# Speech Processing

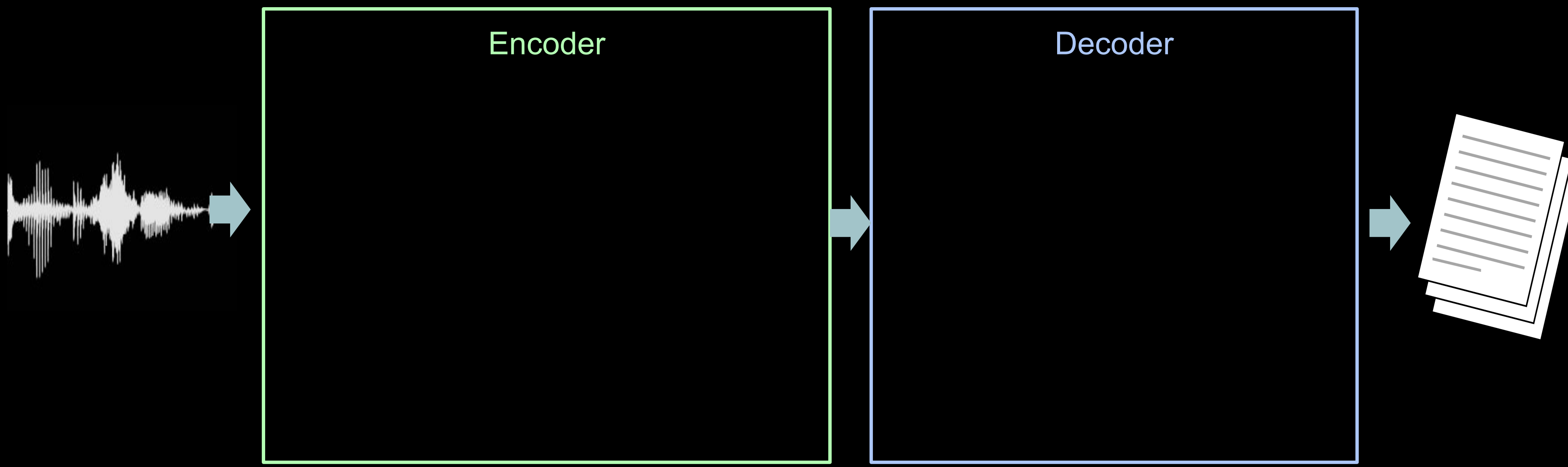
CSE538

# Topics

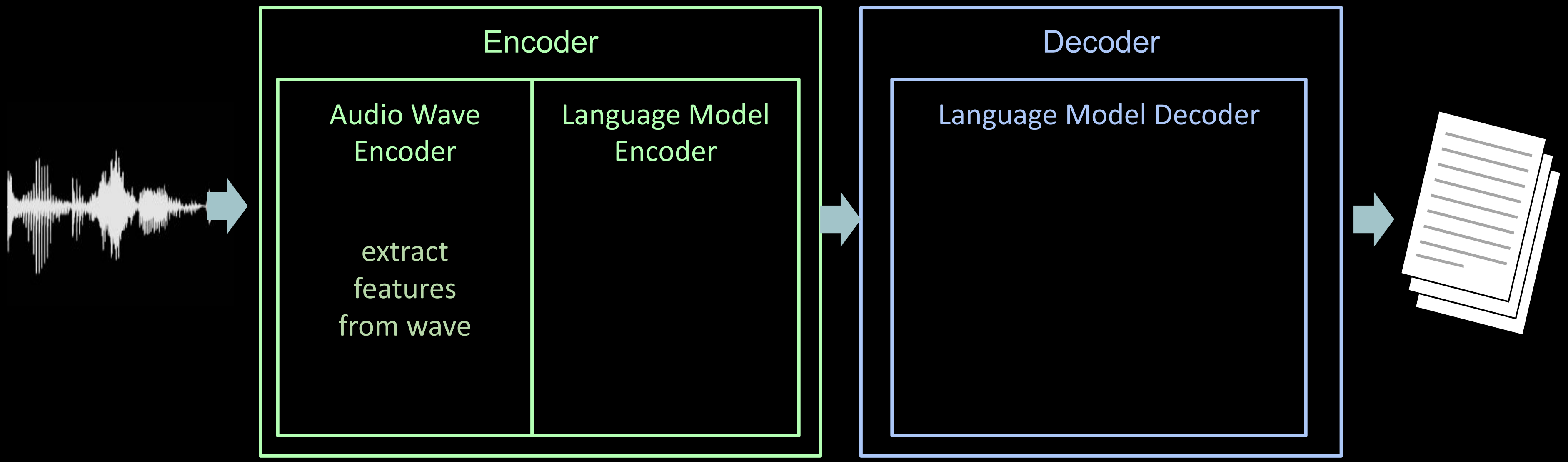
- Concept: Automatic Speech Recognition (ASR)
- Encoding Waves: Spectrograms
- Wave2Vec
- Whisper

