



# Introduction to Speech Technology

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(Some slides are adapted from  
<http://speech.ee.ntu.edu.tw/~tlkagk/courses/DLHLP20> and  
<http://tts.speech.cs.cmu.edu/courses/11492/>)



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# Outline



Introduction



Research Topics

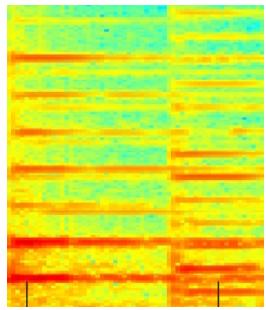


Future horizons

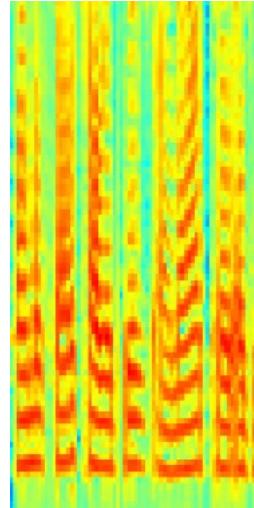
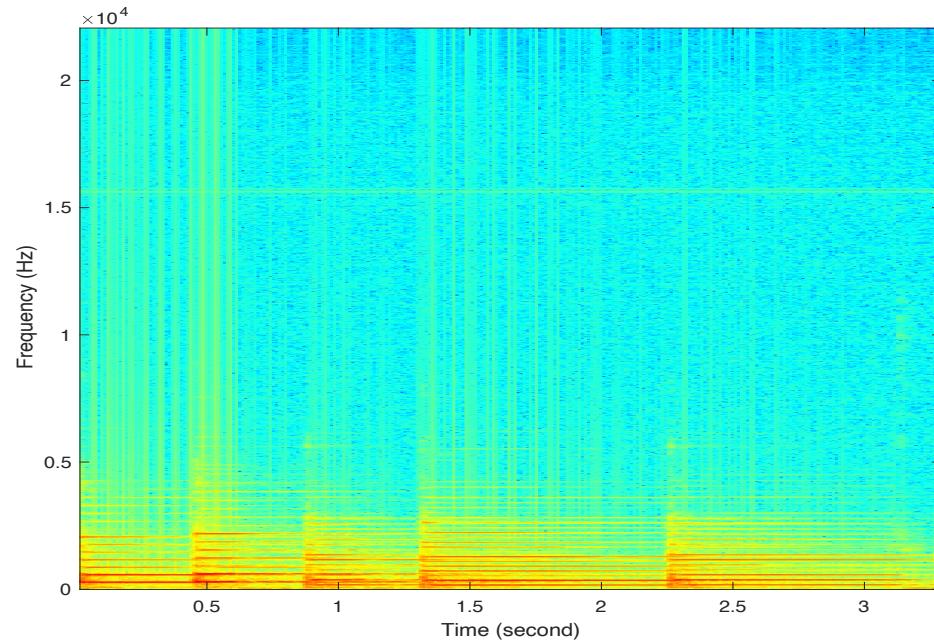


Q & A

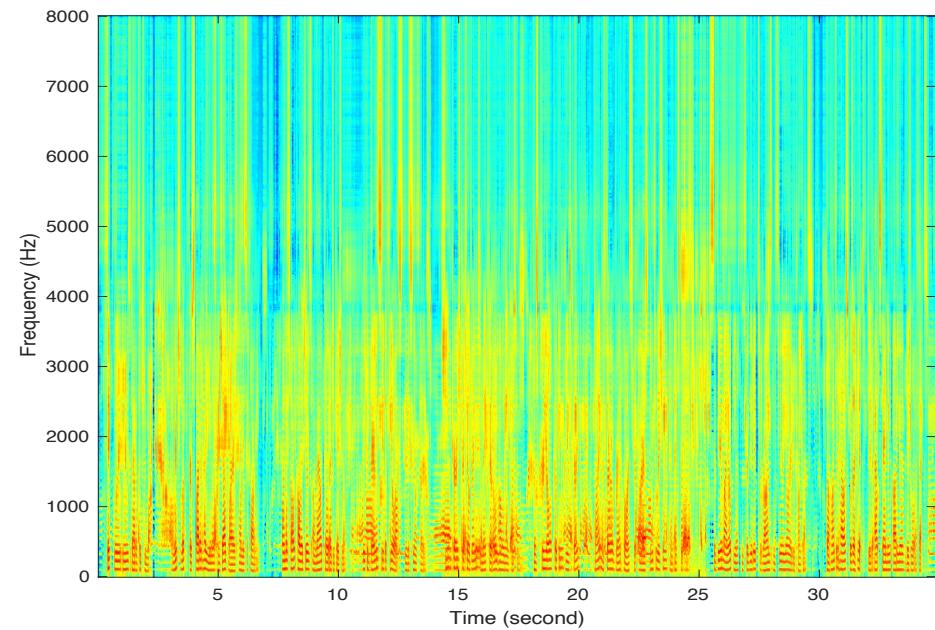
# Audio Signals



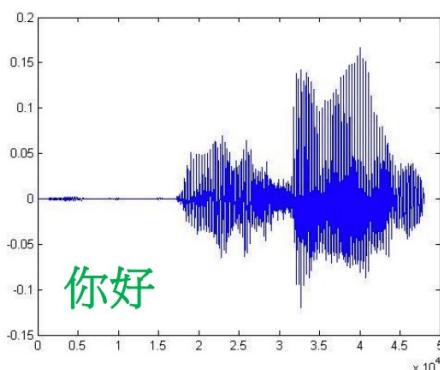
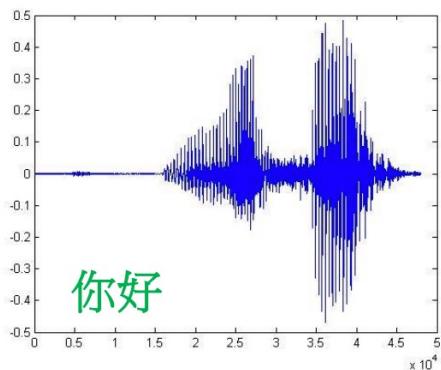
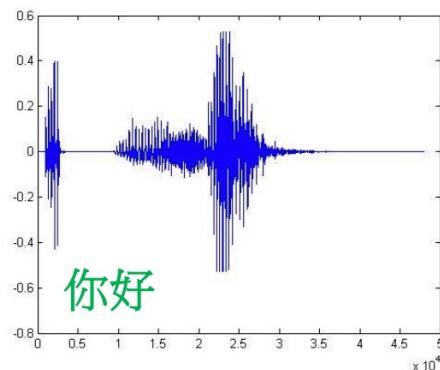
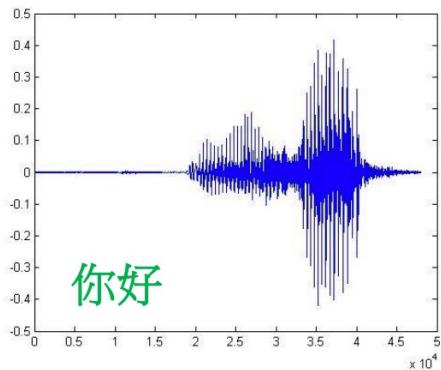
Music



Speech



# Why speech?



- Most natural way for human communication
- Hard to represent (You cannot speak the same twice)
- Hard to search

