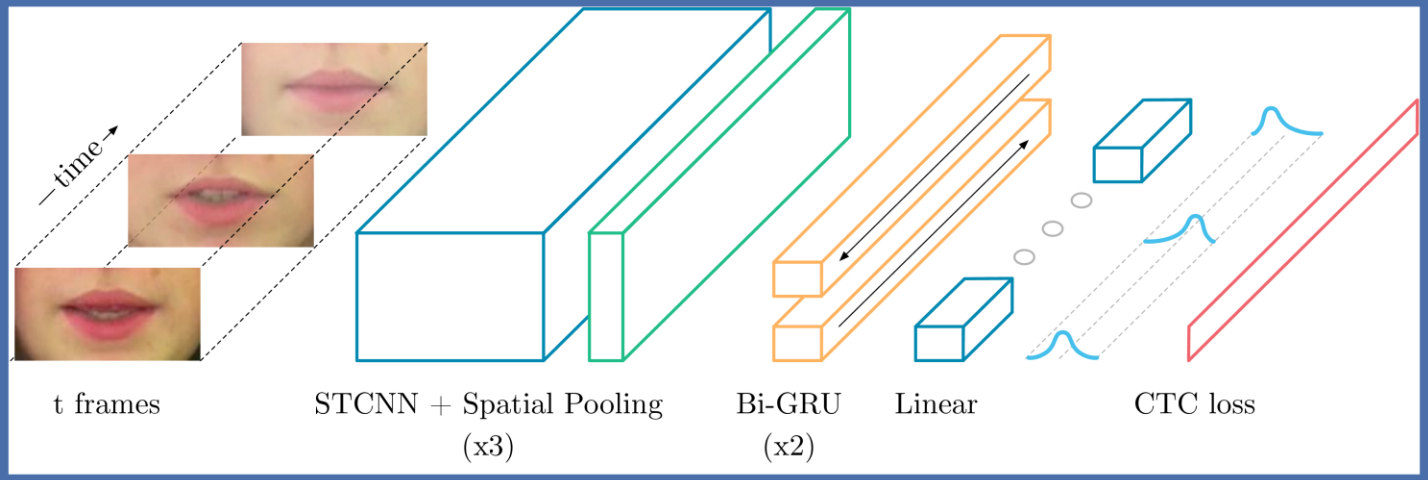
End-to-end everything?

- End-to-end lip-reading
- End-to-end speech synthesis
- End-to-end speech separation

End-to-end lip-reading

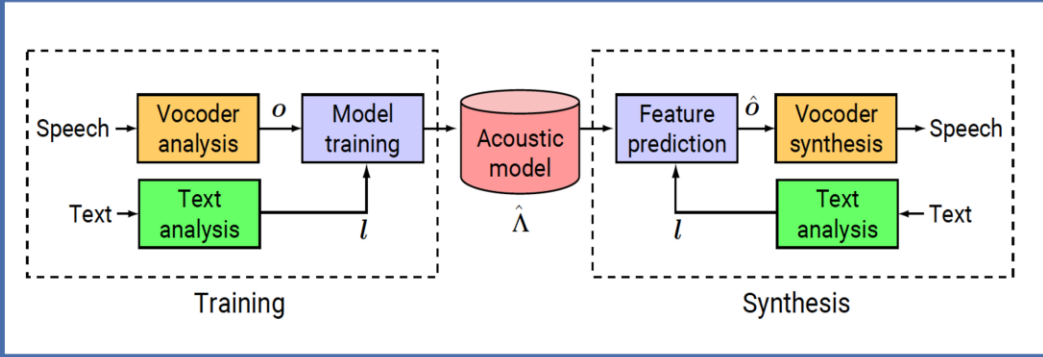
- An end-to-end speech recognition system takes frames of audio features as inputs and outputs a transcription
- Idea: Replace audio frames by photographs of the mouth and train with CTC
- 11.4% WER!