# ASR: Automatic Speech Recognition

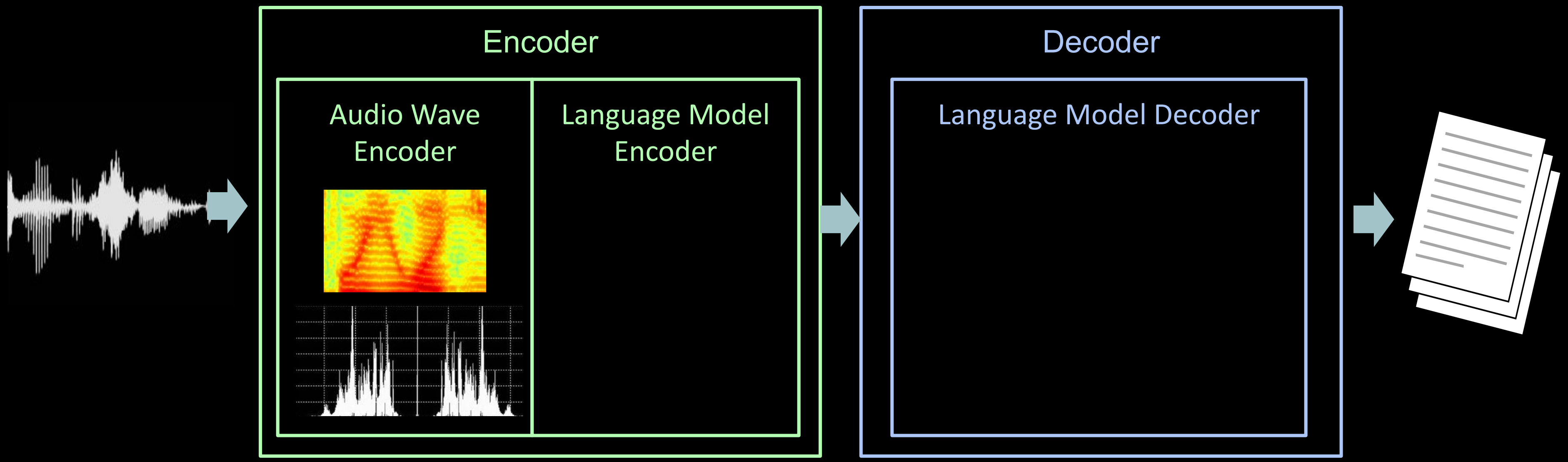
# ASR: Automatic Speech Recognition



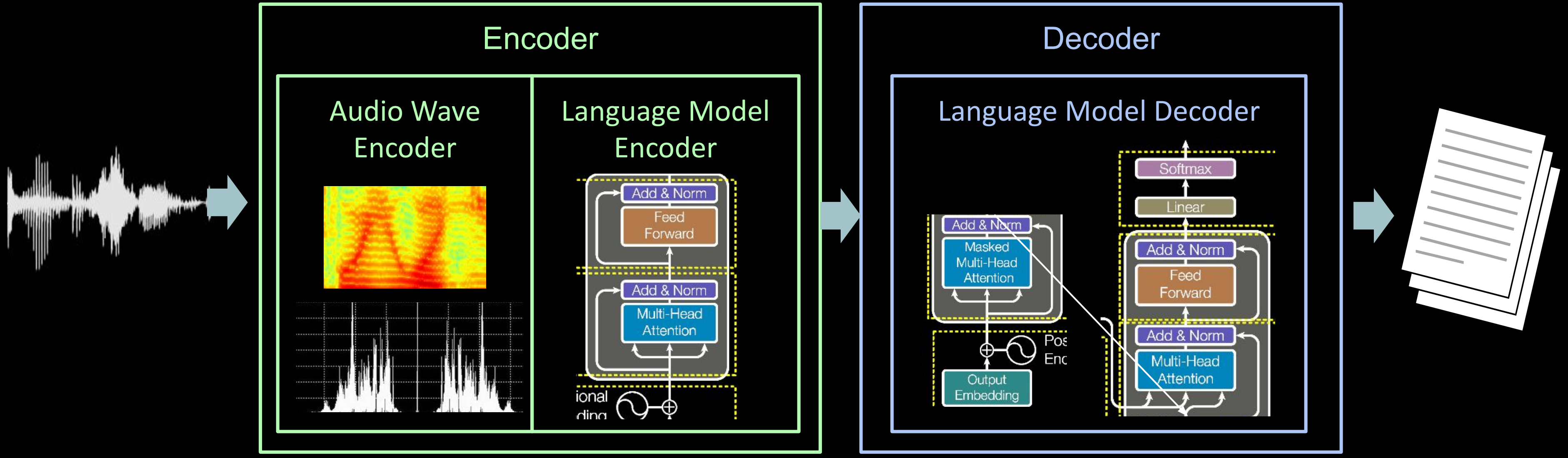
# ASR: Automatic Speech Recognition



# ASR: Automatic Speech Recognition