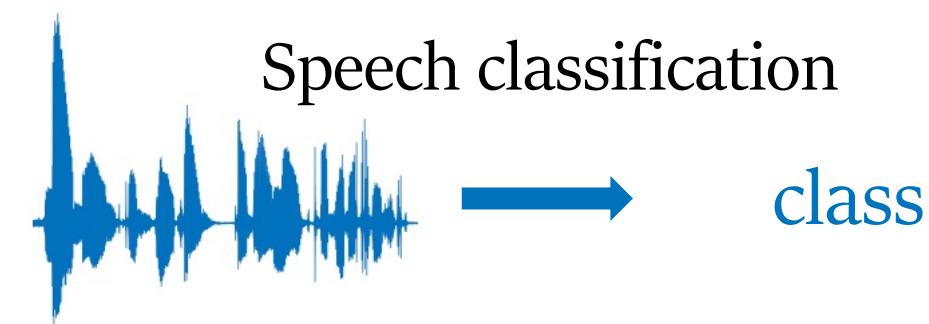
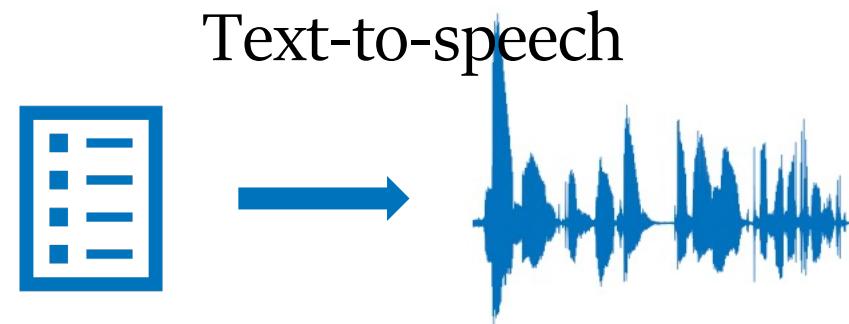
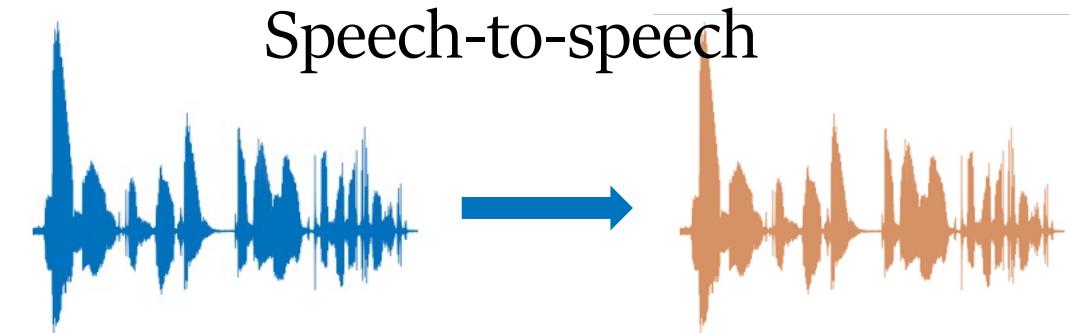
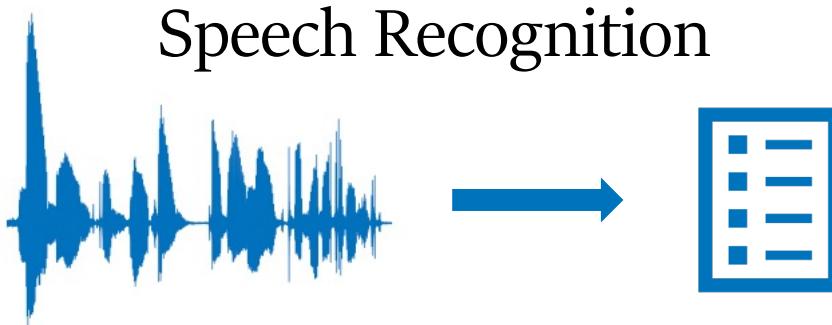


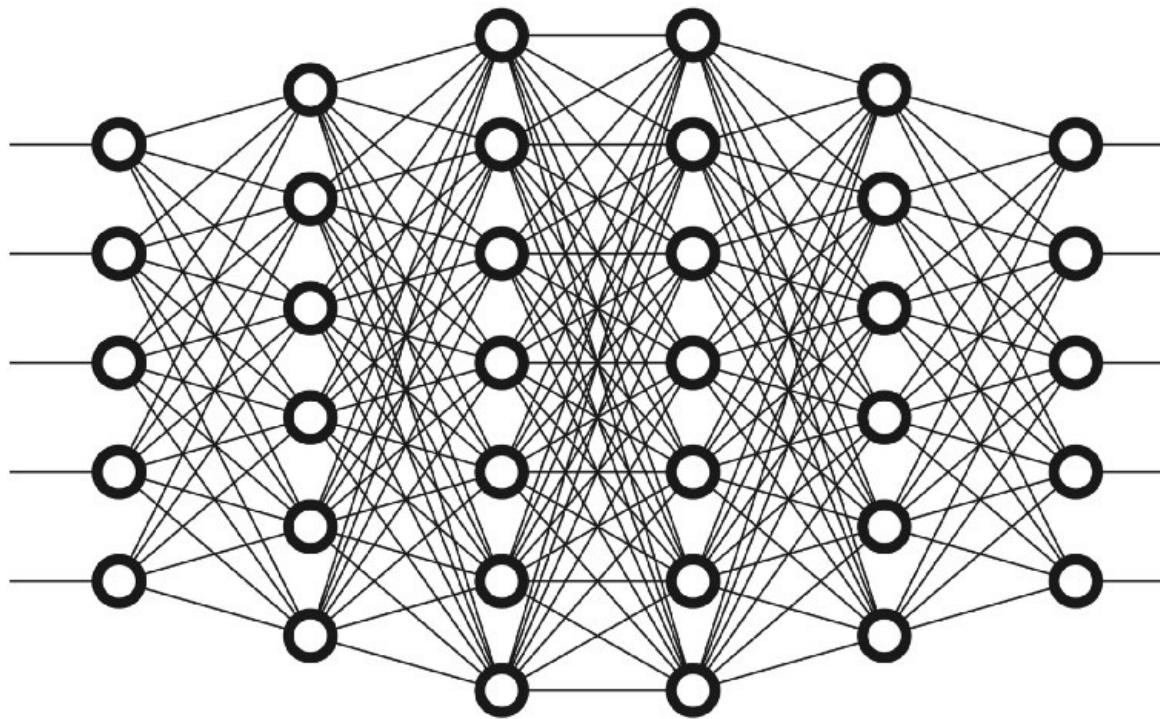
# Speech Applications

- Google Maps
- Apple's Siri, Google Home, Amazon Echo/Alexa
- Screen readers
- Voice biometrics
- ...



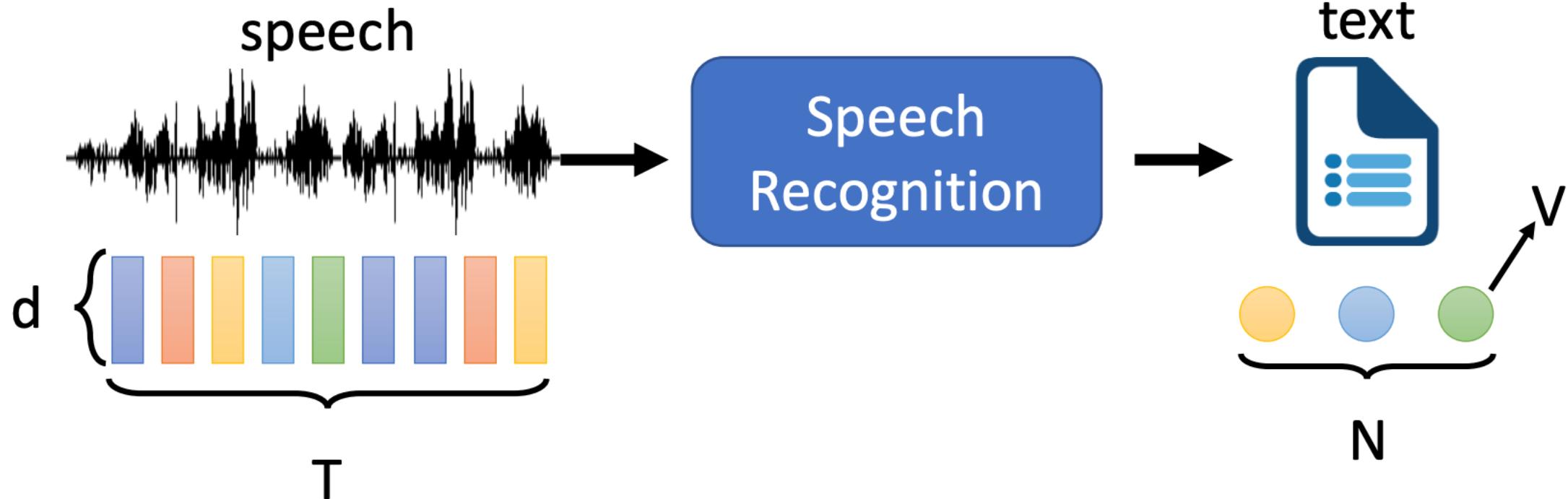
# Overview of speech topics





- Besides training Deep Neural Networks, what does each topic care about?

