Multi-metric Speech Evaluation

Jiatong Shi

Carnegie Mellon University, Langauge Technologies Institute

jiatongs@cs.cmu.edu

Content

- Motivation
- Toolkit Design: VERSA and VERSA-v2
- Efficient Unified Evaluation: Uni-VERSA
- Autoregressive Multi-metric Evaluation: ARECHO
- Future Scope

Motivation

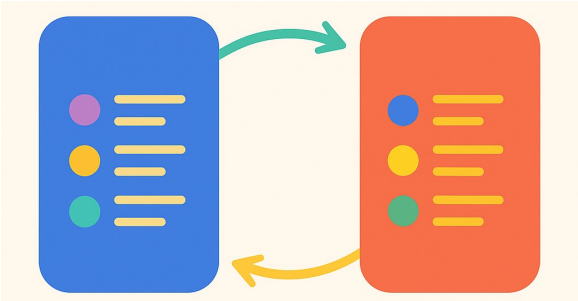
- Speech conveys far more than text

Motivation

- Human subjectiveness are naturally multi-factor
  - No single automatic measure tracks subjective MOS across all noise types, accents, or synthesis artifacts
  - A portfolio of metrics offers higher combined correlation and reliability

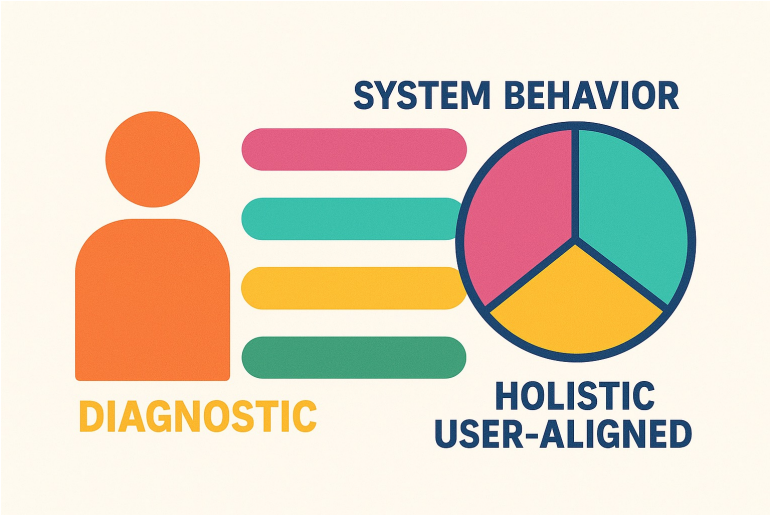
Motivation

- Feeds richer learning objectives
  - Many modern systems train with multi-objective or reinforcement signals derived from several metrics
  - Reliable evaluation on the same set of metrics closes the training-testing loop



Motivation

- Multi-metric mindset towards
  - A diagnostic, holistic, and user-aligned view of system behavior
  - Crucial for both cutting-edge research and real-world deployment



Roadmap

VERSA
Comprehensive Toolkit

Uni-VERSA
Fast-efficient multi-metric estimation

ARECHO
High-performance + interpretable multi-metric estimation

Future
Glance at the future

VERSA: Versatile Evaluation of Speech and Audio

Jiatong Shi[1], Hye-jin Shim[1], Jinchuan Tian[1], Siddhant Arora[1], Haibin Wu[2], Daruis Petermann[3], Jia Qi Yip[4], You Zhang[5], Yuxun Tang[6], Wangyou Zhang[7], Dareen Safar Alharthi[1], Yichen Huang[1], Koichi Saito[8], Jionghao Han[1], Yiwen Zhao[1], Chris Donahue[1], Shinji Watanabe[1]

[1]CMU, [2]Microsoft, [3]IU, [4]NTU, [5]UR, [6]RUC, [7]SJTU, [8]Sony AI

07/17/2025

VERSA: born from challenges

- Plenty of difficulties exist in evaluation for generated speech/audio quality

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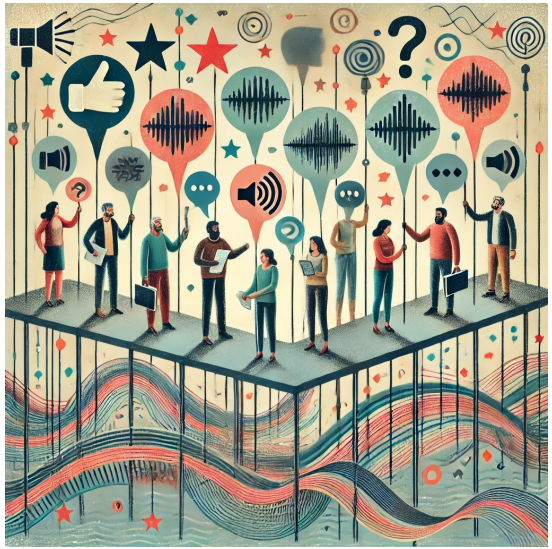
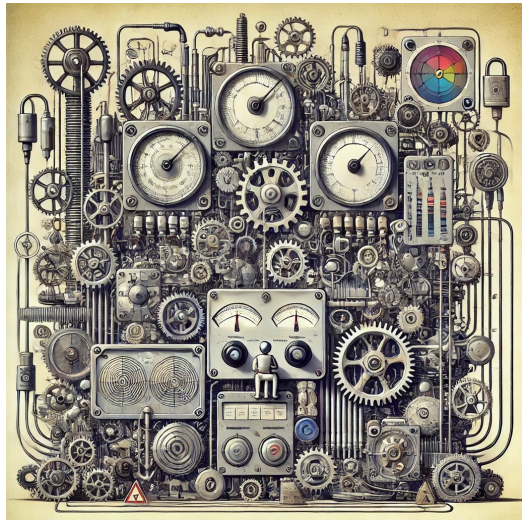
  - Collecting subjective evaluations is not easy



VERSA: born from challenges

- Plenty of difficulties exist in evaluation for generated speech/audio quality
  - Collecting subjective evaluations is not easy
  - Implementing objective evaluations is not easy



VERSA: born from challenges

- Plenty of difficulties exist in evaluation for generated speech/audio quality:
  - Collecting subjective evaluations is not easy
  - Implementing objective evaluations is not easy
  - Increasing need to support multi-domain larger-scale evaluation with unified speech modeling

Introducing VERSA

- VERSA (Versatile Evaluation for Speech and Audio)
  - Targets a general interface for speech and audio evaluation
  - A collection of conventional/recent automatic quality evaluation metrics
  - Highly integration to toolkits / challenges

VERSA Framework

- Simple Command line Interface

```
python versa/bin/scorer.py \
    --score_config egs/general.yaml \
    --gt <ground truth audio list> \
    --pred <candidate audio list> \
    --output_file test_result
```

- Easy Configuration

```yaml
# Example Speaker Similarity YAML config

# speaker related metrics
# -- spk_similarity: speaker cosine similarity
#                    model tag can be any ESPnet-SPK huggingface repo at
#                    https://huggingface.co/espnet
- name: speaker
  model_tag: default
```

```yaml
# Example Speaker Similarity YAML config

# speaker related metrics
# -- spk_similarity: speaker cosine similarity
- name: speaker
  model_tag: espnet/voxcelebs12_ecapa_wavlm_joint
```

VERSA Framework

- Flexible I/O Interface
- Easy Manageable Configuration
- Strict Dependency Control
- Job-scheduling Support
- Continuous Integration Tests
- Efficient Resource Management (cache control)
- Community-driven Effort

```
+---versa
|   |launch.sh # launch examples with SLURM
|   \---egs    # example configs/running scripts
|   |   |general.yaml        # default metric list
|   |   |run_cpu.sh          # run CPU metrics
|   |   |run_gpu.sh          # run GPU metrics
|   |   \---separate_metrics # Config for individual metrics
|   |           mcd_f0.yaml
|   |           spk.yaml
|   |           ...
|   \---versa                # main library
|       |scorer_shared.py    # module register interface
|       \---bin              # binary interface
|               scorer.py    # scorer interface
|               aggregate_results.py  # aggregate corpus-level results
|       \---corpus_metrics   # corpus-level metrics
|               fad.py
|               clap_score.py
|               ...
|       \---utterance_metrics # utterance-level metrics
|               mcd_f0.py
|               spk.py
|               ..
|   \---tools                # external tools
|       install_emo2vec.sh
|       install_fadtk.sh
|       ...
```

Metrics in VERSA

- Up to **90 metrics** in speech and audio evaluation supported currently

- Community-driven efforts for future adaptation!

