

Expressive Speech-to-Speech Translation

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Postdoctoral Researcher at Seamless, FAIR

BISH Bash event on Feb 15th, 2024

AI at Meta

Agenda

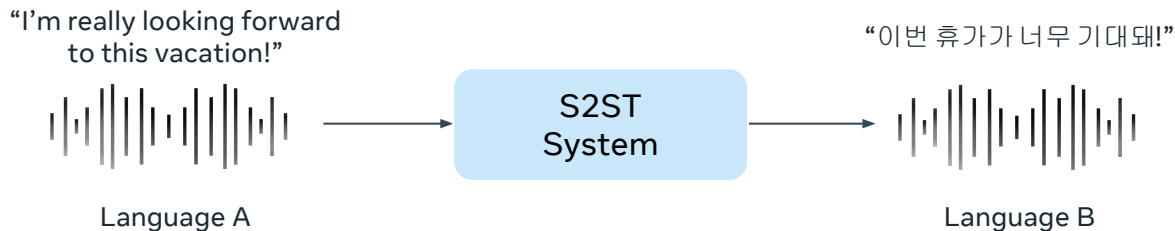
Introduction

SeamlessExpressive

Conclusion

Speech-to-Speech Translation (S2ST) System

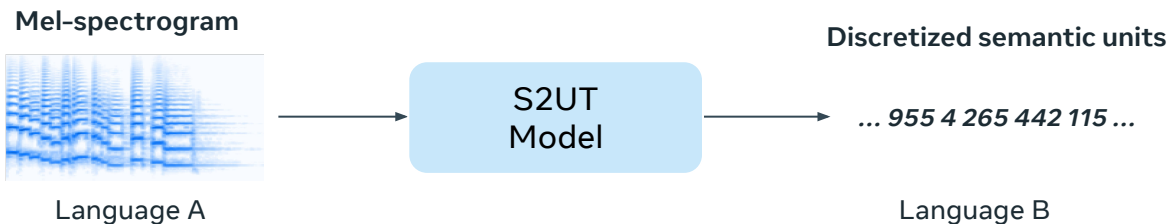
Concept



- Automatically converts speech signal in one language to speech signal in another language.
- Playing a crucial role in breaking down language barriers between different cultures in international conversation situations.

Direct S2ST with Discrete Units

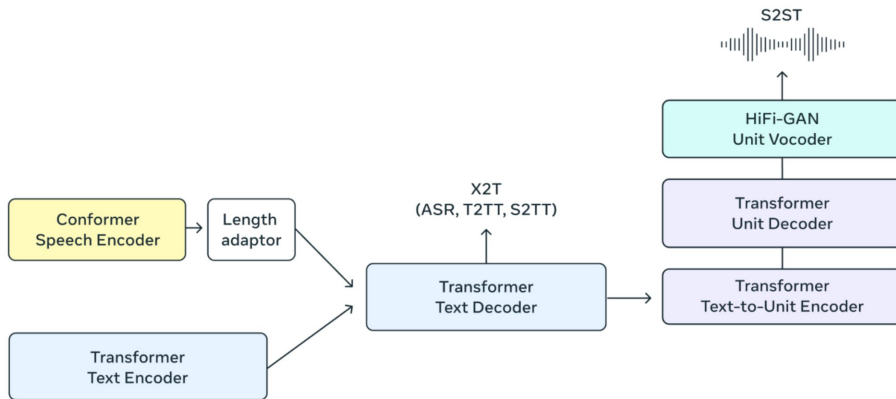
Speech-to-unit translation (S2UT) model [Ann et al., 2021, Inaguma et al., 2023]



- Translate input speech into **discretized semantic units**, e.g., HuBERT [Hsu et al., 2021] and XLS-R [Babu et al., 2022]
 - Generate speech waveform using unit HiFi-GAN vocoder [Kong et al., 2020] from translated units
- Provide **high quality content translation performance**
 - Constraint model's output space into semantic information
 - Leveraging advanced modeling techniques, e.g., model pretraining or data augmentation

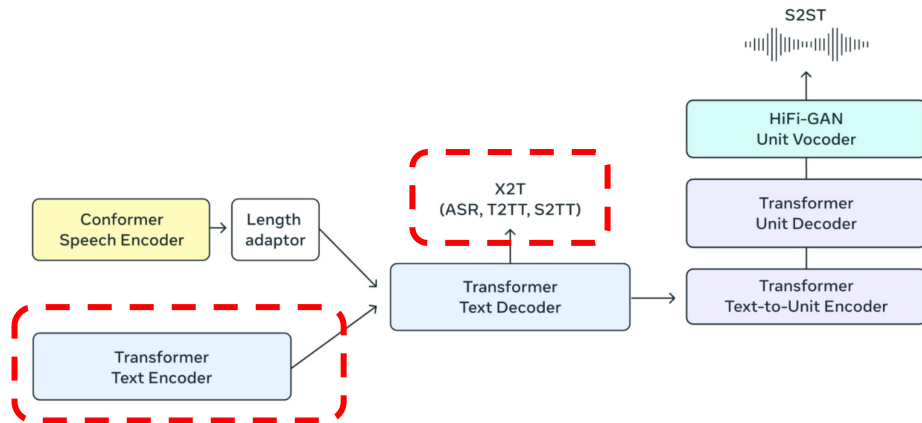
SeamlessM4T: Massively Multilingual & Multimodal Machine Translation Model

State-of-the-art S2UT model [Seamless Communication, 2023]



SeamlessM4T: Massively Multilingual & Multimodal Machine Translation Model

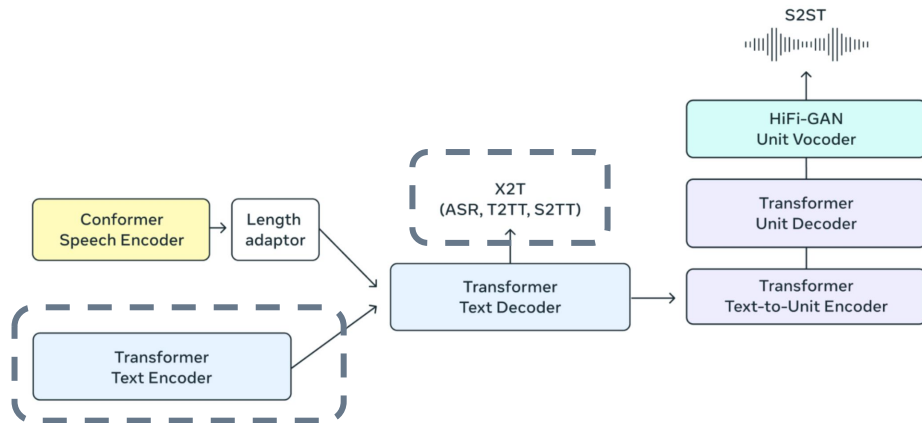
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1. More modalities (Text input & output)

