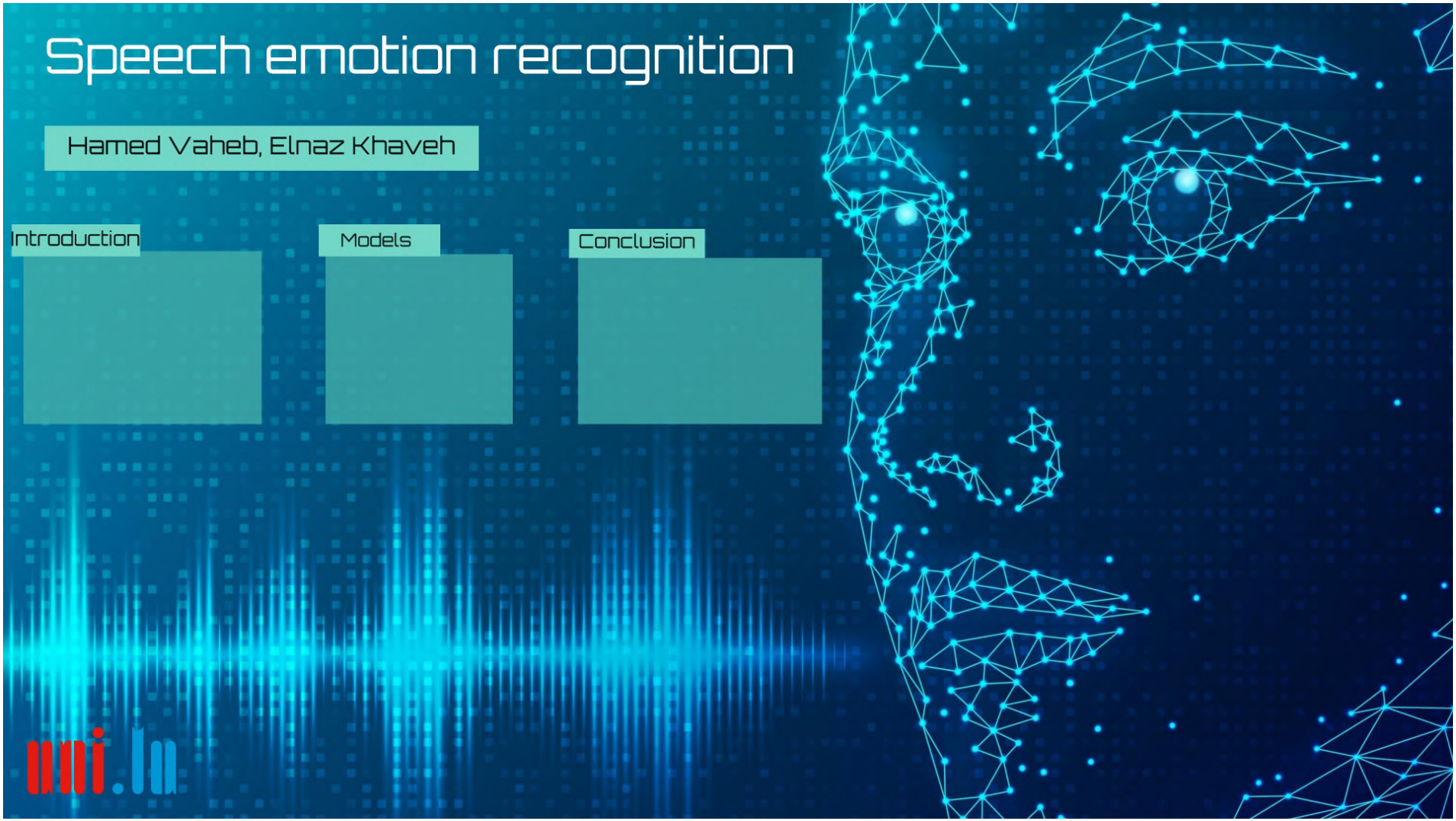
Speech emotion recognition
Hamed Vaheb, Elnaz Khaveh
Introduction
Models
Conclusion


Introduction
Applications
Data set


Introduction
Importance:
Applications
Data set

Introduction

Importance:

- The most natural way to express ourselves

Introduction

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Gregory A. Bryant
First Published June 24, 2020 | Research Article
https://doi.org/10.1177/1754073920930791
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Data set


