

# **Traditional DSP for Audio & Speech**

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Tal Rosenwein

# Goal



# Overview

- Motivation
- Communication
- Anatomy & Speech production system
- Phonetics
- Acoustic/Speech Features
- Traditional Speech Signals Analysis
  - Time Stretching
  - Speech Enhancement- Spectral Subtraction
  - Auto Gain Control (AGC)
  - Audio Compression

# Motivation

- Huge Market
- Make Our Lives Easier
- Save Human Labour
- Remove Bureaucracy



VOICE STATS RESEARCH INSIDER PODCAST AI INDUSTRIES WEBINARS

## Transactions With Voice Assistants on Smart Home Devices Will Hit \$164B in 2025: Report

ERIC HAL SCHWARTZ on November 9, 2020 at 4:00 pm

DSP for Audio, Tal Rosenwein



**Voice and Speech Recognition Market Worth \$26.8 Billion by 2025 at a CAGR of 17.2% from 2019- Meticulous Research®**

February 06, 2020 07:05 ET | Source: [Meticulous Market Research Pvt. Ltd.](#)

Source [1](#). [2](#)

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## VNI Complete Forecast Highlights



- Globally, consumer Internet video traffic was 56.4 EB per month in 2017, the equivalent of 14 billion DVDs per month, or 19 million DVDs per hour.
- Global consumer Internet video traffic grew 40% in 2017.
- Globally, Internet video traffic will be 82% of all consumer Internet traffic by 2022, up from 73% in 2017.

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- **Communication**
- Anatomy & Speech production system
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# Communication

- Speaker produces acoustic wave that emitted from the mouth/nose (nose) and propagates to the ears of the listener
- Multiple organs (nostrils, mouth, throat, teeth, tongue, etc.) are included in speech generation.

# Communication

Conversation flow:

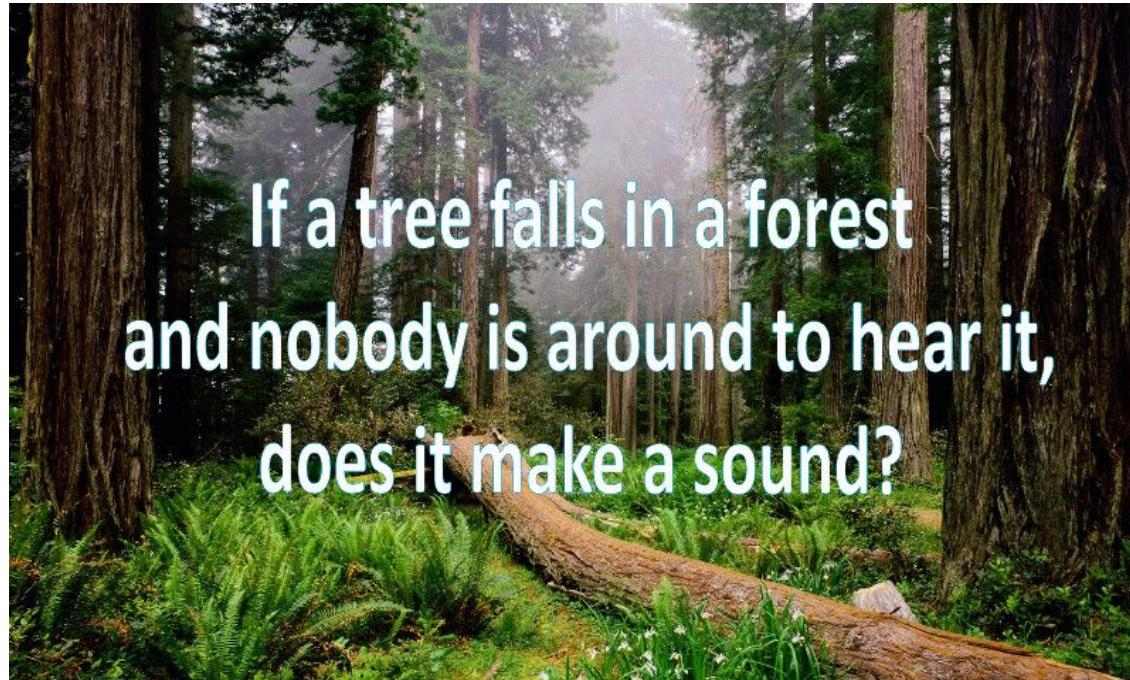
- Creating the notion we want to transmit.
- Mapping / transducing this notion into a linguistic domain
- Choosing the words that best represent this notion
- Arranging the words in order according to linguistic rules of a given language
- Adding prosodic features for emphasize different aspects of the notion we want to convey
- The brain sends a series of motoric commands
- We then move the relevant mussels
- Produce the sequence of sounds
- Transmitting an acoustic wave to the ears of the partner through the medium.

# Overview

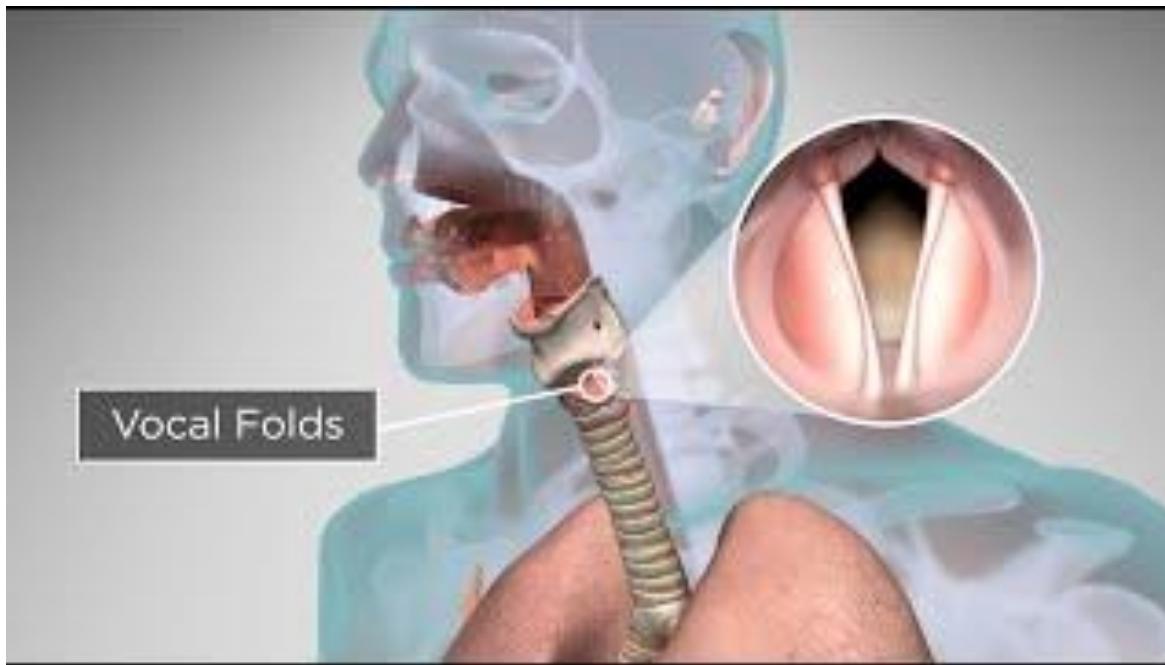
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# **Anatomy & Modelling of Speech Production**

# Audio- Pressure Wave



# Anatomy & Modelling of Speech Production



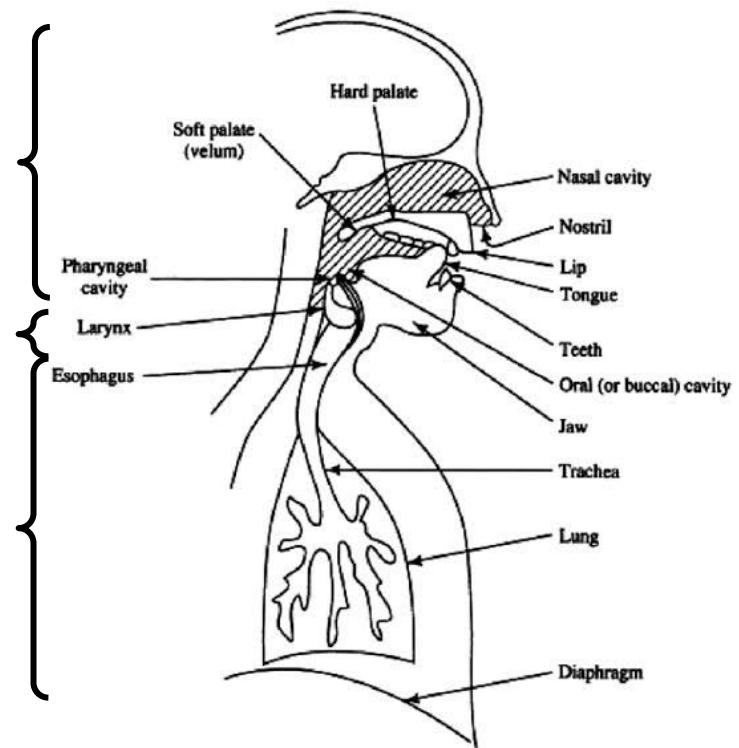
# Speech Production Organs

- [video](#)

Vocal tract

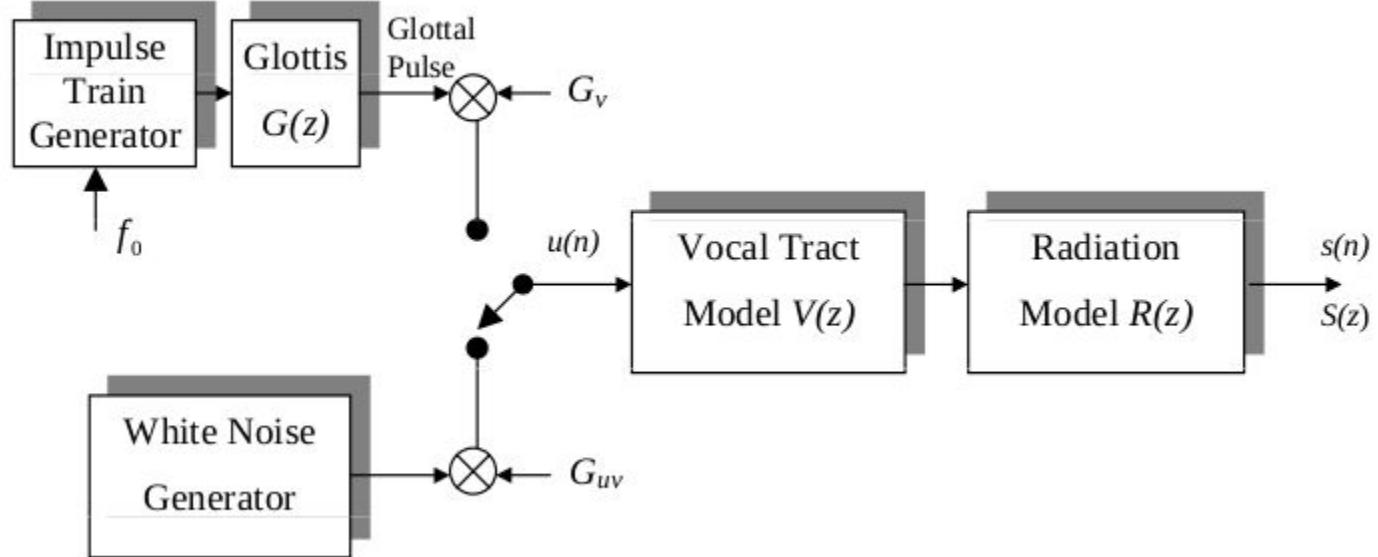
Larynx

Subglottal  
Respiratory  
System



# Speech Production- Source-Filter Model

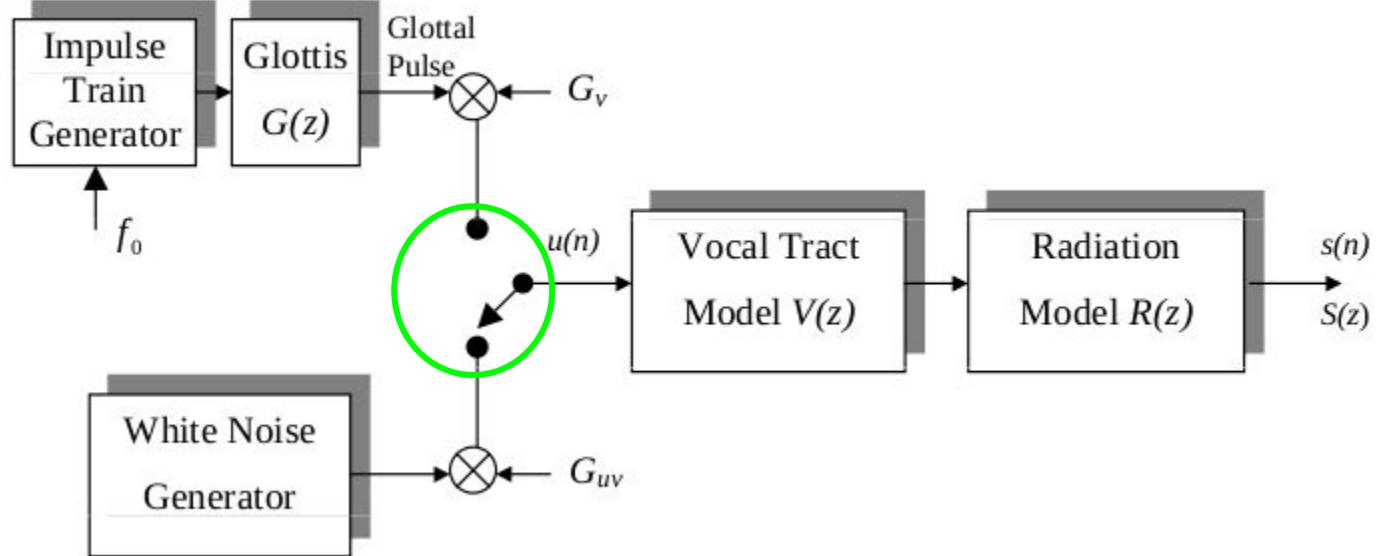
Voiced



Un-Voiced

# Speech Production- Source-Filter Model

Voiced



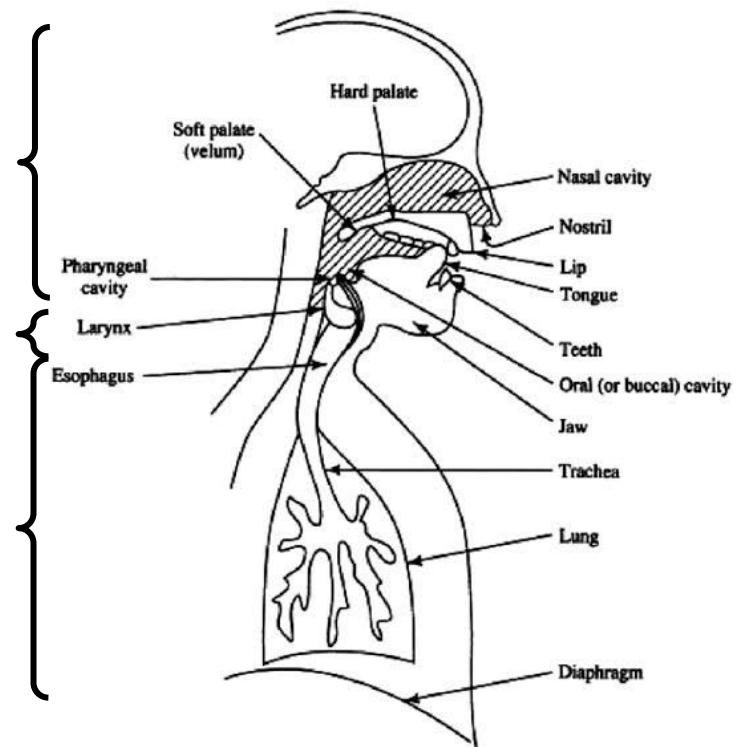
# Speech Production Organs

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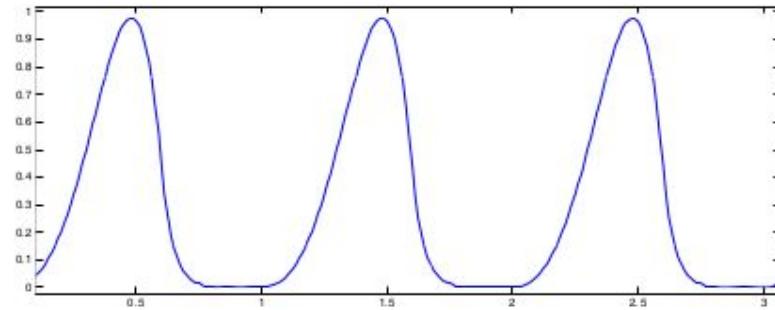
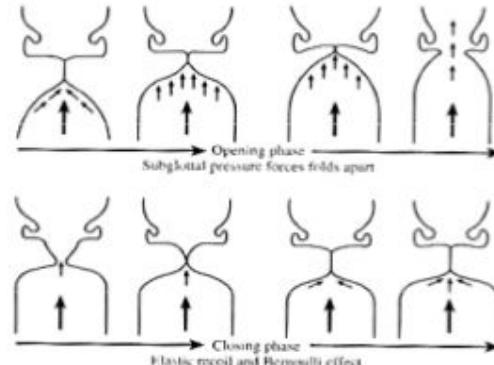
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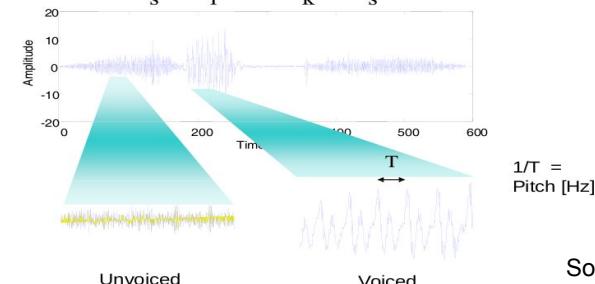
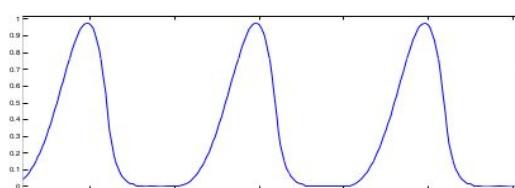
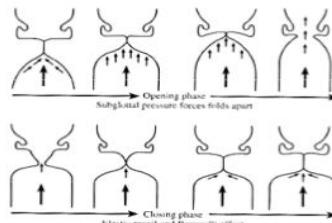
# Speech Production Organs - Larynx

- Larynx is responsible for different phonation modes (voiceless, voiced, whisper)
- During voiceless phonation (e.g. [s] in “star”) and whisper, vocal cords are apart from each other, and the airstream passes through the open glottis (the opening between the vocal cords)
- In voiced phonation (e.g. [a] in “star”), vocal folds are successively opening and closing, creating a periodic waveform. The frequency of vibration is called fundamental frequency (or pitch) and abbreviated F0.
- “vocal cords in action”- [video](#). This [video](#) is less disgusting.