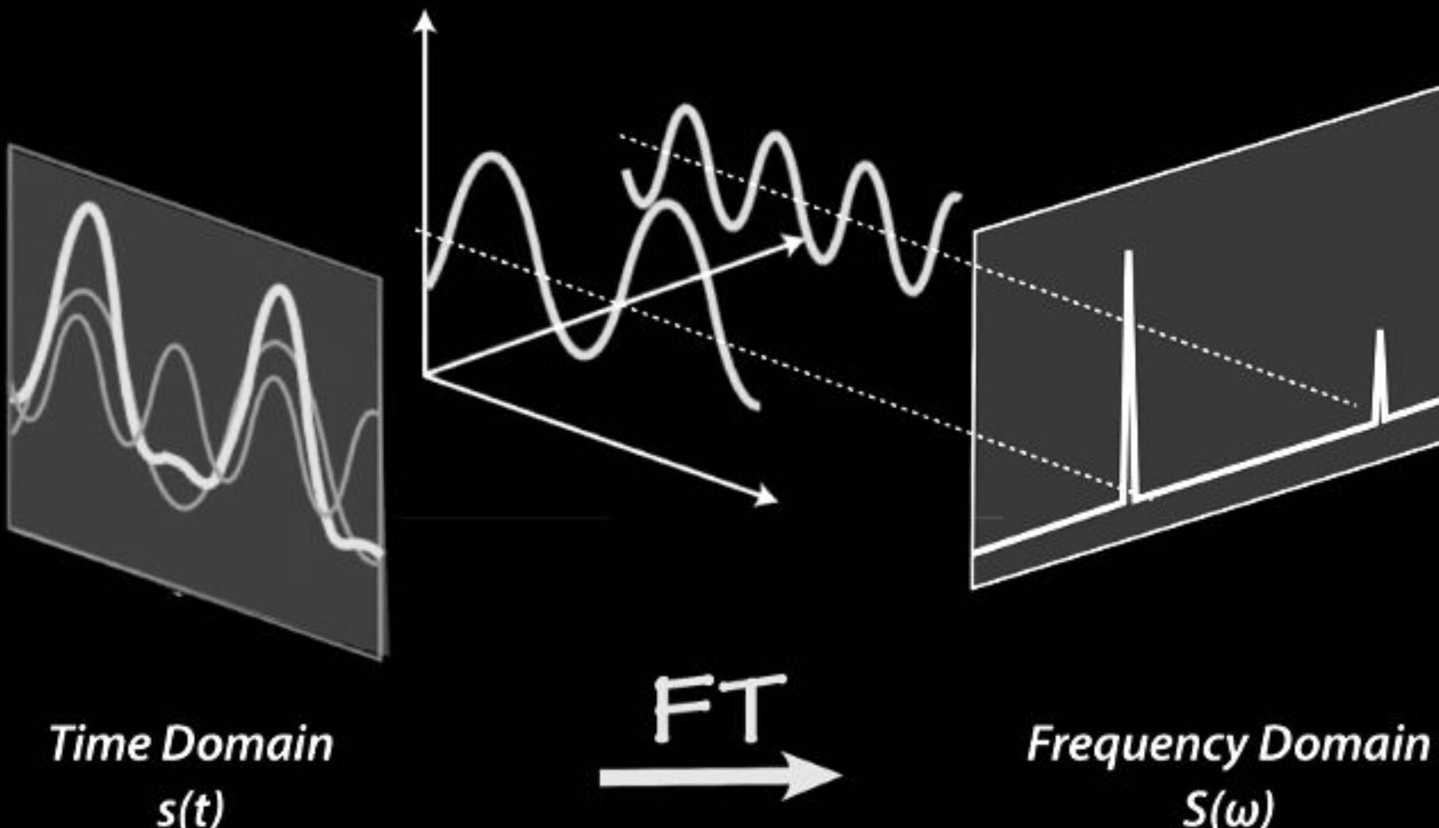
# ASR: Automatic Speech Recognition



# Topics

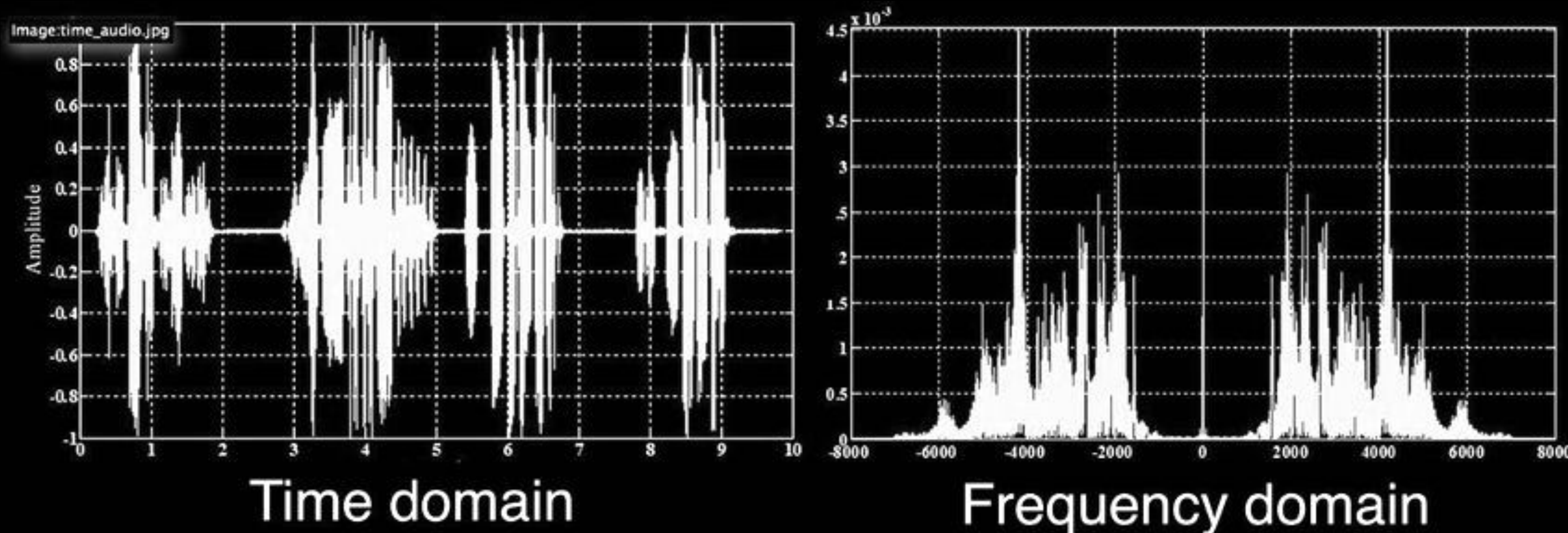
- Concept: Automatic Speech Recognition (ASR)
- **Encoding Waves: Spectrograms**
- Wave2Vec
- Whisper