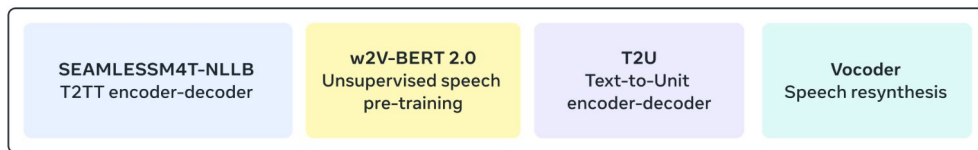
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1. More modalities (Text input & output)

2. Pretrained components



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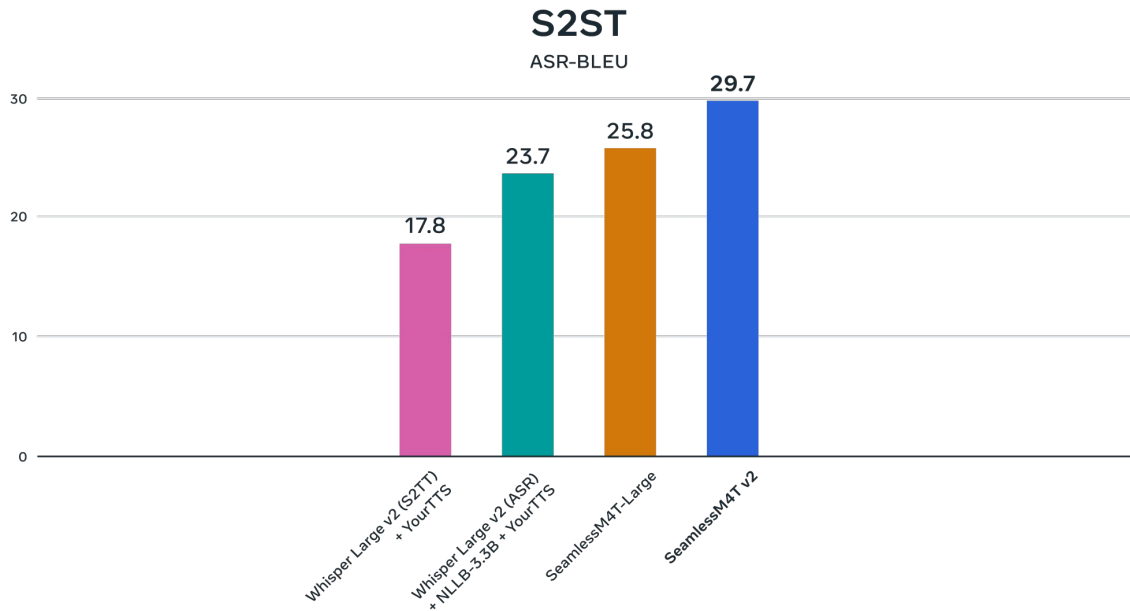
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3. Massively multilingual training data

SEAMLESSM4T-NLLB Dense transformer encoder-decoder	W2V-BERT 2.0 Conformer	SEAMLESSM4T v2-T2U UNITY2's non-autoregressive T2U	VOCODER HiFi-GAN unit vocoder
TEXT-TO-TEXT DATA NLLB-SEED PUBLICBITEXT Automatically Aligned bitexts, MMTBT, SMTBT <i>NLLB Team et al. [2022]</i> Languages: 98 Size: 5B bitexts	UNLABELED SPEECH Publicly available data repositories Languages: 143+ Size: 4.5M hours	ASR DATA Speech audio data with transcriptions Languages: 36 Size: 34.5K hours	TTS DATA Monolingual high-quality text-to-speech data Languages: 36 Size: 396 hours
X2T FINETUNING S2TT data triplets Automatically aligned S2TT pairs ASR data Size: 351K hours		S2ST FINETUNING Pseudo-labeled S2TT data Automatically aligned S2ST pairs Size: 145K hours	

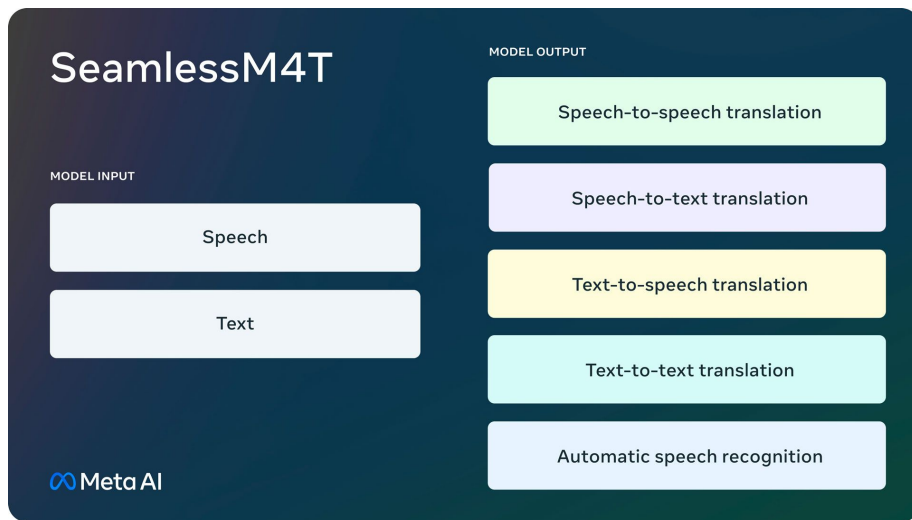
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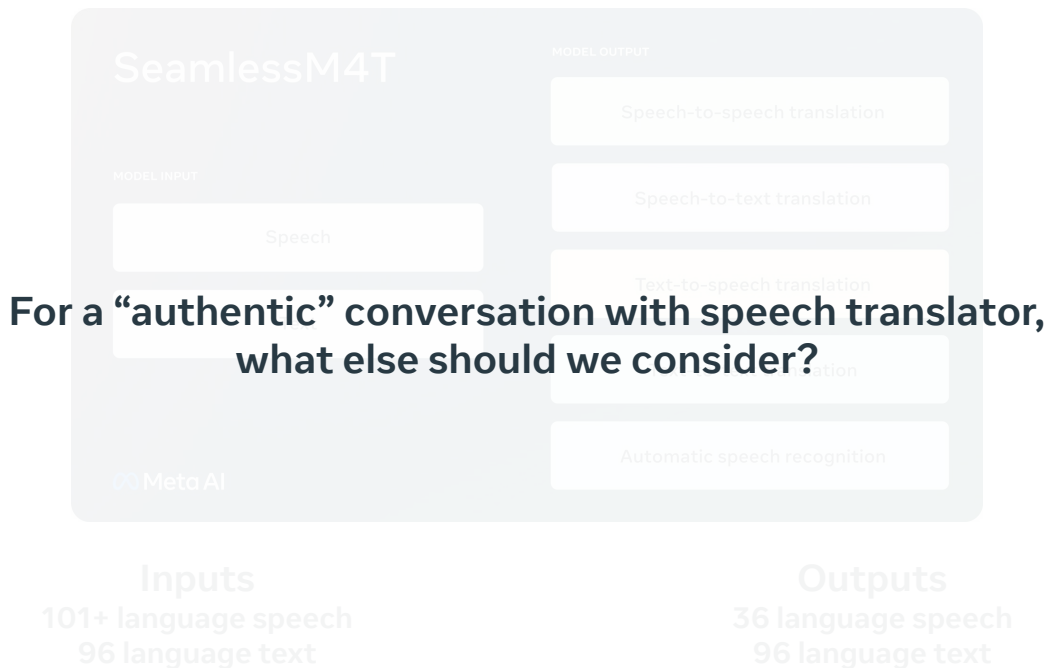