Applications

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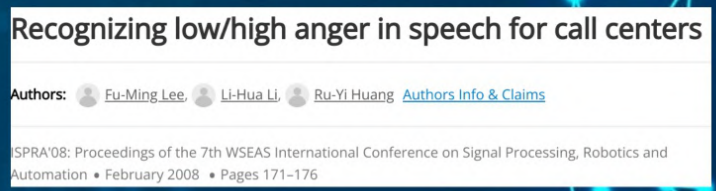
Applications

Applications

- Call centers

Applications

- Call centers



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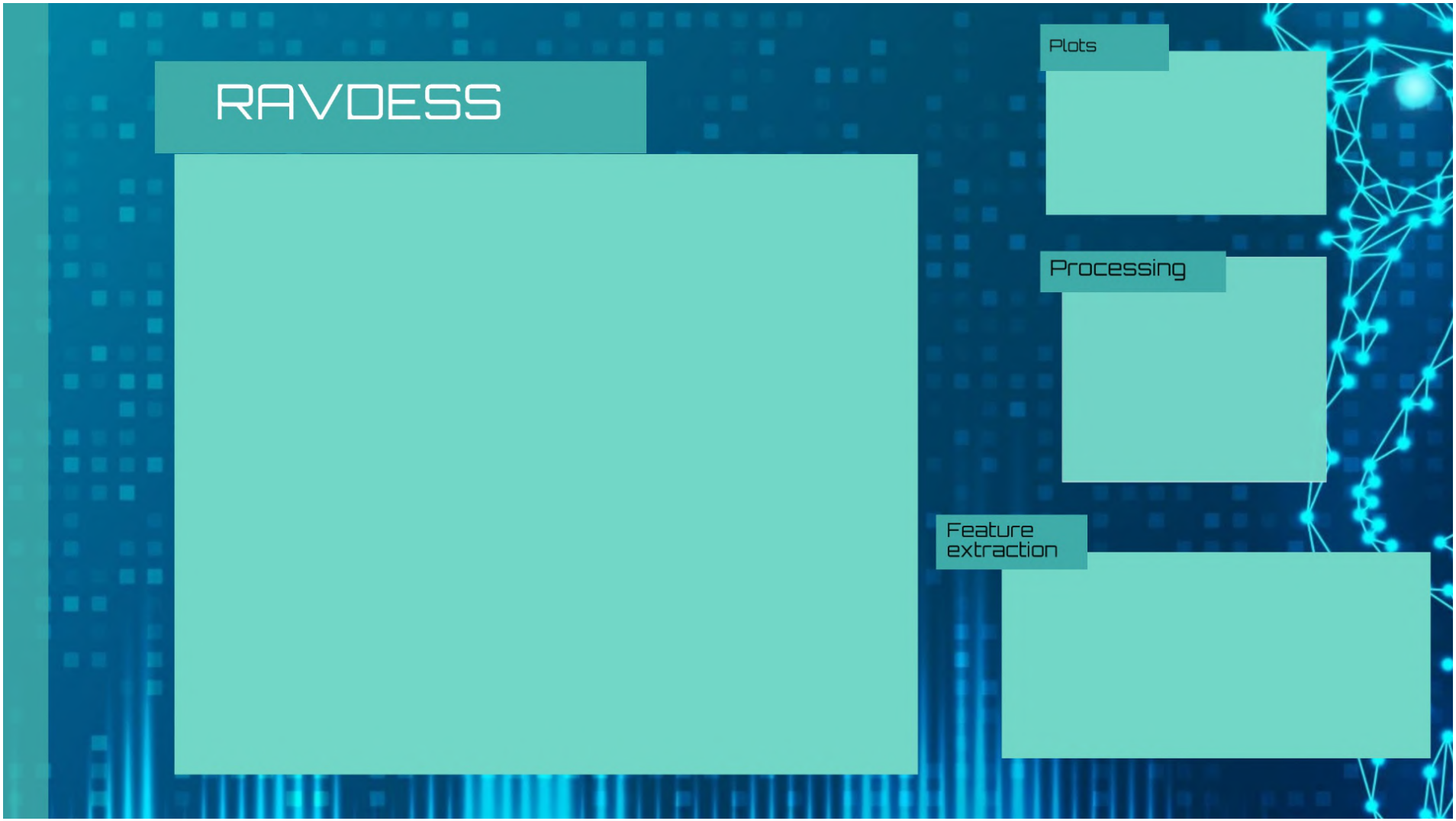
Applications