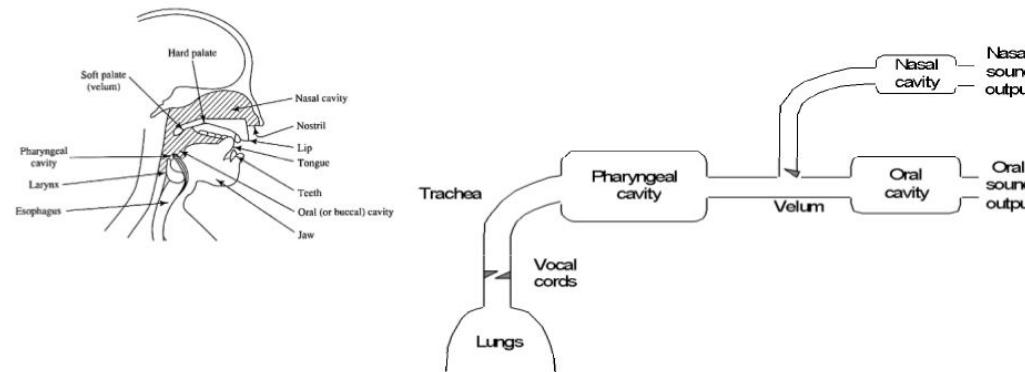
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  - Average F0 values for male, female, and children are about 120, 220 and 330 Hz.
  - The shape of the glottal pulse is individual, and it is an important determinant of the perceived voice quality (“She has a harsh / rough / breathy / clear /.. voice”)

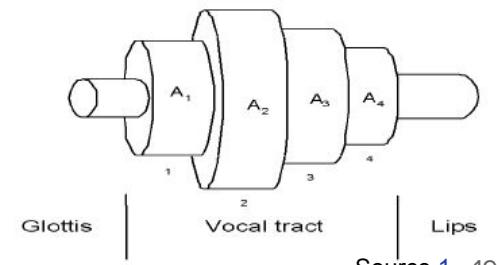


# Speech Production Organs - Vocal Tract

- Includes pharyngeal, oral and nasal cavities. The volumes and shapes of these are individual.
- Can be roughly characterized by its (time-varying) resonance frequencies called formants



- Can be modeled as a hard-walled lossless tube resonator consisting of  $N$  tubes with different cross-sectional areas
- Can be modeled by a (time-varying) filter.
- Example: Car Exhaust



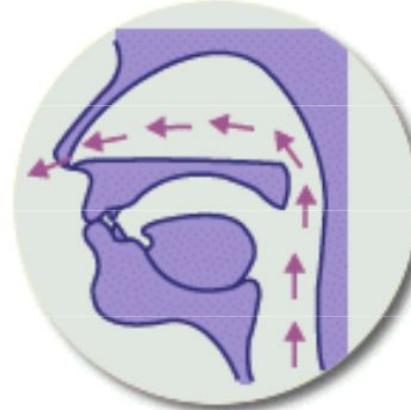
Source 1 19

# Speech Production Organs - Vocal Tract

- [video](#)
- Oral Vs Nasal sounds:
  - Close your nose and say ‘mmmm’ for 5 sec
  - Close your nose and say ‘Laaaaaa’ for 5 sec



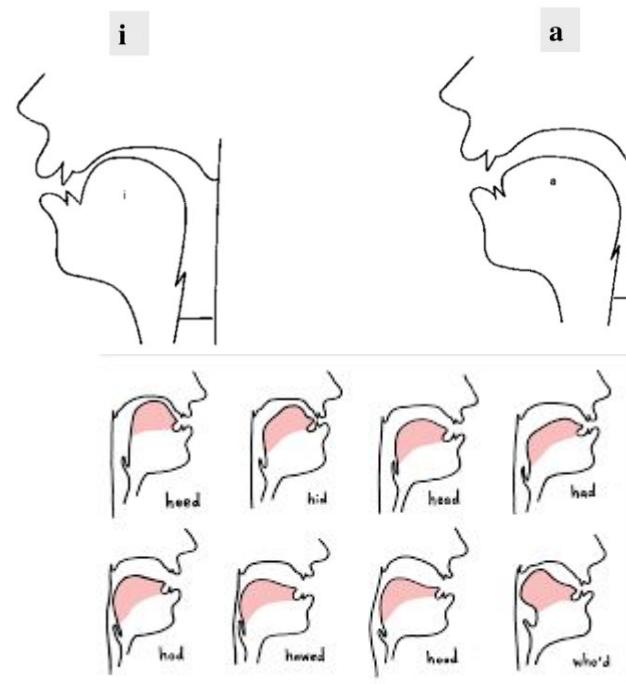
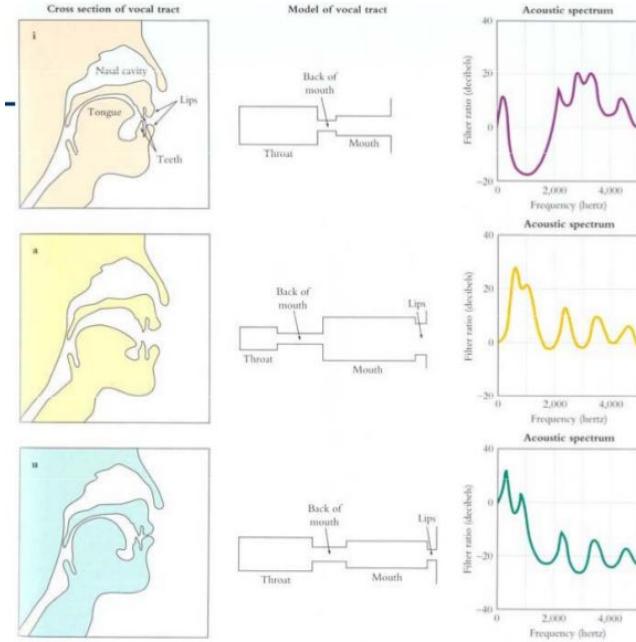
Oral



Nasal

# Speech Production Organs - Vocal Tract

- Vocal Tract (also lips, tongue...) changes when different vowels are pronounced



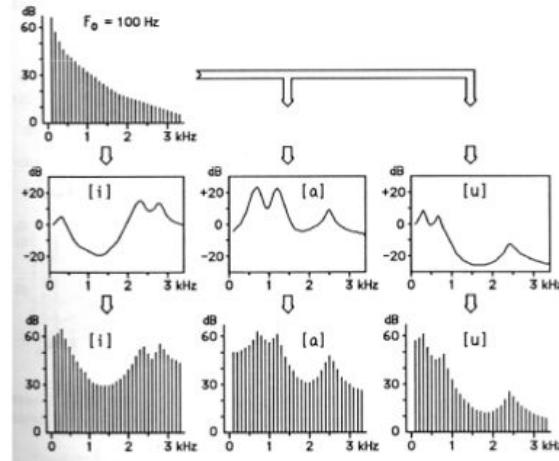
# Speech Production- Source-Filter Model

- The resulting speech spectrum  $S(z)$  is a combination of the source spectrum  $U(z)$  and the vocal tract transfer function  $H(z)$ :

$$S(z) = U(z)H(z) \leftrightarrow s[n] = u[n] * h[n]$$

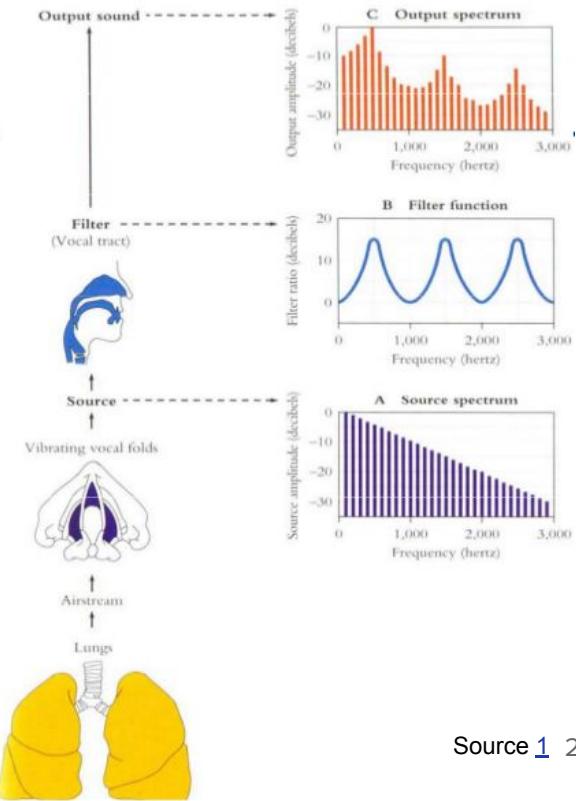
Frequency domain    Time domain

**Source**



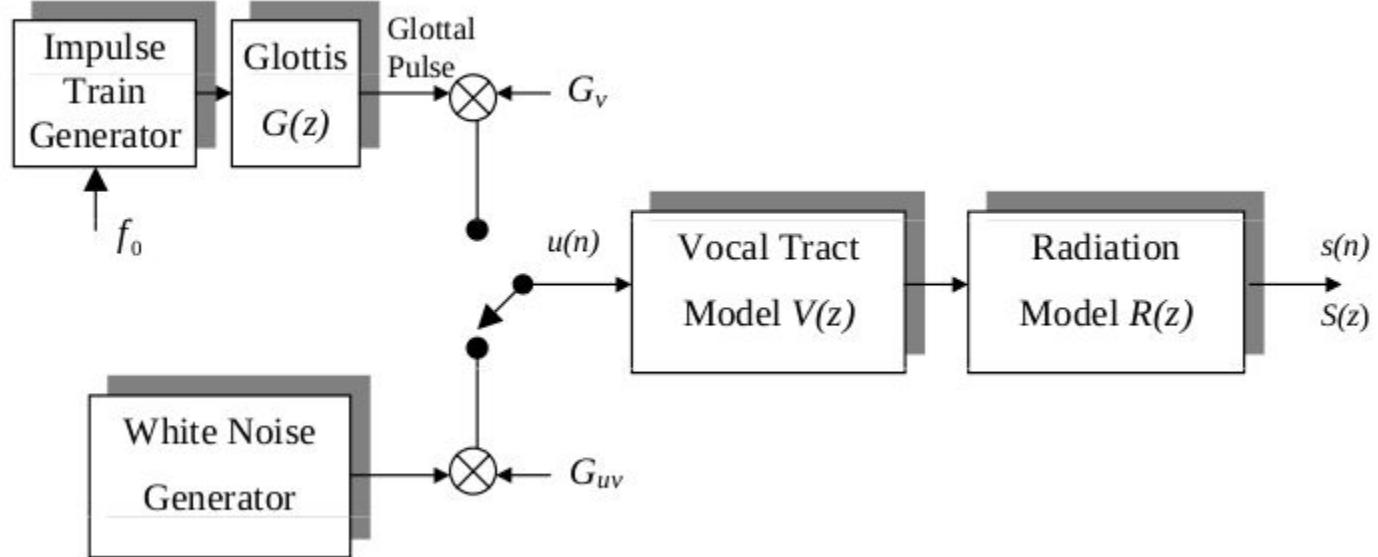
**Filter**

**Source and filter combined**



# Speech Production- Source-Filter Model

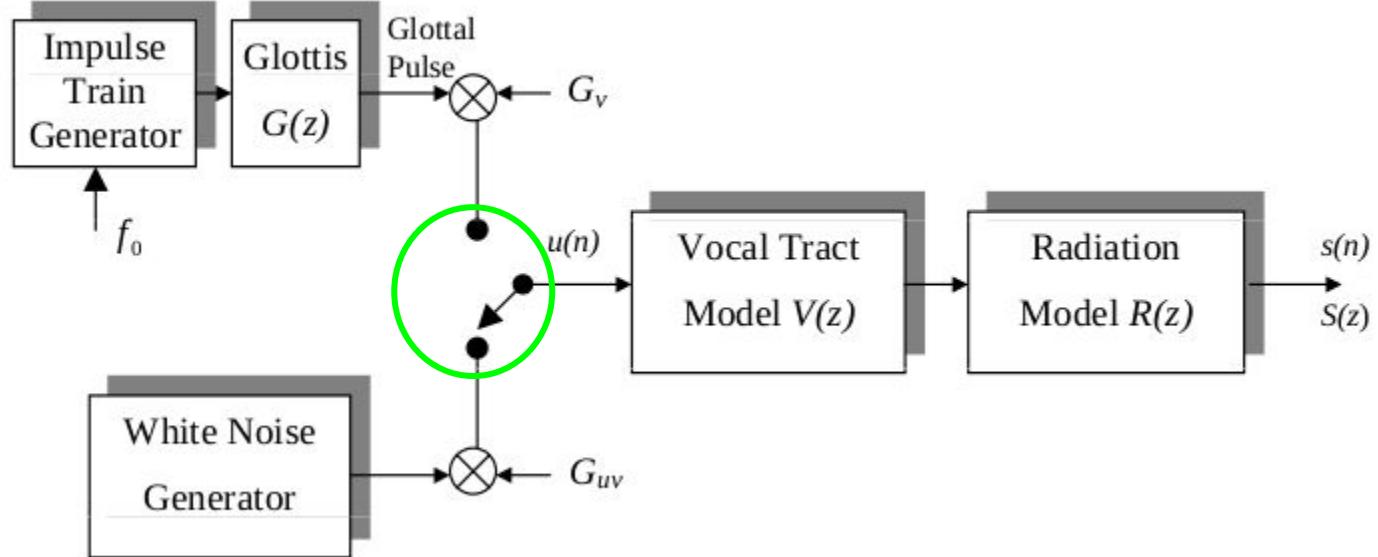
Voiced



Un-Voiced

# Speech Production- Source-Filter Model

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Un-Voiced

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# Phonetics

phonetics :

Overview

Similar and opposite words

Usage examples

## Dictionary

Definitions from [Oxford Languages](#) · [Learn more](#)



phonetics

noun

the study and classification of speech sounds.  
"a phonetics laboratory"

Feedback

# Phonetics

Phonetic has 3 branches:

- **Articulatory phonetics:** how speech-sound is generated, in terms of mechanics
- **Acoustic phonetics:** how speech-sounds are transmitted, in terms of acoustics.
- **Auditory/perceptual phonetics:** how sound is perceived by our brain

# Phonetics

- **Phoneme:** the smallest phonetic unit that has meaning in the language. Represented by slashes by convention.
  - /K/ /IY/ /P/ Vs /D/ /IY/ /P/
- **Phone:** Distinct speech sound or gesture, regardless of whether the exact sound is critical to the meaning of words. Phoneme is the basic / atomic piece to convey a lingual message.
  - “Guimarães”- we can produce  $\tilde{a}$  but it has no meaning in English
- **Allophone:** group of phones represented by the same phoneme (variations of phonemes). For example different pronunciation of the letter t in top, stop, butter, are allophones of the phoneme /t/.

# Phonetics

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  - /K/ /IY/ /P/ Vs /D/ /IY/ /P/

Phoneme	Example	Translation			
AA	odd	AA D	JH	gee	JH IY
AE	at	AE T	K	key	K IY
AH	hut	HH AH T	L	lee	L IY
AO	ought	AO T	M	me	M IY
AW	cow	K AW	N	knee	N IY
AY	hide	HH AY D	NG	ping	P IH NG
B	be	B IY	OW	oat	OW T
CH	cheese	CH IY Z	OY	toy	T OY
D	dee	D IY	P	pee	P IY
DH	thee	DH IY	R	read	R IY D
EH	Ed	EH D	S	sea	S IY
ER	hurt	HH ER T	SH	she	SH IY
EY	ate	EY T	T	tea	T IY
F	fee	F IY	TH	theta	TH EY T AH
G	green	G R IY N	UH	hood	HH UH D
HH	he	HH IY	UW	two	T UW
IH	it	IH T	V	vee	V IY
IY	eat	IY T	W	we	W IY
JH	gee	JH IY	Y	yield	Y IY L D
			Z	zee	Z IY
			ZH	seizure	S IY ZH ER

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- Different lexicons / standards:  
**IPA, ARPABET**

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AY	hide	HH AY D
B	be	B IY
CH	cheese	CH IY Z
D	dee	D IY
DH	thee	DH IY
EH	Ed	EH D
ER	hurt	HH ER T
EY	ate	EY T
F	fee	F IY
G	green	G R IY N
HH	he	HH IY
IH	it	IH T
IY	eat	IY T
JH	gee	JH IY
..	..	..
JH	gee	JH IY
K		key
L		lee
M		me
N		knee
NG		ping
OW		oat
OY		toy
P		pee
R		read
S		sea
SH		she
T		tea
TH		theta
UH		hood
UW		two
V		vee
W		we
Y		yield
Z		zee
ZH		seizure

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- Different lexicons / standards: **IPA**, ARPABET
  - IPA lexicon has 44 phonemes, ARPABET has 46.
  - In English there are 65 phonemes, usually people compress it to 39 phonemes.

# Phonetics

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  - /K/ /IY/ /P/ Vs /D/ /IY/ /P/
- There are some lexicons, such as the CMU dictionary that breaks each word to its phoneme sequence. [Online link](#)

- **Look up the pronunciation for a word or phrase in CMUdict (version 0.7b)**

Show Lexical Stress

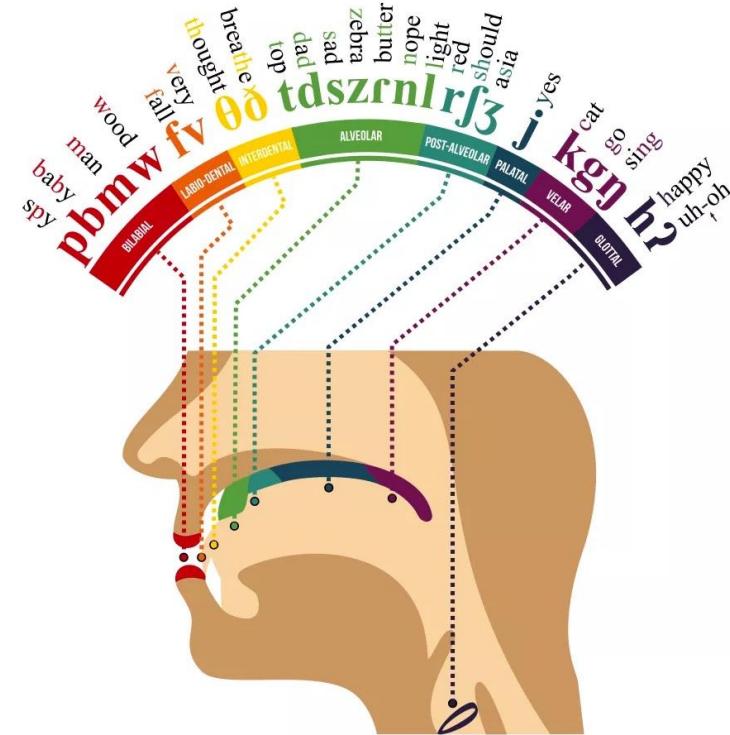
• HI MY NAME IS TAL  
• HH AY . M AY . N EY M . IH Z . T AA L .