Inputs
101+ language speech
96 language text

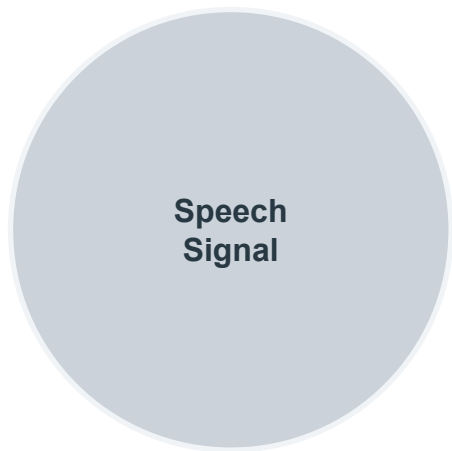
Outputs
36 language speech
96 language text

SeamlessM4T: Massively Multilingual & Multimodal Machine Translation Model

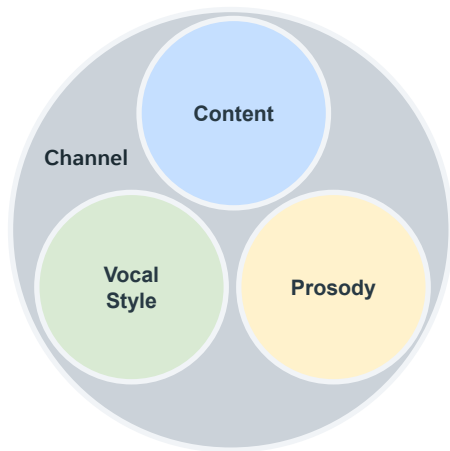
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Disentangled Property of Speech

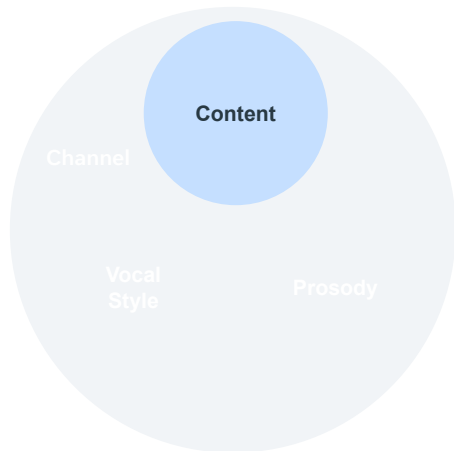


Disentangled Property of Speech



- **Content information**
 - Related to linguistic property
 - E.g., Semantic meaning, language identity, etc.
- **Vocal style information**
 - Related to vocal style
 - E.g., Voice color or speaking style
- **Prosody information**
 - Related to intonation, accent, rhythm, emotion, etc.
- **Channel information**
 - Information other than speech
 - E.g., Background noise or reverberation, etc.

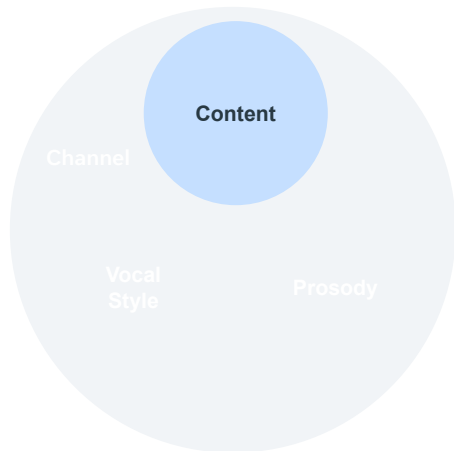
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Target of conventional S2ST models

Disentangled Property of Speech



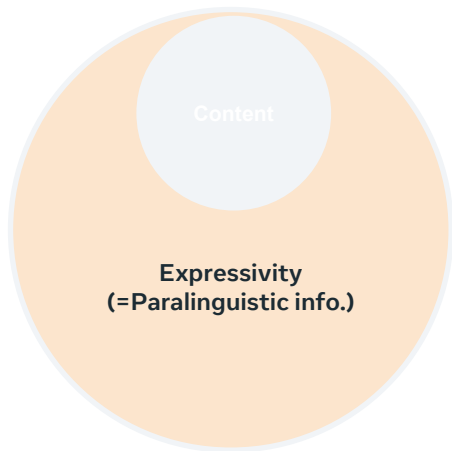
- **Content information**
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Target of conventional S2ST models



Conventional S2ST models ignores paralinguistic information.
So they generate **monotone translated speech**.

Disentangled Property of Speech



- **Content information**
 - Related to linguistic property
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Target of conventional S2ST models



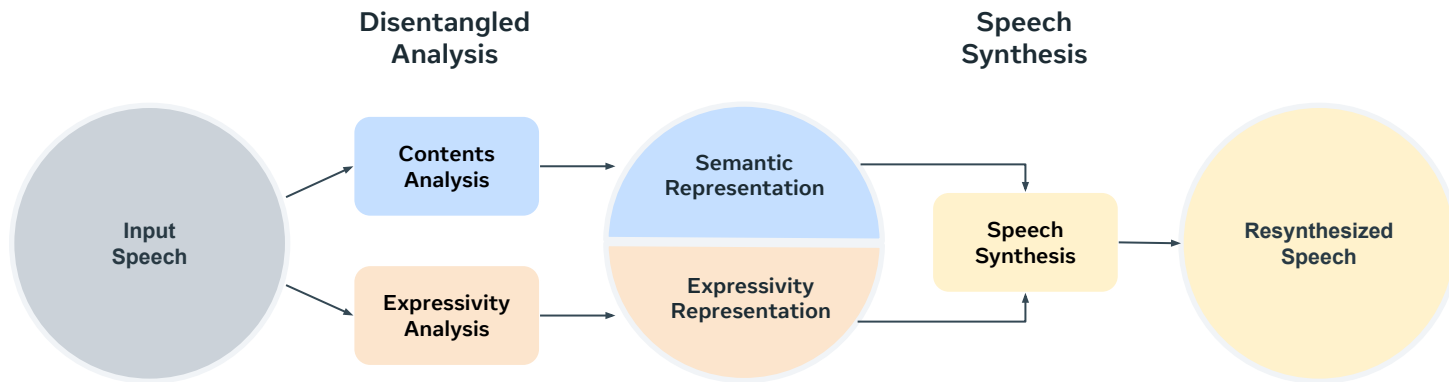
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So they generate monotone translated speech.