Data set


RAVDESS
Plots
Processing
Feature extraction

RAVDESS

- A validated multimodal database

Plots

Processing

Feature extraction

RAVDESS

- A validated multimodal database
- 24 professional actors

Plots

Processing

Feature extraction

RAVDESS

- A validated multimodal database
- 24 professional actors
- Gender-balanced

Plots

Processing

Feature extraction

RAVDESS

- 24 professional actors
- Gender-balanced

Plots

Processing

Feature extraction

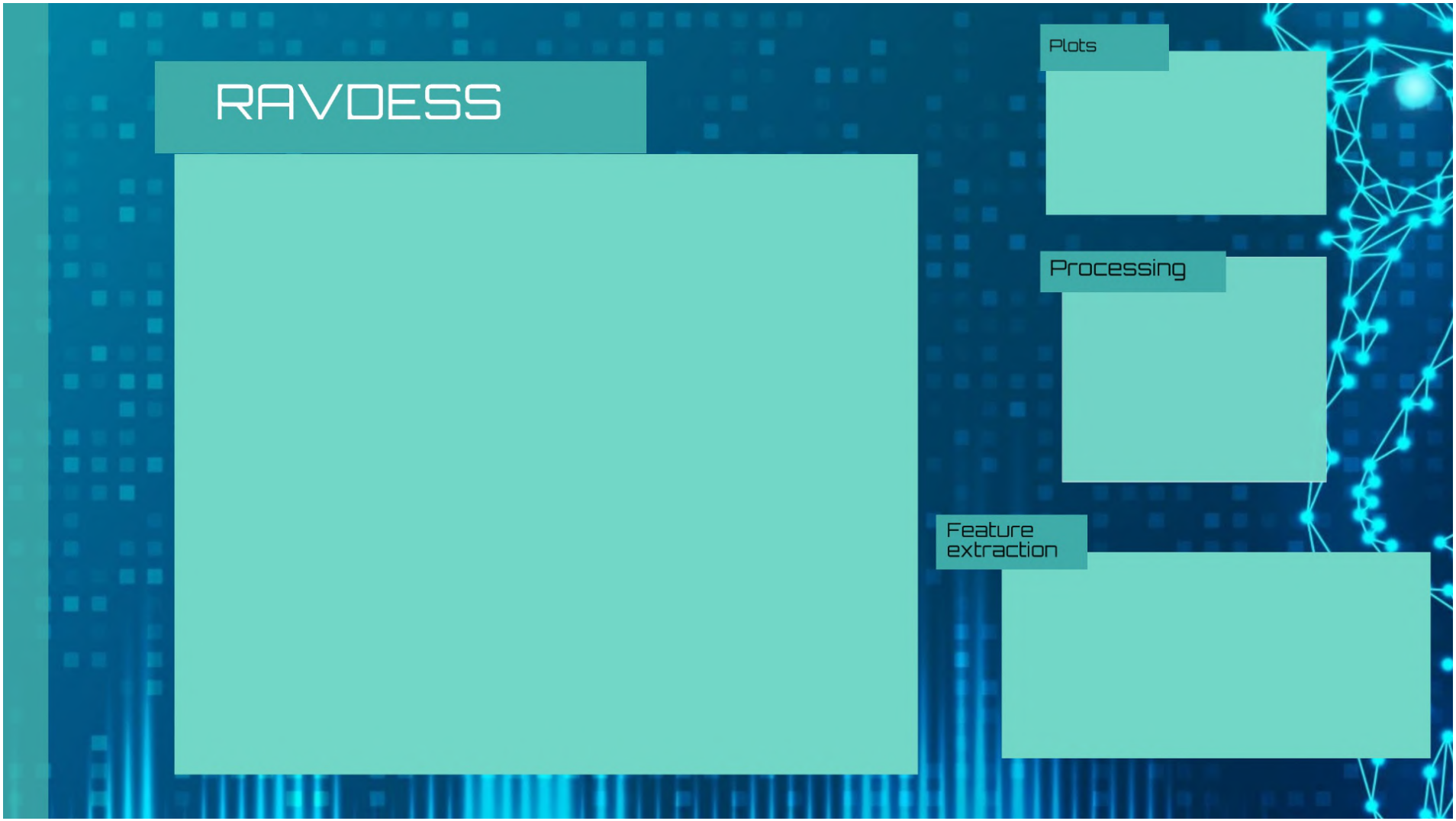
RAVDESS

- Gender-balanced

Plots

Processing

Feature extraction


RAVDESS
Plots
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RAVDESS

- 8 classes :

Plots

Processing

Feature extraction

RAVDESS

- 8 classes :