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- Use this [link](#) to read IPA phoneme sequence

# Phonetics

- **Phoneme:** the smallest phonetic unit that has meaning in the language. Represented by slashes by convention.
  - /K/ /IY/ /P/ Vs /D/ /IY/ /P/
- The articulator has a different setup for each phoneme

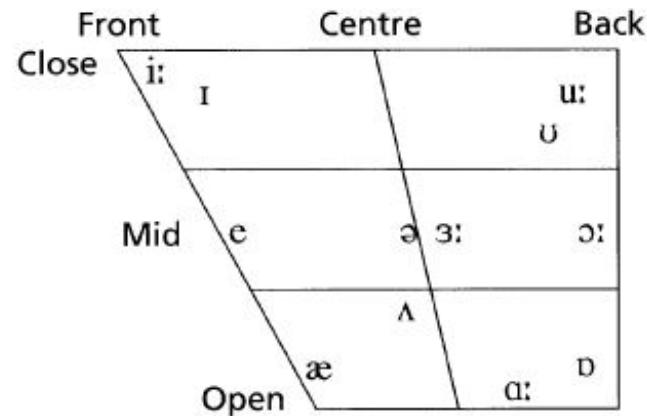


## ENGLISH IPA

WWW.LANGUAGEBASECAMP.COM

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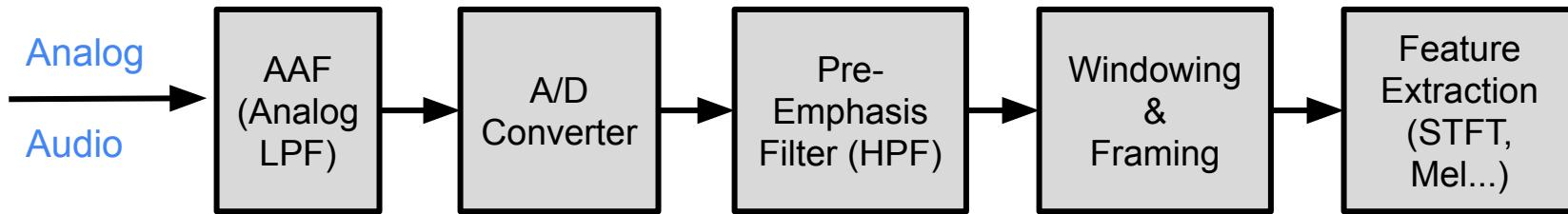


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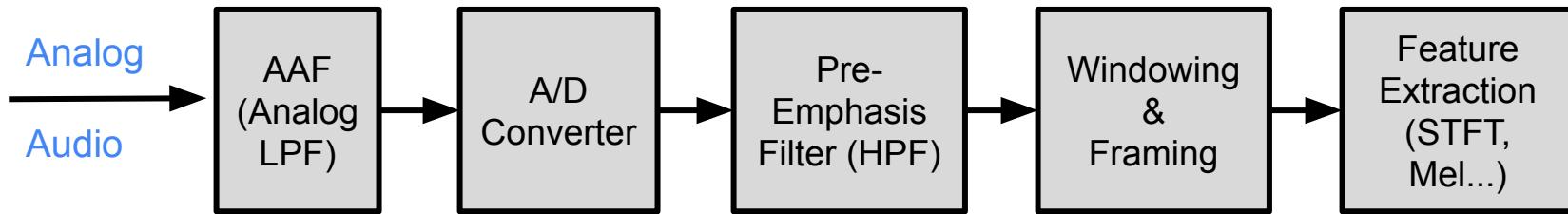
# **Speech & Audio Signal Processing**

# Speech Signal Processing- General Pipeline



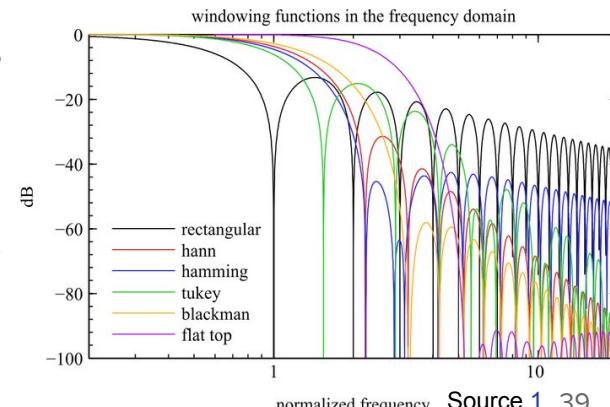
- **Analog audio** input reaches the microphone
- **AAF:** Anti-aliasing filter (AAF) is applied (the analog audio is on infinite frequency response, hence we need to truncate it to a finite one, done in an analog manner because once we will sample the signal we will have aliasing)
- **A/D convertor:** After applying the AAF, we then convert to digital- both magnitude (amplitude- bits) and sampling (discrete- time).
- **DC Removal:** Usually we subtract mean to remove biases due to acquisition problems

# Speech Signal Processing- General Pipeline

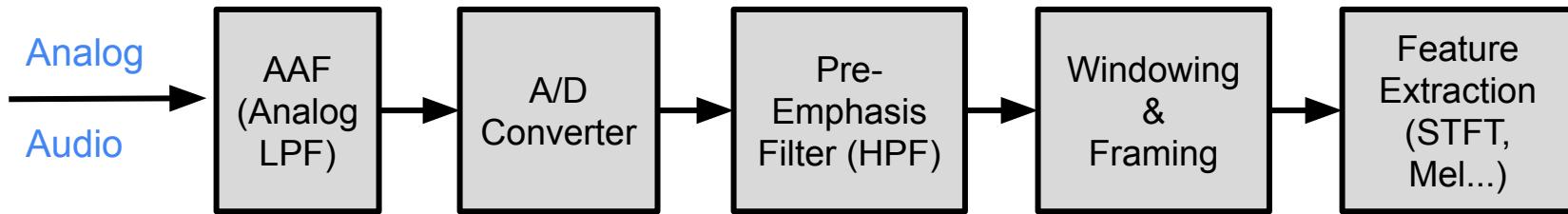


- **Pre-emphasis Filter:** The natural attenuation that arises from voice source is about -12 dB/octave. Pre-emphasis makes higher frequencies of voiced sounds more apparent
- **Windowing:**
  - Non-stationary signals are processed in short frames (assumed stationary) that are overlapping with each other.
  - Typical frame length  $\sim 20\text{-}40$  msec, overlapping  $\sim 30\text{-}75\%$
- **Framing:** Windowing reduces the effect of the spectral artefacts that arise from discontinuities at the frame endpoints. Typically Hamming window is used

$$H(Z) = 1 - \alpha Z^{-1}$$
$$y[n] = x[n] - \alpha x[n-1]$$
$$\alpha \approx 1$$

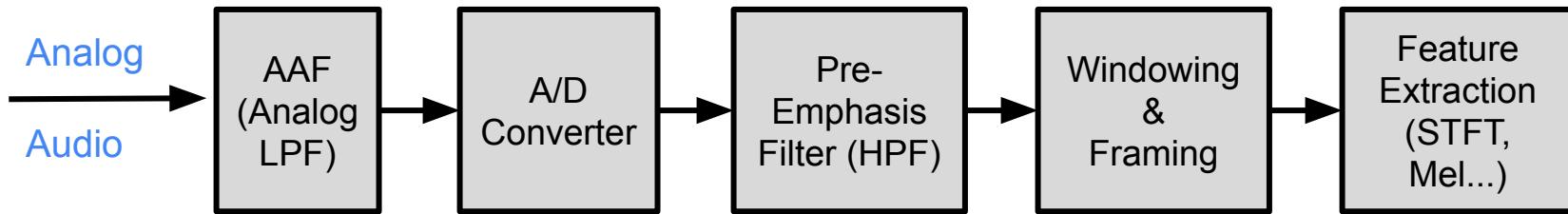


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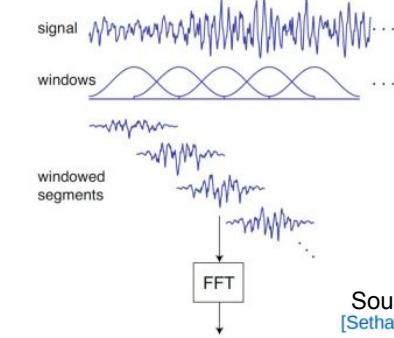
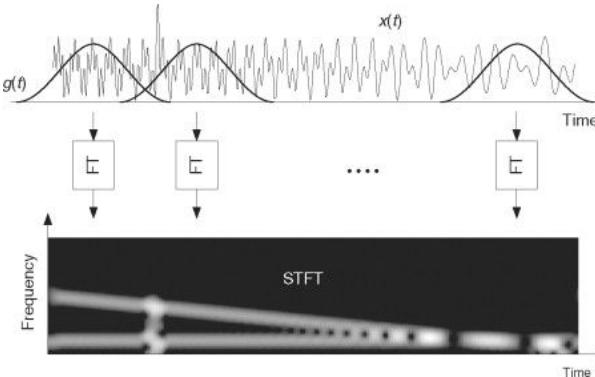
- Feature extraction:
  - A [link](#) to torch.audio tutorial for playing/manipulating audio

# Speech Signal Processing- General Pipeline

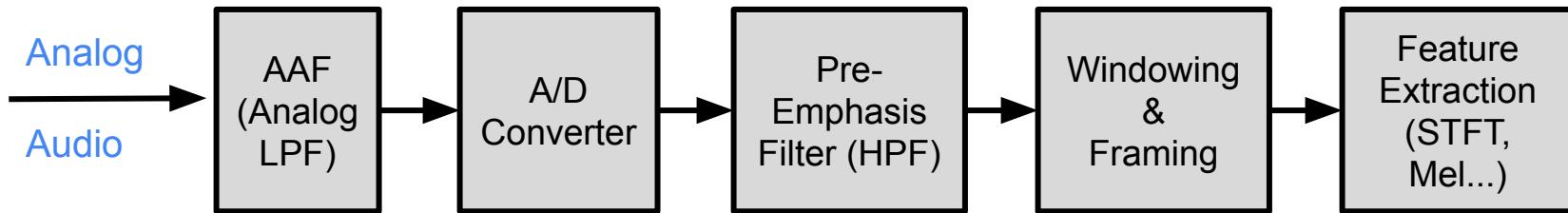


- **STFT:** The most well-known approach to time-frequency analysis makes use of nonparametric, Fourier-based spectral analysis applied to each of the short segments- an operation referred to as the Short-Time Fourier Transform (STFT). In this approach, the definition of the Fourier transform is modified so that a sliding time window  $w[n]$  is included, and defines each time segment to be analyzed, thus resulting in a two-dimensional function.

$$X_n(e^{j\hat{\omega}}) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{-j\hat{\omega}m}$$

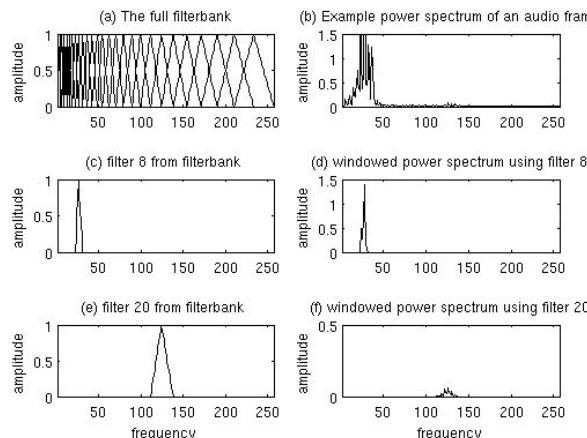


# Speech Signal Processing- General Pipeline

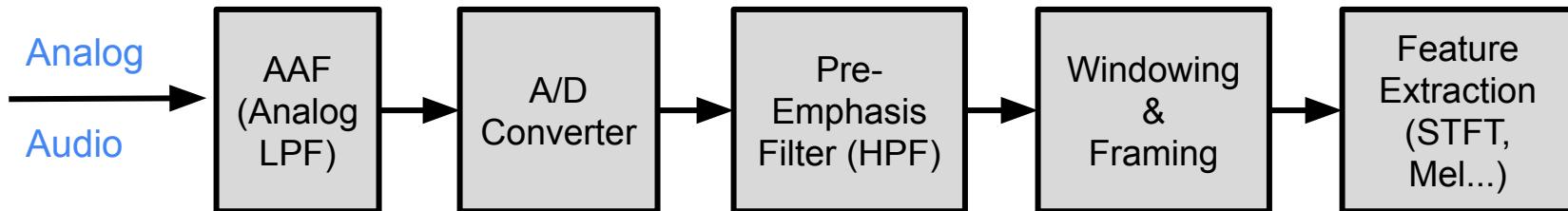


- **Mel Spectrogram:**

- Linear projects. Where the projection matrix is Nfilters X Mag STFT size.
- Typical value: 40-80 filters@16KHz.

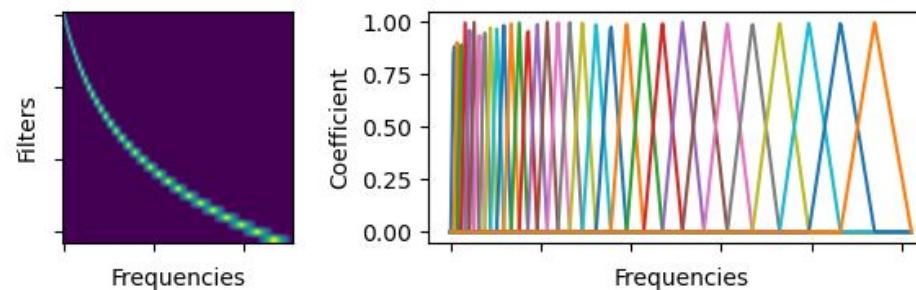


# Speech Signal Processing- General Pipeline

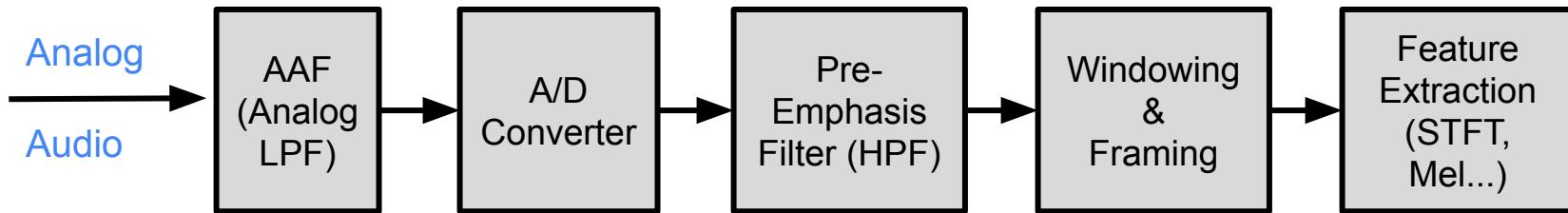


- **Mel Spectrogram:**

- Linear projects. Where the projection matrix is Nfilters X Mag STFT size.
- Typical value: 40-80 filters@16KHz.
- Compression of upper frequencies (according to mel scale- powered by perceptual motivation)

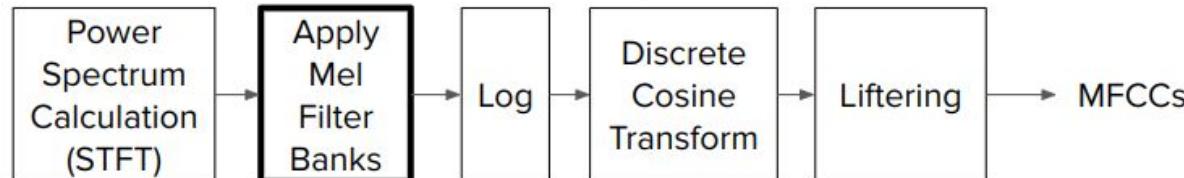


# Speech Signal Processing- General Pipeline

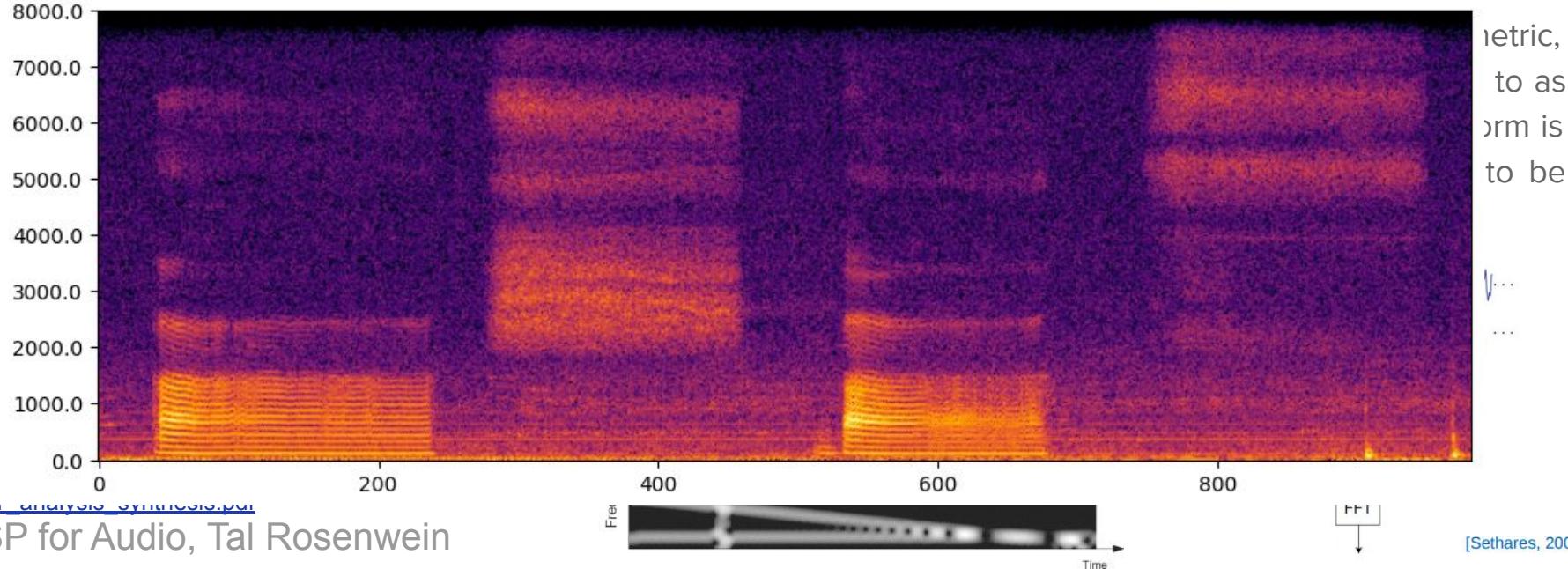
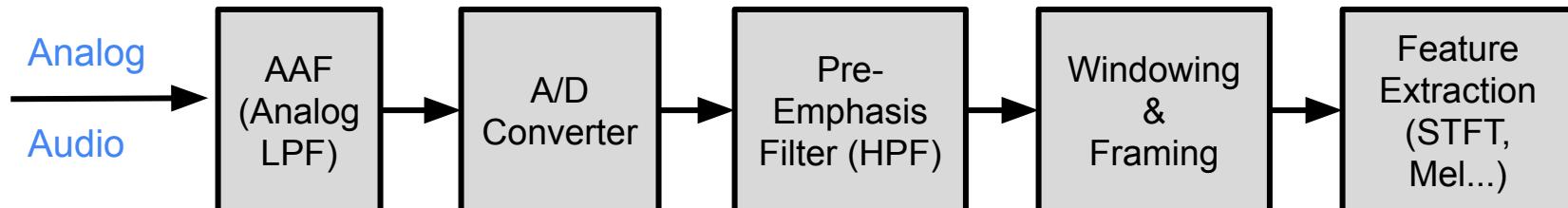