For the naturalistic conversation, **paralinguistic (or expressivity) information also should be conveyed to listener!**

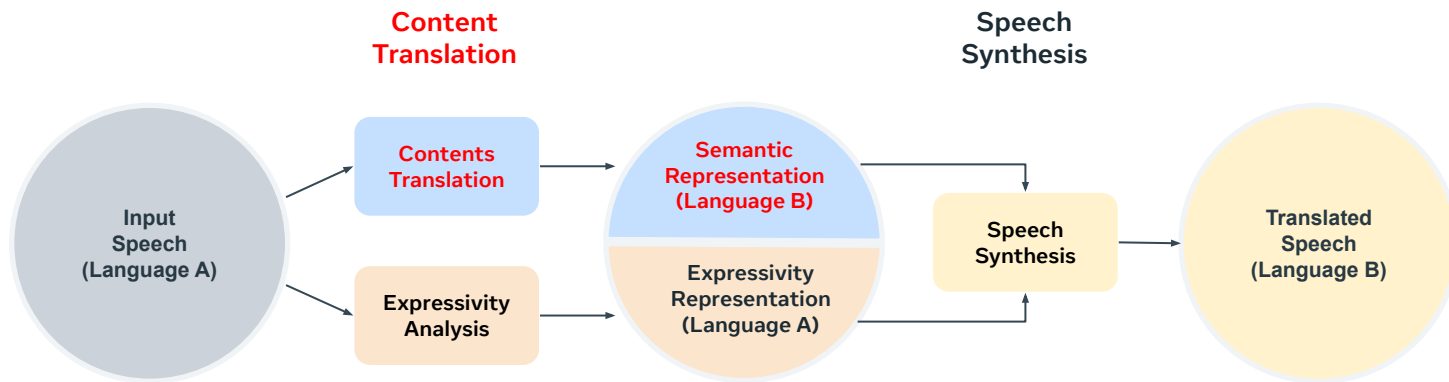
Idea for expressivity-preserved S2ST

Analysis-synthesis framework for disentangled representation of speech components



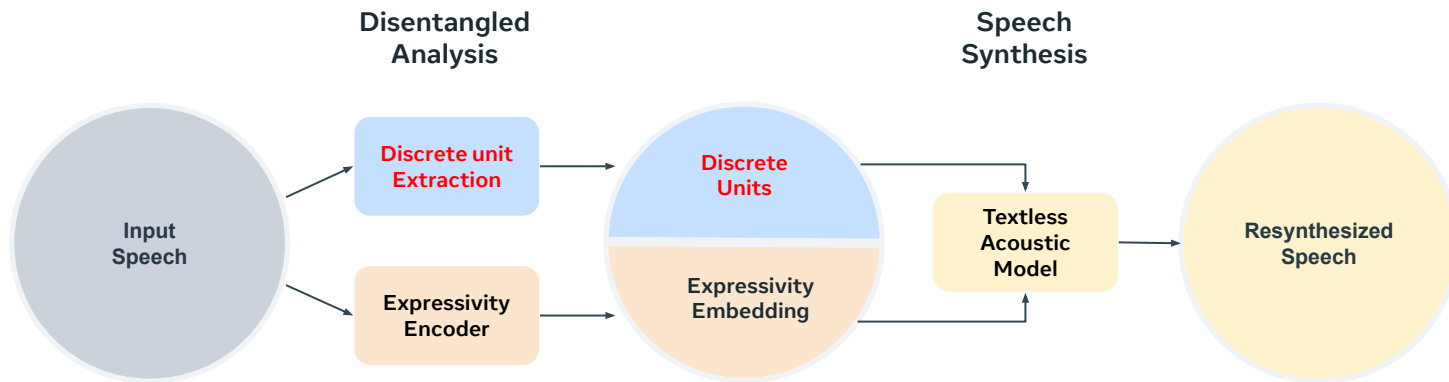
Idea for expressivity-preserved S2ST

Replace semantic representation with the one of target language for expressive S2ST



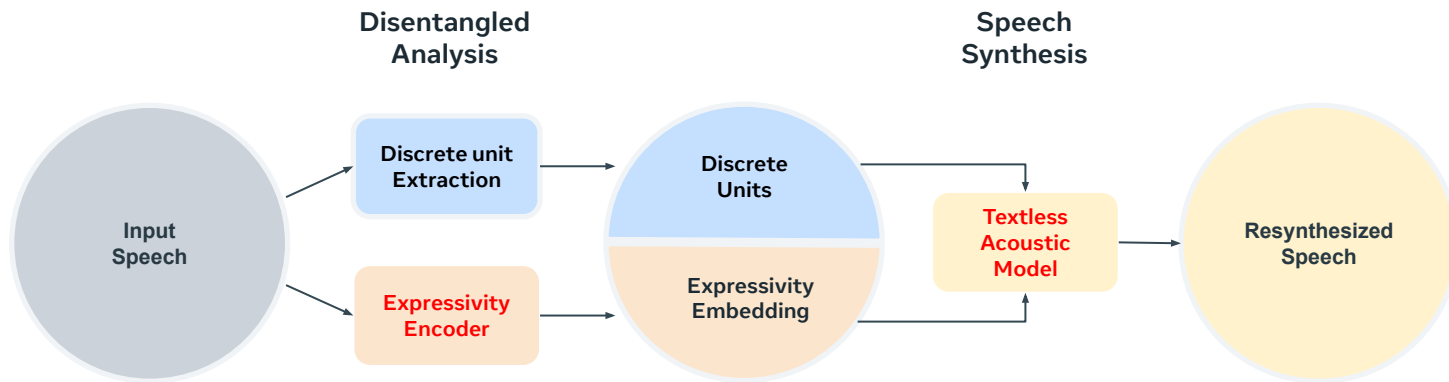
Idea for expressivity-preserved S2ST (detailed)

We know that the **discrete units** are efficient way to represent semantic information



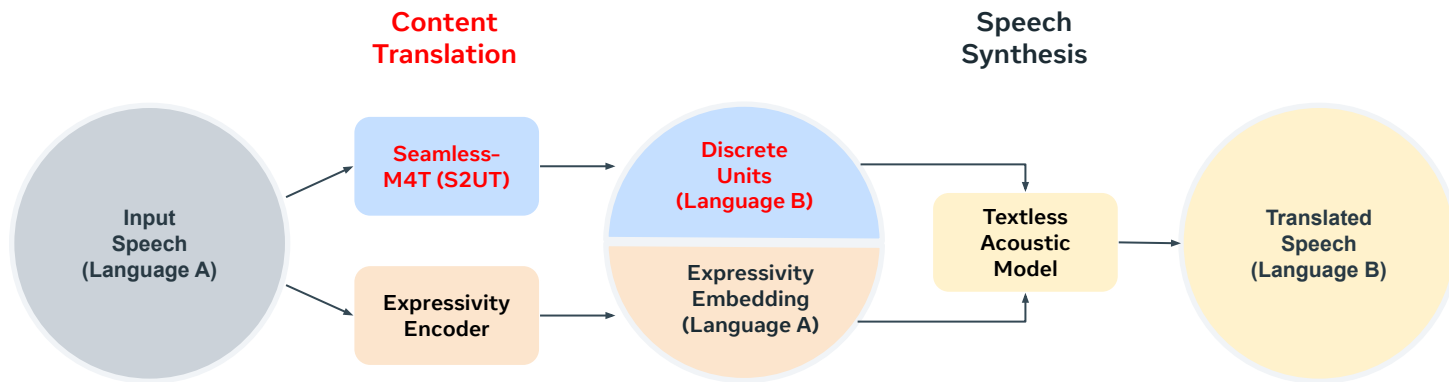
Idea for expressivity-preserved S2ST (detailed)