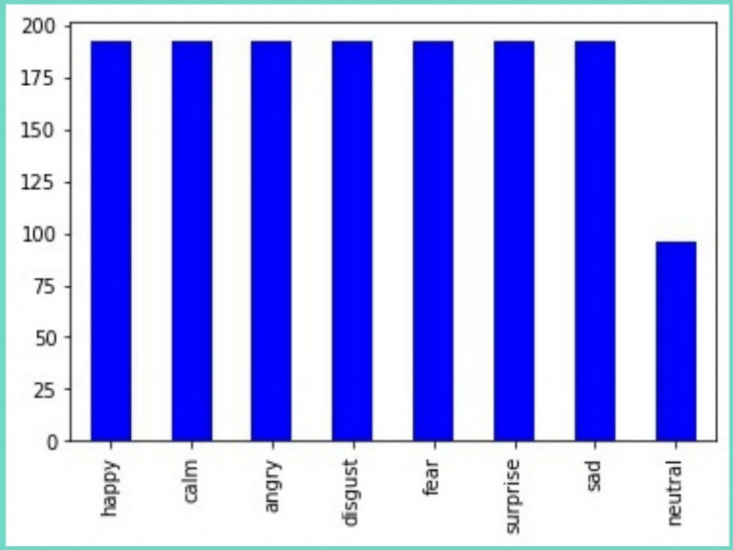
  Neutral, calm, happy, sad, angry, fearful, disgust, surprise

Plots

Processing

Feature extraction

RAVDESS



- 8 classes :

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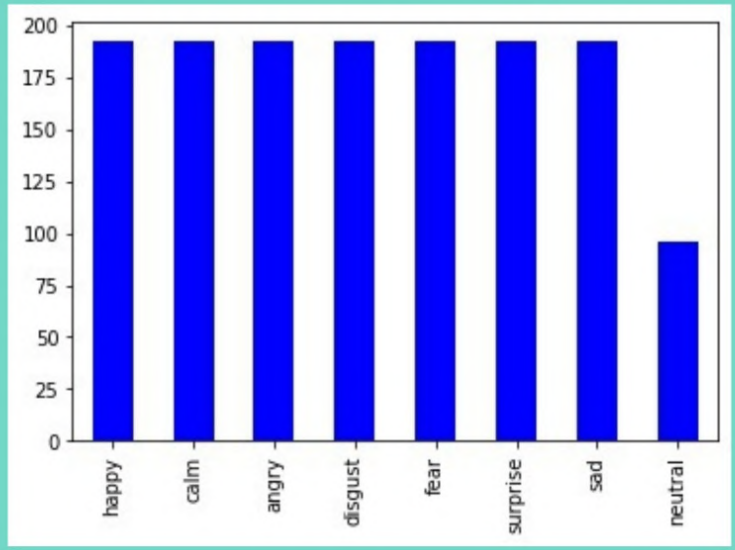
Plots