# Encoding Waves: Fourier Transform



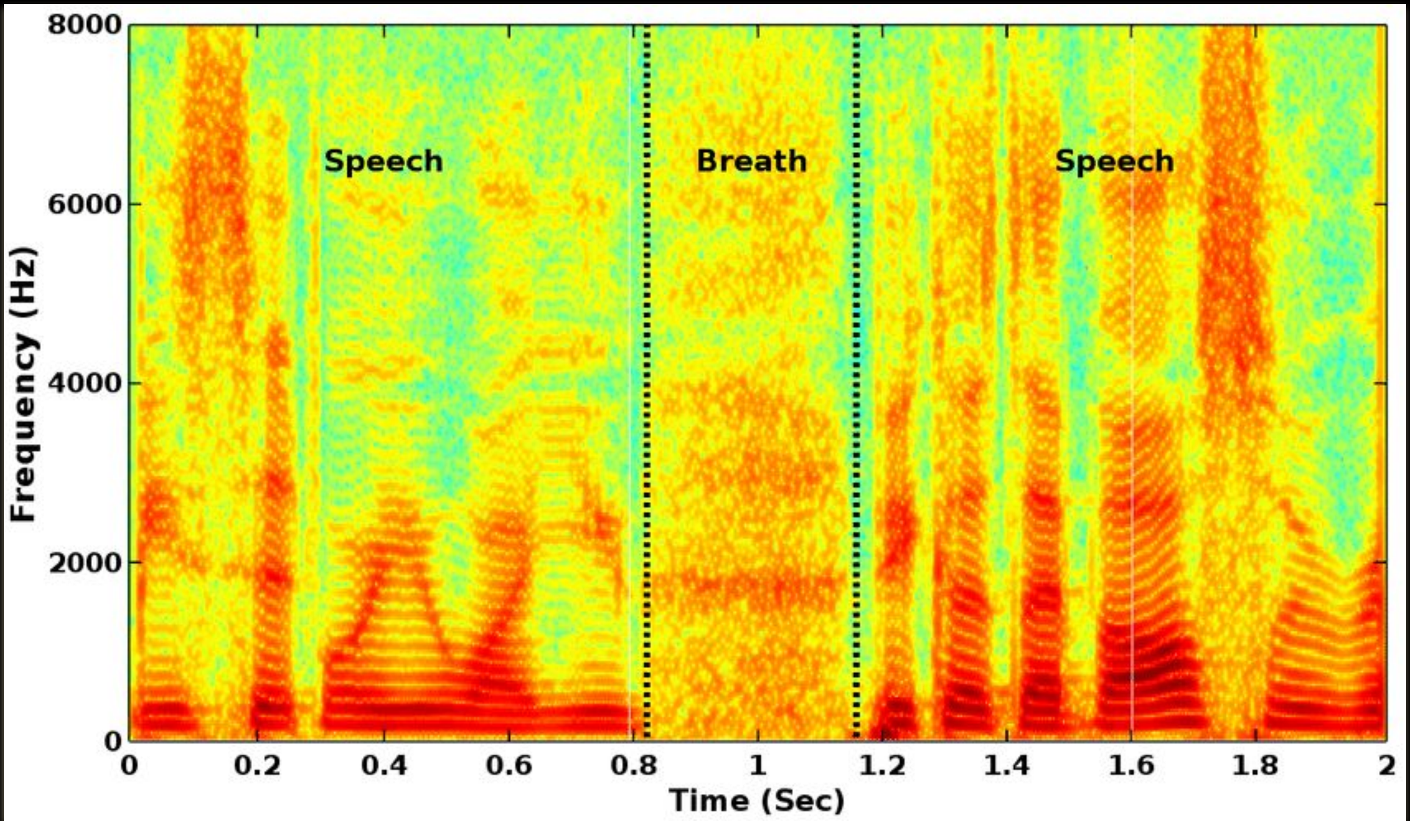

(Choudhary, 2020)

# Encoding Waves: Fourier Transform




(Abdulsalam, Ayad. (2017). Audio Classification Based on Content Features.)