« **LipNet: End-To-End Sentence-Level Lipreading** », Assael et al., 2020

Speech synthesis

- Given a text sequence and information about a speaker, generate speech
- Traditionally not end-to-end (at all)
- Parametric synthesis: control a vocoder (synthesizer) with parameters (pitch, MFCCs, etc.)



- Concatenative speech synthesis: concatenate chunks of audio from a database

End-to-end speech synthesis

- From a sequence of characters, we want to generate a sequence of waveform values

Wavenet: Speech synthesis as language modelling

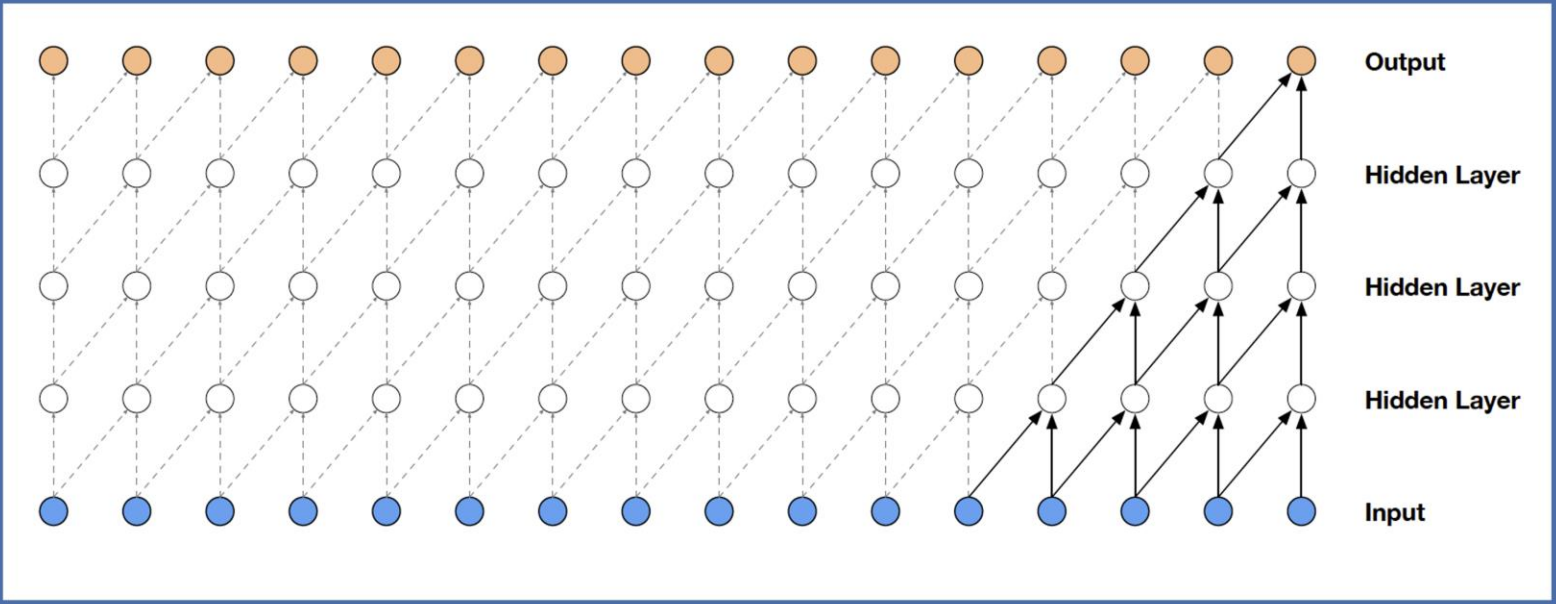
- Idea: autoregressive synthesis of waveform values from previous values

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1})$$

- Similar to a language model (predicts next word based on previous ones)
- Problem: a waveform is continuous (infinite number of possible values, one cannot compute the probability of x_t)
- In practice: waveforms are digital and typically on 16 bits = 65536 values
- Can we train a model to predict one of 65536 classes?
- Yes but too big! We can quantize these 65536 to 256 values with limited loss of quality