Metrics in VERSA

Dependency	Example Evaluation Metrics
Dependent	MCD, F0-RMSE, F0-CORR, SI-SNR, CI-SDR, PESQ, STOI, WARPQ, VISQOL, SpeechDiscreteBLEU, SpeechDiscreteDistance, SpeechBERT, etc.
Independent	DNSMOS, UTMOS, PLCMOS, SingMOS, Torch-squim (PESQ, STOI, SI-SNR), Sheet-SSQA, PAM, SpoofS, SWR, etc.
Non-matching	CER/WER (ESPnet/ESPnet-OWSM, Whisper),, CLAP-score, Log-WMSE, EMO-SIM, APA, LLR, NOMAD, LLR, etc.
Distributional	FAD, KID, Coverage, Density, KLD

Check full list and details about metrics in the paper!

Comparison to existing open-source toolkits

Toolkit	Github Repo	Evaluation-Focus	Supported Metrics
ESPnet	espnet/espnet	❌	16
Amphion	open-mmlab/Amphion	❌	15
Stable-Audio-Metrics	Stability-AI/stable-audio-metrics	✅	3
AudioLDM-Eval	haoheliu/audioldm_eval	✅	9
VERSA	wavlab-speech/versa	✅	

Next VERSA-V2 targets double (130)!

Compared to other open-source toolkits, VERSA is dedicated to speech and audio evaluation with **extensive integration** of both conventional and recent evaluation metrics.

(Check our paper for a full comparison!)

Links and Demos

Paper

GitHub

Colab Demo

Gradio Demo

https://github.com/wavlab-speech/versa.git

Uni-VERSA: Versatile Speech Assessment with a Unified Network

Jiatong Shi, Hye-jin Shim, Shinji Watanabe

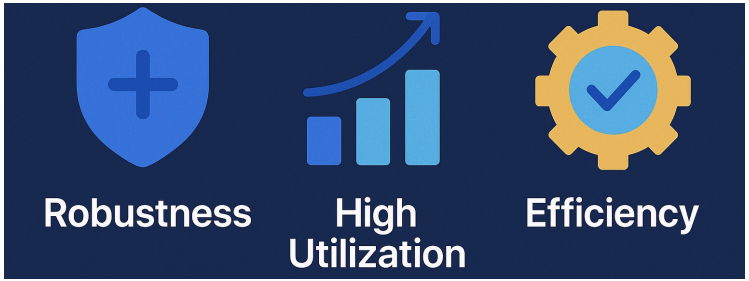
CMU

Further Step from VERSA

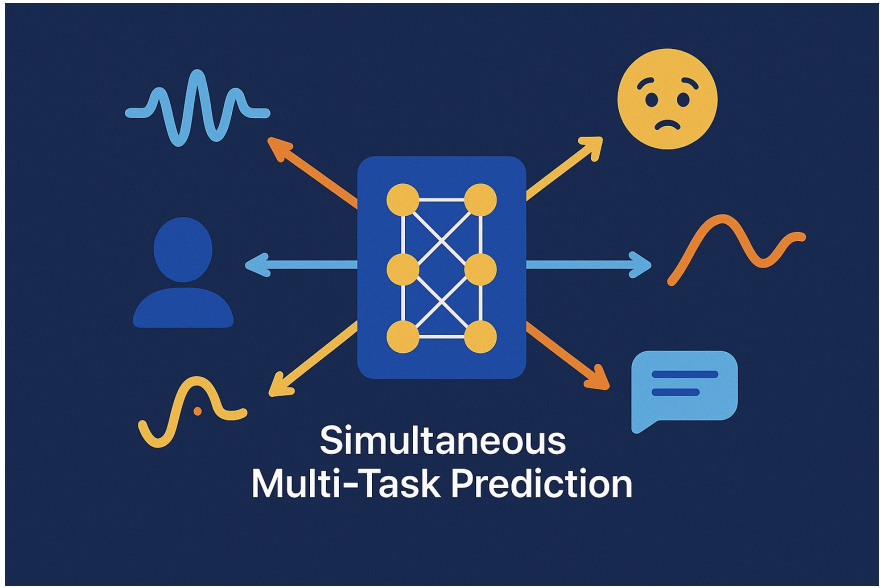
- Can we expand further from VERSA, with a single-unified model?

- What are the potential benefits?

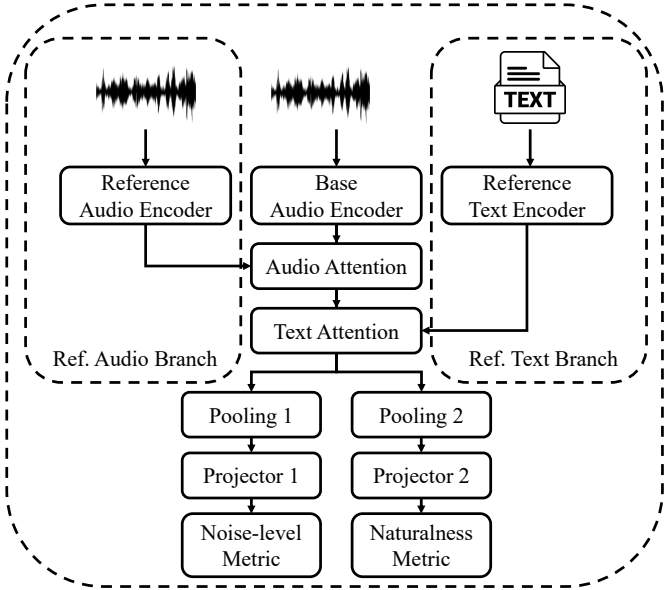
  - Enhanced robustness to various conditions
  - Better utilization of the information
  - Elevated efficiency of inference



General Concept of Uni-VERSA



The Development of Uni-VERSA



Conceptual Diagram of the Problem

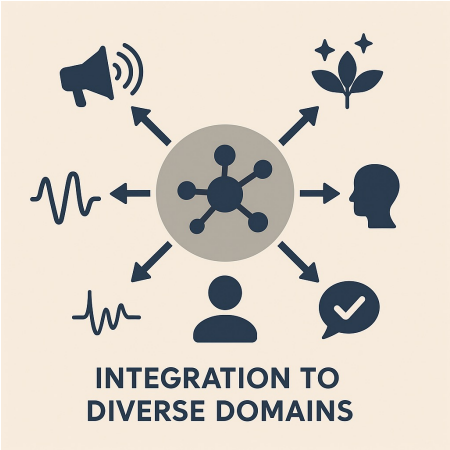
An example of predicting different aspects of speech assessment estimation **simultaneously**

Practical Challenges

- Integration to Diverse Domains
  - Wide range focuses from noise-level, naturalness, prosody information, speaker information, and intelligibility