- **MFCCs (Mel Frequency Cepstral Coefficients)**

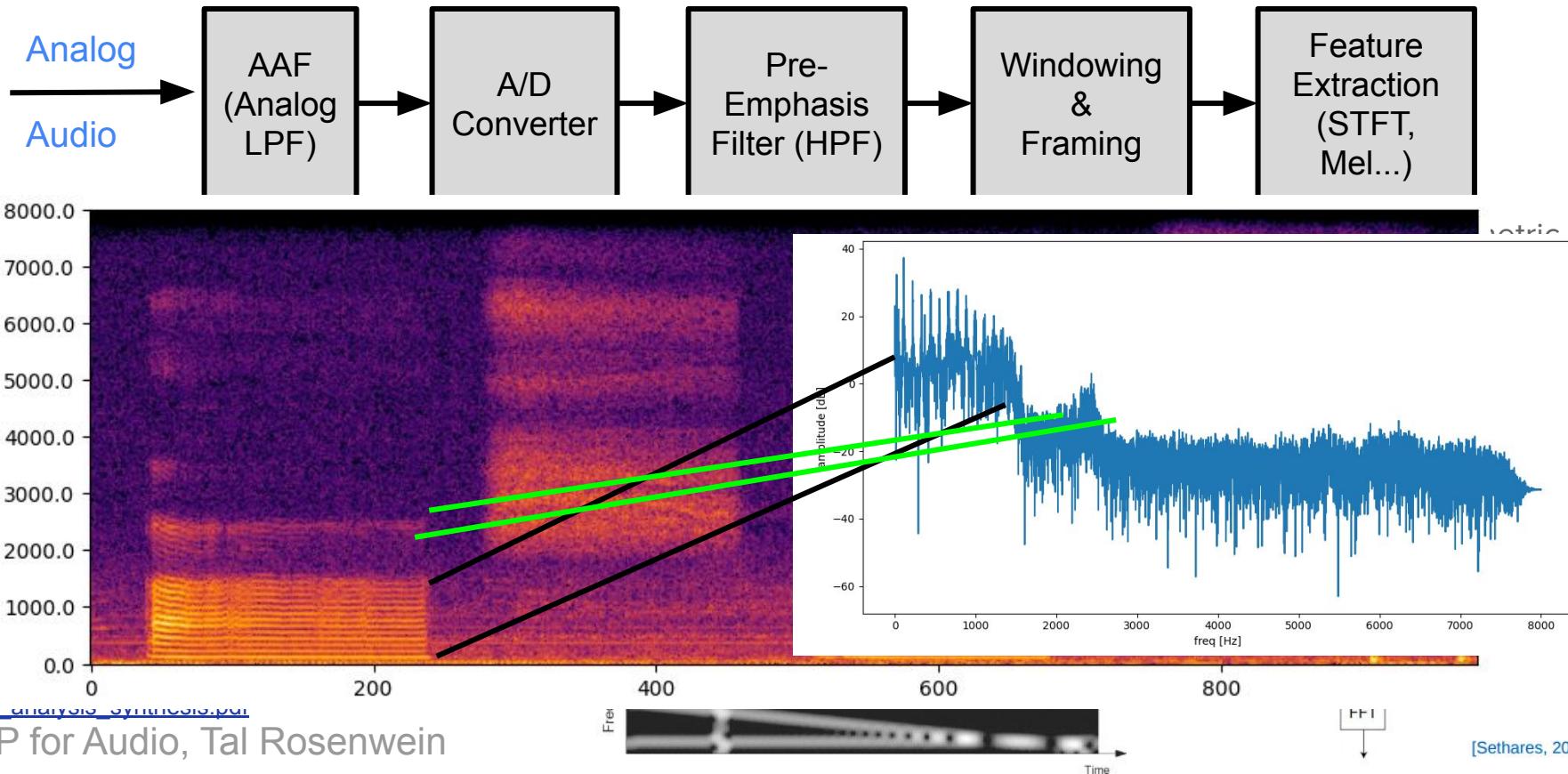
- After receiving Mel filter banks, we apply a series of operations and get the MFCCs.
- Usually 13 coefficients.
- Along with delta and delta-delta (temporal derivatives) which results in 39 coeffs.
- They were widely used due to several reasons, such as interpretation. Will not elaborate as they are currently not in use anymore (only in HuBERT for initialization of the clusters during pre-training).



# Speech Signal Processing- General Pipeline



# Speech Signal Processing- General Pipeline



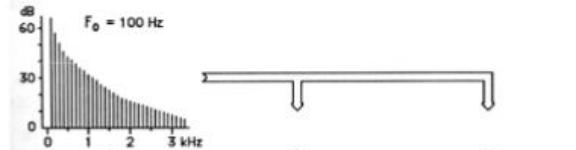
# Speech Production- Source-Filter Model

- The resulting speech spectrum  $S(z)$  is a combination of the source spectrum  $U(z)$  and the vocal tract transfer function  $H(z)$ :

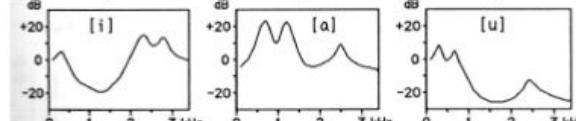
$$S(z) = U(z)H(z) \leftrightarrow s[n] = u[n] * h[n]$$

Frequency domain                          Time domain

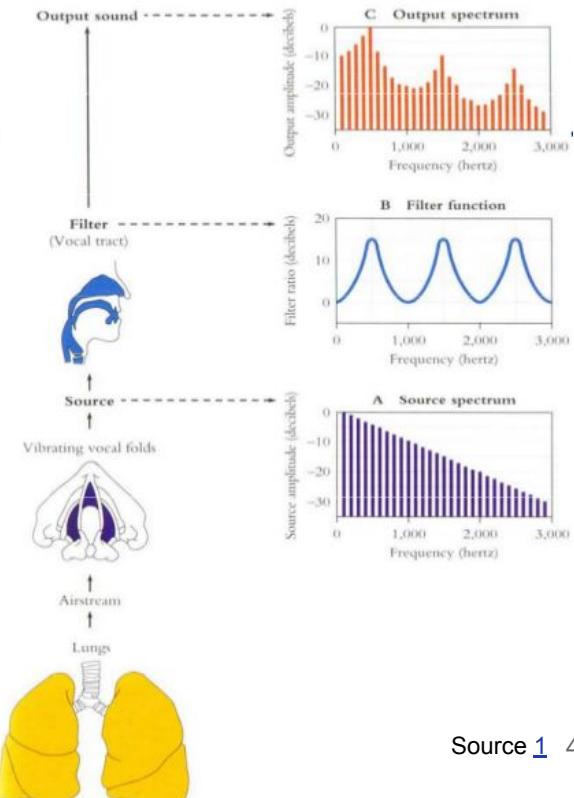
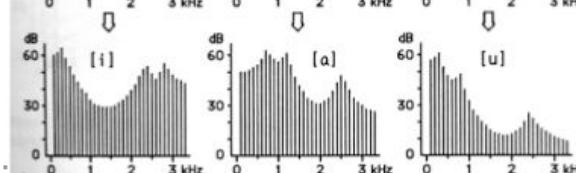
Source



Filter

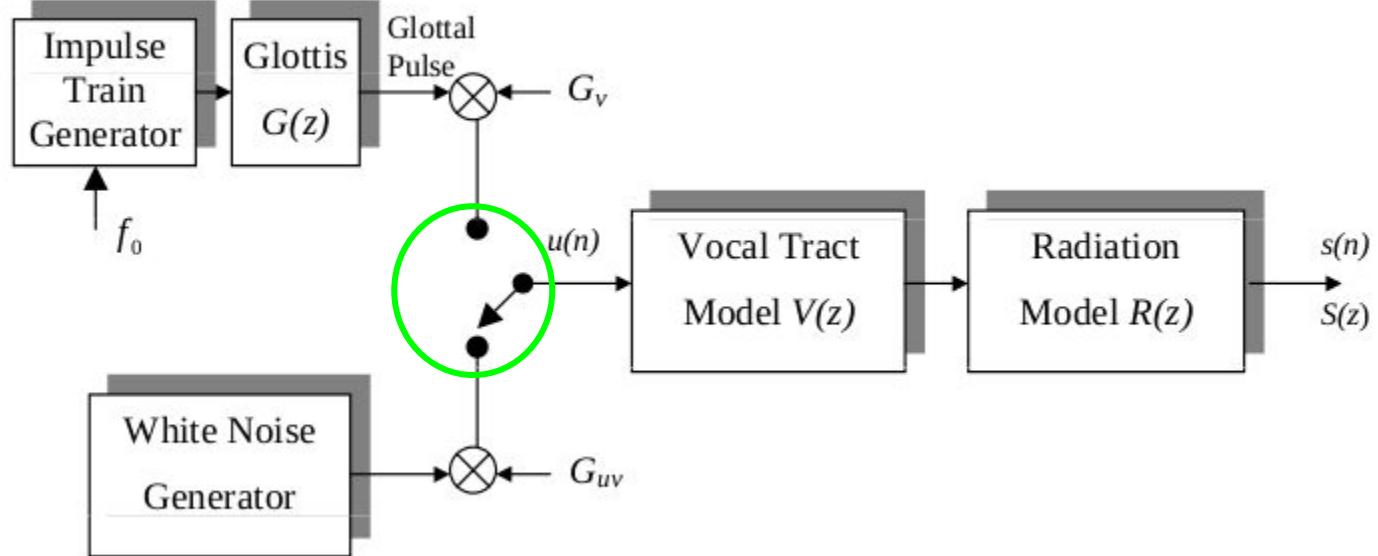


Source and filter combined



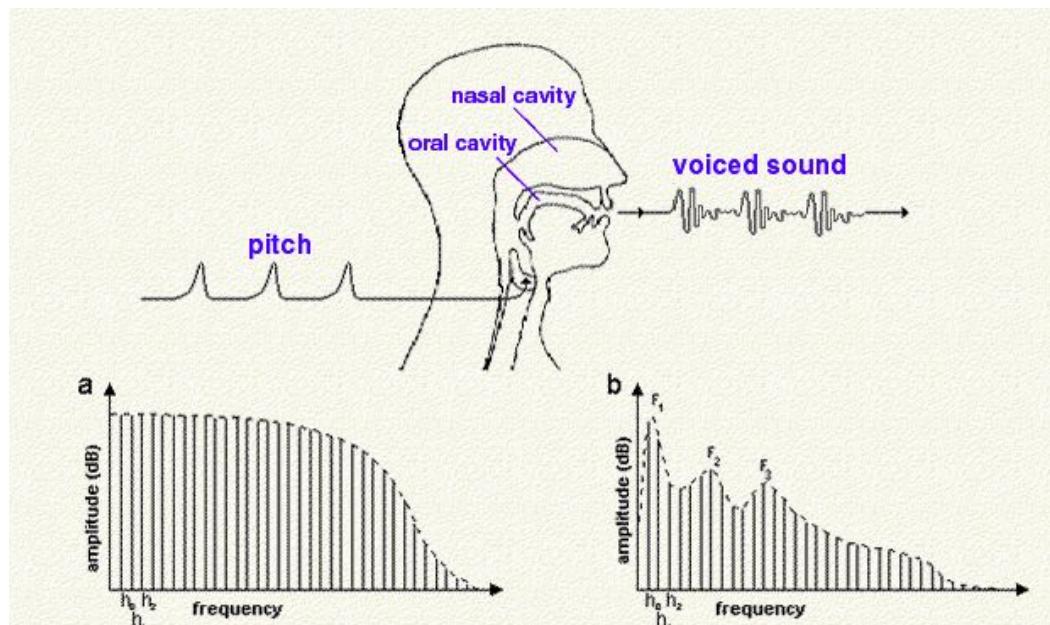
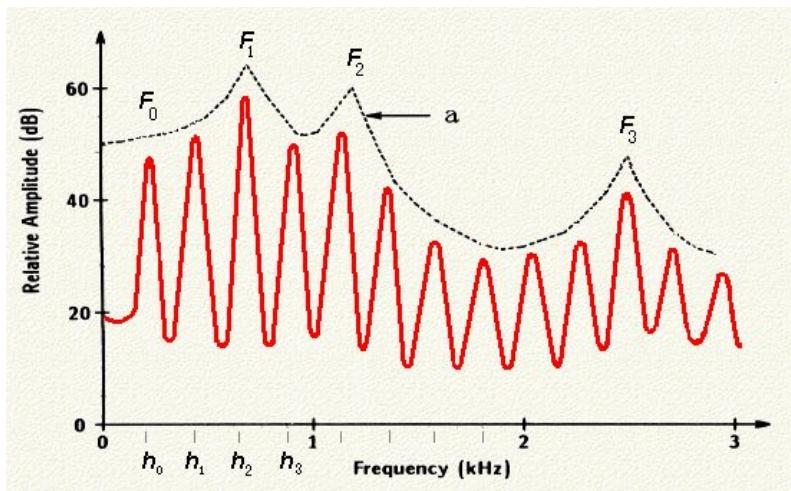
# Speech Production- Source-Filter Model

Voiced



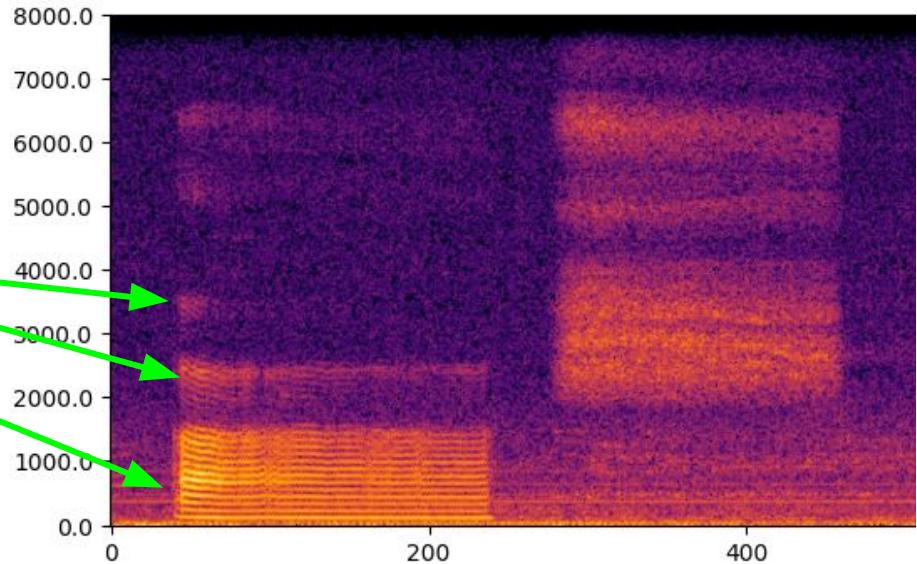
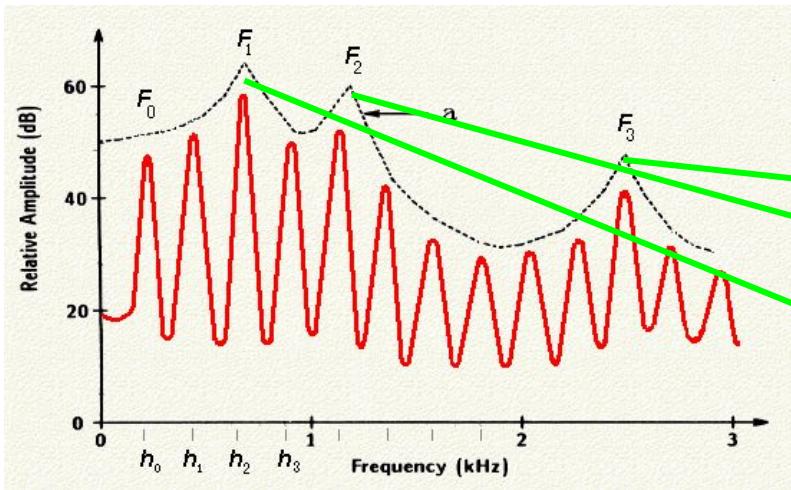
# Speech Signals Analysis

- Pitch, Formants and Spectral Envelope



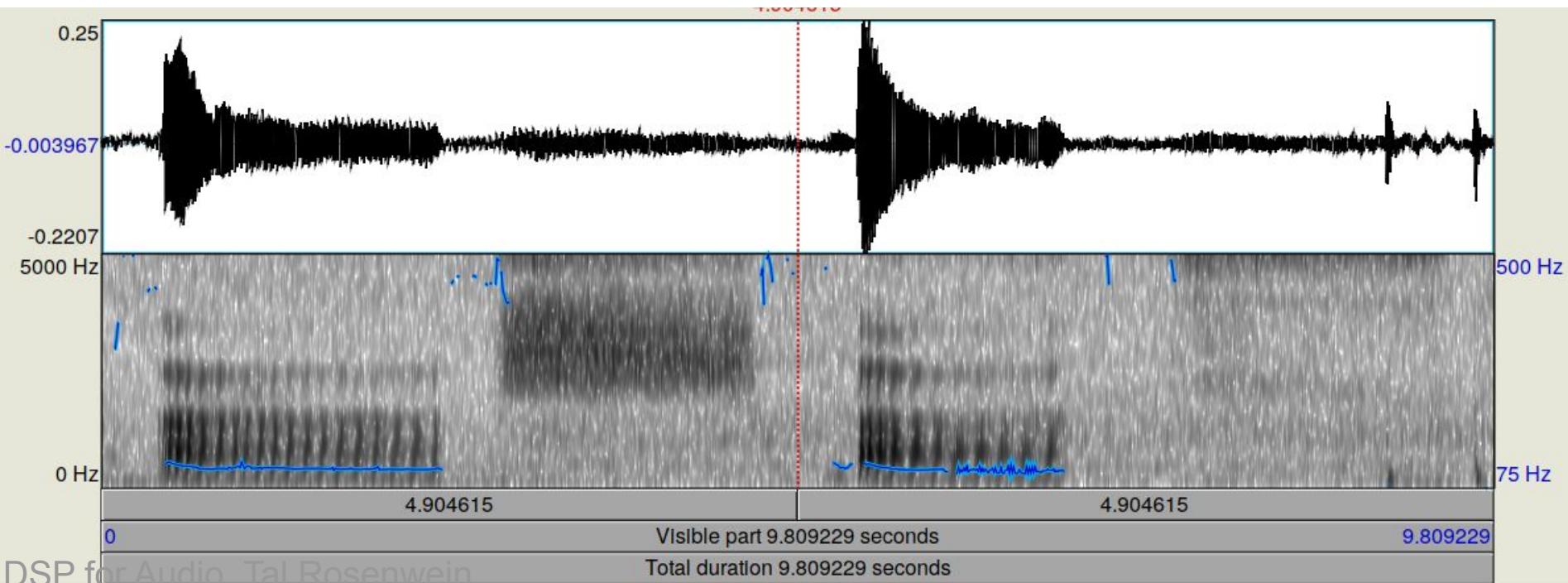
# Speech Signals Analysis

- Pitch, Formants and Spectral Envelope



# Speech Signals Analysis: Pitch Detection

- Various algorithms, such as autocorrelation



# Speech Signals Analysis: Spectral Envelope

- Linear Predictive Coding (LPC)
- Parametric method for representing the **spectral envelope** in a compressed form (was the basis of VoIP). The process is done on frames due to non-stationarity property of the speech signal.