« **WaveNet: A Generative Model for Raw Audio** », van den Oord et al., 2016

Causal convolutions



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Dilated causal convolutions

- At 16kHz, using 1s of previous context requires a receptive field of 16000!
- Double the size of dilation at each layer (up to 512 then restart) to have a spread that grows exponentially with the number of layers
- Allows using large spreads efficiently (between 240 and 300 ms in experiments)

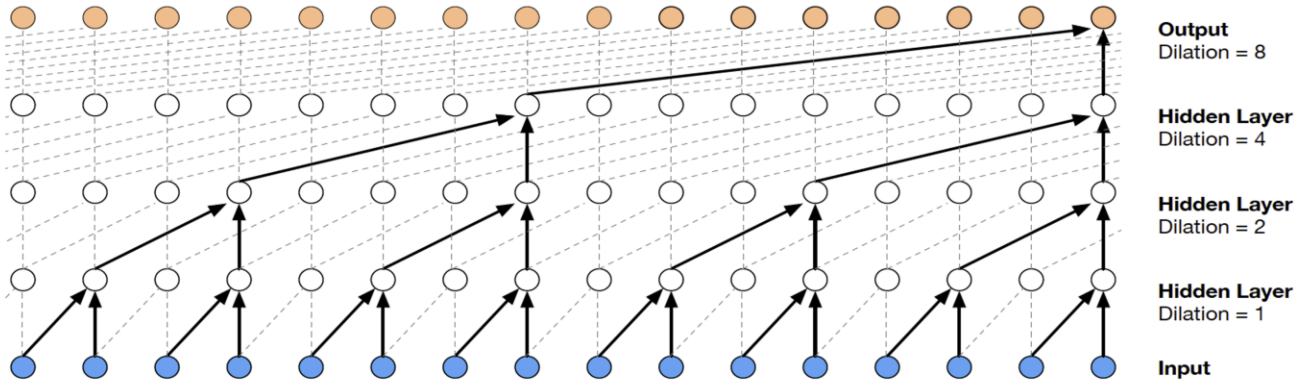

Figure 3: Visualization of a stack of *dilated* causal convolutional layers.

Generating babbling

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1})$$

- If you train this model on a dataset of speech it just learns the distribution of speech and generates « babbling »: sounds like speech but is not real speech

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Generating actual speech

- Condition the model on linguistic features upsampled (with a CNN) to have the same resolution as the waveform
- Phonetic, syllable, word, phrase, and utterance-level features (e.g. number of syllables in a word, phoneme duration, etc.)

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Generating speech from a particular speaker

- We can also condition on other variables, including speaker identity, here represented as a one-hot encoding
- 44 hours of data for 109 speakers => ~24 minutes per speaker
- Cannot generalize to other speakers

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Evaluating speech synthesis: Mean Opinion Score

- Unlike WER there is good enough computational metric for synthesis
- Needs to rely on human evaluations
- Mean Opinion Score (MOS): How natural does it sound to you (1 to 5)?

	Subjective 5-scale MOS in naturalness	
Speech samples	North American English	Mandarin Chinese
LSTM-RNN parametric	3.67 ± 0.098	3.79 ± 0.084
HMM-driven concatenative	3.86 ± 0.137	3.47 ± 0.108
WaveNet (L+F)	$\mathbf{4.21} \pm 0.081$	$\mathbf{4.08} \pm 0.085$
Natural (8-bit μ-law)	4.46 ± 0.067	4.25 ± 0.082
Natural (16-bit linear PCM)	4.55 ± 0.075	4.21 ± 0.071

Evaluating speech synthesis: Subjective comparison

- Among these two samples, which one do you prefer?