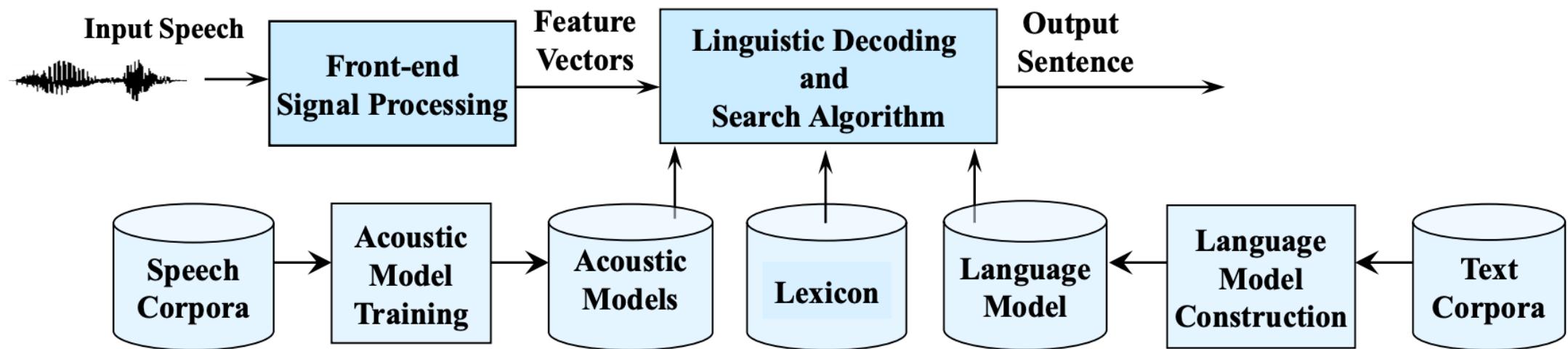
# Speech recognition



- Speech: a sequence of vector (length  $T$ , dimension  $d$ )
- Text: a sequence of token (length  $N$ ,  $V$  different tokens)

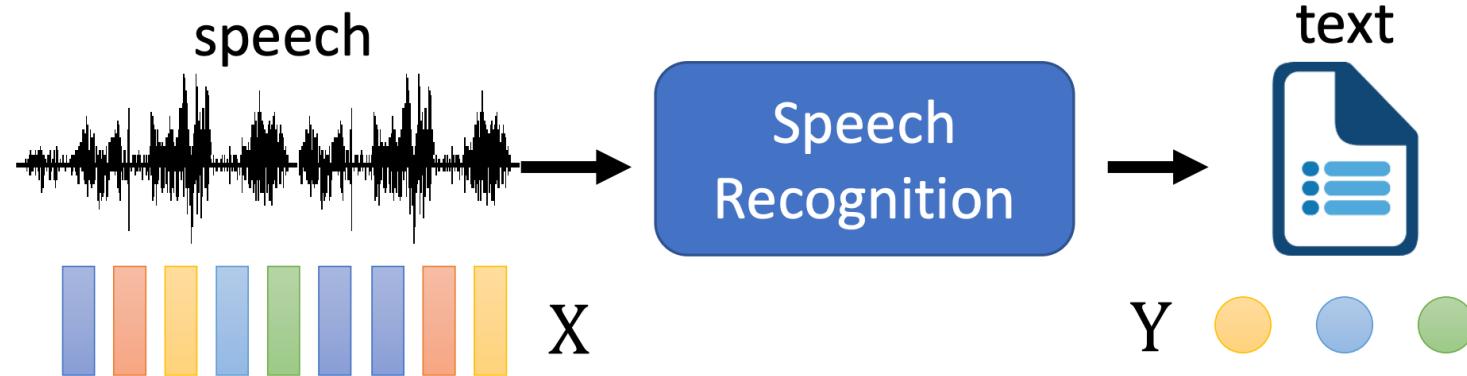
# Speech recognition

## Traditional Speech Recognition



# Speech recognition

- HMM



$$Y^* = \arg \max_Y P(Y|X)$$

*Decode*

$$= \arg \max_Y \frac{P(X|Y)P(Y)}{P(X)}$$

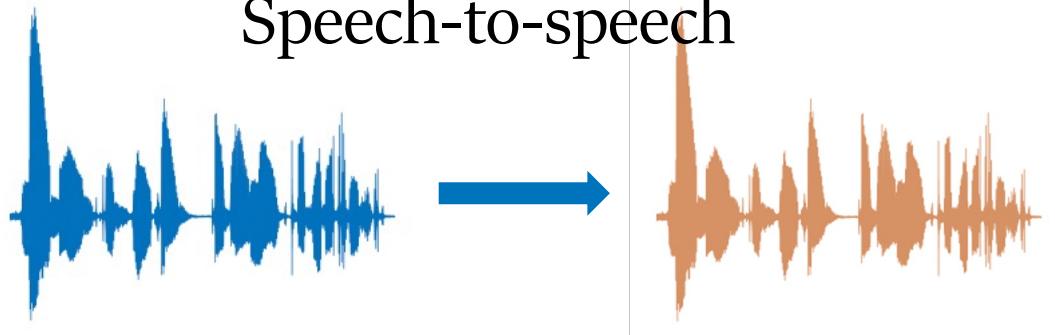
$$= \arg \max_Y P(X|Y)P(Y)$$

$P(X|Y)$ : HMM

Acoustic Model

$P(Y)$ :  
Language Model

Speech-to-speech

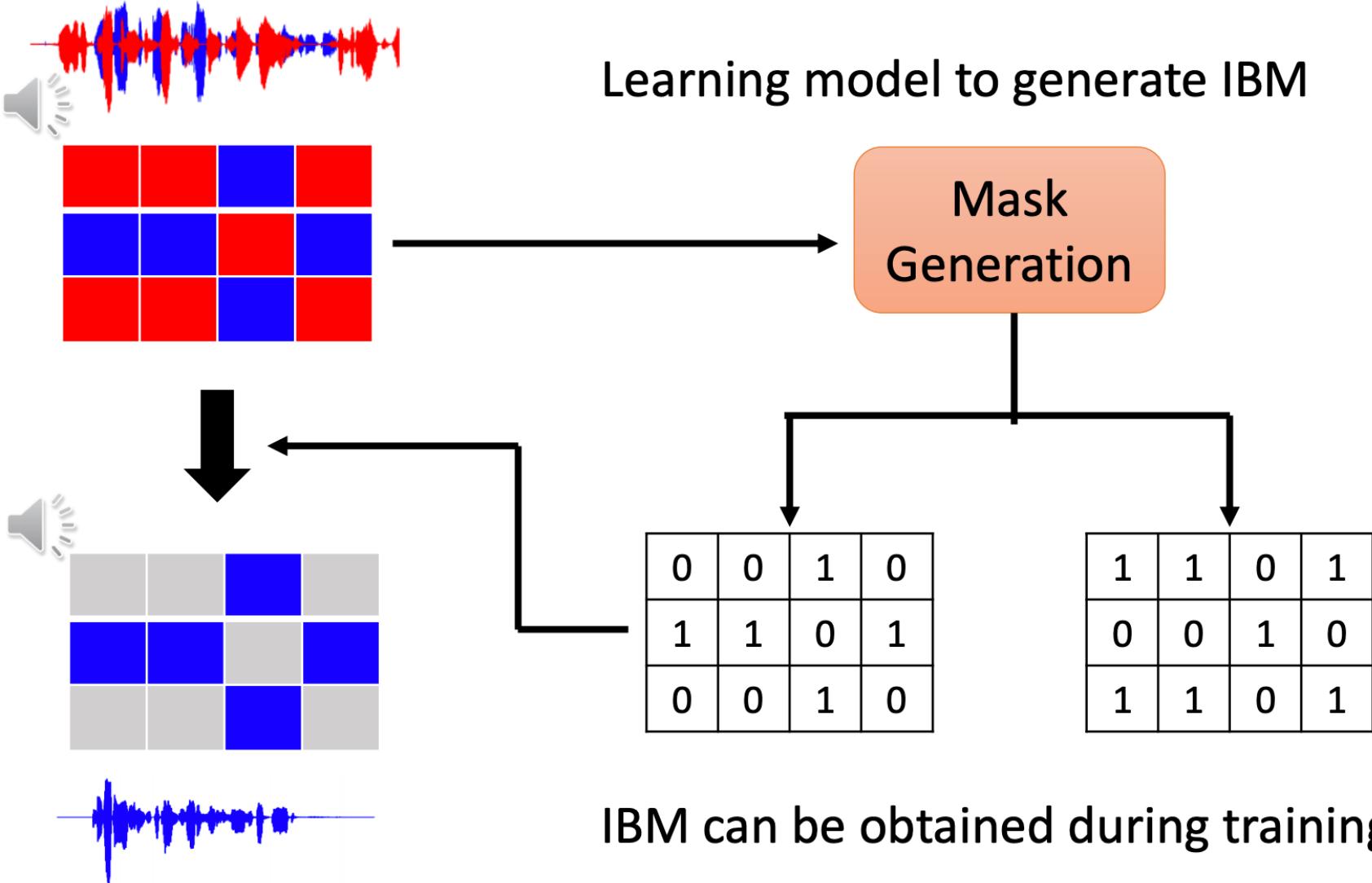


# Speech separation



[https://researcher.watson.ibm.com/researcher/view\\_group.php?id=2819](https://researcher.watson.ibm.com/researcher/view_group.php?id=2819)