Assuming that the stationary signal  $s[n]$ , where  $n=1,2,\dots,N$ , is the output of the system which can be described by (Eq. 1.14) [3]

$$s[n] = -\sum_{i=1}^p a_i^* s[n-i] + G^* u[n] \quad 1.14$$

Where  $a_i^*$  are the linear predictive coefficients which generated the system,  $u[n]$  is the input in the  $n$ 'th sample and  $G^*$  is the gain of the system.

# Speech Signals Analysis: Spectral Envelope

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From Eq. 1.14 one can see that  $s[n]$  is given a linear combination of its past values summed with the input of the system  $u[n]$ . Applying the Z transform on both sides of Eq. 1.14 yields (Eq. 1.15)

$$H(z) = \frac{S(z)}{U(z)} = \frac{G^*}{1 + \sum_{i=1}^p a_i^* z^{-i}} \quad 1.15$$

# Speech Signals Analysis: Spectral Envelope

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We expect that as the model order will increase the prediction error will decrease (Eq. 1.22).

$$\lim_{p \rightarrow \infty} E[e^2[n]] = 0 \quad 1.22$$

Though, as we increase the number of parameters, we will get an estimation which is closer to the real values. This can become a disadvantage when we want to model "typical pattern" of the phonemes. Since this model will be modeling the non-relevant artifacts as well (including the Pitch). Therefore we would like to have model order that emphasizes the relevant formants.

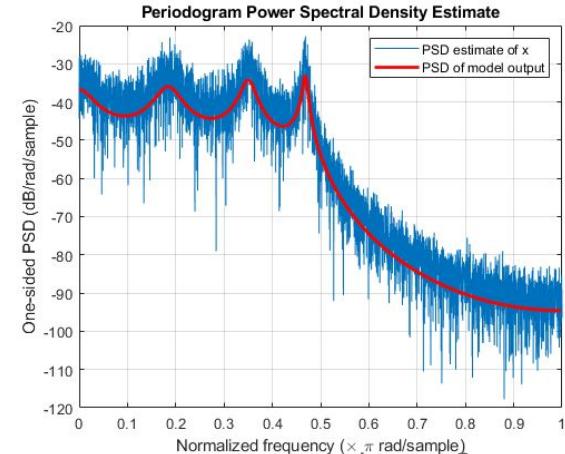
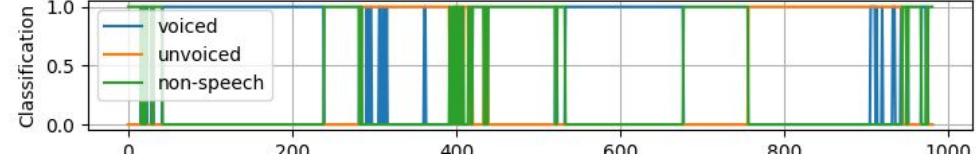
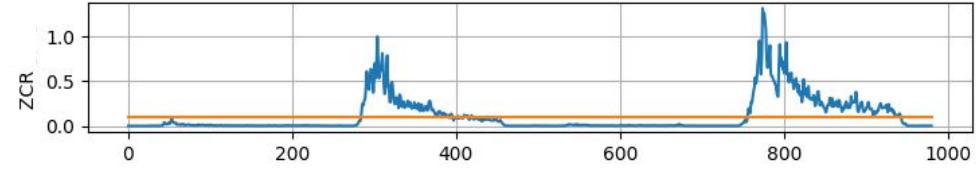
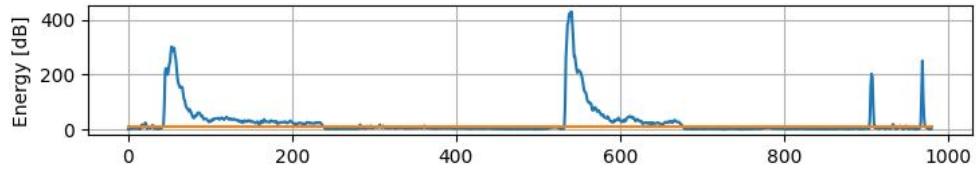
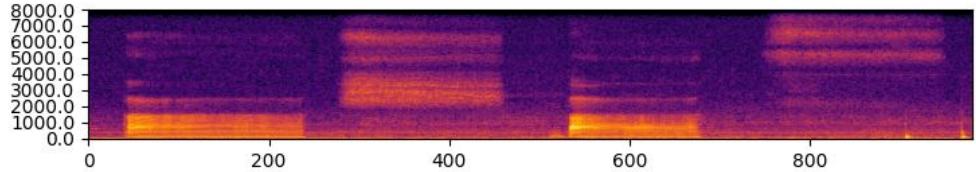


Image Source 1

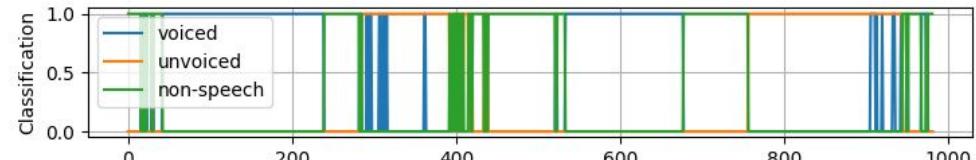
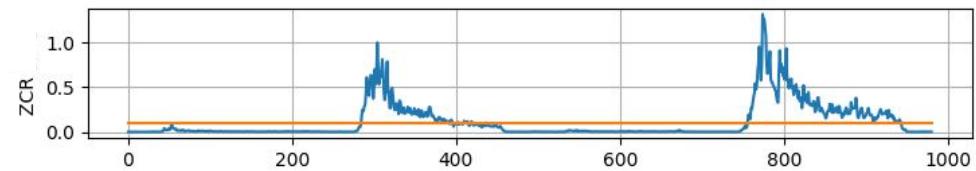
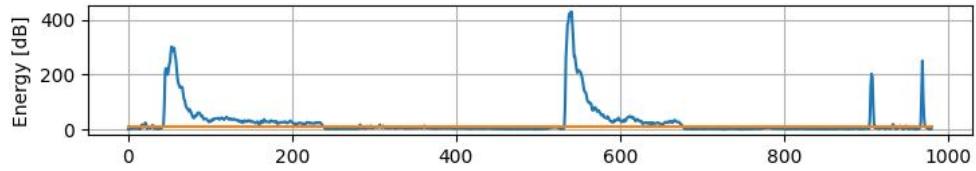
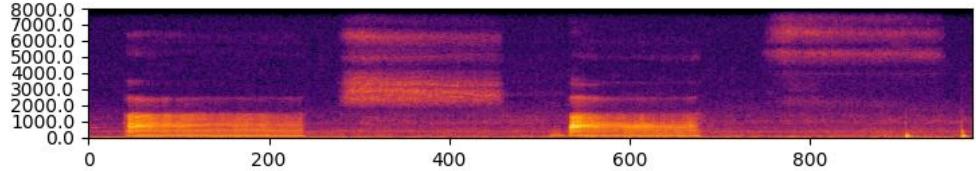
# Speech Signals Analysis: Classification

- Naive Classification:
  - Speech Vs non-speech: Energy
  - Unvoiced: Zero Crossing Rate (ZCR)
  - Voiced: The rest



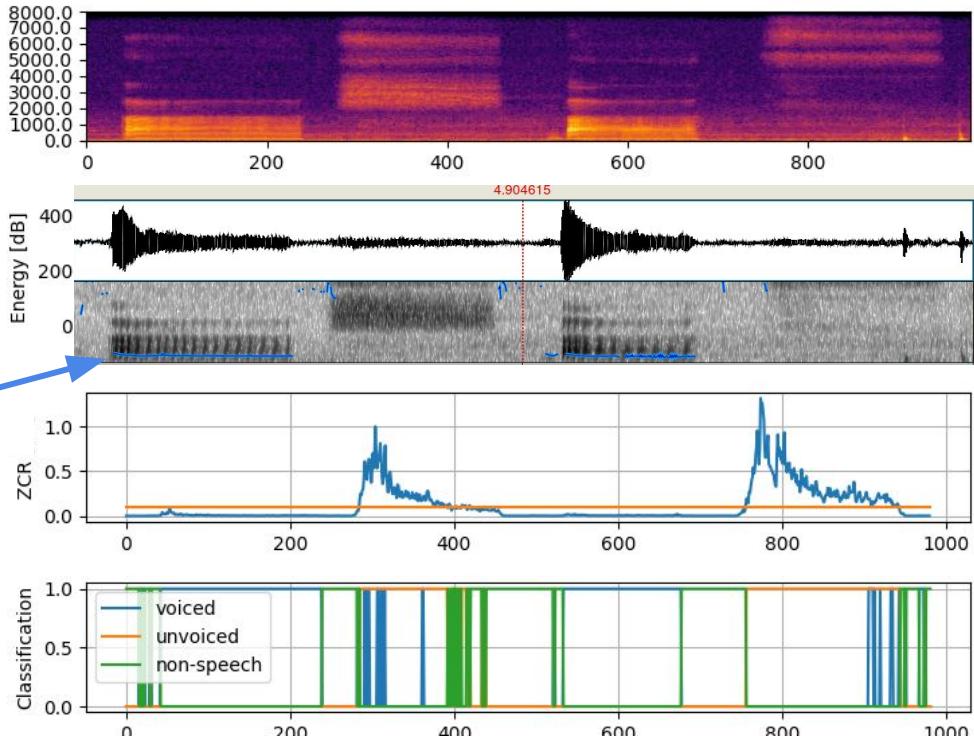
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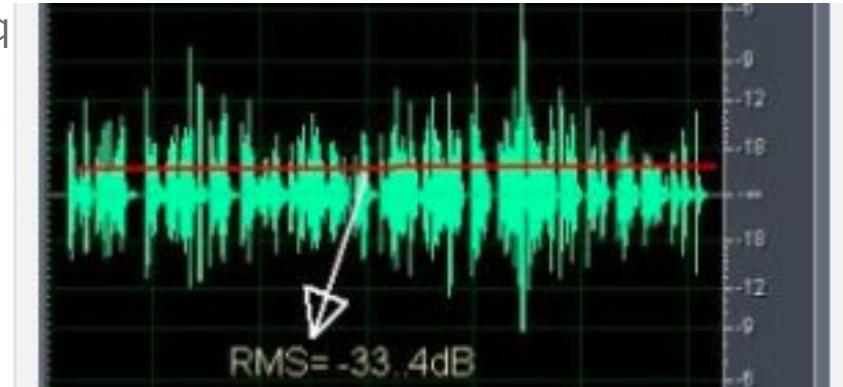
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# Speech Signals Analysis: Energy & RMS

- Sometimes we want to represent some “trends” of signal, but its average has a (zero) constant value.
- 2 accepted measures for an ‘alternative’ average: RMS and Energy
  - RMS: Root-Mean-Squared. Most books define this as the “amount of AC power that produces the same heating effect as an equivalent DC power”
  - Energy: defined as the area under the sq
- Usually calculated in **chunks with hop**.

$$E_s = \sum_{n=-\infty}^{\infty} |x(n)|^2 \quad RMS = \sqrt{\frac{1}{n} \sum_i x_i^2}$$



# Overview

- Motivation
- Communication
- Anatomy & Speech production system
- Phonetics
- Acoustic/Speech Features
- **Traditional Speech Signals Analysis**
  - Time Stretching
  - Speech Enhancement- Spectral Subtraction
  - Auto Gain Control (AGC)
  - Audio Compression

# Applications



# Applications



## Challenges:

1. Delayed signal / packet lost - Time stretching
2. Noisy environment - Noise reduction
3. Speakers with multiple gains - Auto gain control
4. Audio Clipping - Audio Compression
5. Connectivity issues - Variable bitrate vocoders

# Applications



## Challenges:

- |                                   |                           |
|-----------------------------------|---------------------------|
| 1. Delayed signal / packet lost - | Time stretching           |
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# Applications: Time Stretching

- Many applications require to align input and output audio, as in soundtracks. Or we want to hear a YouTube video in a different rate than it was recorded.
- Hence, we would like to change the speed of the wav file
- Doing the naive way:

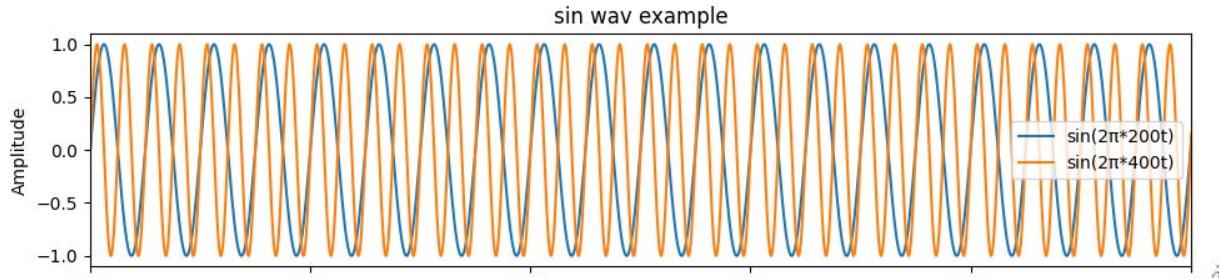
$$f(x) \rightarrow \Im(w) = \int_{-\infty}^{\infty} f(x)e^{-jwx}dx$$

$$f(ax) \rightarrow \frac{1}{|a|} \Im\left(\frac{w}{a}\right)$$

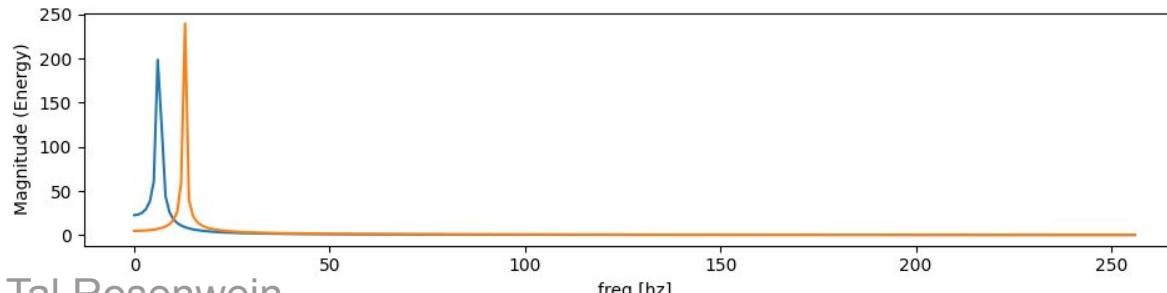
$$\Im(f(ax)) = \int_{-\infty}^{\infty} f(ax)e^{-jwx}dx = |x = ax, dx = \frac{d\bar{x}}{a}| = \int_{-\infty}^{\infty} f(\bar{x})e^{-j\frac{w}{a}\bar{x}} \frac{1}{a} d\bar{x}$$

# Applications: Time Stretching

- Doing the naive way will change the pitch

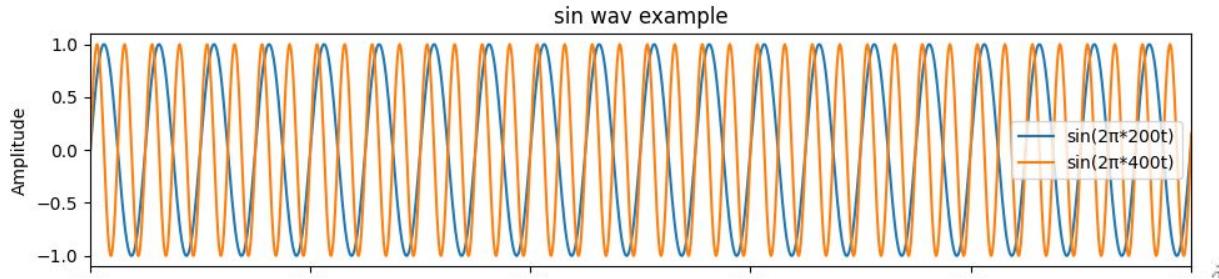


Speeding up the audio  $\rightarrow$  period is shorter  $\rightarrow$  increasing frequency