Fix unit extractor, then **train expressivity encoder** and **acoustic model**

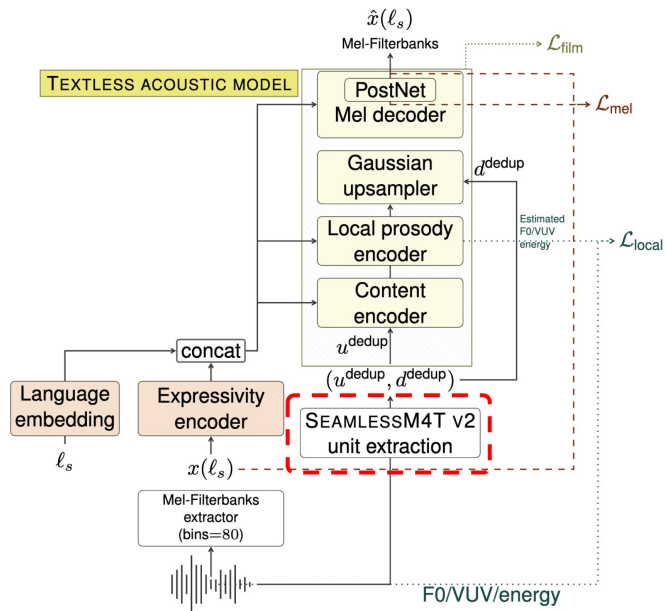


Idea for expressivity-preserved S2ST (detailed)

For S2ST, synthesize speech from **translated units (target language)** and **expressivity embedding (source language)**



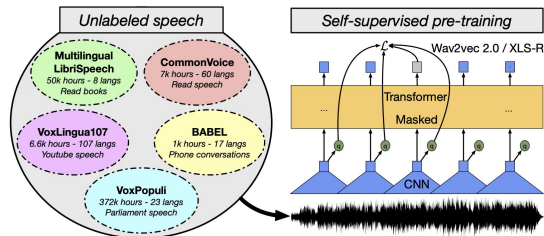
PRETSSEL: Paralinguistic REpresentation-based TextleSS acoustic modEL



[PRETSSEL]

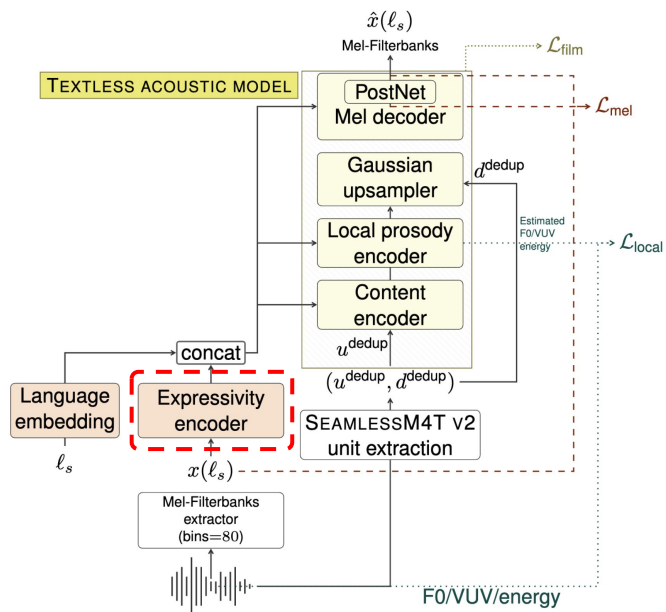
Discrete unit extractor

- Encode linguistic information of input speech
 - Input : Speech waveform
 - Output: Discretized XLS-R 10K units [Babu et al., 2022]
- Pretrained XLS-R model followed by K-means clustering
 - Align with SeamlessM4T unit extractor



[XLS-R model overview]

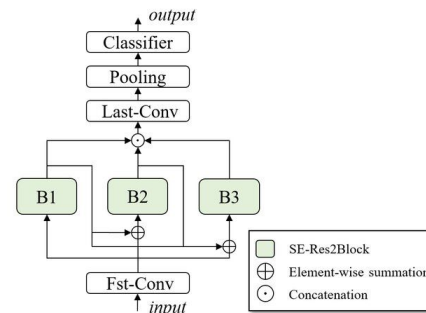
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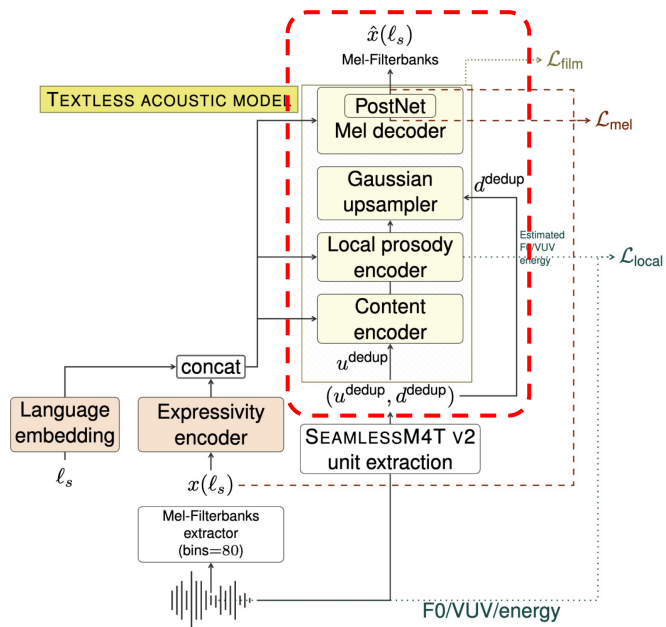
Expressivity encoder

- Encode paralinguistic information of input speech
 - Input : Mel-filterbank features
 - Output: Global expressivity embedding vector
- Modified ECAPA-TDNN architecture [Desplanques et al., 2020]
 - Replace batch norm. layer with layer norm. layer



[ECAPA-TDNN architecture]