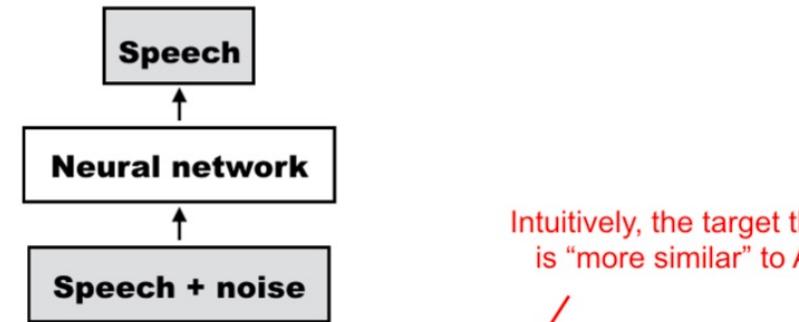
- Ideal binary mask



# Two Problems in the speech separation task

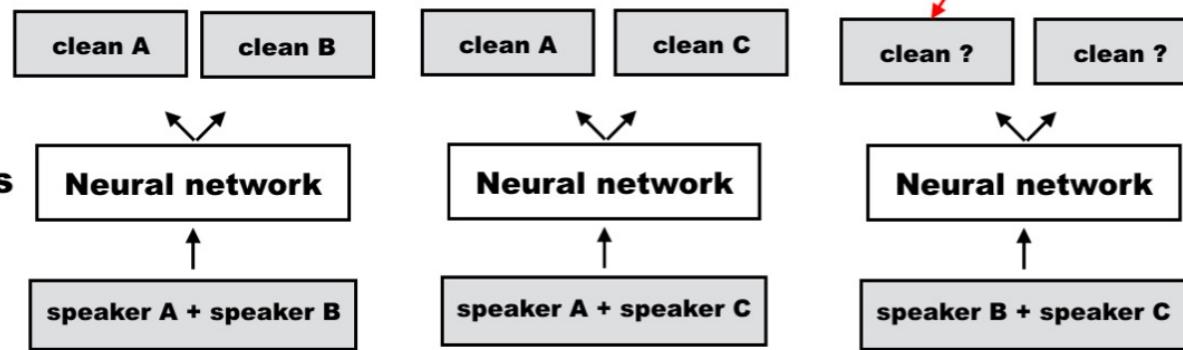


## Single Target



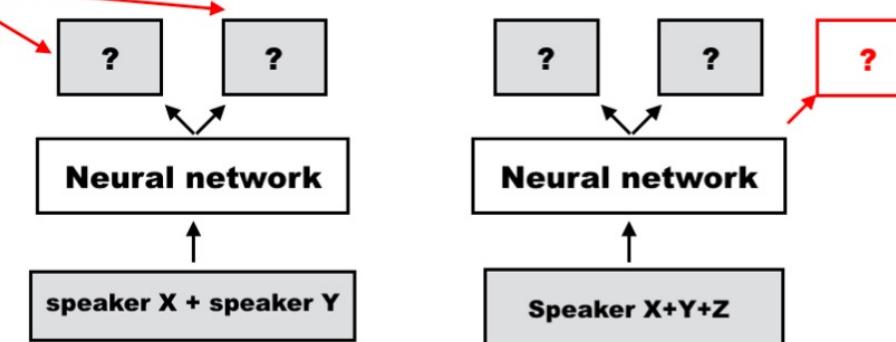
## Two Targets

Permutation problem

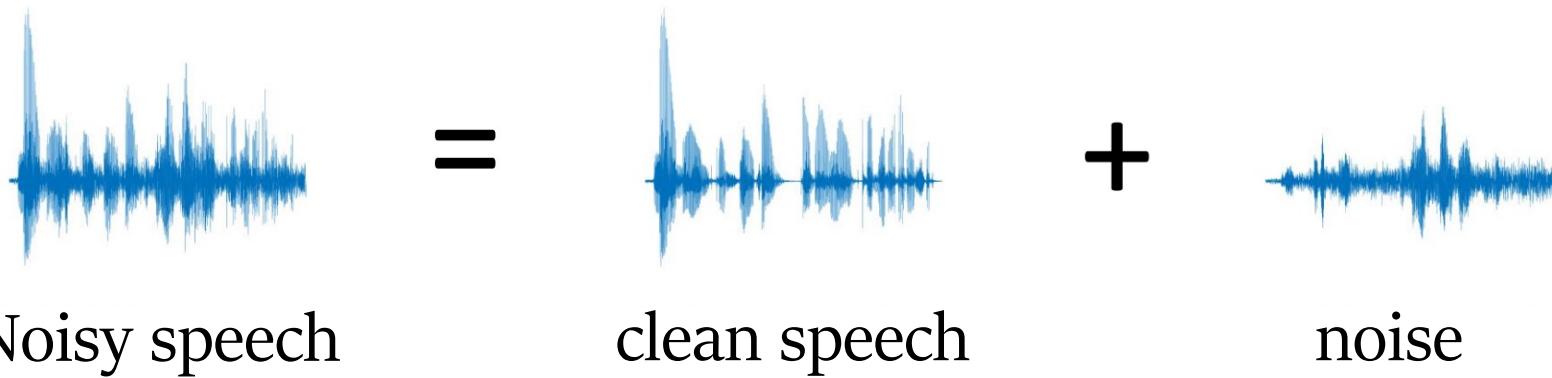


## Uncertain Target

Output dimension mismatch



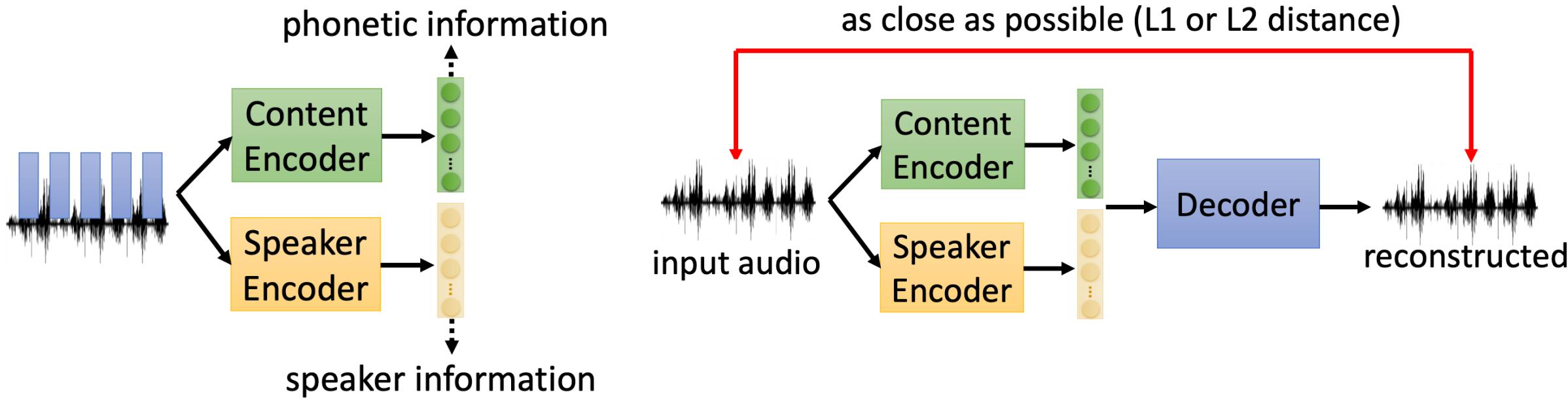
# Speech Enhancement



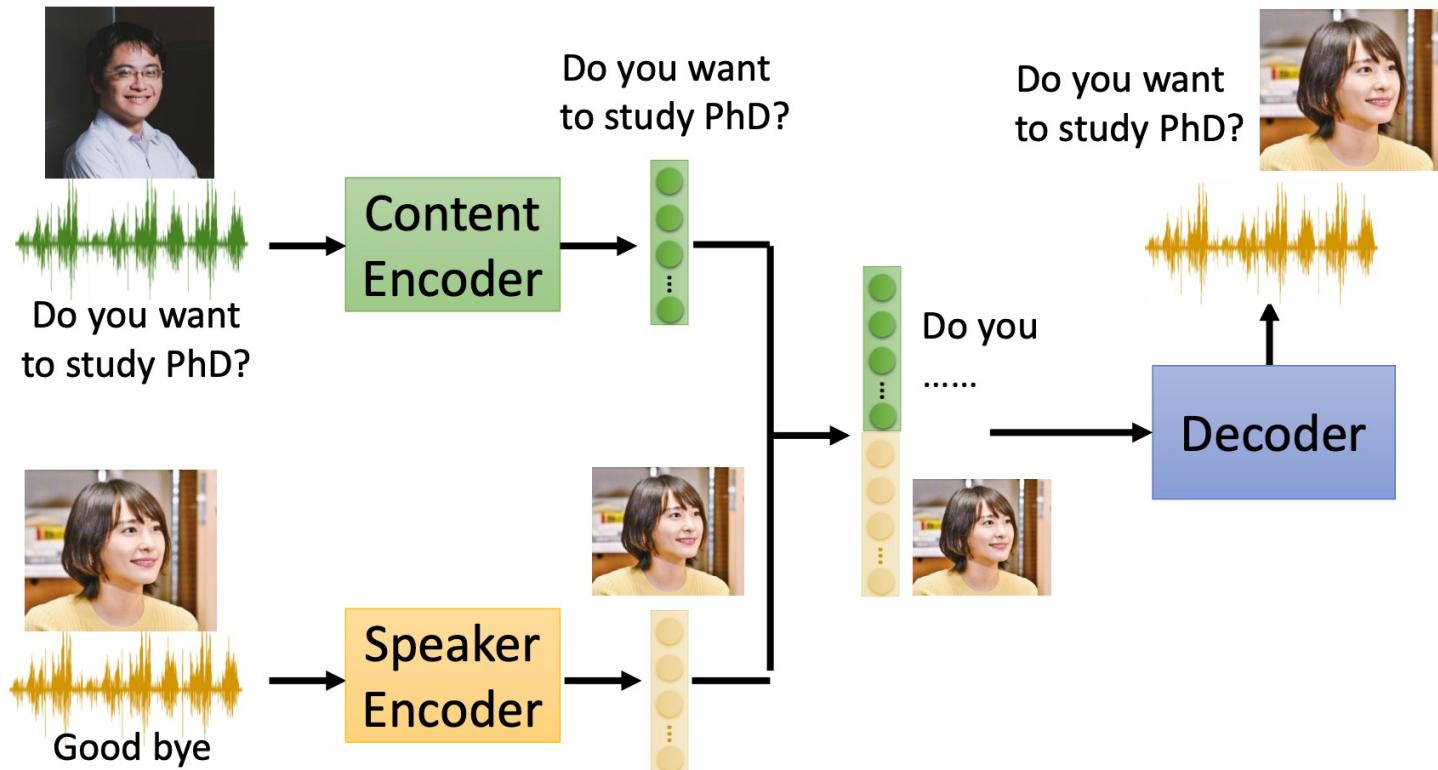
- Well-solved
- Perceptual clean speech

# Voice Conversion

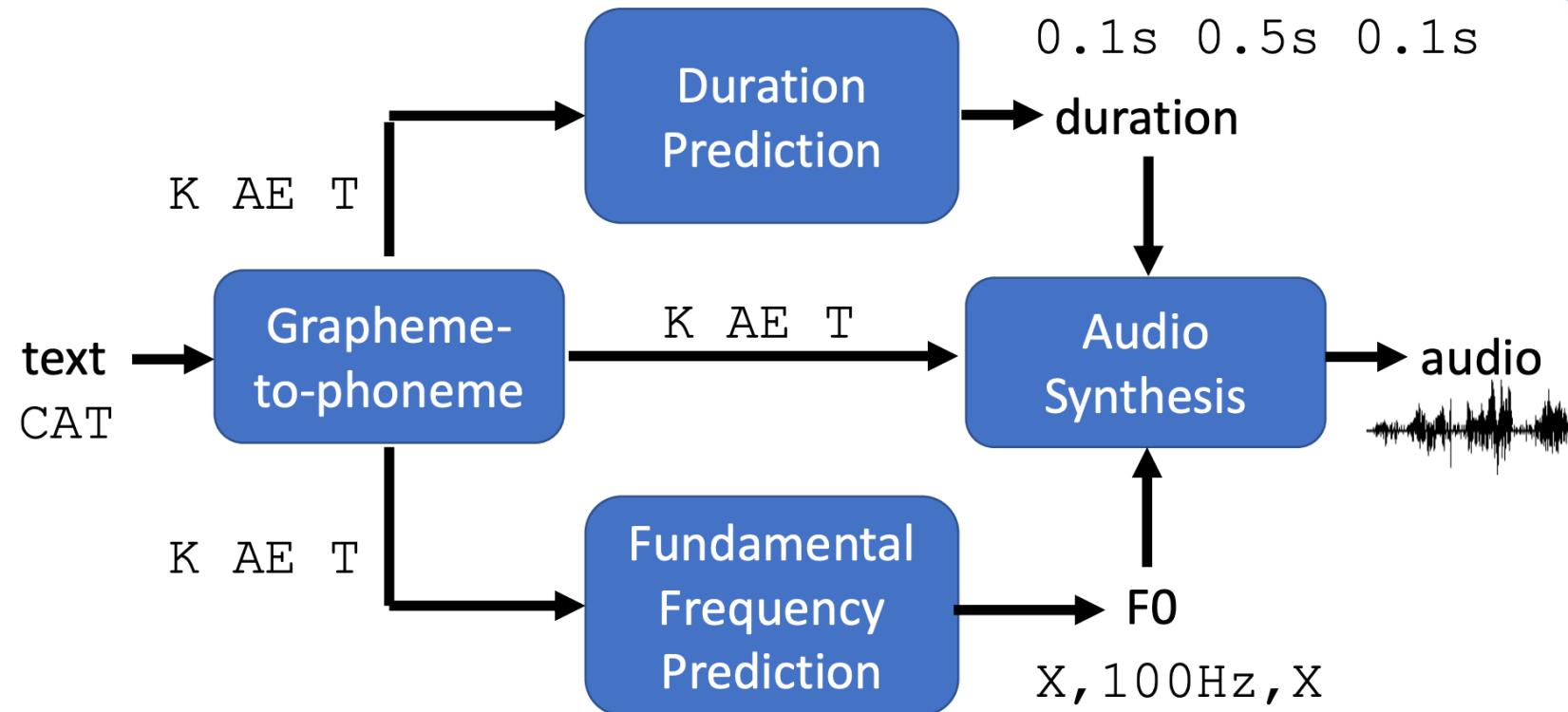
- Feature Disentangle



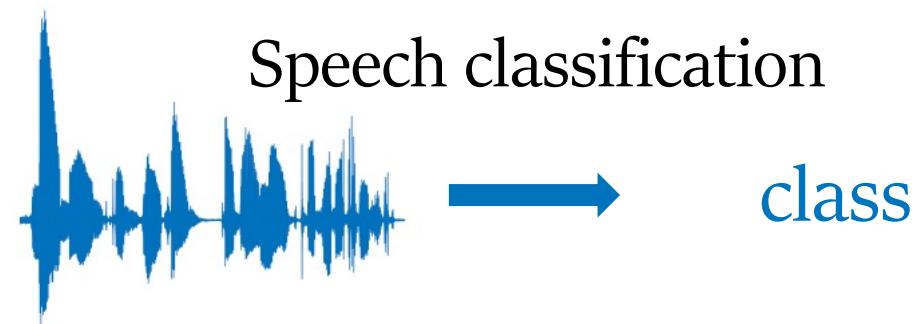
- Inference pipeline



# Text-to-speech



- Natural
- Lack of evaluation metric



# Gender classification

- **Energy Entropy** - Male low and distributed  
Female high and stays for short period of time

$$P(k) = \frac{|X(k)|^2}{\sum_{k=0}^K |X(k)|^2}, \quad H = \sum_{k=0}^{K/2} P(k) \log(P(k));$$

$$M = (E - C_E)(H - C_H),$$

$$EE = \sqrt{(1 + |M|)}$$

- **Short time energy** – Male low , Female High

$$E_{\hat{n}} = \sum_{m=-\infty}^{\infty} (x[m]w[\hat{n}-m])^2 = \sum_{m=-\infty}^{\infty} x^2[m]w^2[\hat{n}-m].$$

- **Zero –crossing rate** – Female ZCR higher than male

$$Z_{\text{CR}}, Z = \frac{1}{N} \sum_{i=1}^{N-1} \frac{\text{sgn}\{x(i)\} - \text{sgn}\{x(i-1)\}}{2}$$

$$\text{sgn}\{x(i)\} = \begin{cases} 1; & x(i) > 0 \\ 0; & x(i) = 0 \\ -1; & x(i) < 0 \end{cases}$$