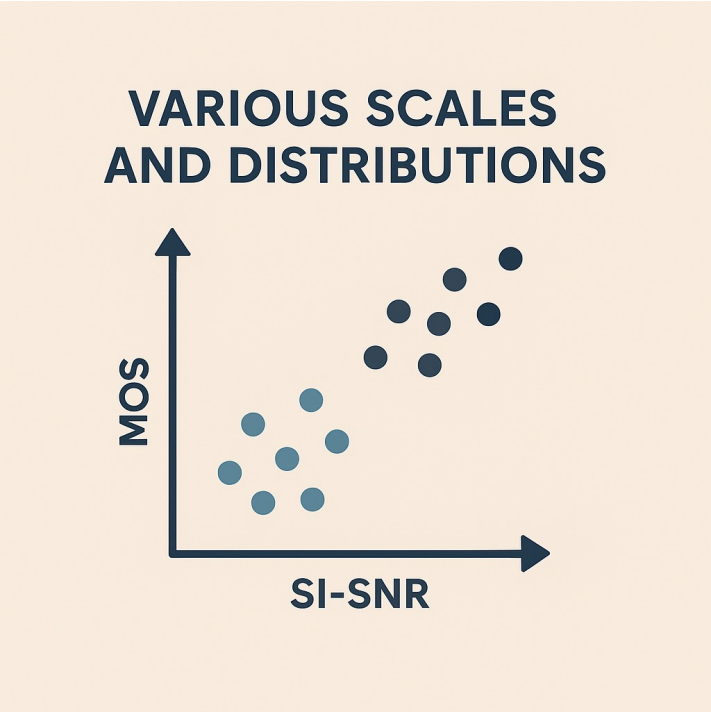
- Various Scales and Distributions

- Semi-supervised Learning



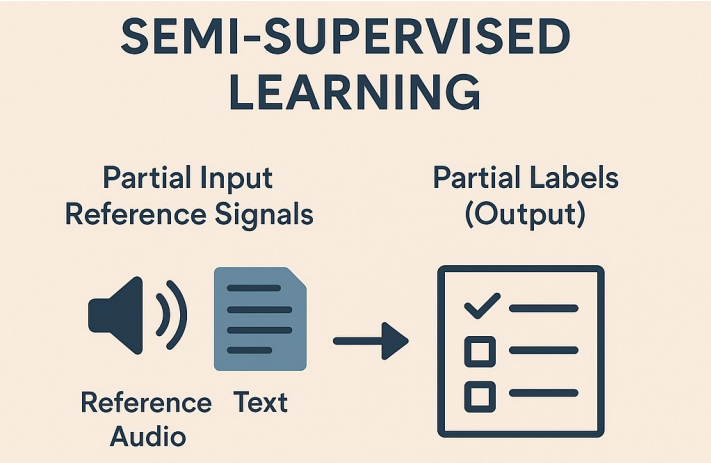
Practical Challenges

- Integration to Diverse Domains
- Various Scales and Distributions
  - SI-SNR vs. MOS
- Semi-supervised Learning



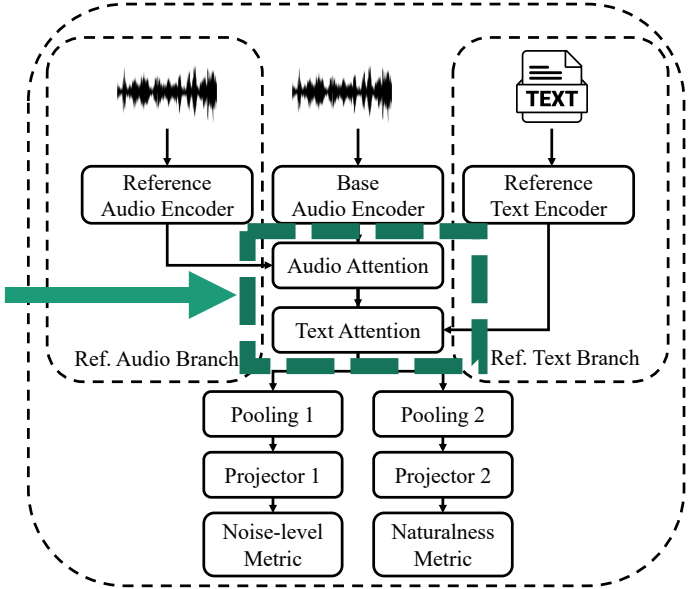
Practical Challenges

- Integration to Diverse Domains
- Various Scales and Distributions
- Semi-supervised Learning
  - Partial Reference Signals
    - Reference Audio, Reference Text
  - Partial Labels



Our Initial Trial

- **Use cross-attention to add reference information**
- Use Individual predictor for each metric
- The simplest solution for the start



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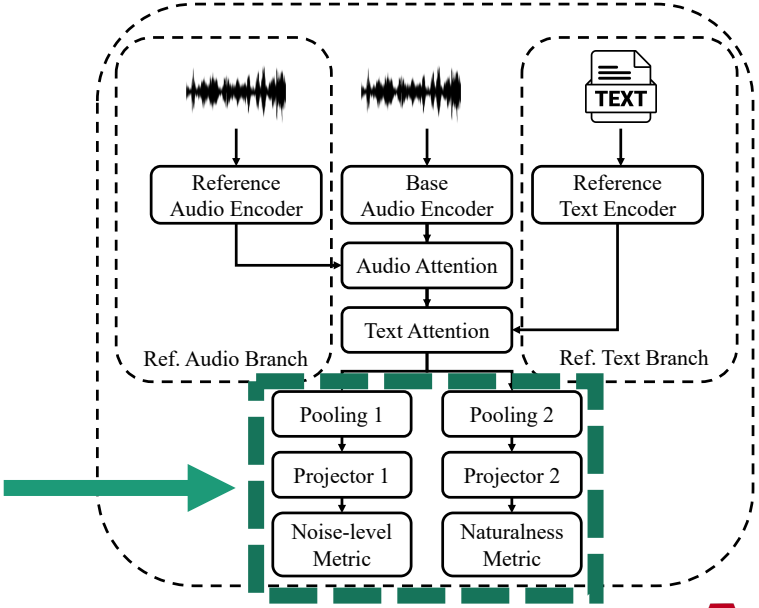

Data Curation

- A curation from URGENT challenge 2024
- Train-dev-test: 249-14-30 hrs
  - 50/50: data with / without reference
- 5 domains -> 11 metrics
  - Utilize expert models from VERSA for the prediction targets
- Evaluation:
  - Correlation coefficient (Pearson, Spearman)

Reference speech / reference text

Domain	Metric	Range	Reference Type
Noise level	SI-SNR	[-inf, inf]	Signal
	PESQ	[1, 4.5]	Signal
	DNSMOS	[1, 5]	/
Prosody	F0-CORR	[-1, 1]	Signal
Naturalness	MOS	[1, 5]	/
	UTMOS	[1, 5]	/
	SHEET-base	[1, 5]	/
Intelligibility	WER	[0, inf]	Text
	STOI	[0, 1]	Signal
	SBERT	[0, 1]	Signal
Speaker characteristics	SPK-SIM	[-1, 1]	Signal

Experimental Setup

- Main Investigation
  - The effect of audio encoder
  - The effect of reference signals
  - The effect of joint prediction

Experimental Results (Audio Encoder)

Pearson / Spearman Correlation Coefficient for Evaluation

Feature	Noise-Level			Prosody	Naturalness			Intelligibility			Speaker	Avg.
	SI-SNR	PESQ	DNSMOS	F0-CORR	MOS	UTMOS	SHEET-base	WER	STOI	SBERT	SPK-SIM	
Fbank	.69 / .73	.78 / .80	.90 / .89	.56 / .51	.72 / .72	.92 / .91	.85 / .85	.57 / .53	.79 / .74	.80 / .73	.75 / **.76**	.76 / .73
HuBERT	.84 / .83	.80 / .81	.90 / **.89**	.61 / .56	.78 / .77	.97 / .95	.93 / .93	.74 / .71	.92 / .89	.94 / .89	.76 / .71	.83 / .80
MR-HuBERT	.85 / .85	**.83** / **.85**	.90 / .88	**.65** / .60	**.78** / **.78**	**.97** / **.95**	**.94** / **.94**	.74 / .74	.91 / .89	.94 / .90	**.79** / .75	.84 / .82
WavLM	**.85** / **.85**	.82 / .84	**.90** / .88	.64 / **.61**	.77 / .77	.97 / .94	.93 / .94	**.79** / **.79**	**.93** / **.89**	**.95** / **.91**	.79 / .74	**.84** / **.82**

Four Encoder:

- Fbank: Mel-filterbank spectrogram
- HuBERT: Hidden unit BERT pre-trained audio encoder (Hsu et al. 2021)
- MR-HuBERT: Multi-resolution HuBERT (Shi et al. 2024)
- WavLM: Enhanced HuBERT with noise/multi-speaker augmentation (Chen et al. 2022)

Experimental Results (Audio Encoder)

Pearson / Spearman Correlation Coefficient for Evaluation

Feature	Noise-Level			Prosody	Naturalness			Intelligibility			Speaker	Avg.
	SI-SNR	PESQ	DNSMOS	F0-CORR	MOS	UTMOS	SHEET-base	WER	STOI	SBERT	SPK-SIM	
Fbank	.69 / .73	.78 / .80	.90 / .89	.56 / .51	.72 / .72	.92 / .91	.85 / .85	.57 / .53	.79 / .74	.80 / .73	.75 / **.76**	.76 / .73
HuBERT	.84 / .83	.80 / .81	.90 / **.89**	.61 / .56	.78 / .77	.97 / .95	.93 / .93	.74 / .71	.92 / .89	.94 / .89	.76 / .71	.83 / .80
MR-HuBERT	.85 / .85	**.83** / **.85**	.90 / .88	**.65** / .60	**.78** / **.78**	**.97** / **.95**	**.94** / **.94**	.74 / .74	.91 / .89	.94 / .90	**.79** / .75	.84 / .82
WavLM	**.85** / **.85**	.82 / .84	**.90** / .88	.64 / **.61**	.77 / .77	.97 / .94	.93 / .94	**.79** / **.79**	**.93** / **.89**	**.95** / **.91**	.79 / .74	**.84** / **.82**

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hen et al. 2022)

The effect of audio encoder is **significant**

->

Fbank << HuBERT < MR-HuBERT ~ WavLM

Experimental Results (Reference Signal)

Pearson / Spearman Correlation Coefficient for Evaluation

Model	Noise-Level			Prosody	Naturalness			Intelligibility			Speaker	Avg.
	SI-SNR	PESQ	DNSMOS	F0-CORR	MOS	UTMOS	SHEET-base	WER	STOI	SBERT	SPK-SIM	
No Ref.	.84 / .84	**.85 / .86**	.90 / .89	.64 / .60	.77 / .78	.97 / .94	**.94 / .94**	.79 / .78	.90 / .86	.93 / .90	.79 / .75	.85 / .82
Audio Ref.	.84 / .82	.82 / .83	.90 / .89	**.66 / .62**	.78 / .78	**.97 / .95**	.94 / .94	.78 / .76	.92 / .89	.95 / .92	**.81** / .77	.85 / .82
Text Ref.	.84 / .83	.84 / .86	**.90 / .89**	.64 / .57	**.79 / .79**	.97 / .94	.93 / .93	.78 / .76	.92 / **.90**	**.96 / .93**	.80 / **.78**	**.85 / .83**
Full Ref.	**.85 / .85**	.82 / .84	.90 / .88	.64 / .61	.77 / .77	.97 / .94	.93 / .94	**.79 / .79**	**.93** / .89	.95 / .91	.79 / .74	.84 / .82

Four Models:

- No reference: model without reference
- Audio reference: model with reference audio
- Text reference: model with reference text
- Full reference: model with both reference signals

Experimental Results (Reference Signal)

Pearson / Spearman Correlation Coefficient for Evaluation

Model	Noise-Level			Prosody	Naturalness			Intelligibility			Speaker	Avg.
	SI-SNR	PESQ	DNSMOS	F0-CORR	MOS	UTMOS	SHEET-base	WER	STOI	SBERT	SPK-SIM	
No Ref.	.84 / .84	**.85 / .86**	.90 / .89	.64 / .60	.77 / .78	.97 / .94	**.94 / .94**	.79 / .78	.90 / .86	.93 / .90	.79 / .75	.85 / .82
Audio Ref.	.84 / .82	.82 / .83	.90 / .89	**.66 / .62**	.78 / .78	**.97 / .95**	.94 / .94	.78 / .76	.92 / .89	.95 / .92	**.81** / .77	.85 / .82
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Full Ref.	**.85 / .85**	.82 / .84	.90 / .88	.64 / .61	.77 / .77	.97 / .94	.93 / .94	**.79 / .79**	**.93** / .89	.95 / .91	.79 / .74	.84 / .82

Notable Findings:

- Models without certain references **sometimes outperform** those with more references
- Examples:
  - Model using reference text: Lower WER prediction correlations
  - Model without audio references: Best PESQ prediction results

Experimental Results (Reference Signal)

Pearson / Spearman Correlation Coefficient for Evaluation

Model	Noise-Level			Prosody	Naturalness			Intelligibility			Speaker	Avg.
	SI-SNR	PESQ	DNSMOS	F0-CORR	MOS	UTMOS	SHEET-base	WER	STOI	SBERT	SPK-SIM	
No Ref.	.84 / .84	**.85 / .86**	.90 / .89	.64 / .60	.77 / .78	.97 / .94	**.94 / .94**	.79 / .78	.90 / .86	.93 / .90	.79 / .75	.85 / .82
Audio Ref.	.84 / .82	.82 / .83	.90 / .89	**.66 / .62**	.78 / .78	**.97 / .95**	.94 / .94	.78 / .76	.92 / .89	.95 / .92	**.81** / .77	.85 / .82
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th more references

Potential cause: Uni-VERSA model **overfitting** when given redundant reference signals

Further verifications: the PESQ for training set with audio references are much better than those without.

Experimental Results (Joint Prediction)

Pearson / Spearman Correlation Coefficient for MOS Evaluation

Feature	Pred. Type	LCC	SRCC
Fbank	Single	.53	.55
	Joint	.72	.72
WavLM	Single	**.80**	**.80**
	Joint	.77	.77

With weak features (Fbank), joint prediction show benefits

With WavLM, joint prediction may not be helpful to performance

Do we still need multi-metric prediction?

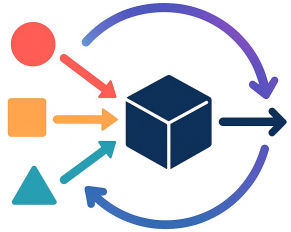
Benefits from Uni-VERSA

- Efficiency
  - Using Uni-VERSA can enjoy up to **109x** speed up (same batch size)
    - With only the 11 metrics included
    - Why?

Benefits from Uni-VERSA

- Efficiency
  - Using Uni-VERSA can enjoy up to **109x** speed up
    - With only the 11 metrics included
    - Why?
      - Full GPU inference
      - Reduced shared forward from audio encoder representation
      - Parallel prediction

Benefits from Uni-VERSA



- Multi-metric model as a loss term for generation tasks
  - Convert non-differentiable metrics into backward-friendly objectives
  - Enjoy efficient loss computation (multi-metric with a single model)
  - Reduce the need of real-world data
- E.g., Improving Speech Enhancement with Multi-Metric Supervision from Learned Quality Assessment (Wei et al. 2025)

Links and Demos

Paper

Colab Demo

Huggingface Pre-trained Models

Code

ARECHO: Autoregressive Evaluation via Chain-Based Hypothesis Optimization for Speech Multi-Metric Estimation

Jiatong Shi[1], Yifan Cheng[2], Bo-hao Su[1], Hye-jin Shim[1], Jinchuan Tian[1],

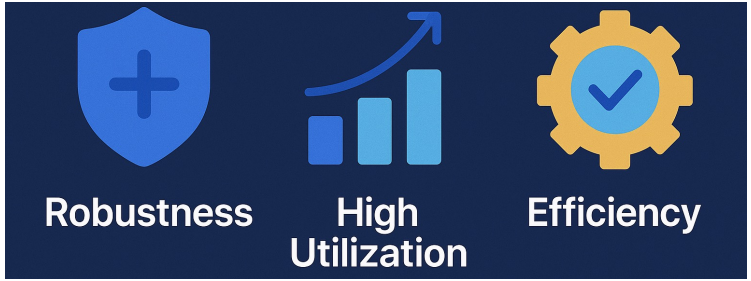
Samuele Cornell[1], Yiwen Zhao[1], Siddhant Arora[1], Shinji Watanabe[1]