	Subjective preference (%) in naturalness					
Language	**LSTM**	**Concat**	**WaveNet** (L)	**WaveNet** (L+F)	No preference	p value
North	23.3	**63.6**			13.1	$\ll 10^{-9}$
American	18.7		**69.3**		12.0	$\ll 10^{-9}$
English	7.6			**82.0**	10.4	$\ll 10^{-9}$
		32.4	**41.2**		26.4	0.003
		20.1		**49.3**	30.6	$\ll 10^{-9}$
			17.8	**37.9**	44.3	$\ll 10^{-9}$
Mandarin	**50.6**	15.6			33.8	$\ll 10^{-9}$
Chinese	25.0		23.3		51.8	0.476
	12.5			**29.3**	58.2	$\ll 10^{-9}$
		17.6	**43.1**		39.3	$\ll 10^{-9}$
		7.6		**55.9**	36.5	$\ll 10^{-9}$
			10.0	**25.5**	64.5	$\ll 10^{-9}$

Limitations of WaveNet : linguistic features

- It's end-to-end in a sense, but still needs linguistic features computed separately
- Tacotron generates speech directly from characters

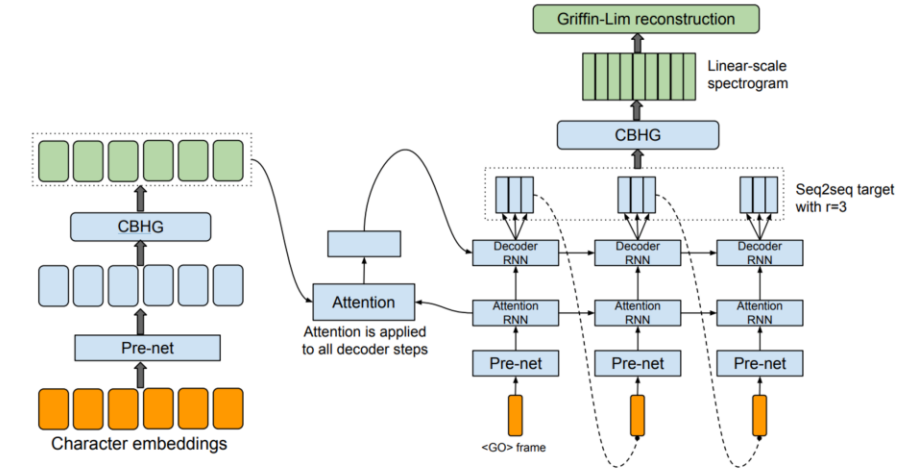


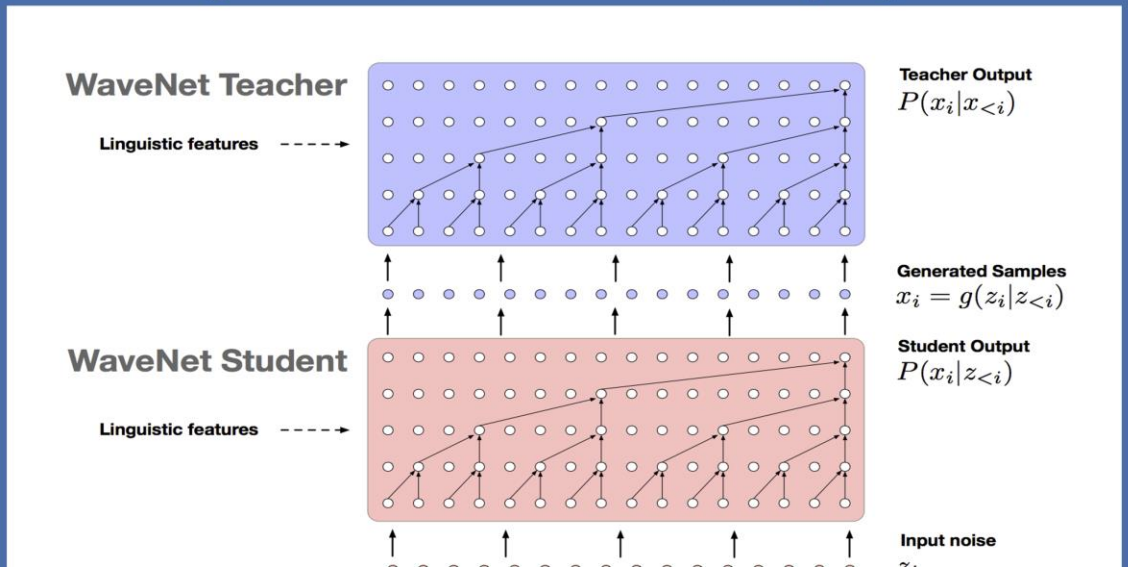
Figure 1: *Model architecture. The model takes characters as input and outputs the corresponding raw spectrogram, which is then fed to the Griffin-Lim reconstruction algorithm to synthesize speech.*