Processing

Feature extraction

RAVDESS



Neutral, calm, happy, sad, angry, fearful, disgust, surprise

Plots

Processing

Feature extraction

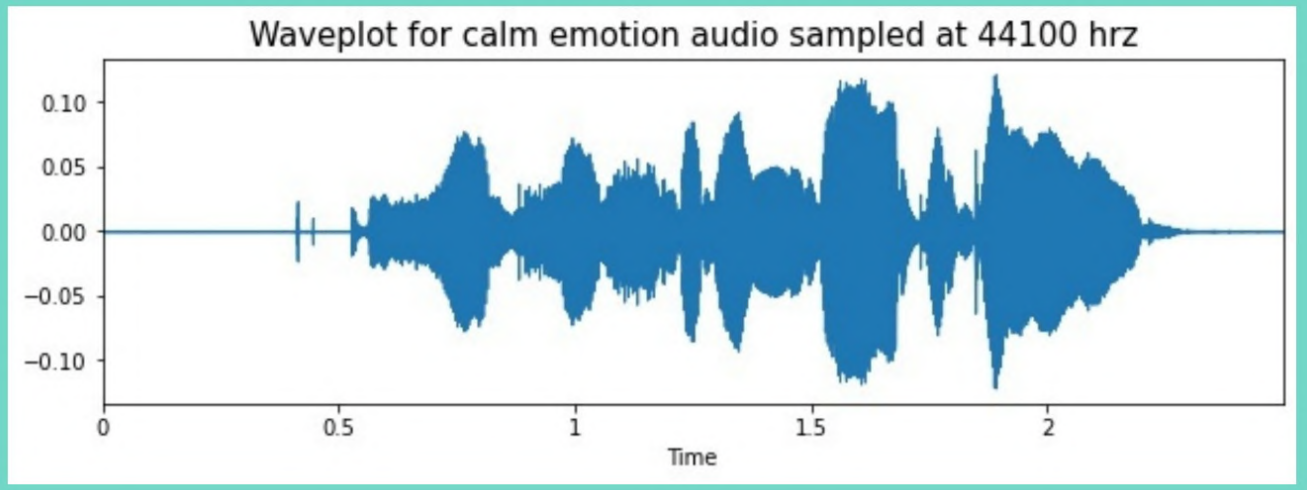
RAVDESS

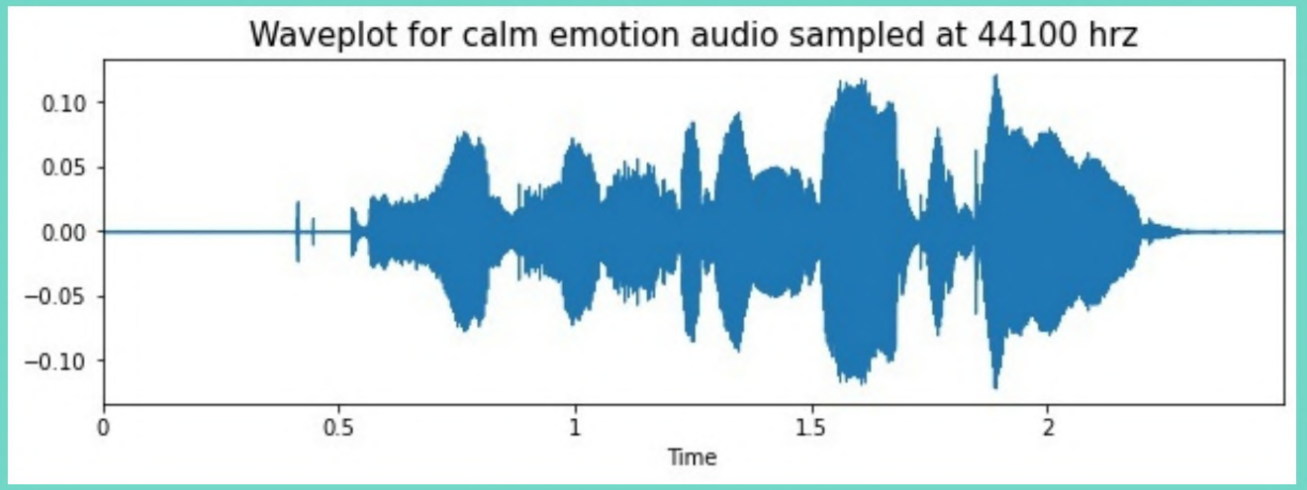
Neutral, calm, happy, sad, angry, fearful, disgust, surprise

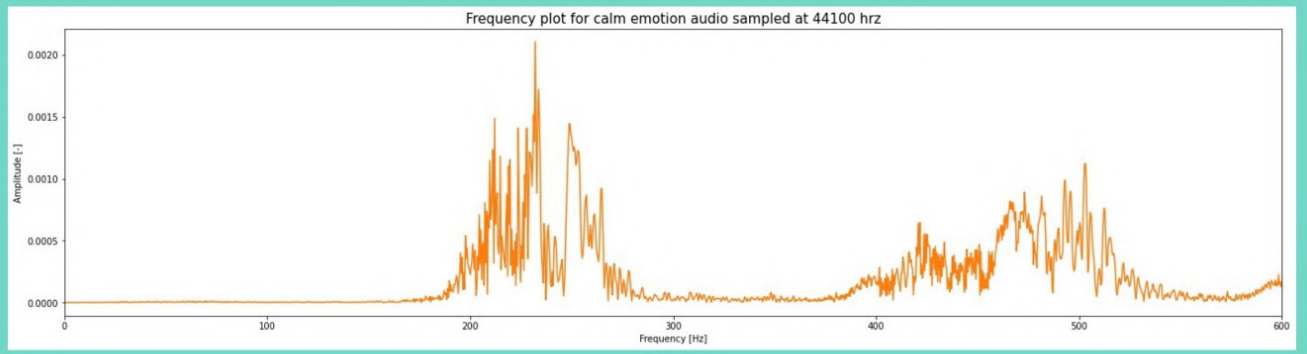
Plots

Processing

Feature extraction


Waveplot for calm emotion audio sampled at 44100 hrz
0.10
0.05
0.00
−0.05
−0.10
0
0.5
1
1.5
2
Time