[1]CMU, [2]HUST

07/17/2025

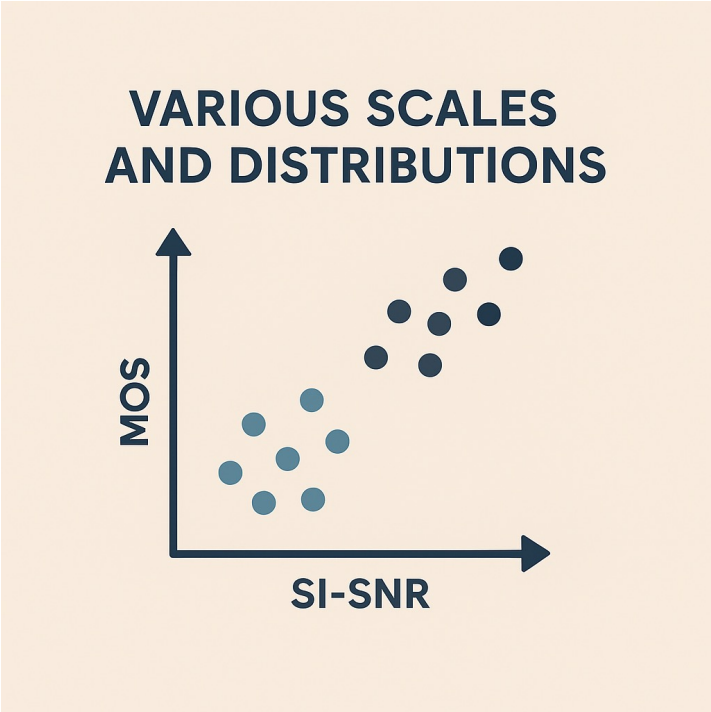
Successes in Uni-VERSA

- Robustness to various conditions
- Better utilization of the information
- Elevated efficiency of inference



However, challenges remains

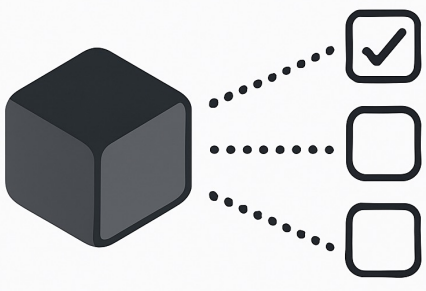
- **Diverse Scale Issues**
- Limited Data Availability
- Dependency Modeling with Flexible Control



However, challenges remains

- Diverse Scale Issues

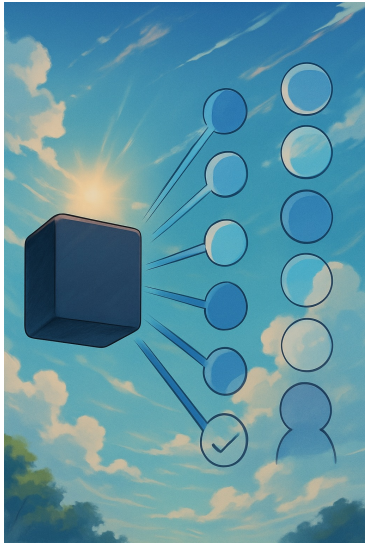
- **Limited Data Availability**
  - **In Uni-VERSA, we use a metric-balanced set**
  - **Reality is not the case though**



- Dependency Modeling with Flexible Control

However, challenges remains

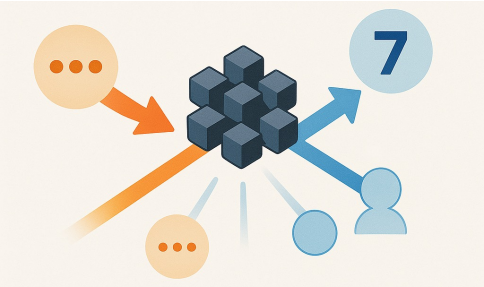
- Diverse Scale Issues
- Limited Data Availability
- **Dependency Modeling with Flexible Control**
  - **Difficulty in leveraging dependency benefits**
  - **Inefficient modeling with incomplete labels**



ARECHO: Autoregressive Evaluation

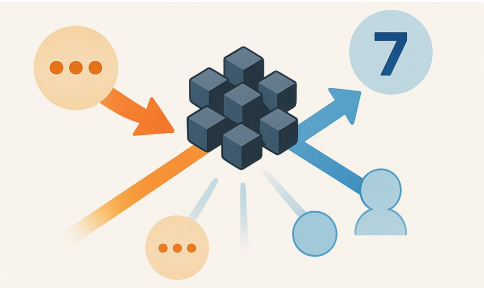
- Tokenizing Everything
- Dynamic Classifier Chain
- Two-step Confidence-oriented Decoding

Everything in Tokenization



- Categorical metrics -> direct tokenization
- Numerical metrics -> quantile-based partitioning
  - Flexibly control the distribution of token bins with different distribution percentiles

Everything in Tokenization

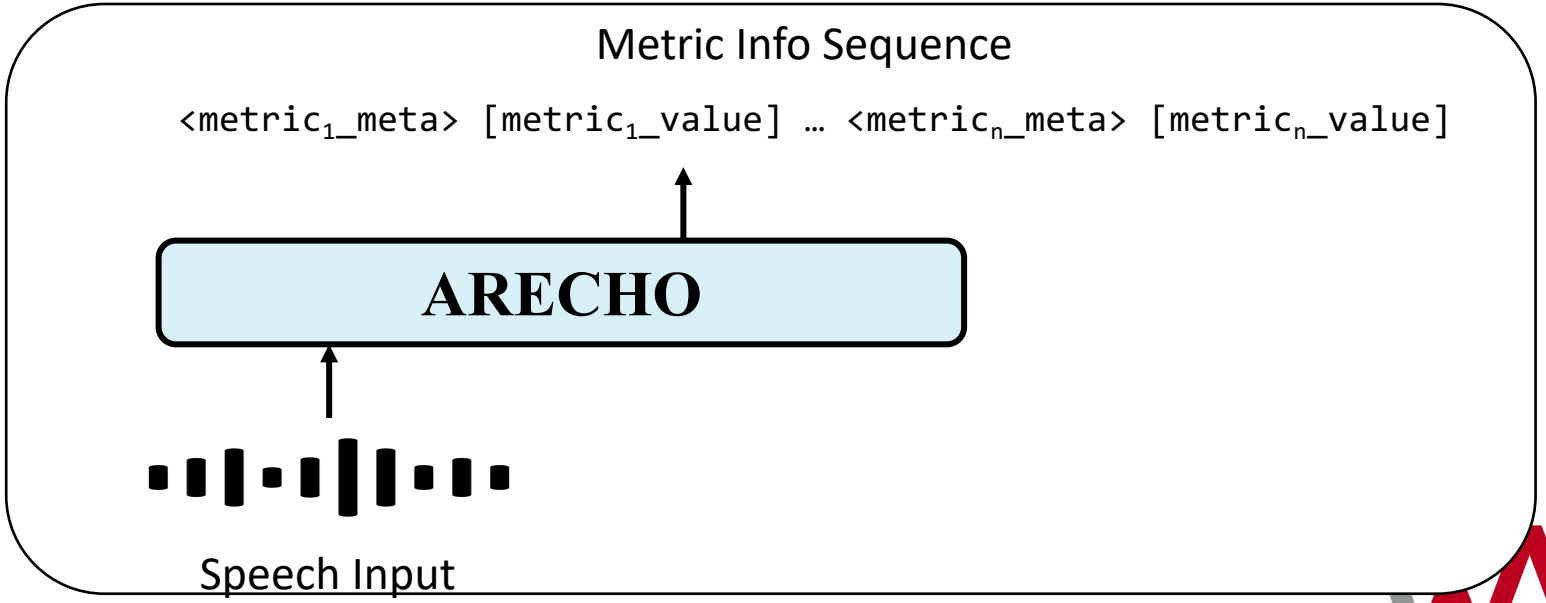


- Categorical metrics -> direct tokenization
- Numerical metrics -> quantile-based partitioning
  - Flexibly control the distribution of token bins with different distribution percentiles