Limitations of WaveNet : autoregressive synthesis

- Autoregressive synthesis is not parallelizable: generating x_t requires having generated previous steps
- Extremely slow (can take minutes to generate 1s of speech)

Parallel WaveNet

- Student trained to minimize the KL-divergence between its distribution and the teacher's
- The Student is not autoregressive!
- As good as the autoregressive, 1000x faster, deployed in Google Assistant



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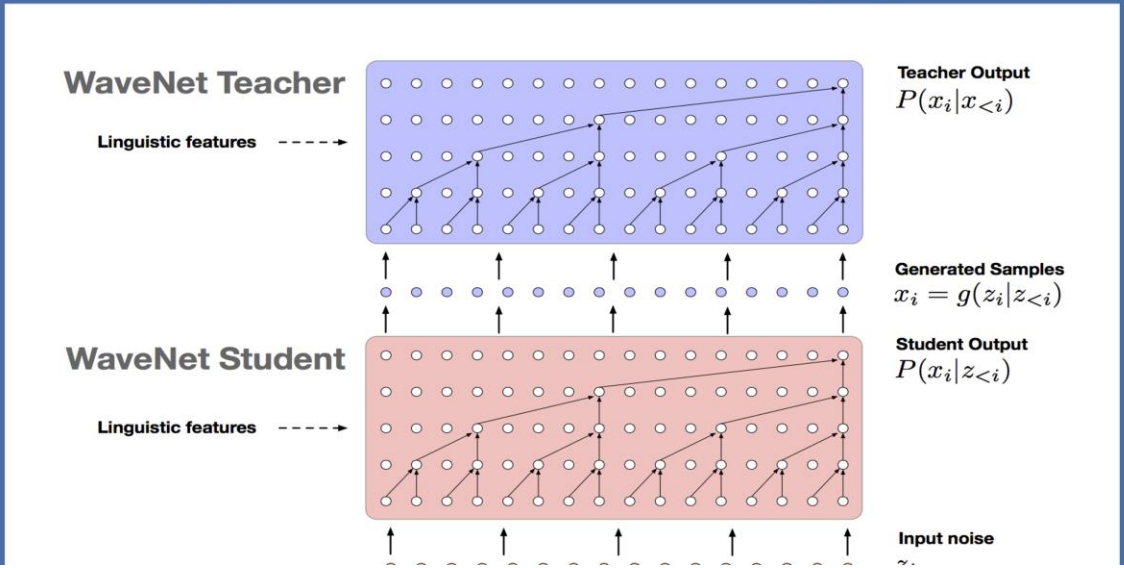


Voice technology « in the wild »

IDEAL SETTING

COMMON SETTING

- Voice technology (voice search, voice identification, youtube subtitling) works well in an ideal setting: one person speaking, no noise.
- Unfortunately, these conditions are often idealistic.