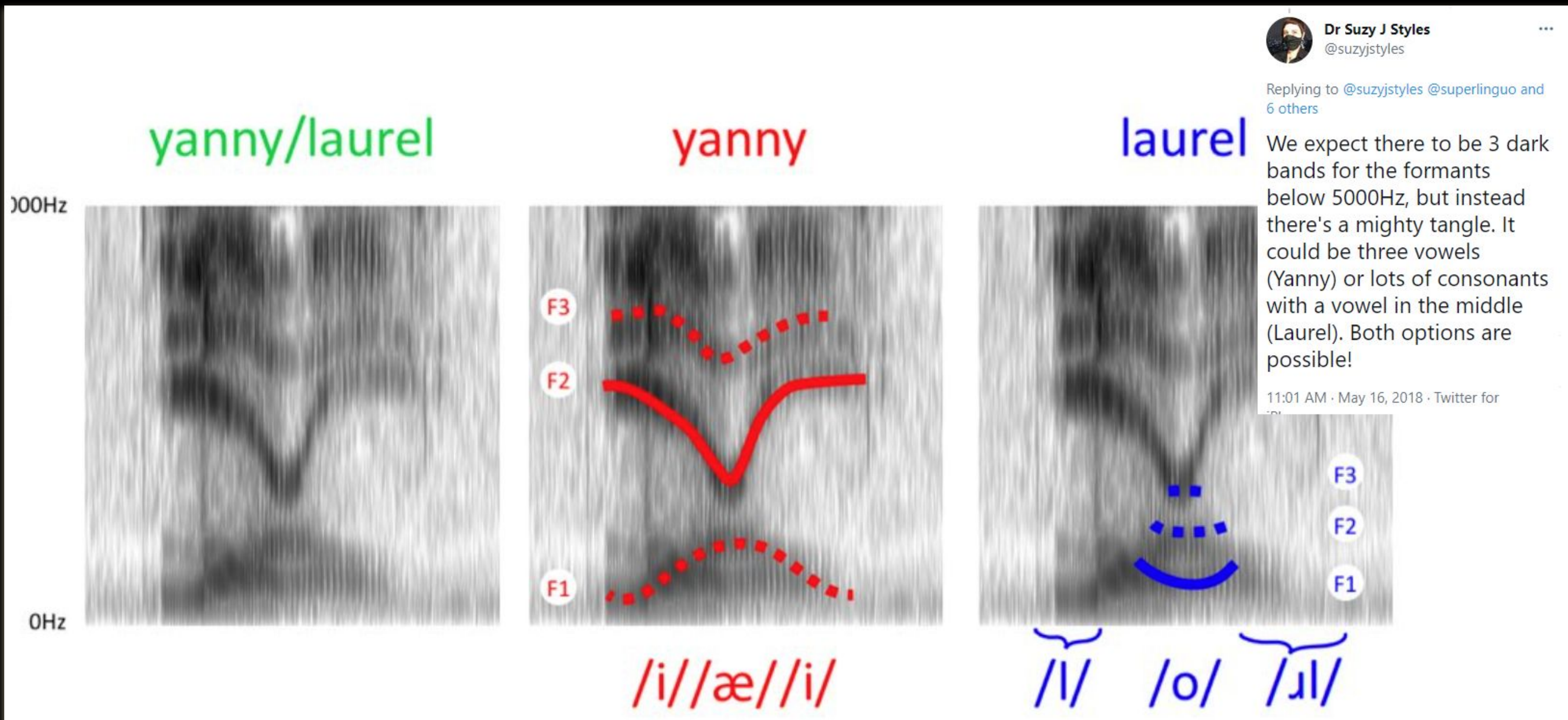
# Spectrogram




(Dumpalla & Alluri, ICSC 2017)

# Yanny Laurel

wiki/File:YannyLaurel.ogg



# Spectrogram in Practice: The Mel Spectrum

**Motivation:** Hearing perception is logarithmic to frequency:

Less ability to distinguish 1 hertz change at higher frequencies

In music: Low A (A0) is 27.5*hrtz* versus A1 is 55hrtz;    A4 is 440 hrtz versus  A5 is 880hrtz

$$mel(f) = 1127\ln(1 + \frac{f}{700}) \quad (16.7)$$

(SLP3-16)

# Spectrogram in Practice: The Mel Spectrum

**Motivation:** Hearing perception is logarithmic to frequency:

Less ability to distinguish 1 hertz change at higher frequencies

In music: Low A (A0) is 27.5*hrtz* versus A1 is 55hrtz;    A4 is 440 hrtz versus  A5 is 880hrtz

$$mel(f) = 1127\ln\left(1 + \frac{f}{700}\right) \qquad (16.7)$$

(SLP3-16)

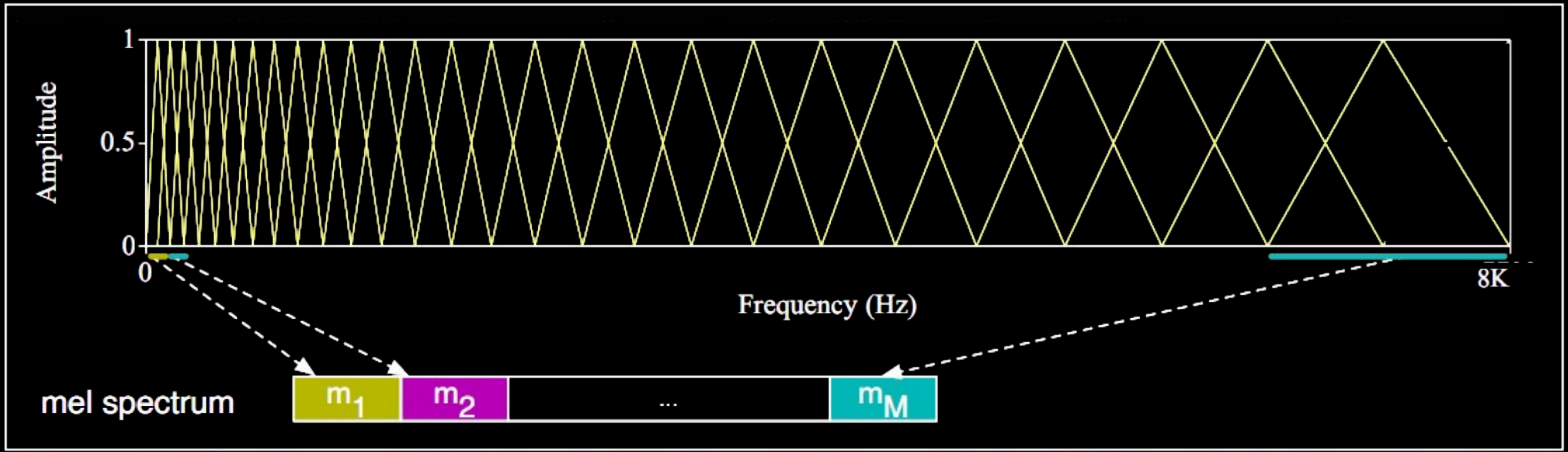



**Figure 16.7** The mel filter bank (Davis and Mermelstein, 1980). Each triangular filter, spaced logarithmically along the mel scale, collects energy from a given frequency range.

# Topics

- Concept: Automatic Speech Recognition (ASR)
- Encoding Waves: Spectrograms
- **Wave2Vec**
- Whisper

# Wave2Vec Objective

Autoregressive future sample prediction

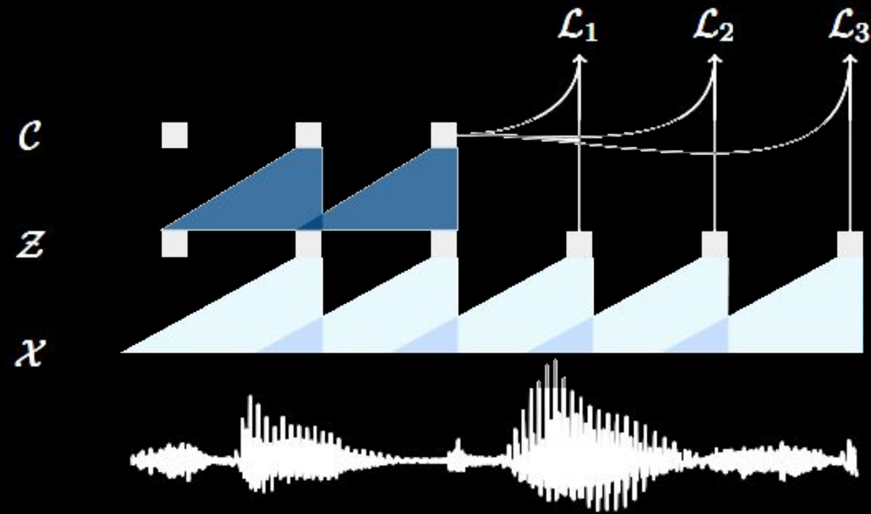



Figure 1: Illustration of pre-training from audio data $\mathcal{X}$ which is encoded with two convolutional neural networks that are stacked on top of each other. The model is optimized to solve a next time step prediction task.