A direct fix to:
- Diverse metric scales / types

Dynamic Classifier Chain

- Main concept is as simple as an autoregressive network:



Metric Sequence

- Motivating Example
  - <Gender> [Male] <Emotion> [Happy] <MOS> [3.78]

- During Training, we randomly shuffle the metric order
  - <Gender> [Male] <Emotion> [Happy] <MOS> [3.78]
  - <Emotion> [Happy] <Gender> [Male] <MOS> [3.78]
  - <MOS> [3.78] <Gender> [Male] <Emotion> [Happy]
  - …

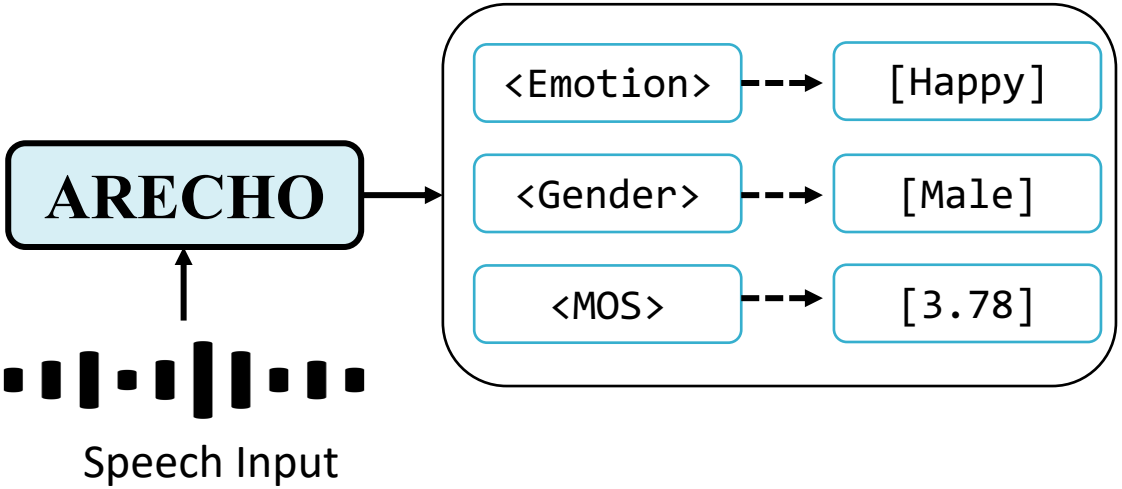
Metric Sequence

Key features:

- **Dependency control:** prior metric predictions are part of the sequence history
- **Metric identification:** Metadata token specify which metric to predict, even when value formats overlap
- **Flexible Inference:** beginning with a metadata token, generate the corresponding value token -> arbitrary queries enable dynamic/chain-style reasoning
- **Direct fix to limited labels:** simply omits the unavailable labels (no need for masking / imputation)

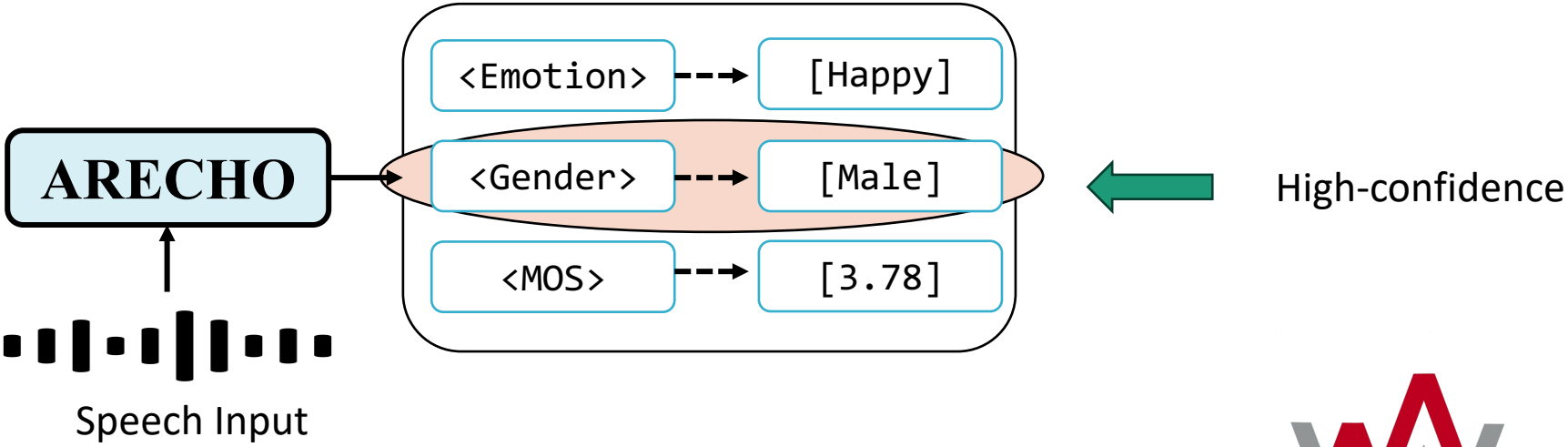
Two-step Confidence-oriented Decoding

- Make decoding decision every two steps



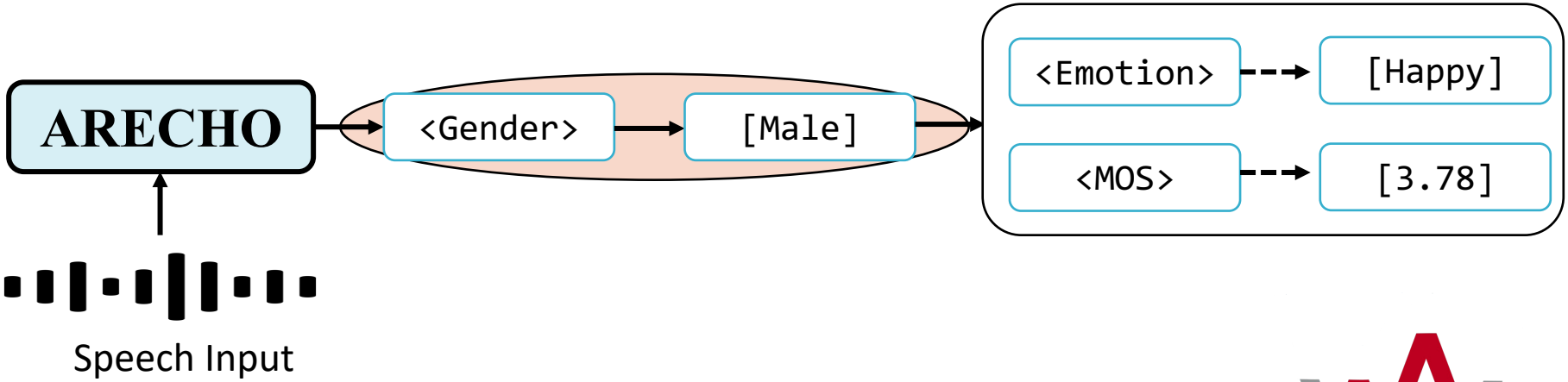
Two-step Confidence-oriented Decoding

- Make decoding decision every two steps



Two-step Confidence-oriented Decoding

- Make decoding decision every two steps



Experiments

- Dataset combination
  - Basic speech data -> sampled from OWSM (Peng et al. 2023)
  - Corrupted speech data (simulation) -> simulated based on URGENT challenge (Zhang et al. 2024)
  - Enhanced speech data -> samples from the URGENT challenge submission (Zhang et al. 2024)
  - Synthesized speech data -> synthesized data from NISQA and VoiceMOS (Mittag et al. 2021; Huang et al. 2022)