PRETSSEL: Paralinguistic REpresentation-based TextleSS acoustic modEL

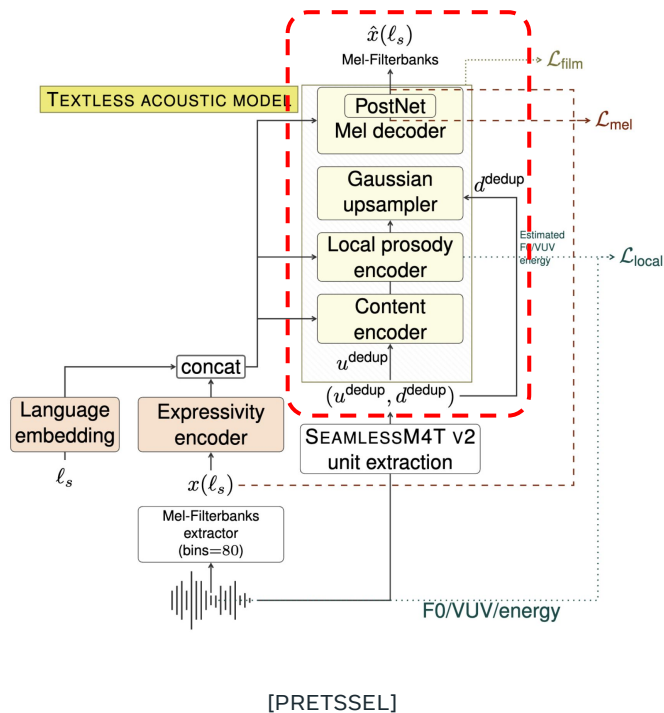


[PRETSSEL]

Textless acoustic model

- Synthesize speech from disentangled representations
 - Input : (1) XLS-R 10K units, (2) Expressivity embedding
 - Linguistic*
 - Paralinguistic*
 - Output: Mel-filterbank features
- Modified FastSpeech2 architecture [Ren et. al., 2021]
 - Contents encoder
 - Encode unit representations
 - Feed-forward Transformer (FFT) blocks
 - Local prosody encoder
 - Predict and embed F0 and energy to encoder output
 - Mel-decoder
 - Predict output Mel-filterbank features
 - Feed-forward Transformer (FFT) blocks

PRETSSEL: Paralinguistic REpresentation-based TextleSS acoustic modEL



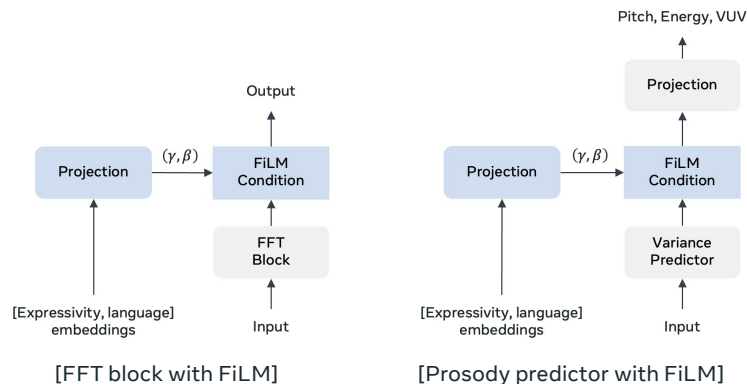
Textless acoustic model (cont.)

1. FiLM conditioning layer for better expressivity conditioning

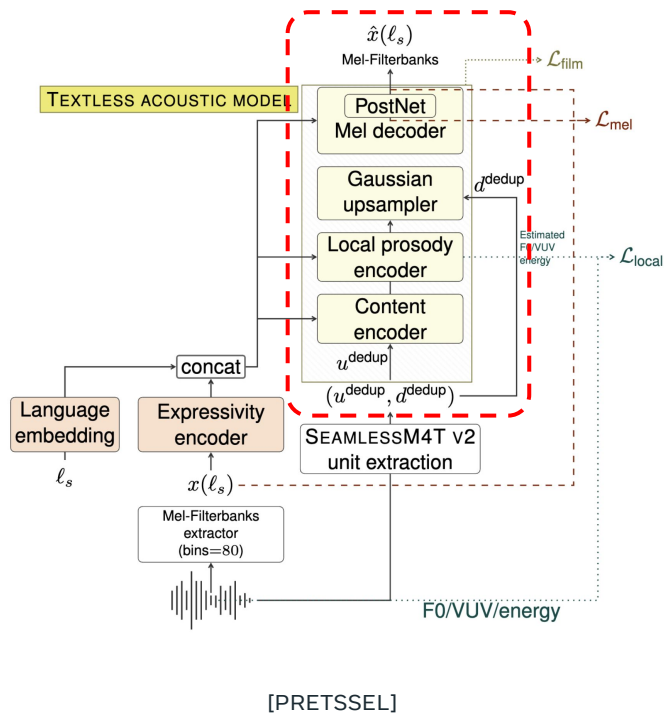
- Formula [Oreshkin et al., 2018]
 - $$\text{FiLM}(x, c) = (\gamma + 1) \cdot x + \beta$$

$$\gamma = \text{proj}(c) \cdot \theta_\gamma$$

$$\beta = \text{proj}(c) \cdot \theta_\beta$$
- Apply FiLM to FFT blocks and prosody predictors
 - Use **Expressivity and language embeddings** as condition



PRETSSEL: Paralinguistic REpresentation-based TextleSS acoustic modEL



Textless acoustic model (cont.)

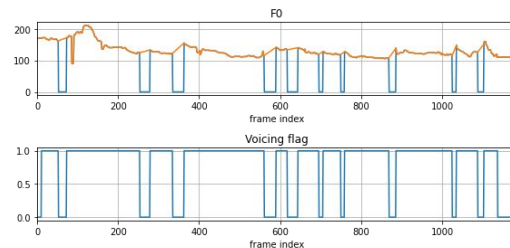
2. Duration modeling

- Obtain unit duration from external S2UT model
- Use **Gaussian upsampler** [Shen et al. 2020]

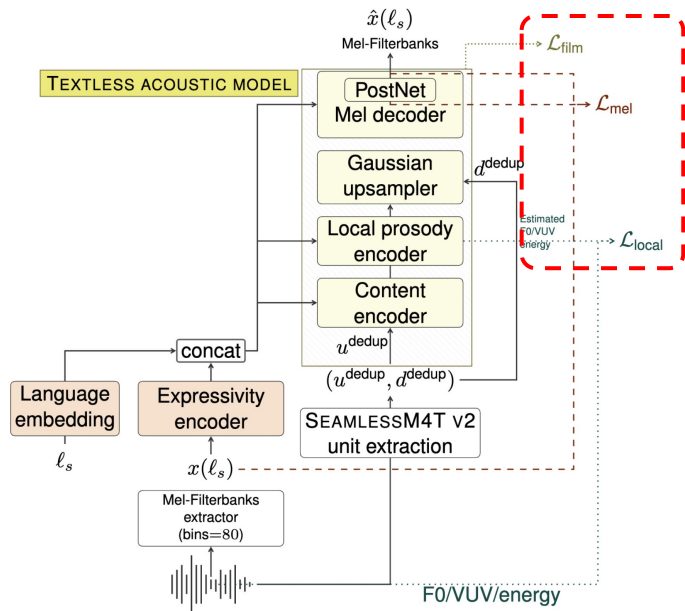
$$c_i = \frac{d_i}{2} + \sum_{j=1}^{i-1} d_j, \quad w_{ti} = \frac{\mathcal{N}(t; c_i, \sigma_i^2)}{\sum_{j=1}^N \mathcal{N}(t; c_j, \sigma_j^2)}, \quad \mathbf{u}_t = \sum_{i=1}^N w_{ti} \mathbf{h}_i.$$