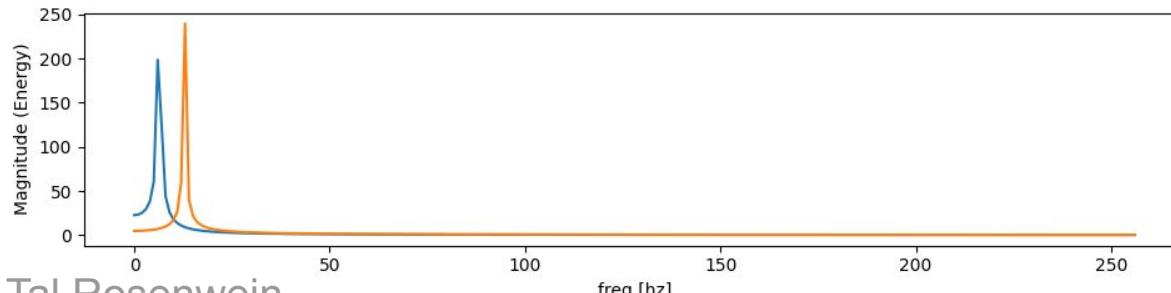


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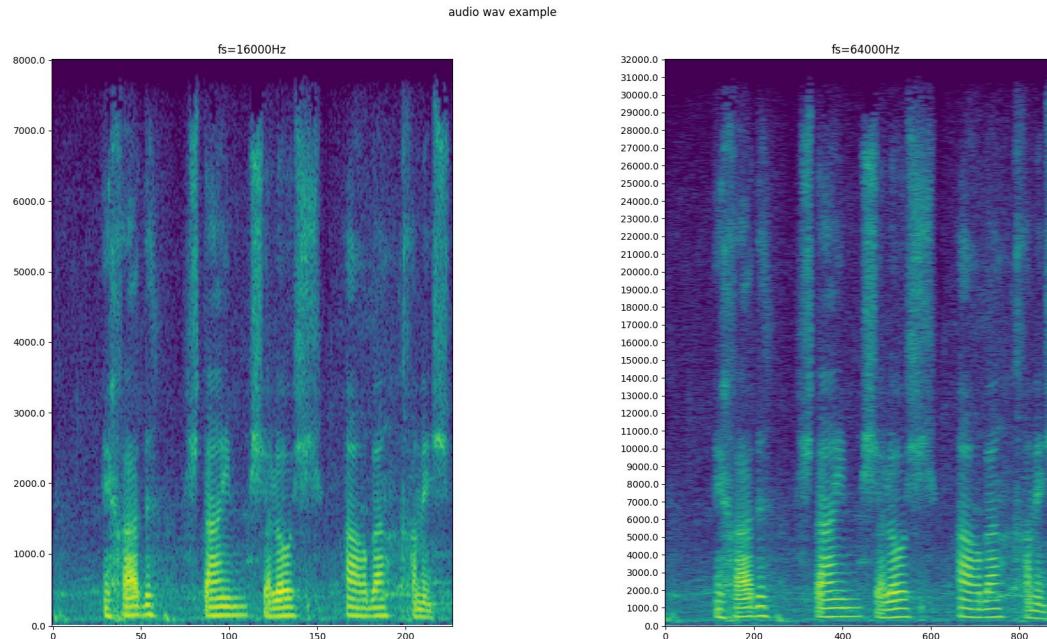


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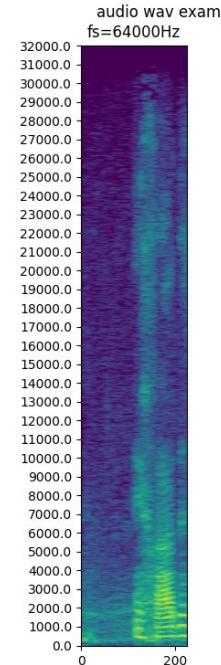
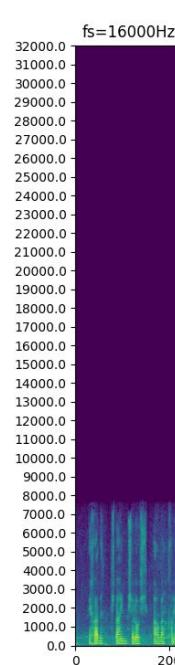
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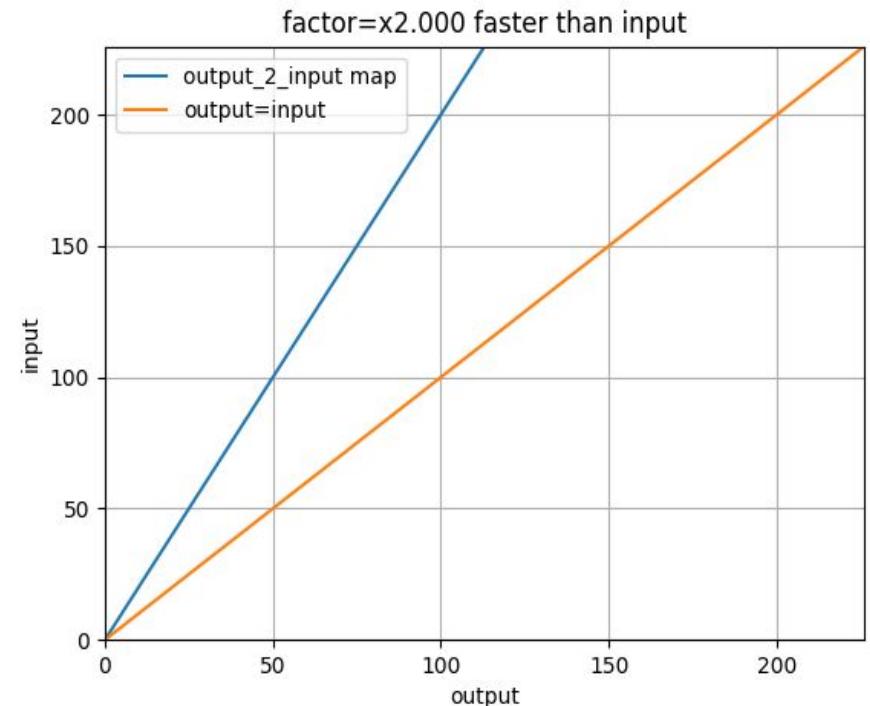
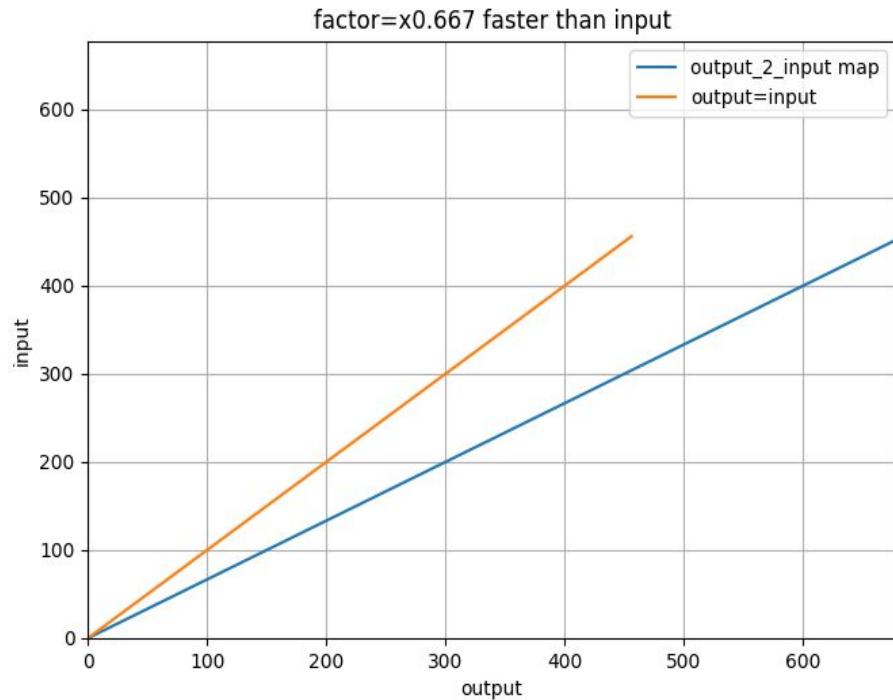
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  - Set the alignment between input and output times
    - Must be monotonic w.r.t the input
    - Can be fixed / non-fixed alignment

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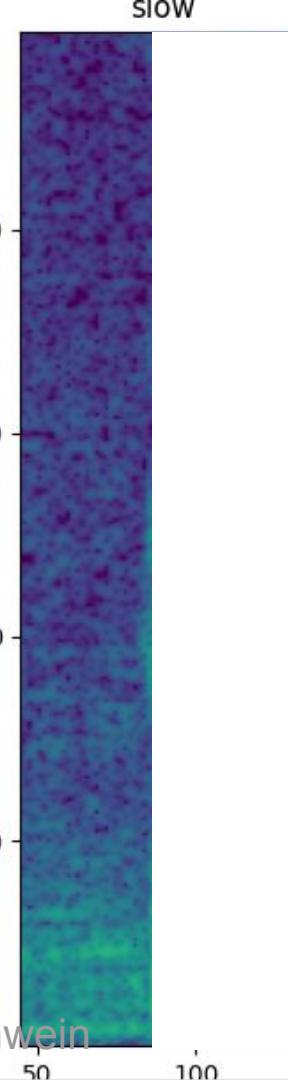


# Applications: Time Stretching

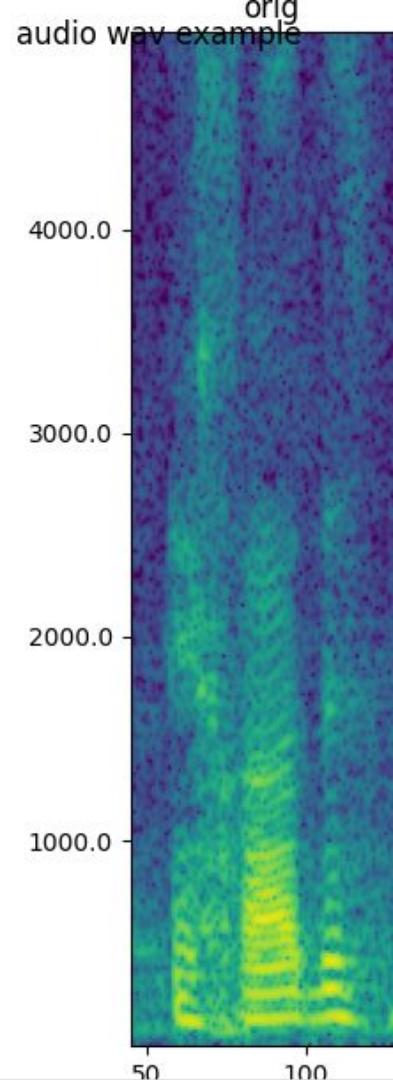
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# Applicat

- We need to much distortion
- **Phase Voc**
  - Set the
  - N
  - C
- **Iterate**
  - C
  - C



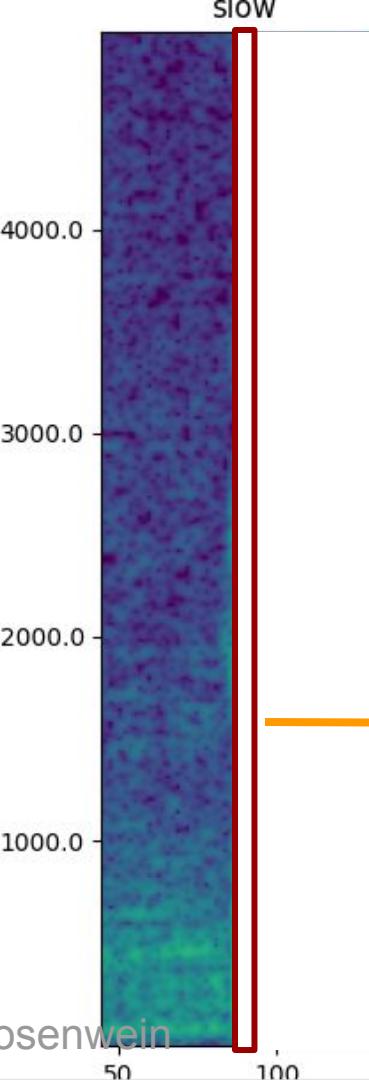
out\_t=90



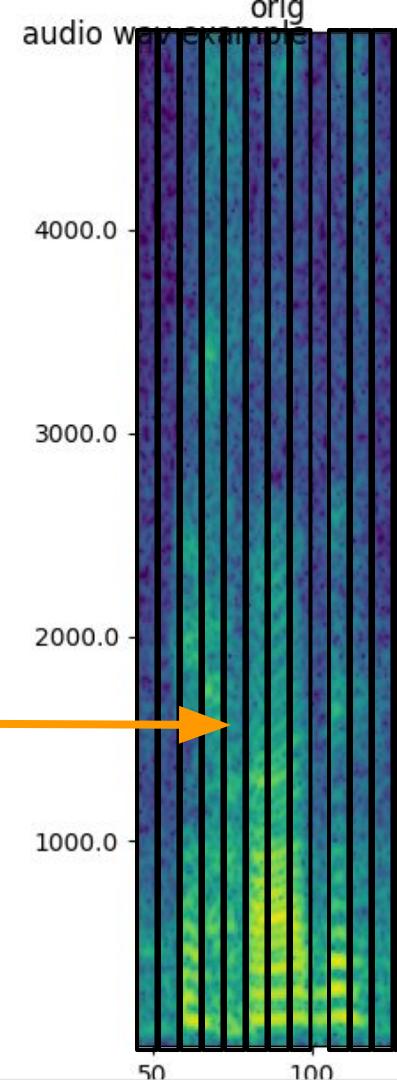
ch without too  
output should  
at time, and  
n  
neighbours values.

# Applications

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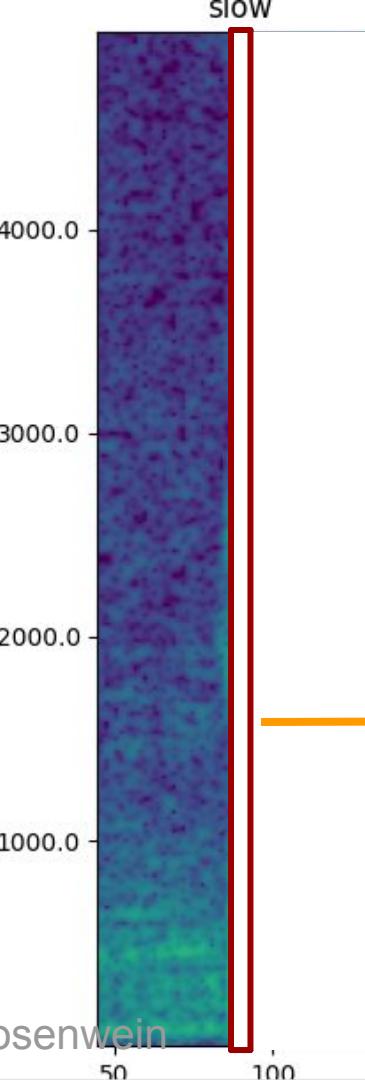
out\_t=90  
in\_t=55.2



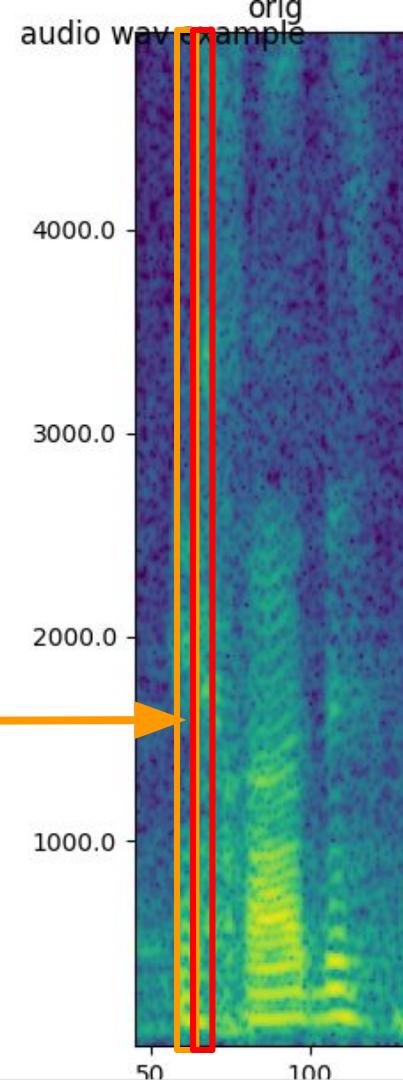
• Output without too much distortion.  
• output should be at time, and  
• n neighbours values.

# Applications

- We need to slow down without too much distortion
- **Phase Vocoding**
  - Set the parameters:
    - $N = 100$
    - $C = 0.5$
  - Iterate
    - $C = \frac{C + \text{mean}(C_{\text{neighbours}})}{2}$



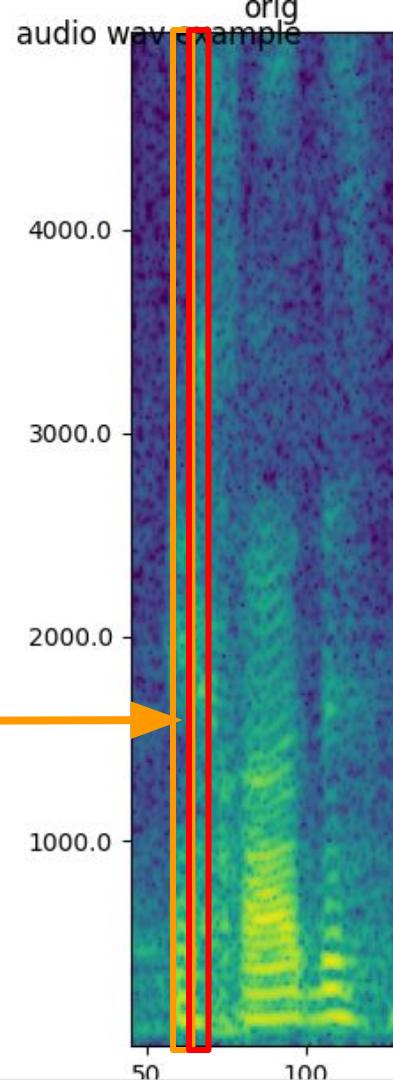
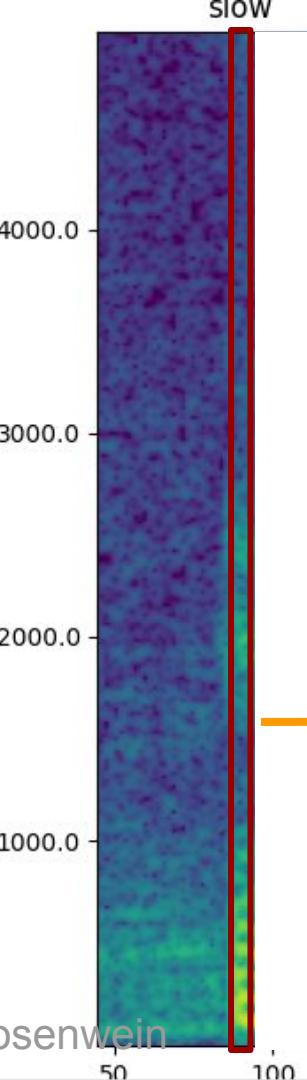
out\_t=90  
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• output should be at time, and  
•  $C = \frac{C + \text{mean}(C_{\text{neighbours}})}{2}$