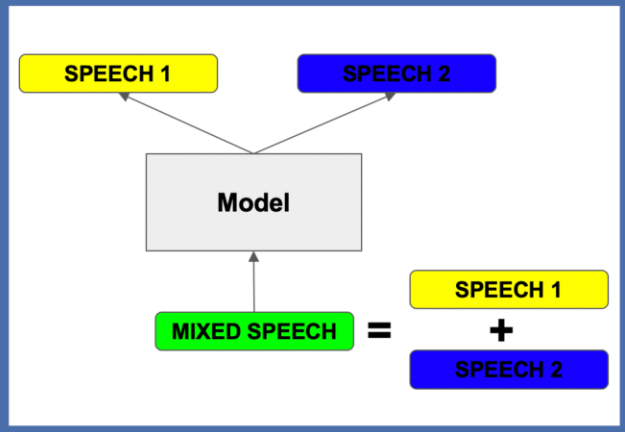
Speech separation

- Speech separation task:
- **inputs**: a single recording with several people speaking at the same time
- **outputs**: the voice of each speaker

Speech separation and the permutation problem

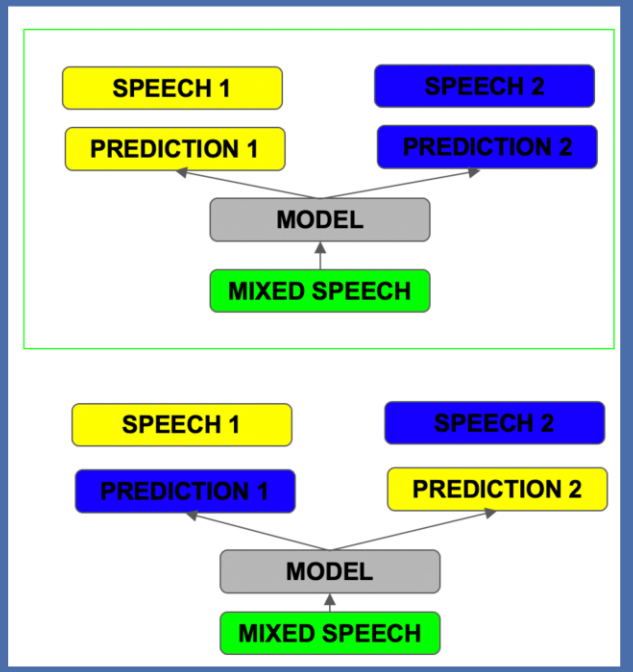
- **Task: given a mix of K unknown voices, extract the speech of each person**

- **Main challenge: Speaker permutation**
  - During training, the target speaker assigned to each channel is necessarily arbitrary (no obvious split e.g. female/male, british/us)
  - Result: channels are inconsistent
  - Main solution: **permutation invariant training**



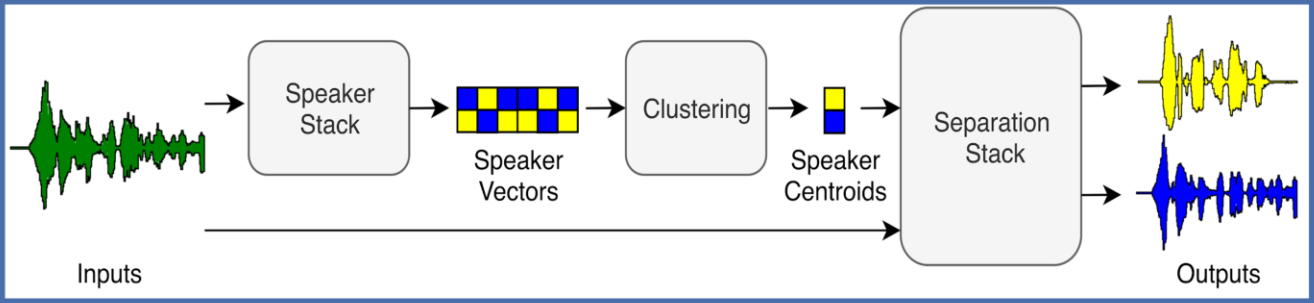
Permutation invariant training

- **Compute loss (MSE, NLL, etc.) over all permutations and backprop the minimum**
- **Problems:**
  - To learn to be consistent along a sentence, need to compute P-I loss along long windows (~4s) for one gradient step
  - Need to compute k! losses (k=nb speakers)
- **Solution?:**
  - Listen to the mixture and identify who is speaking
  - Then separate the speech of each speaker