- **Spectral Centroid**

$$\text{Centroid} = \frac{\sum_{n=0}^{N-1} f(n)x(n)}{\sum_{n=0}^{N-1} x(n)}$$

- **Frame based teager energy**

$$f_i = w_i^2 X(w_i). \quad T_i = \left( \sum_{k=1}^K f_k \right)^{1/2}.$$

- **Position of Maximum FFT coefficient**

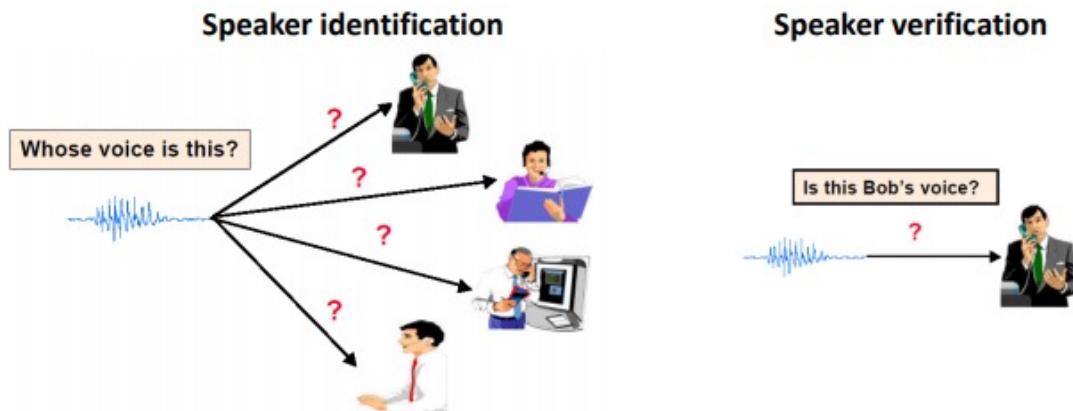
Position of Maximum FFT coefficient divided by sampling frequency

# Emotion recognition



- Categorized emotion, sometimes confusing
- Dataset, actor performance
- Continuous change of emotion

# Speaker recognition



- **Speaker Verification:**

Supervised binary classification: Given a speech sequence and a claimed identity, accept or reject the identity.

- **Speaker Identification:**

Supervised multi-class classification: Determine which speaker (from a predetermined set of speakers) has uttered the sequence.

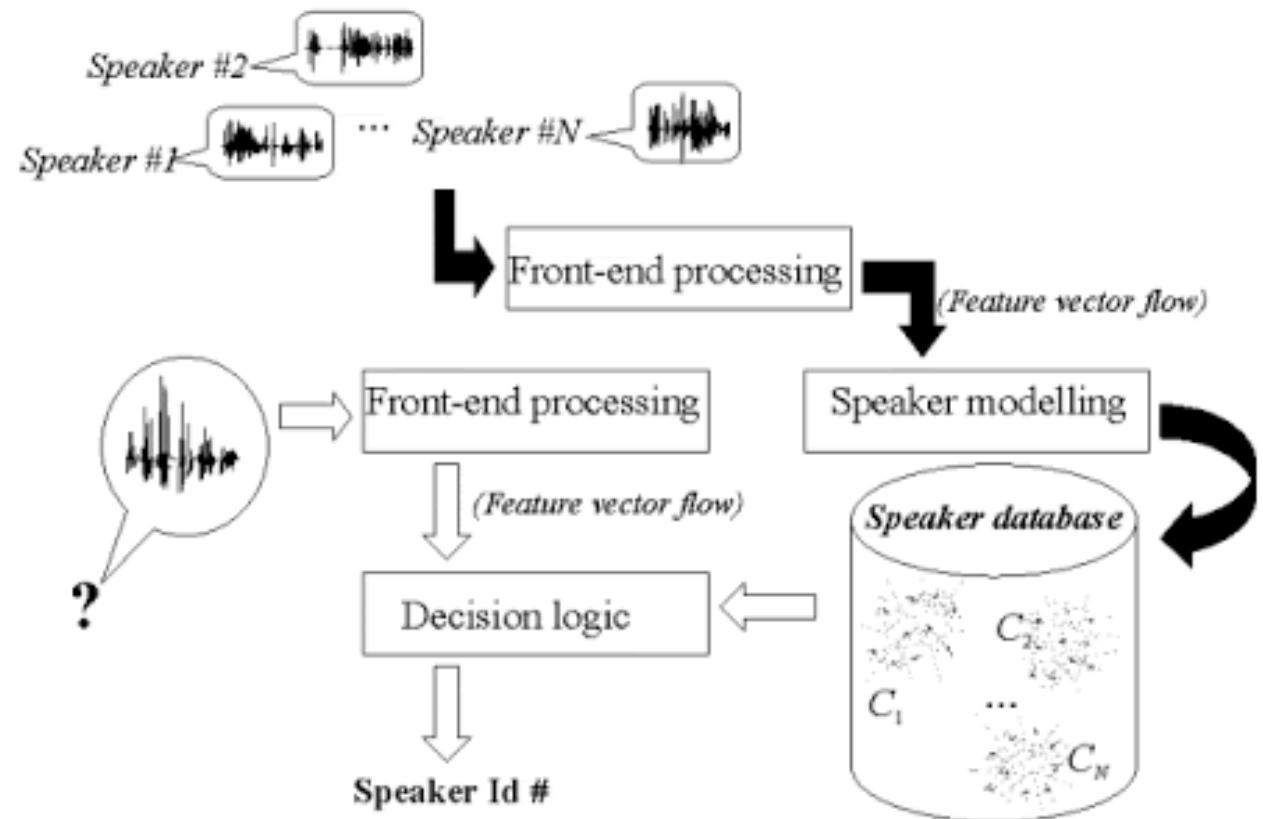
- **Speaker Diarization:**

Clustering and segmentation: Partition an input audio stream into homogeneous segments. according to the

# Speaker recognition

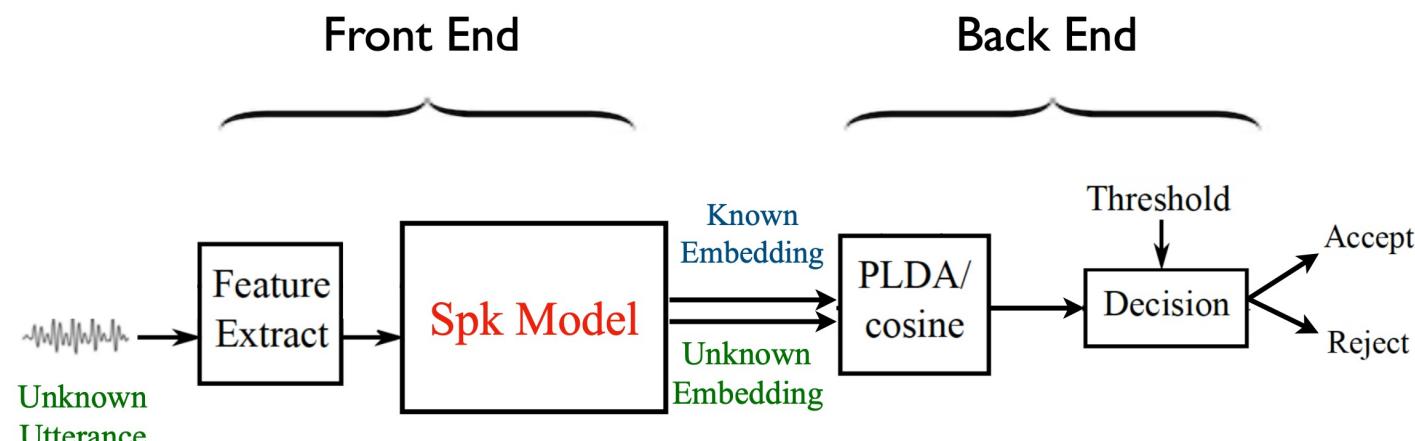
Speaker Embedding:

- Represent speaker info
- Measure the similarity



# Speaker verification

- Verify the identity of a speaker



# Voice Anti-spoofing



Decision  
Genuine or Spoofing attacks

AI TECHNOLOGY

# Clone a Voice in Five Seconds With This AI Toolbox

A new Github project introduces a remarkable Real-Time Voice Cloning Toolbox that enables anyone to clone a voice from as little as five seconds of sample audio.



LATEST HARD FORK PLUGGED FUNDAMENTALS WORK 2030

## I trained an AI to copy my voice and it scared me silly



by ABHIMANYU GHOSHAL — Jan 22, 2018 in INSIGHTS



Hey Google, turn on  
the Christmas tree.