(Steffen Schneider et al., 2019)

raw mel spectrogram

| | | | nov93dev | | nov92 | |
|---|---|---|---|---|---|---|
| | | | LER | WER | LER | WER |
| Deep Speech 2 (12K h labeled speech; Amodei et al., 2016) | | | - | 4.42 | - | 3.1 |
| Trainable frontend (Zeghidour et al., 2018a) | | | - | 6.8 | - | 3.5 |
| Lattice-free MMI (Hadian et al., 2018) | | | - | 5.66† | - | 2.8† |
| Supervised transfer-learning (Ghahremani et al., 2017) | | | - | 4.99† | - | 2.53† |
| 4-GRAM LM (Heafield et al., 2013) | | | | | | |
| Baseline | – | – | 3.32 | 8.57 | 2.19 | 5.64 |
| wav2vec | Librispeech | 80 h | 3.71 | 9.11 | 2.17 | 5.55 |
| wav2vec | Librispeech | 960 h | 2.85 | 7.40 | 1.76 | 4.57 |
| wav2vec | Libri + WSJ | 1,041 h | 2.91 | 7.59 | 1.67 | 4.61 |
| wav2vec large | Librispeech | 960 h | 2.73 | 6.96 | 1.57 | 4.32 |
| WORD CONVLM (Zeghidour et al., 2018b) | | | | | | |
| Baseline | – | – | 2.57 | 6.27 | 1.51 | 3.60 |
| wav2vec | Librispeech | 960 h | 2.22 | 5.39 | 1.25 | 2.87 |
| wav2vec large | Librispeech | 960 h | 2.13 | 5.16 | 1.02 | 2.53 |
| CHAR CONVLM (Likhomanenko et al., 2019) | | | | | | |
| Baseline | – | – | 2.77 | 6.67 | 1.53 | 3.46 |
| wav2vec | Librispeech | 960 h | 2.14 | 5.31 | 1.15 | 2.78 |
| wav2vec large | Librispeech | 960 h | 2.11 | 5.10 | 0.99 | 2.43 |

Table 1: Replacing log-mel filterbanks (Baseline) by pre-trained embeddings improves WSJ performance on test (nov92) and validation (nov93dev) in terms of both LER and WER. We evaluate pre-training on the acoustic data of part of clean and full Librispeech as well as the combination of all of them. † indicates results with phoneme-based models.

# Wave2vec 2

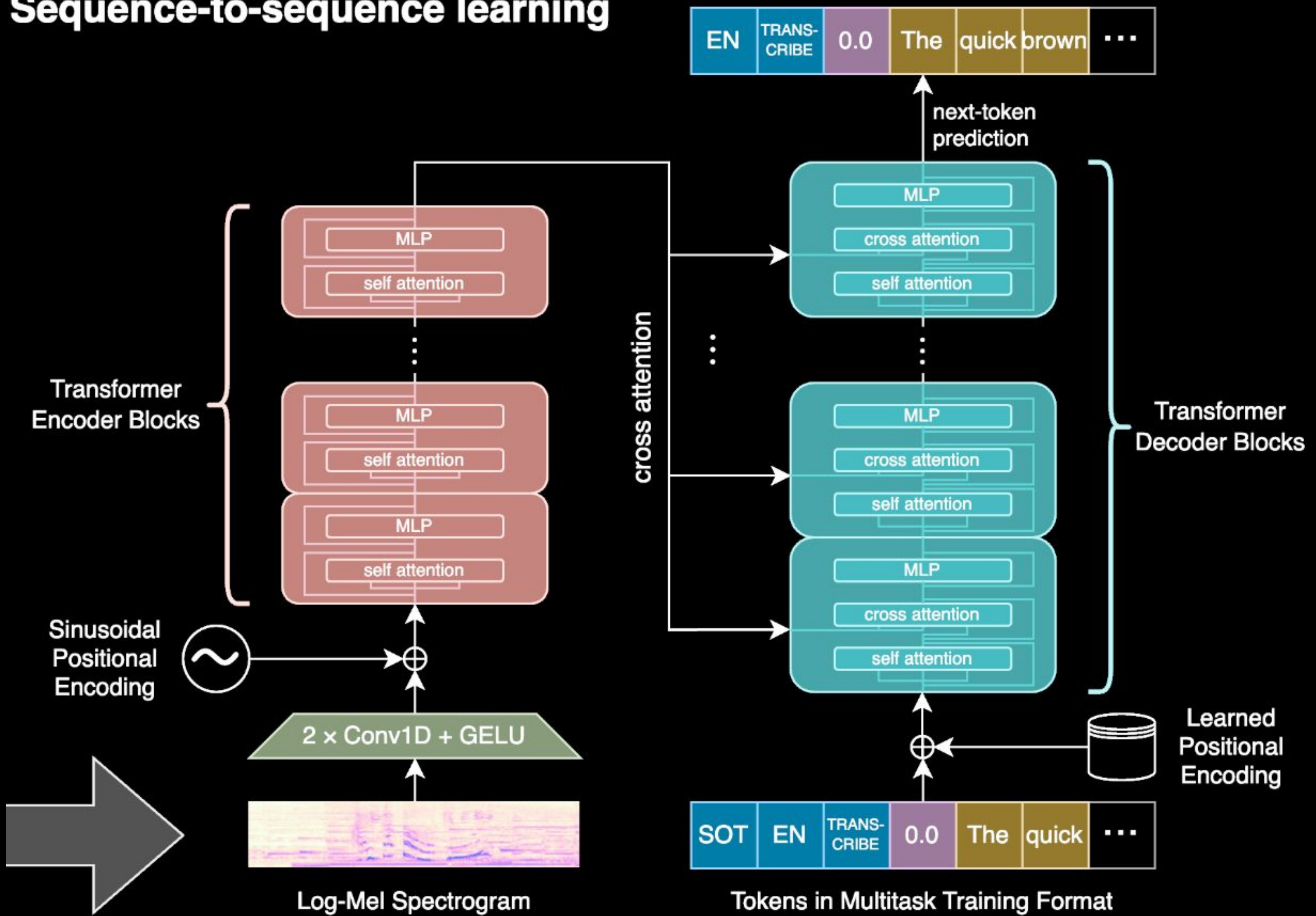
https://ai.meta.com/blog/wav2vec-20-learning-the-structure-of-speech-from-raw-audio/