Wavesplit: end-to-end speech separation by speaker clustering

- The speaker stack listens to mixed speech and extract N vectors per time step, each represents one speaker
- A clustering algorithm groups these vectors to have N vectors for the entire sequence
- The separation stack uses each vector to extract the speech of the corresponding speaker



« **Wavesplit: End-to-End Speech Separation by Speaker Clustering**», Zeghidour and Grangier, 2020

Dynamic mixing: generating new example mixtures on the fly

- To train a speech separation system, clean speech of N speakers are summed to create an artificial mixture (in standard datasets)
- Instead of relying on a fixed number of artificial mixtures, we generate an infinity from clean speech, by resampling randomly which sequence we mix and the volume of each speaker
- We can also randomly add background noise and reverberation to increase diversity of examples

« **Wavesplit: End-to-End Speech Separation by Speaker Clustering**», Zeghidour and Grangier, 2020

Results

- The main metric is Signal-to-Distortion Ratio, which measures the separation quality (the higher the better), in a logarithmic scale

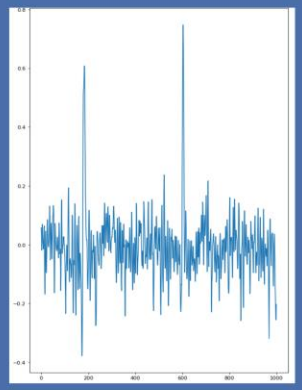
MODEL	SDR (2 speakers)	SDR (3 speakers)	SDR (2 speakers w/ noise)
Previous state-of-the-art	20.3	16.9	12.4
Wavesplit	21.2	17.3	15.4
Wavesplit w/ Dynamic mixing	**22.3**	**17.8**	**16.0**

« **Wavesplit: End-to-End Speech Separation by Speaker Clustering**», Zeghidour and Grangier, 2020

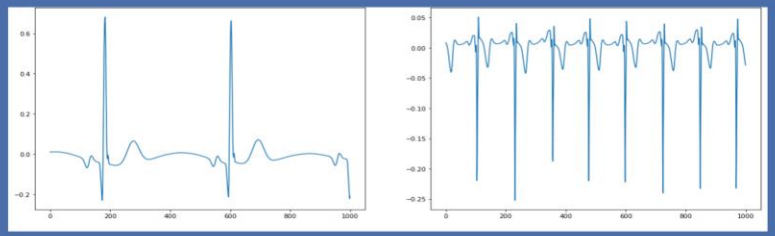
Beyond speech: separating fœtal and maternal heart rate from electrocardiograms

- Monitoring foetal health from its heart rate is common at various stages of pregnancy
- Hard task: the sensor gets the mother heart beats, the foetus', and noise
- **Wavesplit can separate both from a single sensor**

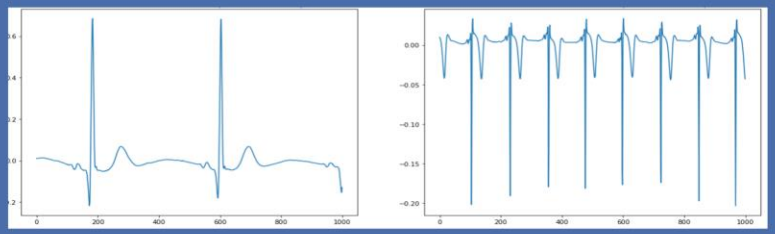
ABDOMINAL SENSOR



MOTHER **FOETUS**



REAL



SEPARATED WITH WAVESPLIT