Experiments

- Dataset combination
  - Basic speech data -> sampled from OWSM (Peng et al. 2023)
  - ge
  - (
  - Synthesized speech data -> synthesized data from NISQA and VoiceMOS (Mittag et al. 2021; Huang et al. 2022)

Two combination:
- Base (a 300h domain-balanced training set)
- **Scale (a 2kh larger-scale training set)**

Covered metrics in ARECHO

- 47 independent metrics
- 25 dependent metrics
- 7 non-matching metrics
- 8 ground truth metrics from data annotations

- → Sum up to 87 metrics (65 numerical + 22 categorical)

Main Results

MSE: Mean square error;
LCC: Linear correlation coefficient
KTAU: Ktau ranking-based correlation
Acc: Accuracy
F1: F1 measure

Data	Domain	Model	Token	Chain	Regression Metrics MSE (↓)	LCC (↑)	KTAU (↑)	Classification Metrics Acc (↑)	F1 (↑)
Scale	Dev.	UniVERSA	✗	✗	116.01	0.89	0.37	0.73	0.49
		UniVERSA-T	✓	✗	**27.98**	**0.86**	0.37	0.74	**0.52**
		ARECHO	✓	✓	29.61	0.85	**0.37**	**0.75**	**0.52**
	Enhanced	UniVERSA	✗	✗	43.05	**0.84**	0.34	0.72	0.47
		UniVERSA-T	✓	✗	69.94	0.80	0.36	0.74	0.50
		ARECHO	✓	✓	**32.63**	0.83	**0.37**	**0.75**	**0.53**
	Corrupted	UniVERSA	✗	✗	151.97	**0.88**	0.37	0.75	0.54
		UniVERSA-T	✓	✗	39.80	0.77	0.37	0.76	0.54
		ARECHO	✓	✓	**34.37**	0.84	**0.38**	**0.77**	**0.56**
	Synthesized	UniVERSA	✗	✗	**6.46**	0.84	0.32	0.71	0.47
		UniVERSA-T	✓	✗	8.23	0.84	0.34	0.73	0.49
		ARECHO	✓	✓	8.63	**0.85**	**0.36**	**0.75**	**0.54**
	Avg. Test	UniVERSA	✗	✗	67.16	**0.85**	0.35	0.73	0.50
		UniVERSA-T	✓	✗	39.32	0.80	0.36	0.74	0.51
		ARECHO	✓	✓	**25.21**	0.84	**0.37**	**0.76**	**0.54**

Effect of tokenization
-> Consistent improvements on classification metrics due to mitigated scale differences

				Chain	Regression Metrics			Classification Metrics	
					MSE (↓)	LCC (↑)	KTAU (↑)	Acc (↑)	F1 (↑)
				✗	116.01	0.89	0.37	0.73	0.49
				✗	**27.98**	**0.86**	0.37	0.74	**0.52**
				✓	29.61	0.85	**0.37**	**0.75**	**0.52**
	Enhanced	UniVERSA	✗	✗	43.05	**0.84**	0.34	0.72	0.47
		UniVERSA-T	✓	✗	69.94	0.80	0.36	0.74	0.50
		ARECHO	✓	✓	**32.63**	0.83	**0.37**	**0.75**	**0.53**
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		UniVERSA-T	✓	✗	39.80	0.77	0.37	0.76	0.54
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		UniVERSA-T	✓	✗	8.23	0.84	0.34	0.73	0.49
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		ARECHO	✓	✓	**25.21**	0.84	**0.37**	**0.76**	**0.54**

Main Results

Effect of AR Modeling
-> Consistent improvements with AR modeling

Data	Domain	Model	Token	Chain	Regression Metrics MSE (↓)	LCC (↑)	KTAU (↑)	Classification Metrics Acc (↑)	F1 (↑)
Scale	Dev.	UniVERSA	✗	✗	116.01	0.89	0.37	0.73	0.49
		UniVERSA-T	✓	✗	**27.98**	**0.86**	0.37	0.74	**0.52**
		ARECHO	✓	✓	29.61	0.85	**0.37**	**0.75**	**0.52**
	Enhanced	UniVERSA	✗	✗	43.05	**0.84**	0.34	0.72	0.47
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	Corrupted	UniVERSA	✗	✗	151.97	**0.88**	0.37	0.75	0.54
		UniVERSA-T	✓	✗	39.80	0.77	0.37	0.76	0.54
		ARECHO	✓	✓	**34.37**	0.84	**0.38**	**0.77**	**0.56**
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		UniVERSA-T	✓	✗	8.23	0.84	0.34	0.73	0.49
		ARECHO	✓	✓	8.63	**0.85**	**0.36**	**0.75**	**0.54**
	Avg. Test	UniVERSA	✗	✗	67.16	**0.85**	0.35	0.73	0.50
		UniVERSA-T	✓	✗	39.32	0.80	0.36	0.74	0.51
		ARECHO	✓	✓	**25.21**	0.84	**0.37**	**0.76**	**0.54**

Main Results

Metric-wise fine-grained control may help

Data	Domain	Model	Token	Chain	Regression Metrics MSE (↓)	LCC (↑)	KTAU (↑)	Classification Metrics Acc (↑)	F1 (↑)
Scale	Dev.	UniVERSA	✗	✗	116.01	0.89	0.37	0.73	0.49
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		ARECHO	✓	✓	**25.21**	0.84	**0.37**	**0.76**	**0.54**

Dependency Modeling

Top 5 – Bottom 5 metrics ranked by average position (Avg. Pos.) across three test sets

An option to show **dependency reasoning** in ARECHO

Test Set	Rank	Metric Name	Avg. Pos.
Enhanced	Top-1	Q-SpeakerGender	16.50
	Top-2	Q-SpeechImpairment	20.35
	Top-3	Q-SpeechStyle	21.47
	Btm-3	SNR Simulation	163.52
	Btm-2	NISQA Real MOS	167.91
	Btm-1	VoiceMOS Real MOS	171.58
Corrupted	Top-1	RIR Room Size	1.82
	Top-2	Q-SpeechImpairment	12.65
	Top-3	Q-SpeechDelivery	13.15
	Btm-3	CER	167.26
	Btm-2	NISQA Real MOS	170.62
	Btm-1	VoiceMOS Real MOS	171.38
Synthesized	Top-1	Q-Background	12.09
	Top-2	NISQA Coloration	27.51
	Top-3	Q-Purpose	27.95
	Btm-3	C_{bak}	154.75
	Btm-2	SNR Simulation	158.64
	Btm-1	CER	161.61

Dependency Modeling

Metrics related to

- Structured annotations
- Acoustic scene characteristics

Appear early in prediction sequence

Test Set	Rank	Metric Name	Avg. Pos.
Enhanced	Top-1	Q-SpeakerGender	16.50
	Top-2	Q-SpeechImpairment	20.35
	Top-3	Q-SpeechStyle	21.47
	Btm-3	SNR Simulation	163.52
	Btm-2	NISQA Real MOS	167.91
	Btm-1	VoiceMOS Real MOS	171.58
Corrupted	Top-1	RIR Room Size	1.82
	Top-2	Q-SpeechImpairment	12.65
	Top-3	Q-SpeechDelivery	13.15
	Btm-3	CER	167.26
	Btm-2	NISQA Real MOS	170.62
	Btm-1	VoiceMOS Real MOS	171.38
Synthesized	Top-1	Q-Background	12.09
	Top-2	NISQA Coloration	27.51
	Top-3	Q-Purpose	27.95
	Btm-3	C_{bak}	154.75
	Btm-2	SNR Simulation	158.64
	Btm-1	CER	161.61

Dependency Modeling

Depending on the context, some metrics are **inherently harder** to predict (e.g., SNR simulation for enhanced and synthesized test sets)