# Topics

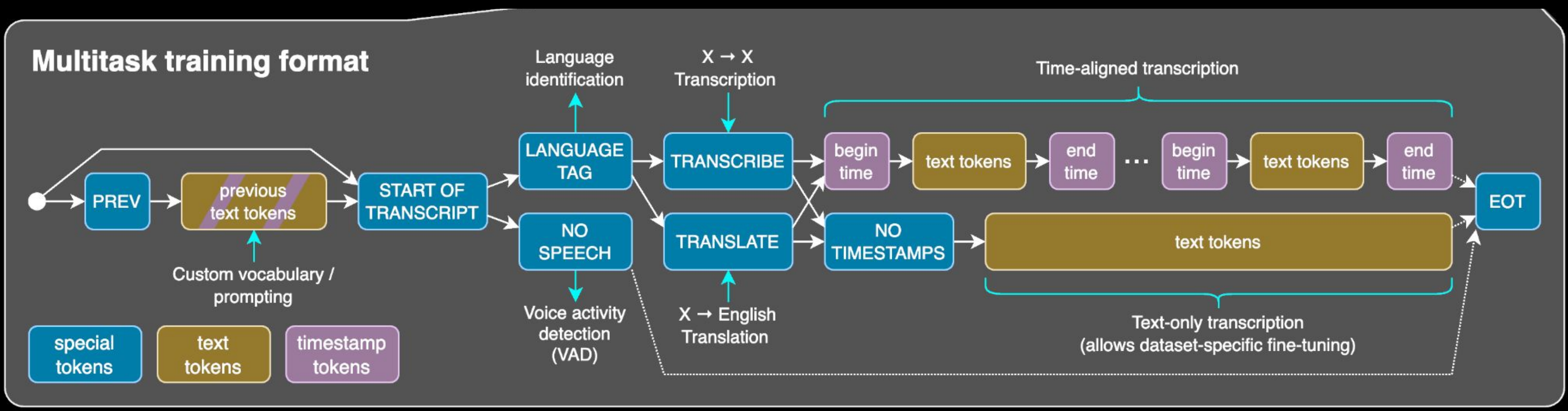
- Concept: Automatic Speech Recognition (ASR)
- Encoding Waves: Spectrograms
- Wave2Vec
- **Whisper**

# Whisper

## Sequence-to-sequence learning



# Whisper


Multitask training format
Language identification
X → X Transcription
Time-aligned transcription
PREV
previous text tokens
START OF TRANSCRIPT
LANGUAGE TAG
NO SPEECH
TRANSCRIBE
TRANSLATE
begin time
text tokens
end time
...
begin time
text tokens
end time
NO TIMESTAMPS
text tokens
EOT
Custom vocabulary / prompting
Voice activity detection (VAD)
X → English Translation
Text-only transcription (allows dataset-specific fine-tuning)
special tokens
text tokens
timestamp tokens

# Whisper

| Model | Layers | Width | Heads | Parameters |
|---|---|---|---|---|
| Tiny | 4 | 384 | 6 | 39M |
| Base | 6 | 512 | 8 | 74M |
| Small | 12 | 768 | 12 | 244M |
| Medium | 24 | 1024 | 16 | 769M |
| Large | 32 | 1280 | 20 | 1550M |

