional metrics:
  - MOS (5-scale)
  - P-MOS (5-scale prosody MOS)

Automatic Evaluation (Content & Error Rates)

- Content evaluation:
  - METEOR, ROUGE-L (ASR-transcribed text)
  - GPT-4-based preference test
- Error rates:
  - STT WER (entire test set)
    - Cascaded: Whisper-large-v3 outputs
    - End-to-end models: intermediate transcriptions
  - TTS WER (50 dialogs, 5 samples each> 평균사용)
    - Whisper-large-v3 used as ASR

METEOR: 생성된 응답 텍스트와 정답 텍스트 간의 일치도
ROUGE-L: 생성된 응답 텍스트와 정답 텍스트 간의 최장 공통 부분열(LCS)을 기반으로한 일치도

STT: 전사된 텍스트의 정확도
TTS: 모델이 생성한 응답 텍스트를 음성으로 변환한 후, 이 음성을 다시 ASR 모델로 텍스트화했을 때(재전사) 발생하는 오류율

Results

논문 주장: ground truth결과와 win, lose가 거의 동등하게 나옴> > USDM의 높은 성능을 보여줌
의문점: 그렇다면 나머지 모델도 ground truth랑 비교했을 때의 결과를 보여줘야하는 것 아닌지?

The results are presented in Table 1 and 2. In human preference tests that consider comprehensive factors, our model is preferred similarly to the Ground Truth and demonstrates superior preferences

Table 1: Human evaluation results of our model and the baselines. We report the MOS and P-MOS scores with a 95% confidence interval.

Method	Overall			Acoustic	
	win	*tie*	*lose*	MOS	P-MOS
Ground Truth	45.9%	8.0%	46.1%	4.51 ± 0.05	4.35 ± 0.05
USDM				4.31 ± 0.07	4.31 ± 0.06
Cascaded	55.3%	4.9%	39.8%	4.26 ± 0.07	4.22 ± 0.07
From Scratch	53.3%	7.6%	39.1%	3.71 ± 0.11	3.65 ± 0.10
SpeechGPT [25]	53.8%	6.9%	39.3%	4.08 ± 0.09	4.04 ± 0.08

MOS: 평균음향 점수
P-MOS: 운율평균 점수

Results

논문 주장: Scratch모델과 비교했을 때 pretrain되지 않으면 성능 낮아진다 > > USDM의 높은 성능을 보여줌

의문점:

1) ground truth와의 win/lose비율이 비슷하다로 usdm의 높은 성능을 강조한 앞 결과로는 현재 결과 설득x

2) casacaded방식이 STT,TTS 성능 훨씬 잘나옴.
앞의 결과도 오차범위 내,
>> 그렇다면 casacaded방식이 더 우수한 것 아닌가?

Table 2: GPT-4 evaluation and quantitative results of our model and the baselines.

Method	Semantic					WER	
	win	*tie*	*lose*	METEOR	ROUGE-L	STT	TTS
Ground Truth	32.7%	19.6%	47.7%	–	–		2.2%
USDM	–	–	–	13.1	15.7	7.4%	2.0%
Cascaded	42.7%	24.6%	32.7%	12.5	15.0	3.8%	1.3%
From Scratch	79.7%	10.1%	10.2%	8.6	10.6	58.1%	64.0%
SpeechGPT [25]	61.0%	13.1%	25.9%	9.9	11.8	12.4%	23.2%

METEOR: 생성된 응답 텍스트와 정답 텍스트 간의 일치도
ROUGE-L: 생성된 응답 텍스트와 정답 텍스트 간의 최장 공통 부분열(LCS)을 기반으로한 일치도
STT: 전사된 텍스트의 정확도
TTS: 모델이 생성한 응답 텍스트를 음성으로 변환한 후, 이 음성을 다시 ASR 모델로 텍스트화했을 때(재전사) 발생하는 오류율

[input tokens (text + speech)]

↓

CustomMistralModel (Transformer stack)

↓

hidden states [H]

↓

lm_head (Linear)

↓

logits over (text + speech vocab)

↓

softmax → next token