Test Set	Rank	Metric Name	Avg. Pos.
Enhanced	Top-1	Q-SpeakerGender	16.50
	Top-2	Q-SpeechImpairment	20.35
	Top-3	Q-SpeechStyle	21.47
	Btm-3	SNR Simulation	163.52
	Btm-2	NISQA Real MOS	167.91
	Btm-1	VoiceMOS Real MOS	171.58
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	Top-2	Q-SpeechImpairment	12.65
	Top-3	Q-SpeechDelivery	13.15
	Btm-3	CER	167.26
	Btm-2	NISQA Real MOS	170.62
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Synthesized	Top-1	Q-Background	12.09
	Top-2	NISQA Coloration	27.51
	Top-3	Q-Purpose	27.95
	Btm-3	C_{bak}	154.75
	Btm-2	SNR Simulation	158.64
	Btm-1	CER	161.61

Dependency Modeling

Q-Gender	Q-SpeechImpariment	Q-SpeakingStyle	Q-EnvQuality	Q-PitchRange	Q-VocComplexity	Q-VolumeLevel	RealLanguage	Q-ContentRegister	SRMR
SpoofS	NISQA-NOI	Q-Emotion	AA-PC	Q-Background	AA-PQ	Q-ChannelType	LID	Q-Clarity	SE-CI-SDR
DNSMOSP.835	SWR/SCR	Q-Purpose	WER	Q-VoiceType	SingMOS	SE-SI-SNR	Q-Lang	Q-SpeechRate	SCOREQ
NISQA-COL	Q-EmoVocalization	NISQA-LOUD	Q-SpeakerCount	Q-Age	PAM	UTMOS	AA-CE	NISQA-MOS	DNSMOSP.808
SSQA	PLCMOS	Q-Pitch	AA-CU	CER	SE-SDR	UTMOSv2	NISQA-DIS	CI-SDR	D-Distance
STOI	SE-SAR	SDR	SI-SNR	MCD	D-BERT	F0Corr	F0RMSE	SPK-SIM	D-BLEU
PESQ	URGENT MOS	SAR	CD	WSS	LLR	EMO-SIM	NCM	Covl	Reference Text Length
VISQOL	Csig	CSII-MID	Cbak	CSII-HIGH	SCOREQ w. Ref.	ASR-Mismatch	CSII-LOW	NOMAD	RIR Room Size
Noresqa	FWSEGSNR	RT60	Predicted Text Length	SNR Simulation	NISQA Real MOS	VoiceMOS Real MOS			

Check full metric order in the paper!

Future works

- Scaling!
- ARECHO as a reward model
- ARECHO + Uni-VERSA
- From low-level information to high-level understanding
- From fixed metric set to natural language
    - How to combine the information
    - How to activate the usage

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Icons and images are either from flaticon.com or generated from GPT-4o.

Thank you for listening!

TABLE V

COMPARISON OF SUPERVISION STRATEGIES USING DIFFERENT LOSS CONFIGURATIONS ON DNS20 TEST SETS, REPORTED AS (SYNTHETIC / SYNTHETIC REVERB). LPS DENOTES LEVENSHTEIN PHONEME SIMILARITY. RANK DENOTES THE OVERALL RANKING SCORE NORMALIZED TO [0, 1]. BEST RESULTS ARE IN **BOLD**, BASED ON FULL-PRECISION VALUES.

#	SQA Model	$\lambda_{spec}/\lambda_{score}/\lambda_{feat}$	SDR ↑	PESQ ↑	LSD ↓	MCD ↓	LPS ↓	ESTOI ↑	SBERT ↑	SpkSim ↑
1	Noisy		9.09 / 9.16	1.58 / 1.82	3.13 / 2.05	5.63 / 5.02	0.90 / 0.67	0.81 / **0.78**	0.88 / 0.86	**0.95** / **0.88**
2	None	1 / 0 / 0	18.21 / 10.97	2.86 / 1.99	2.49 / 2.37	2.03 / 3.99	0.96 / 0.83	0.93 / 0.77	0.93 / 0.88	0.93 / 0.84
3	Uni-VERSA	1 / 1 / 1	18.29 / 10.75	2.91 / 1.88	2.45 / 2.33	**1.98** / 3.99	0.96 / 0.83	0.93 / 0.76	0.93 / 0.87	0.93 / 0.83
4	Uni-VERSA-Ext (proposed)	1 / 1 / 1	18.27 / 10.72	2.91 / 1.90	2.41 / 2.32	1.99 / 3.94	0.96 / 0.83	0.93 / 0.77	0.93 / 0.88	0.93 / 0.83
5		1 / 1 / 0	**18.30** / 10.74	**2.91** / 1.88	2.48 / 2.35	1.99 / 3.99	0.96 / **0.83**	0.93 / 0.76	0.93 / 0.87	0.93 / 0.83
6		1 / 0 / 1	18.25 / 10.80	2.91 / 1.91	**2.41** / **2.31**	1.99 / **3.91**	0.96 / 0.83	0.93 / 0.77	0.93 / 0.88	0.93 / 0.84
7		0 / 1 / 1	17.93 / **11.15**	2.90 / **1.95**	2.50 / 2.46	2.20 / 3.98	**0.96** / 0.83	**0.93** / 0.77	**0.93** / **0.88**	0.92 / 0.82
8		0 / 1 / 0	1.56 / -1.43	1.04 / 1.03	5.71 / 5.84	7.64 / 9.51	0.29 / 0.15	0.33 / 0.18	0.59 / 0.52	0.19 / 0.08
9		0 / 0 / 1	17.94 / 11.12	2.90 / 1.95	2.49 / 2.46	2.19 / 3.99	0.96 / 0.83	0.93 / 0.77	0.93 / 0.88	0.92 / 0.83
		(continued)	CER ↓	UTMOS ↑	SIGMOS.OVRL ↑	SCOREQ ↑	DNSMOS ↑	Distill-MOS ↑	NISQA ↑	**Rank [22]** ↓
1	Noisy		**0.25** / 0.26	2.37 / 1.30	2.32 / 2.07	2.79 / 2.10	2.48 / 1.39	3.06 / 2.32	2.58 / 1.66	0.60 / 0.48
2	None	1 / 0 / 0	0.34 / 0.27	3.60 / 1.38	3.06 / 2.42	3.98 / 2.53	3.25 / 2.59	4.07 / 2.74	4.25 / 2.36	0.42 / 0.40
3	Uni-VERSA	1 / 1 / 1	0.32 / 0.26	3.61 / 1.38	3.11 / 2.46	4.03 / 2.51	3.24 / 2.52	4.09 / 2.65	4.26 / 2.34	0.35 / 0.48
4	Uni-VERSA-Ext (proposed)	1 / 1 / 1	0.31 / 0.25	3.69 / 1.39	3.00 / 2.50	4.09 / 2.69	3.28 / 2.61	4.29 / 2.67	4.49 / 2.72	**0.33** / 0.42
5		1 / 1 / 0	0.33 / 0.25	3.61 / 1.38	3.12 / 2.47	4.03 / 2.50	3.25 / 2.52	4.08 / 2.62	4.29 / 2.36	0.38 / 0.51
6		1 / 0 / 1	0.32 / 0.22	3.69 / 1.39	3.01 / 2.52	4.09 / 2.69	3.26 / 2.58	4.22 / 2.64	4.47 / 2.71	0.34 / 0.38
7		0 / 1 / 1	0.31 / 0.24	3.84 / 1.42	**3.14** / 2.58	**4.21** / **2.85**	**3.33** / **2.77**	**4.46** / **2.76**	**4.59** / **2.94**	0.39 / **0.38**
8		0 / 1 / 0	0.77 / 1.05	2.34 / **1.64**	2.47 / 2.17	3.07 / 2.66	2.75 / 2.35	2.77 / 2.24	2.75 / 1.93	0.77 / 0.76
9		0 / 0 / 1	0.32 / **0.23**	**3.84** / 1.42	3.13 / **2.59**	4.21 / 2.84	3.33 / 2.76	4.41 / 2.69	4.56 / 2.92	0.39 / 0.38