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## Fraudsters Used AI to Mimic CEO's Voice in Unusual Cybercrime Case

Scams using artificial intelligence are a new challenge for companies



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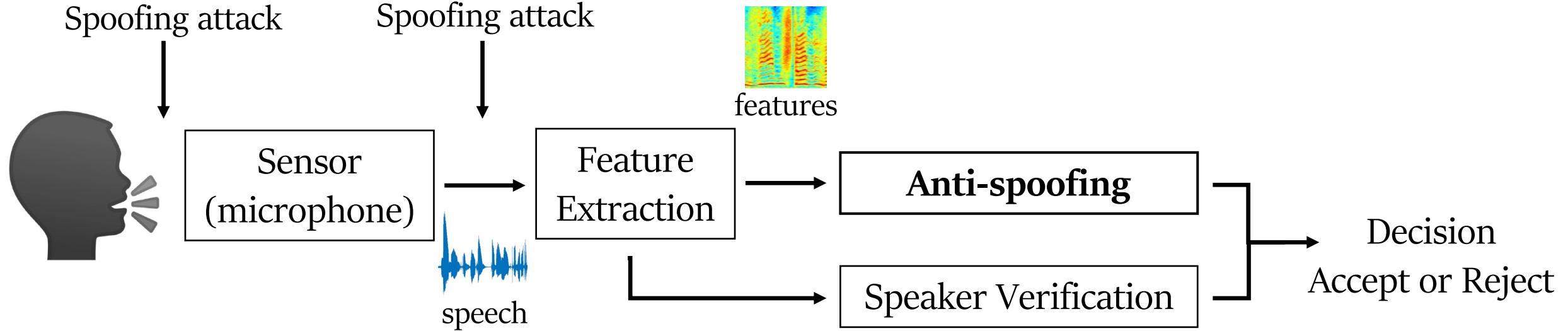
# Voice Anti-spoofing

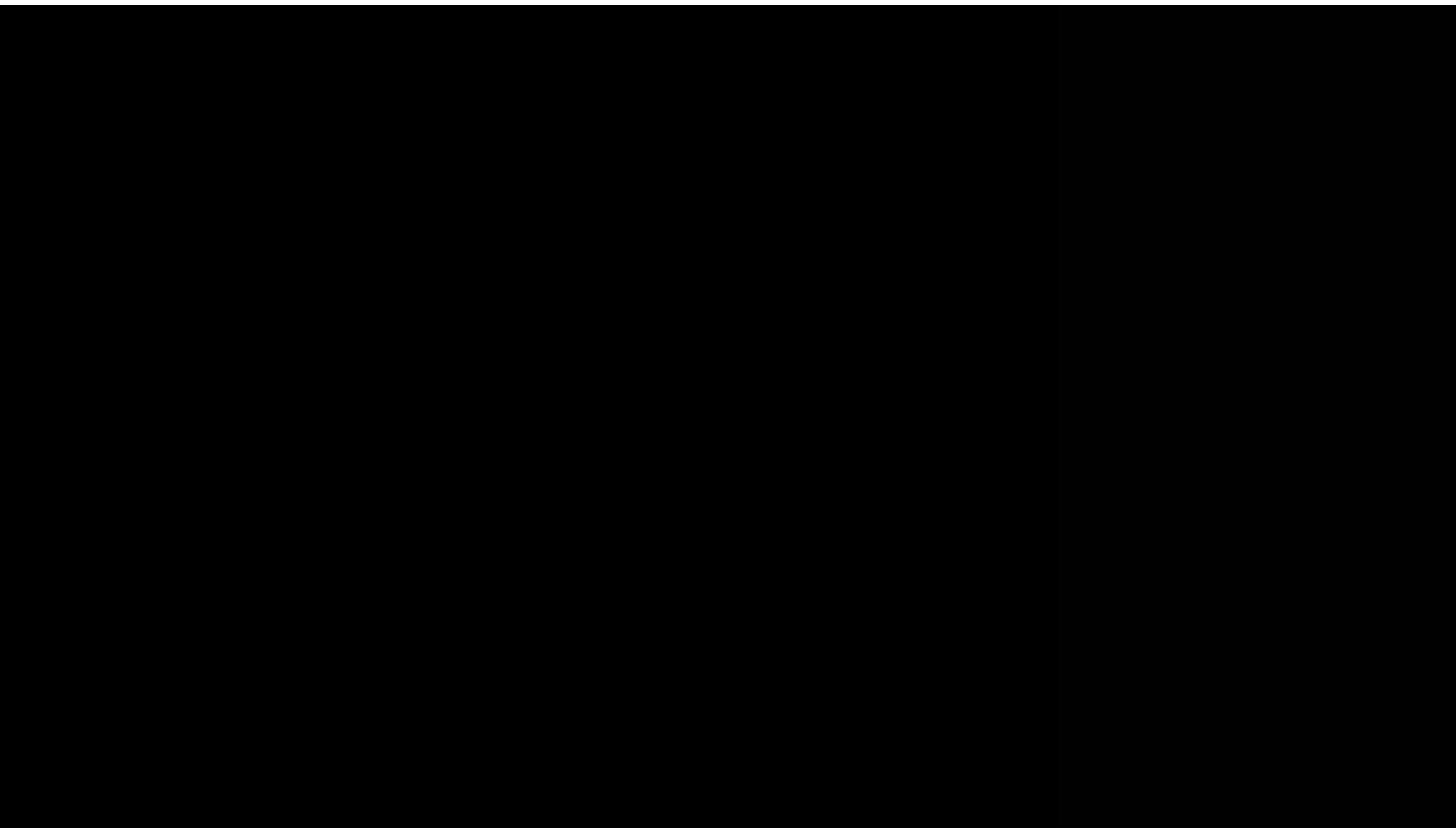
- Detect spoofing attacks (fake speech)