# Applications

- We need to  
much distortion
- **Phase Vocals**
  - Set the  
■ N
  - C
- **Iterate**
  - C
  - C



out\_t=90  
in\_t=55.2

$$\text{Out\_Mag}[90] = 0.8 * \text{In\_Mag}[55] + 0.2 * \text{In\_Mag}[56]$$

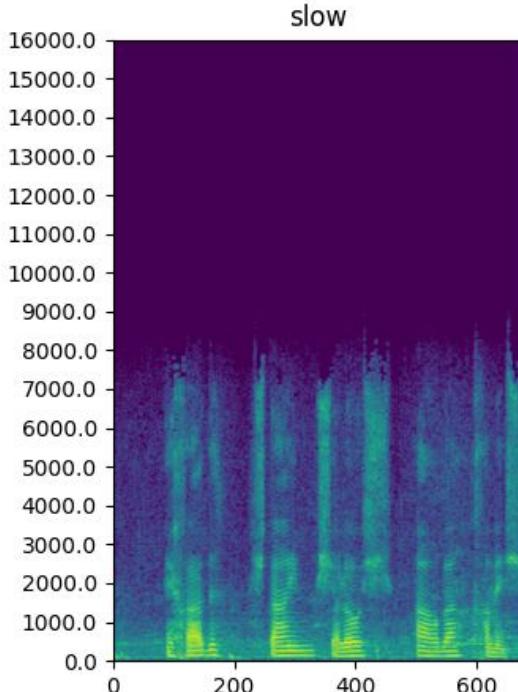
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# Applications: Time Stretching

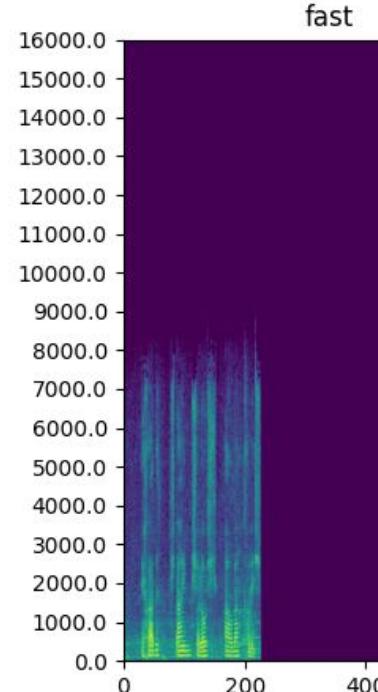
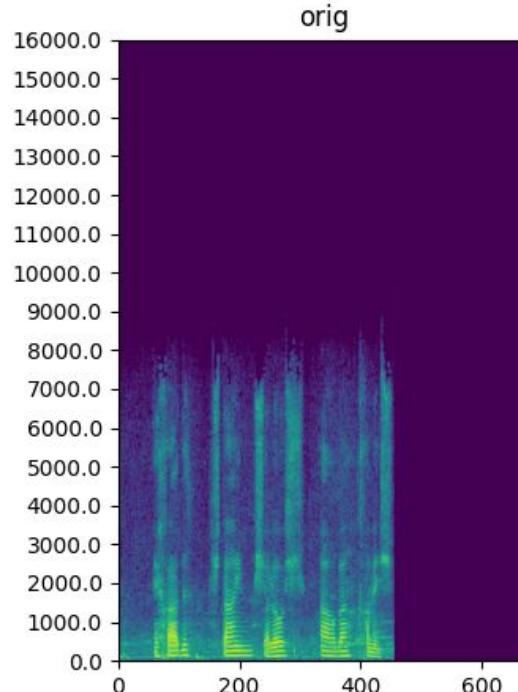
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      - **Mag:**Find nearest neighbour within the input vector for that time, and interpolation between adjacent frames in the spectrogram
      - **Phase:** Add prev value to the diff between the nearest neighbours values. (keep the rate of change similar as the input)
    - Append to prev value to form the output STFT.

# Applications: Time Stretching

- 
- 



audio wav example



(keep the rate of change similar as the input)

# Applications: Time Stretching

- We need to find **an approximation** that will stretch while keeping the pitch without too much distortion.
- **Phase Vocoder**
  - Example
- Learnable methods ([ScalerGAN](#))

# Applications



## Challenges:

1. Delayed signal / packet lost - Time stretching
2. **Noisy environment** - **Noise reduction**
3. Speakers with multiple gains - Auto gain control
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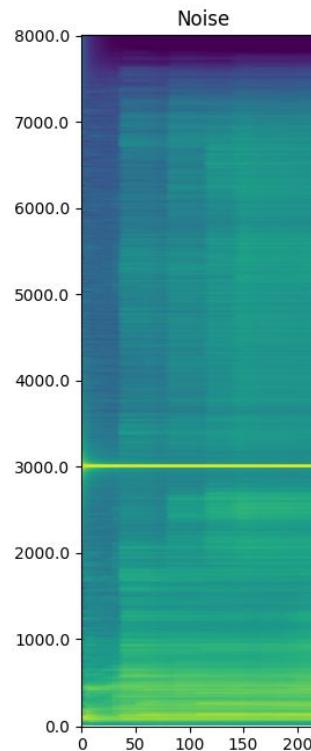
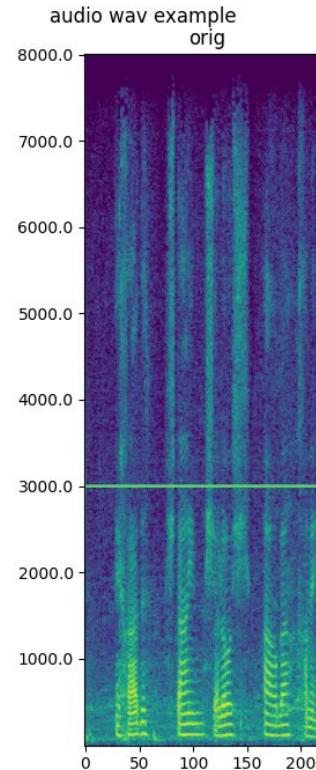
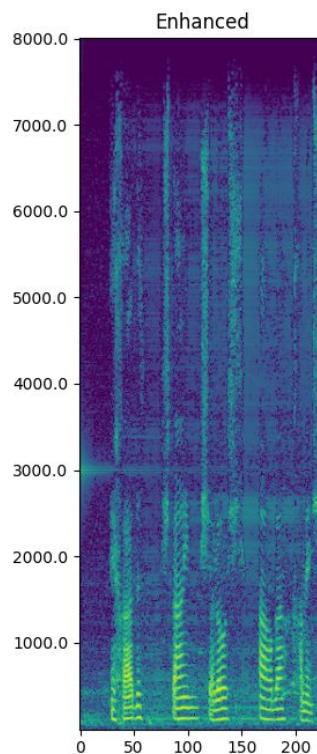
# Applications: Speech Enhancement

- When we record audio it is noisy as the we are not in studio.
- We would like to remove background noise from the acquired signal

$$y[n] = x[n] + s[n]$$

- Where: **y[n]** is the acquired signal, **x[n]** is the desired signal, and **s[n]** is stationary background noise signal

# Applications: Speech Enhancement

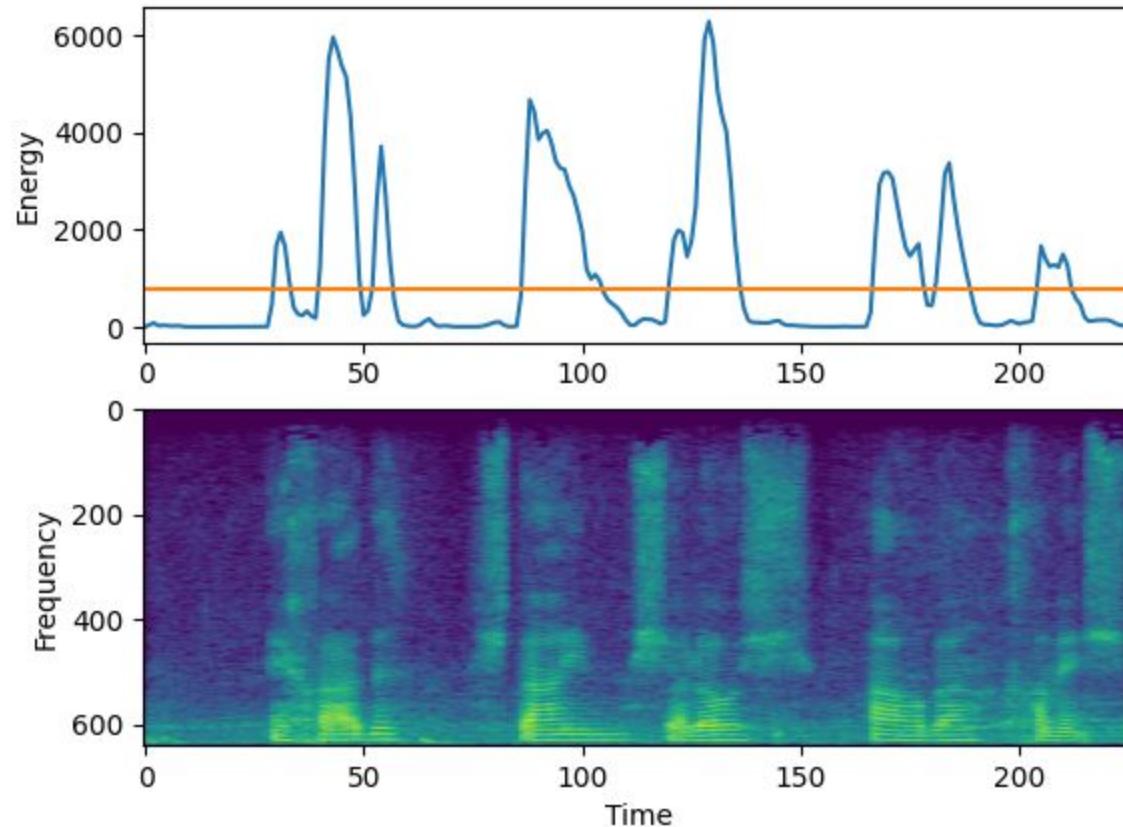


# Applications: Speech Enhancement

- Approach: Subtract the estimated noisy magnitude from the acquired signal.
- Therefore, we need to estimate the noise:
  - **Locate segments / frames where there is no speech (using VAD)**
  - Aggregate statistics to a buffer: (determine buffer size)
  - Average the buffer to form the noise estimation (assuming non stationary signals will be averaged out)
  - Subtracting the noise estimation from the input signal  $y[n]$

# Applica

- Approach:
- Therefore
  - Loca
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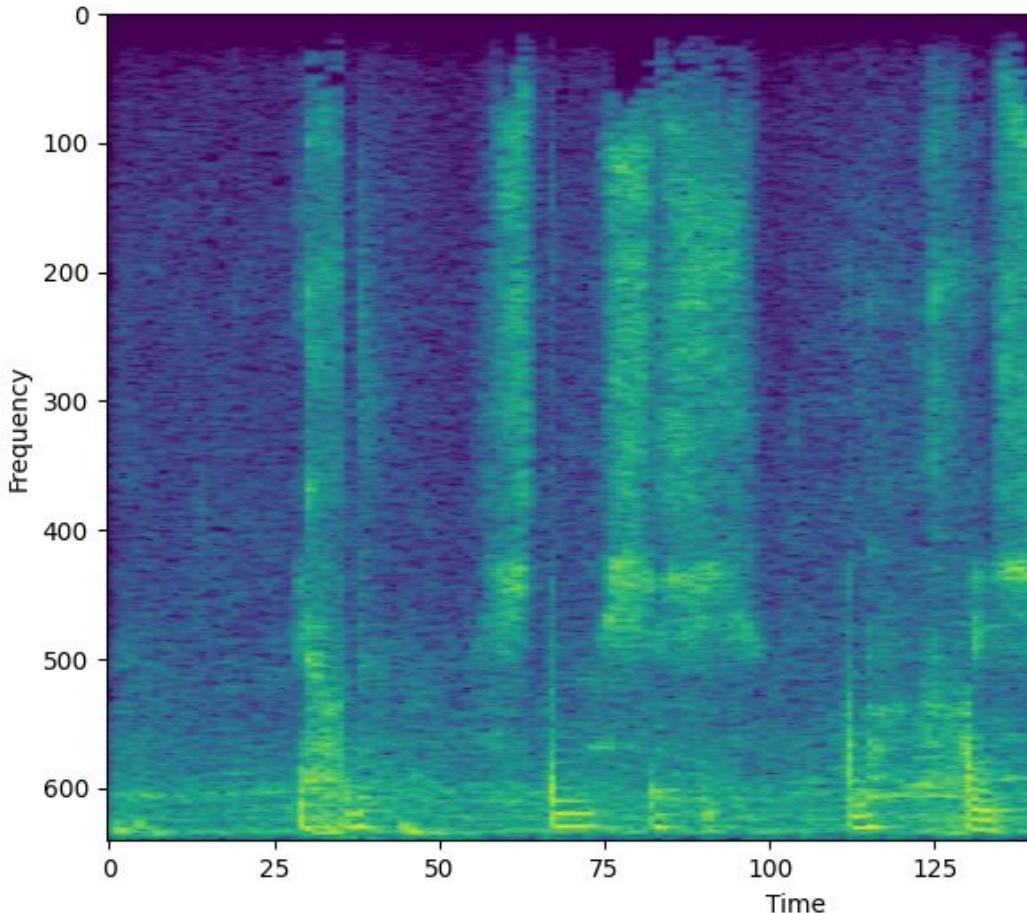
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from the acquired signal.

speech (using VAD)  
**buffer size)**

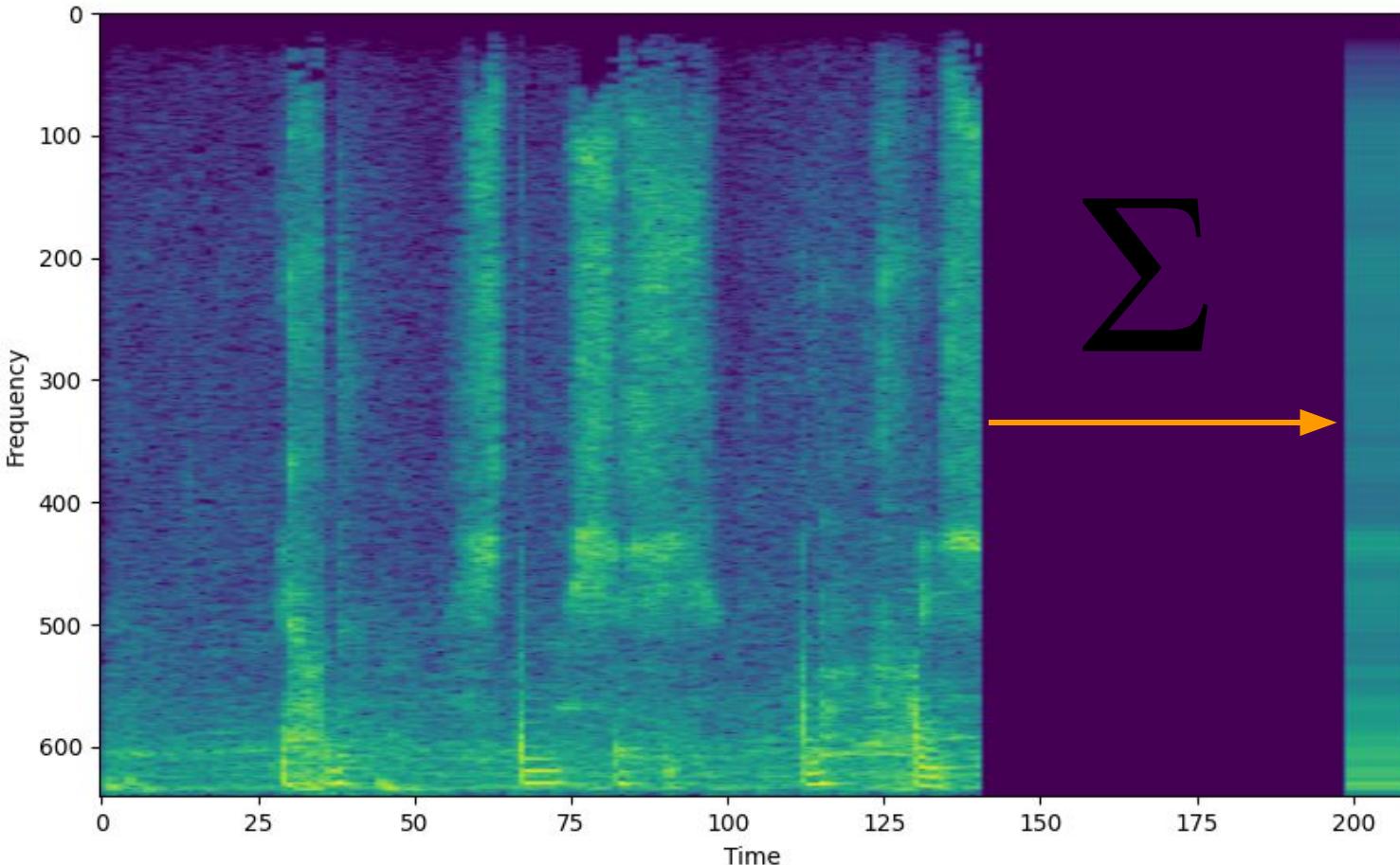
(assuming non stationary signals will

: signal  $y[n]$



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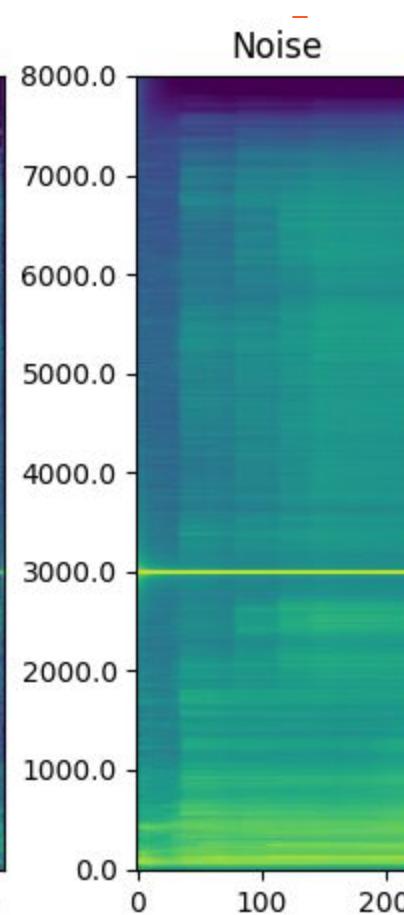
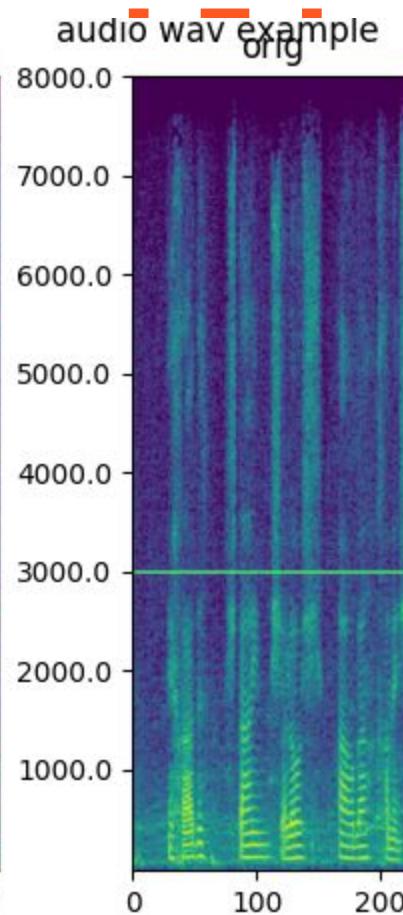
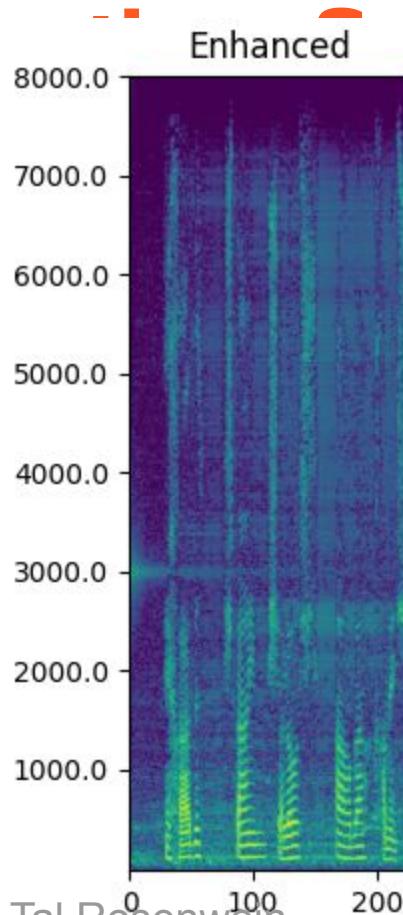
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# Appli