3. Individual F0 and voicing flag (VUV) modeling

- Interpolate F0 to **obtain continuous F0 and VUV**,
- Predict them separately



PRETSSEL: Paralinguistic REpresentation-based TextleSS acoustic modEL



[PRETSSEL]

Training criteria

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{mel}} + \lambda_l \cdot \mathcal{L}_{\text{local}} + \lambda_f \cdot \mathcal{L}_{\text{film}},$$

- Mel-reconstruction loss

$$\mathcal{L}_{\text{mel}} = \mathcal{L}_1(\hat{y}_{\text{before}}, y) + \mathcal{L}_2(\hat{y}_{\text{before}}, y) + \mathcal{L}_1(\hat{y}_{\text{after}}, y) + \mathcal{L}_2(\hat{y}_{\text{after}}, y),$$

- L1 and L2 losses of before and after PostNet

- Local prosody prediction loss

$$\mathcal{L}_{\text{local}} = \mathcal{L}_2(\hat{p}, p) + \text{BCE}(\hat{u}, u) + \mathcal{L}_2(\hat{e}, e),$$

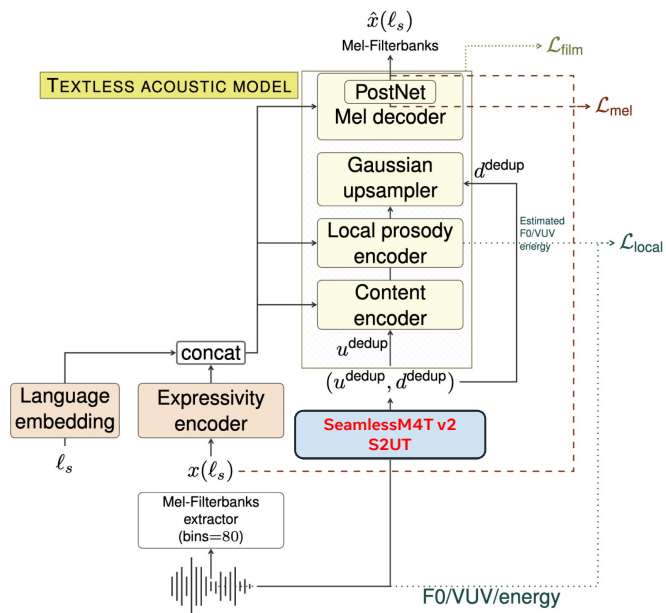
- L2 losses for pitch and energy
- Binary cross entropy loss for VUV

- FiLM regularization loss

$$\mathcal{L}_{\text{film}} = \sum_{\theta_\gamma, \theta_\beta} (\theta_\gamma^2 + \theta_\beta^2),$$

- L2 regularization for FiLM parameters

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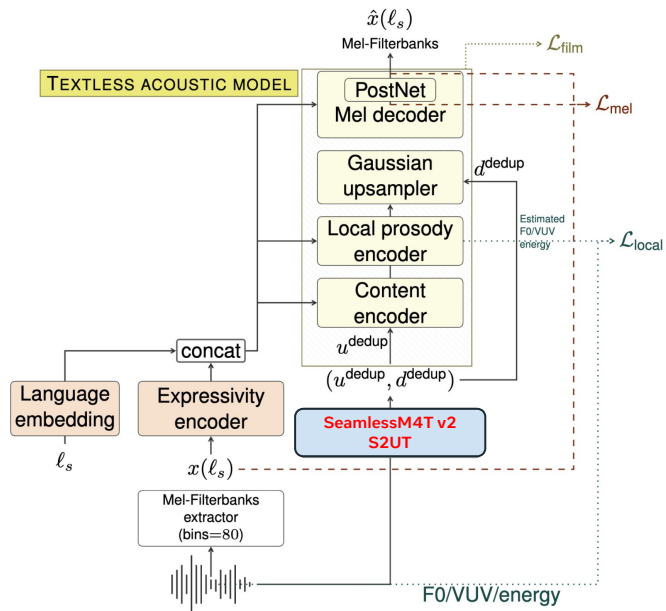


[PRETSSEL]

Expressive S2ST inference










1. Extract expressivity embedding at source language
 - Execute expressivity encoder
2. Obtain XLS-R 10K units at target language
 - Execute SeamlessM4T S2UT model
3. Generate Mel-filterbank features at target language
 - Execute textless acoustic model
4. Generate speech waveform from Mel-filterbank features
 - Execute HiFi-GAN vocoder [Kong et al., 2020]

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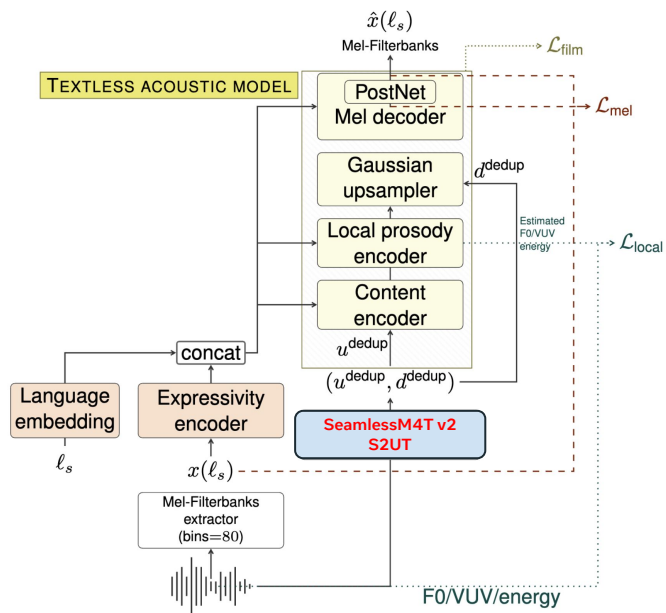


[PRETSSEL]

S2ST samples

	Source Speech	SeamlessM4T V2	SeamlessM4T V2 + PRETSSEL
Happy			
Sad			
Enunciated			