Impersonation /  
Replay  
Spoofing attack

Text-to-speech /  
Voice conversion  
Spoofing attack

Generalization Issue





<https://vimeo.com/345075279>

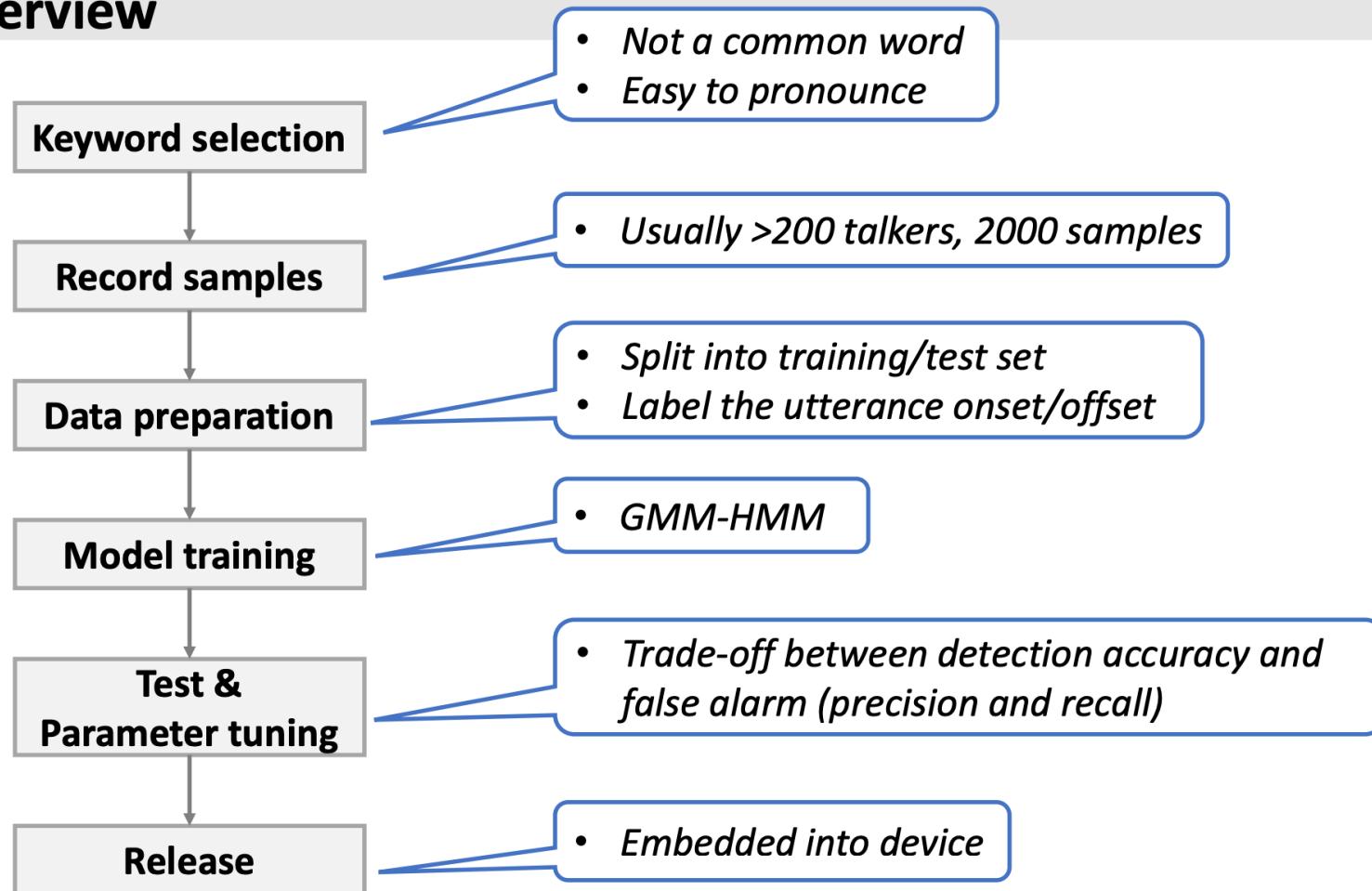
Anti-Spoofing Demo from ID R&D



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# Keyword spotting

## Overview



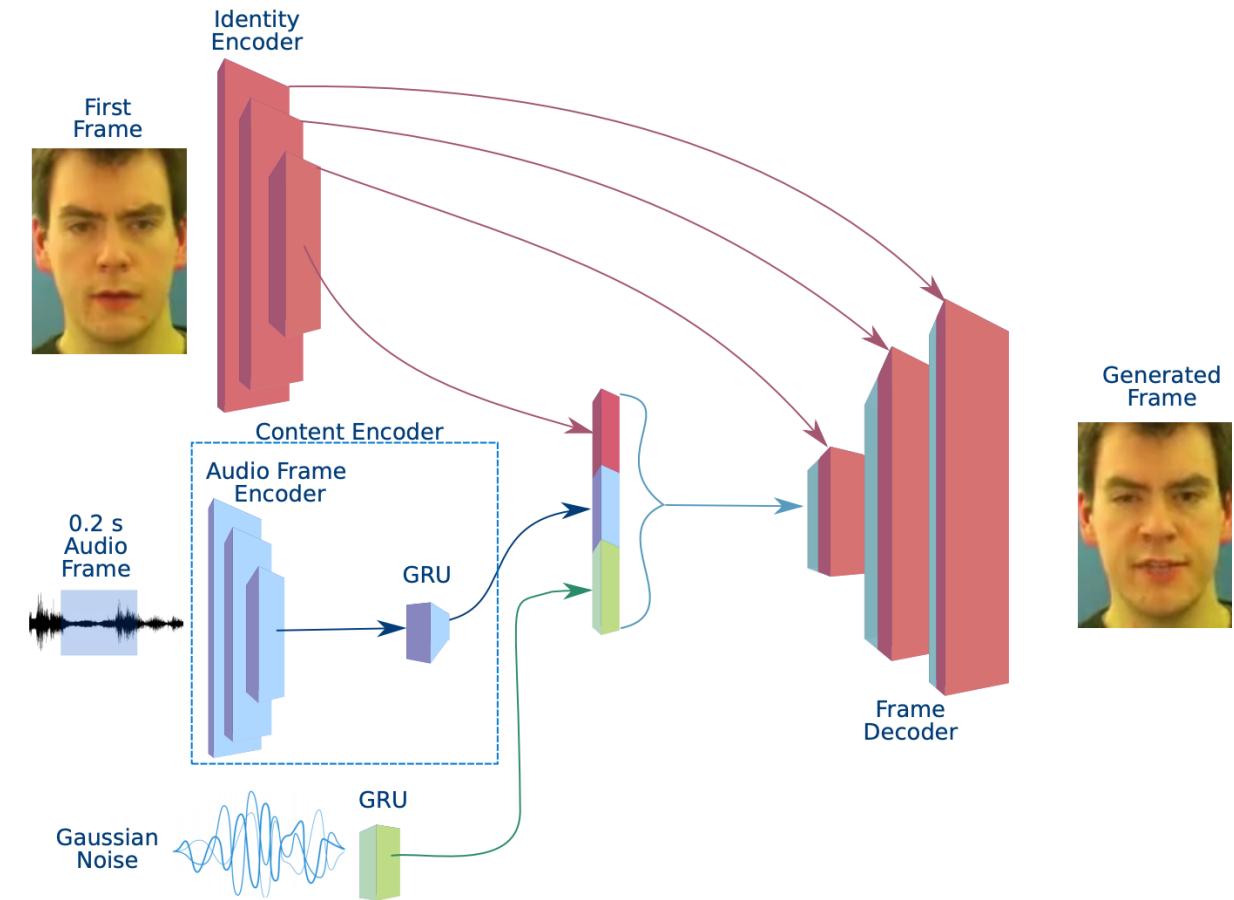


# Other topics



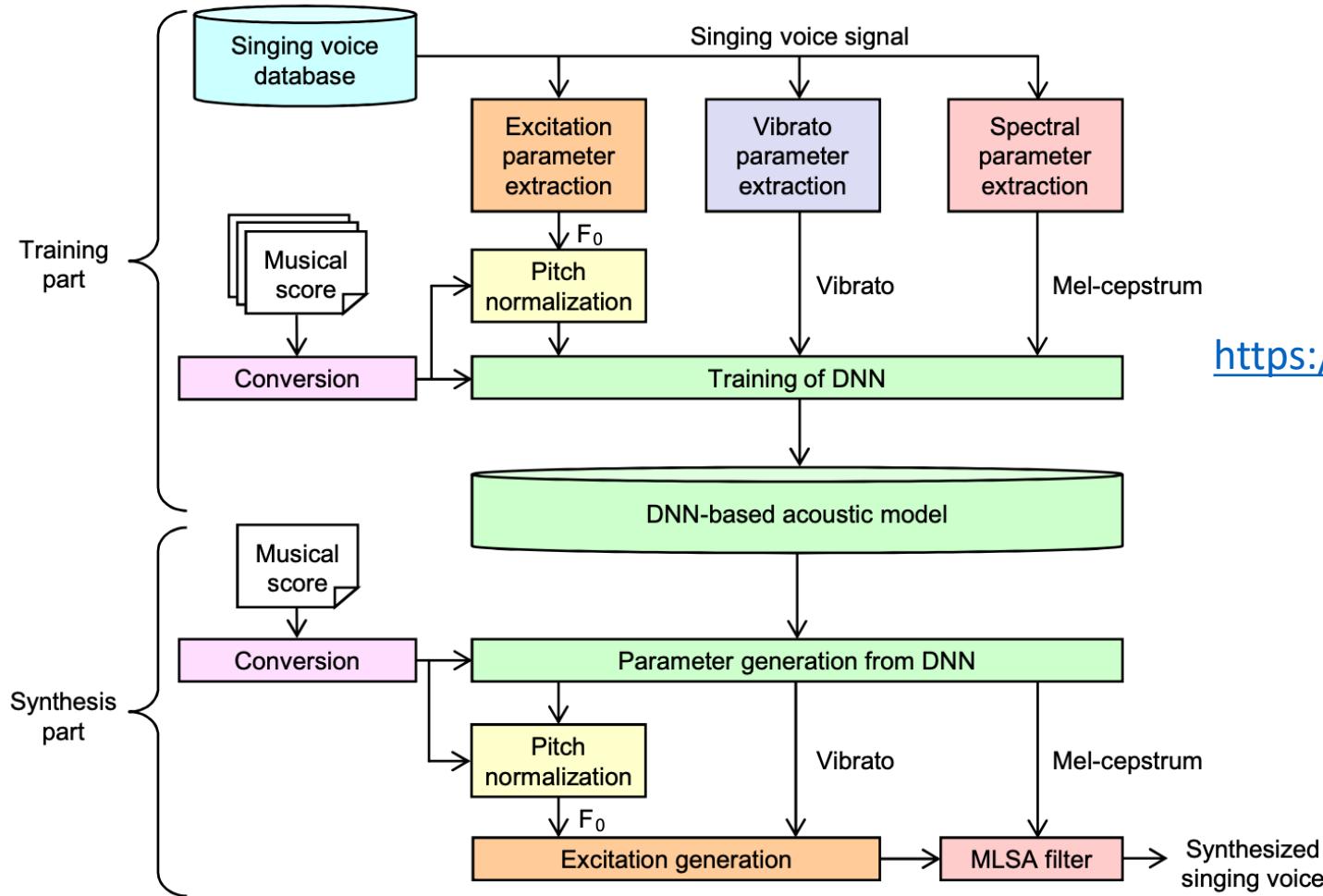
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# Talking face generation



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# Singing voice synthesis



<https://bytesings.github.io/paper1.html>

# Future horizons

- General speech understanding
- Disentangled speech representation
- Human-Computer Interaction with speech



Thank you !



Q & A

# Speech Features

- Resonance peak
- Features (What aspects does each one models? ):
- PLP
- MFCC
- PNCC

# Audio Feature Extraction

## Mel-Frequency Cepstral Coefficients (MFCC)



### Steps

1. Audio frame → FFT → Spectrum
2. Spectrum → Mel-Filters → Log-Mel Spectrum
3. Perform cepstral analysis
4. Take the first multiple cepstral coefficients as MFCCs