- Apprc
- There



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inary signals will

# Applications: Speech Enhancement

- Python and Audacity examples
- Challenges:
  - Updating vs freezing the noise estimation vector: pros and cons
  - Musical noises may appear when filtering is too aggressive:

$$o[n] = \alpha y[n] + (1 - \alpha) \bar{x}[n]$$

- Learnable methods (DEMUCS)

# Applications



## Challenges:

1. Delayed signal / packet lost - Time stretching
2. Noisy environment - Noise reduction
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4. Audio Clipping - Audio Compression
5. Connectivity issues - Variable bitrate vocoders

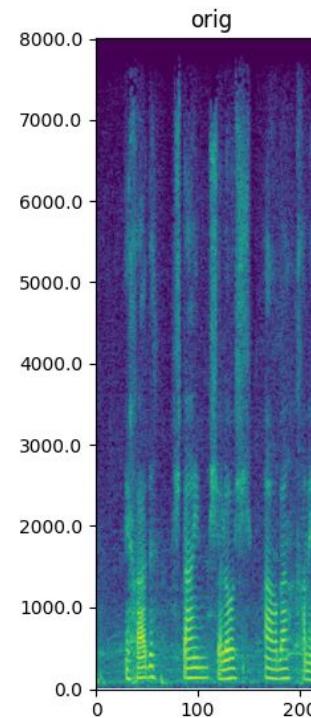
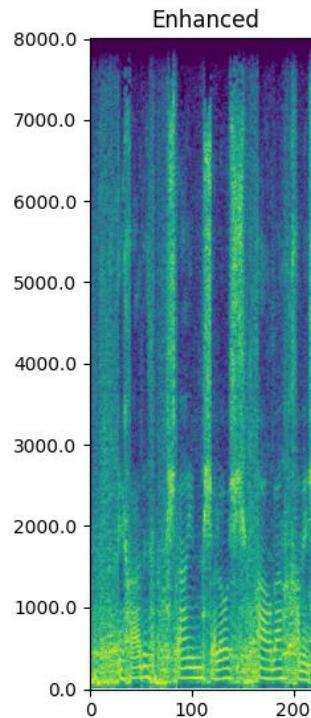
# Applications: Auto Gain Control

- In many cases we would like to have a constant “volume” regardless of how the speaker is speaking.
  - Our algorithm is sensitive to RMS
  - Our users are sensitive to RMS
- Hence we need to determine the desired RMS and normalize the audio accordingly
  - Applying the same factor to all frames will result in a constant amplification
  - So we need to do it frame-by-frame

# Applications: Auto Gain Control

audio wav example

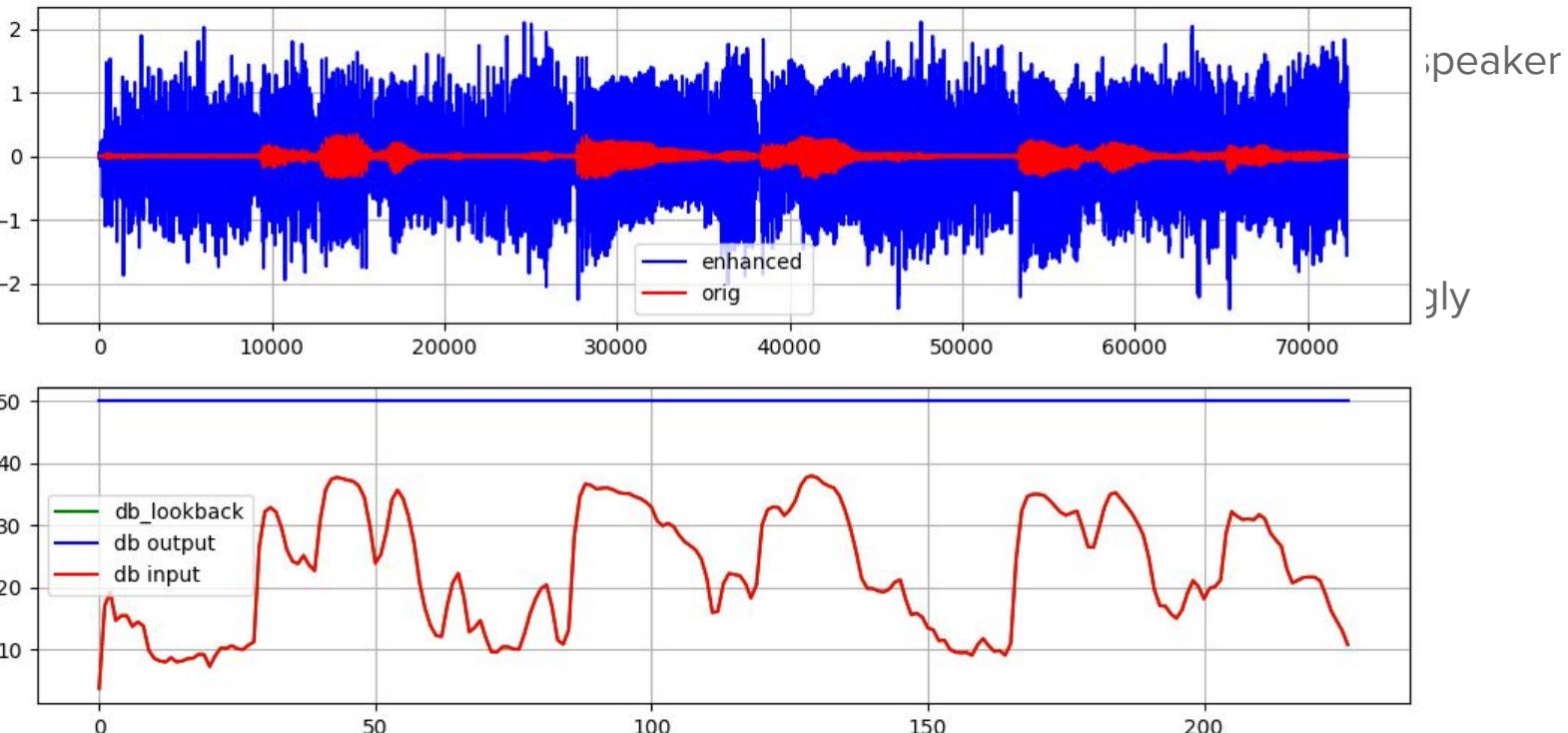
- In many cases we want to hear what the speaker is speaking.
  - Our algorithm does this automatically
  - Our users can control it
- Hence we need to increase the volume
  - Applying the AGC
  - So we need to know how the speaker is speaking



of how the speaker is speaking  
dio accordingly  
nplification

# Applications: Auto Gain Control

- In this slide
- Here



# Applications: Auto Gain Control

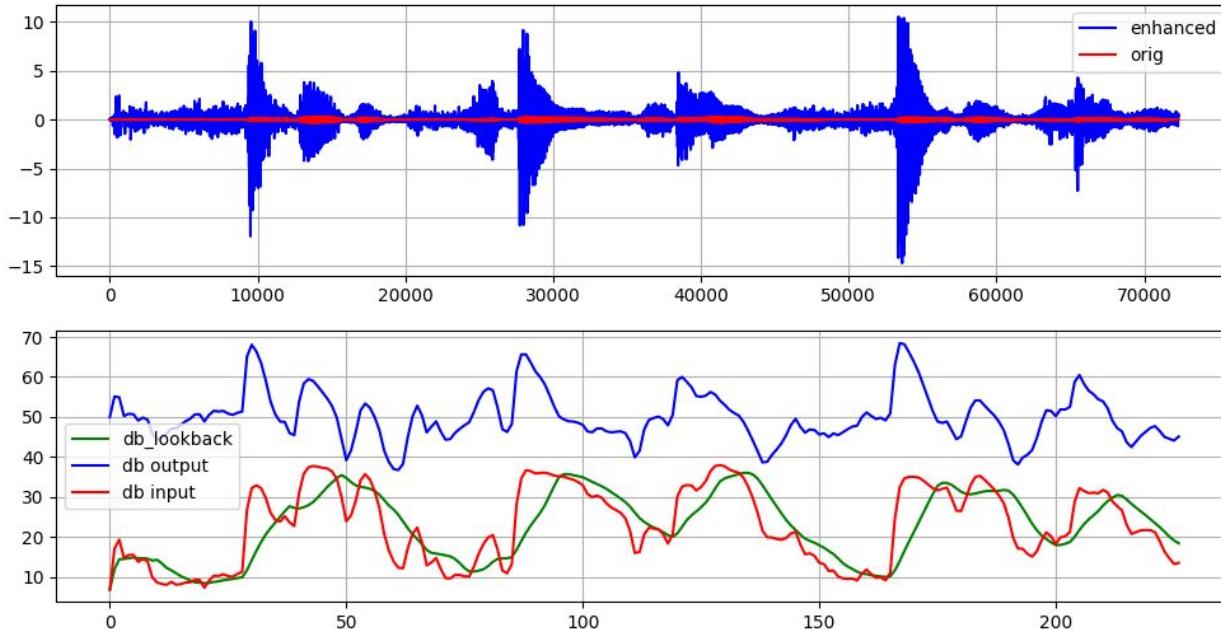
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  - Our users are sensitive to RMS
- Hence we need to determine the desired RMS and normalize the audio accordingly
  - Applying the same factor to all frames will result in a constant amplification
  - So we need to do it frame-by-frame- “pumping” effect
  - So we will aggregate stats

# Applications: Auto Gain Control

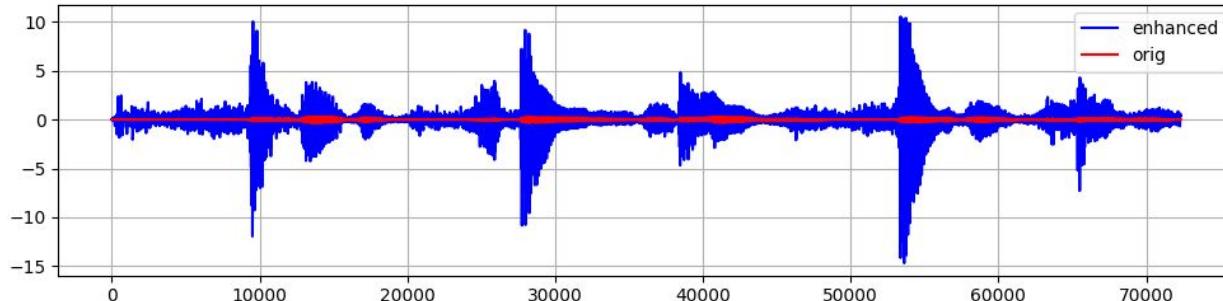
- In is C C H C
- He C C



speaker  
gly

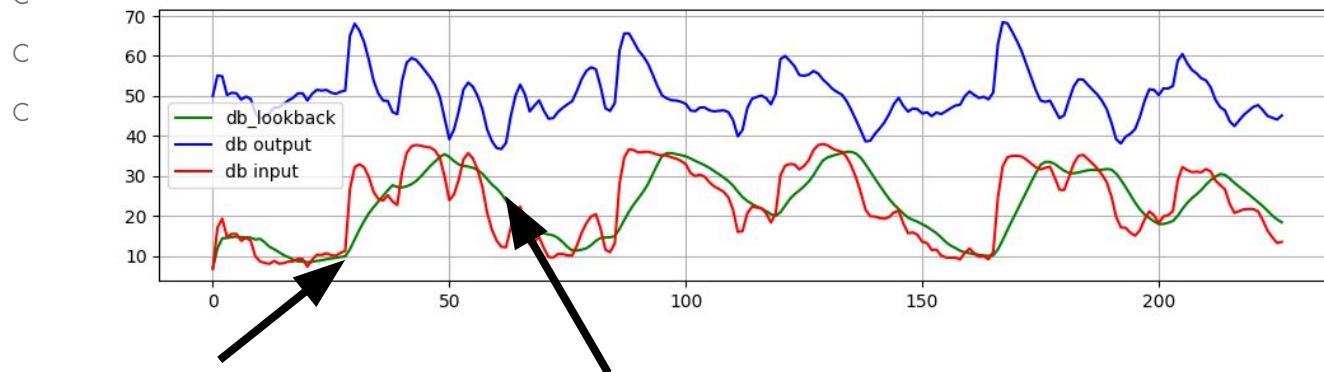
# Applications: Auto Gain Control

- In is C C
- He C C



speaker

gly



Attack (Red > Green)

Release (Red < Green)

# Applications: Auto Gain Control

- In many cases we would like to have a constant “volume” regardless of how the speaker is speaking.
  - Our algorithm is sensitive to RMS
  - Our users are sensitive to RMS
- Hence we need to determine the desired RMS and normalize the audio accordingly
  - Applying the same factor to all frames will result in a constant amplification
  - So we need to do it frame-by-frame- “pumping” effect
  - So we will aggregate stats
- Additional challenges:
  - Overflow: results in clipping (compression, sigmoid)
  - Do not amplify noise: determine energy threshold (noise floor)
  - Smooth transient noises: Attack and release: using hard decision / soft decision (exponential decay).

# Applications

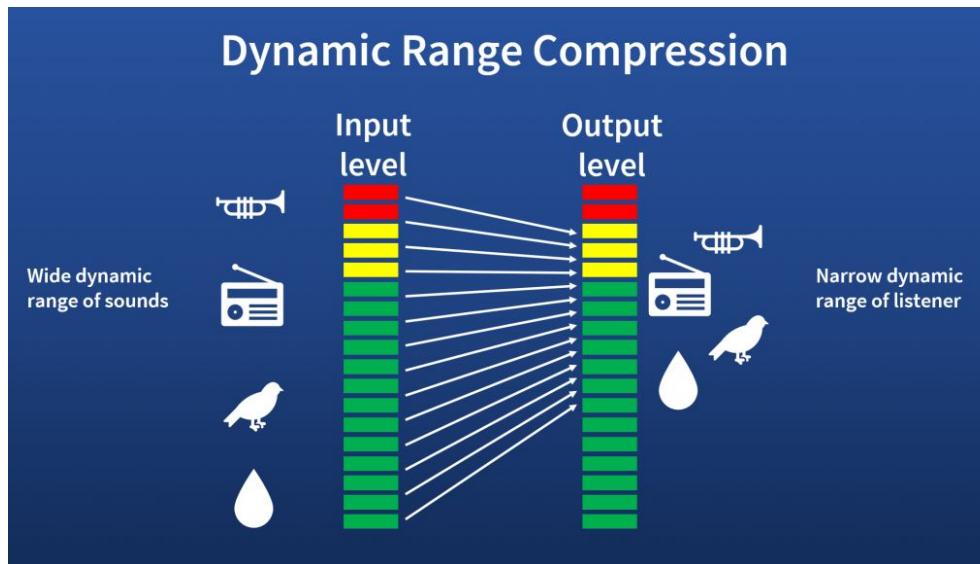


## Challenges:

1. Delayed signal / packet lost - Time stretching
2. Noisy environment - Noise reduction
3. Speakers with multiple gains - Auto gain control
4. **Audio Clipping** - **Audio Compression**
5. Connectivity issues - Variable bitrate vocoders

# Applications: Audio Compression

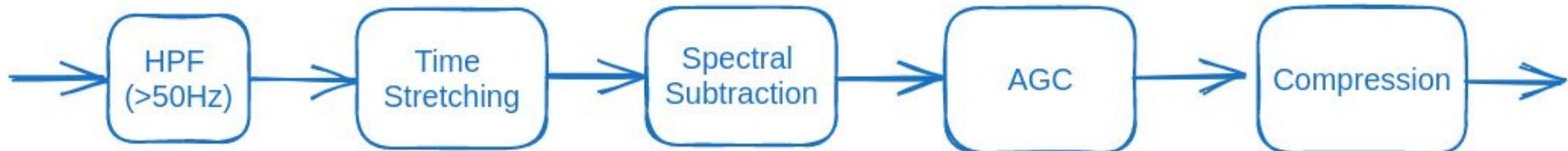
- In many cases we would like to have a different dynamic range
  - People with hearing loss
  - Audio editing- emphasis some parts or making audio sound better



# Applications: Audio Compression

- In many cases we would like to have a different dynamic range
  - People with hearing loss
  - Audio editing- emphasis some parts or making audio sound better
- We need to determine the mapping between the input and output gains
  - Attack and release: when / how fast do we want to apply compression: only on non-transient parts.

# Applications



# Applications



## Challenges:

1. Delayed signal / packet lost - Time stretching
2. Noisy environment - Noise reduction
3. Speakers with multiple gains - Auto gain control
4. Audio Clipping - Audio Compression
- 5. Connectivity issues - Variable bitrate vocoders**

# Overview

- Motivation
- Communication
- Anatomy & Speech production system
- Phonetics
- Acoustic/Speech Features
- Traditional Speech Signals Analysis
  - Time Stretching
  - Speech Enhancement- Spectral Subtraction
  - Auto Gain Control (AGC)
  - Audio Compression