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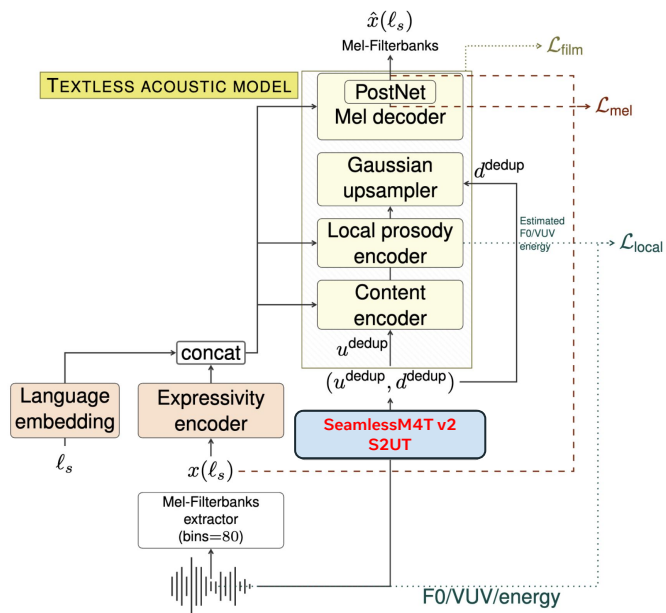
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S2ST samples

	Source Speech	SeamlessM4T V2	SeamlessM4T V2 + PRETSSEL
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- PRETSSEL can clearly transfer source speech's utterance-level expressivity!
 - e.g., vocal style or global emotion!

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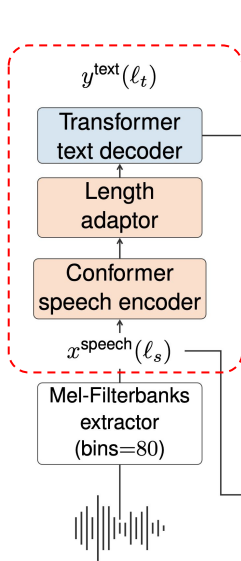
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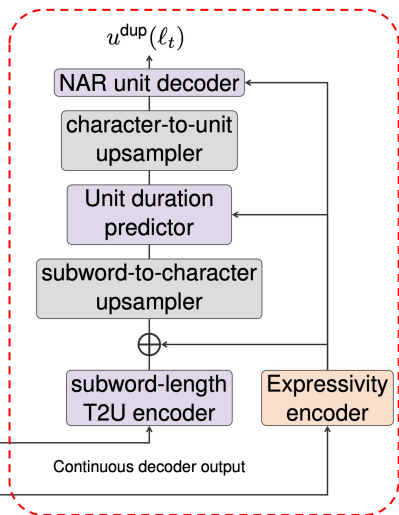
- PRETSSEL can clearly transfer source speech's utterance-level expressivity!
 - e.g., vocal style or global emotion!
- However, phrase-level expressivity are still missed in the output speech...
 - e.g., Rhythm, pause

Prosody UnitY2: Expressivity-aware S2UT model

2. Pretrained S2TT



1. Expressive T2U



[Prosody UnitY2]

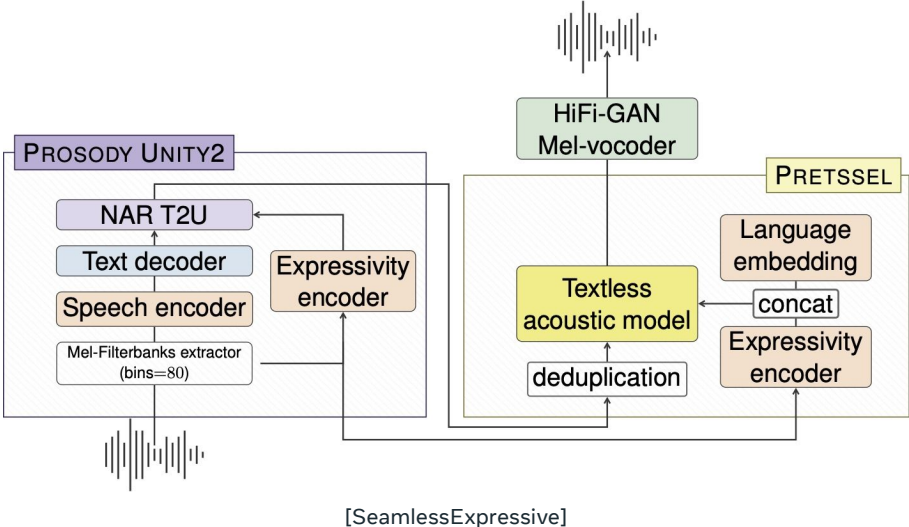
Expressivity-variant of SeamlessM4T V2

- Expressive text-to-unit (T2U) architecture
 - Inject expressivity embedding to various positions of T2U model
 - Output of subword-length T2U encoder
 - Unit-duration predictor using FiLM layer
 - Unit decoder using FiLM layer

➔ *Can transfer expressivity information of input speech!*
- Fine-tuning from pretrained S2TT module
 - Initialize S2TT model from SeamlessM4T V2's S2TT model
 - Fine-tune entire S2UT model using expressive S2ST data

➔ *Can be efficiently trained!*

SeamlessExpressive: Expressivity-preserved Speech-to-Speech Translation



Performance Evaluation - Metrics

- **ASR-BLEU.** Content translation quality
- **V-SIM.** Vocal style preservation performance
- **AutoPCP.** Utterance-level prosody preservation performance
- **Rhythm.** Phrase-level prosody preservation performance
 - **Speech rate.** Spearman correlation of speech rates between two speeches
 - **Pause.** Pause alignment score

Performance Evaluation - Results

- Eng to [Spa, Deu, Fra] translation

Model	ASR-BLEU↑	V-Sim↑	AutoPCP↑	Speech rate↑	Pause↑
SeamlessM4T v2	38.82	0.05	2.31	0.13	0.14
SeamlessM4T v2 + PRETSSEL	38.59	0.27	2.87	0.15	0.16
SeamlessExpressive	40.18	0.28	3.19	0.64	0.39

- [Spa, Deu, Fra] to Eng translation

Model	ASR-BLEU↑	V-Sim↑	AutoPCP↑	Speech rate↑	Pause↑
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- Use of PRETSSEL dramatically improved utterance level expressivity preservation performance.

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1. Use of PRETSSEL dramatically improved utterance level expressivity preservation performance.
2. Prosody UnitY2 dramatically improved phrase-level expressivity preservation performance.
3. **With PRETSSEL and Prosody UnitY2, SeamlessExpressive achieved best performances for all metrics.**

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SeamlessExpressive Demo



References

- [Lee et al., 2021] Ann Lee, et al. “Direct speech-to-speech translation with discrete units,” in *Proc. ACL*, 2021
- [Inaguma et al., 2023] Hirofumi Inaguma et al. “Unity: Two-pass direct speech-to-speech translation with discrete units.,” *arXiv*, 2023
- [Seamless Communication, 2023] Seamless Communication, “SeamlessM4T-Massively Multilingual & Multimodal Machine Translation.,” *arXiv*, 2023
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