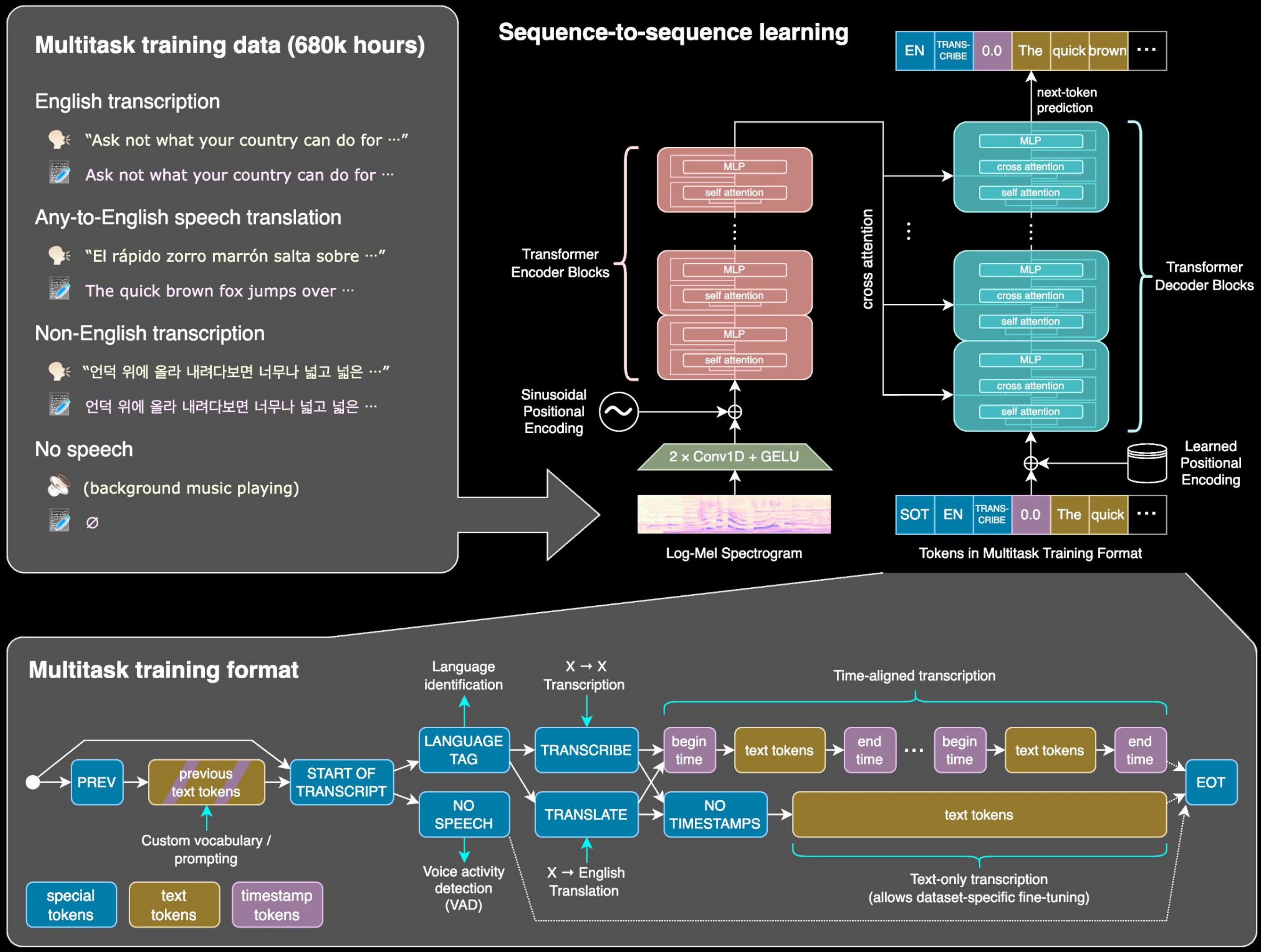
*Table 1.* Architecture details of the Whisper model family.

| Dataset | wav2vec 2.0 Large (no LM) | Whisper Large V2 | RER (%) |
|---|---|---|---|
| LibriSpeech Clean | **2.7** | **2.7** | 0.0 |
| Artie | 24.5 | **6.2** | 74.7 |
| Common Voice | 29.9 | **9.0** | 69.9 |
| Fleurs En | 14.6 | **4.4** | 69.9 |
| Tedlium | 10.5 | **4.0** | 61.9 |
| CHiME6 | 65.8 | **25.5** | 61.2 |
| VoxPopuli En | 17.9 | **7.3** | 59.2 |
| CORAAL | 35.6 | **16.2** | 54.5 |
| AMI IHM | 37.0 | **16.9** | 54.3 |
| Switchboard | 28.3 | **13.8** | 51.2 |
| CallHome | 34.8 | **17.6** | 49.4 |
| WSJ | 7.7 | **3.9** | 49.4 |
| AMI SDM1 | 67.6 | **36.4** | 46.2 |
| LibriSpeech Other | 6.2 | **5.2** | 16.1 |
| Average | 29.3 | **12.8** | 55.2 |

*Table 2.* **Detailed comparison of effective robustness across various datasets.** Although both models perform within 0.1% of each other on LibriSpeech, a zero-shot Whisper model performs much better on other datasets than expected for its LibriSpeech performance and makes 55.2% less errors on average. Results reported in word error rate (WER) for both models after applying our text normalizer.

# Current Challenges for ASR

- Live simultaneous transcription
- Single-channel multi-speaker transcription ("Cocktail room problem")
- Multilingual transcription



Multitask training data (680k hours)
English transcription
"Ask not what your country can do for ⋯"
Ask not what your country can do for ⋯
Any-to-English speech translation
"El rápido zorro marrón salta sobre ⋯"
The quick brown fox jumps over ⋯
Non-English transcription
"언덕 위에 올라 내려다보면 너무나 넓고 넓은 ⋯"
언덕 위에 올라 내려다보면 너무나 넓고 넓은 ⋯
No speech
(background music playing)
∅
Sequence-to-sequence learning
EN
TRANS-CRIBE
0.0
The
quick
brown
⋯
next-token prediction
MLP
cross attention
self attention
Transformer Encoder Blocks
Transformer Decoder Blocks
cross attention
Sinusoidal Positional Encoding
2 × Conv1D + GELU
Log-Mel Spectrogram
Learned Positional Encoding
SOT
EN
TRANS-CRIBE
0.0
The
quick
⋯
Tokens in Multitask Training Format
Multitask training format
Language identification
X → X Transcription
Time-aligned transcription
PREV
previous text tokens
START OF TRANSCRIPT
LANGUAGE TAG
NO SPEECH
TRANSCRIBE
TRANSLATE
begin time
text tokens
end time
⋯
begin time
text tokens
end time
NO TIMESTAMPS
text tokens
EOT
Custom vocabulary / prompting
Voice activity detection (VAD)
X → English Translation
Text-only transcription (allows dataset-specific fine-tuning)
special tokens
text tokens
timestamp tokens