Waveplot for calm emotion audio sampled at 44100 hrz
0.10
0.05
0.00
−0.05
−0.10
0
0.5
1
1.5
2
Time


Frequency plot for calm emotion audio sampled at 44100 hrz
Amplitude [-]
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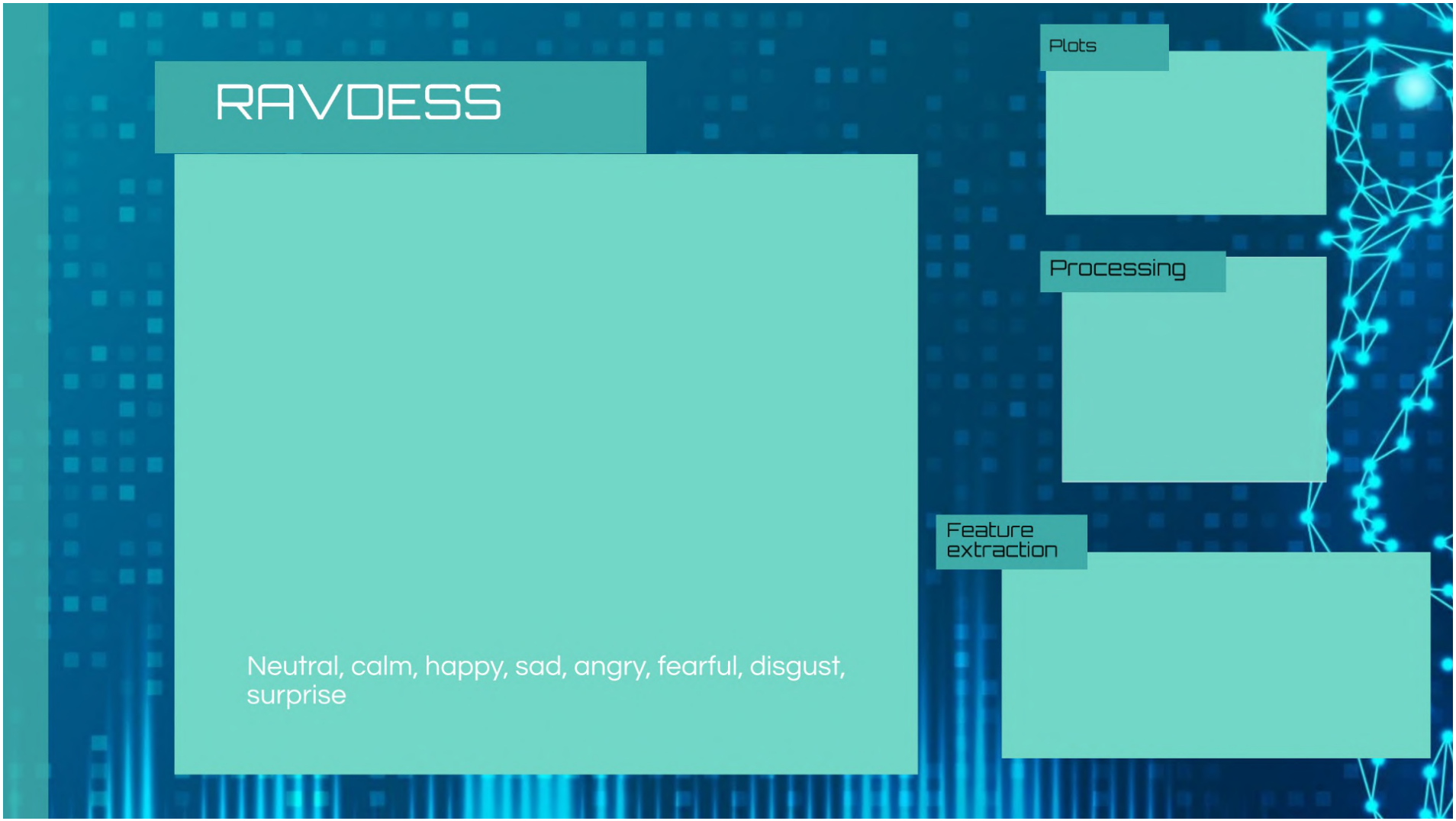
0.0015
0.0010
0.0005
0.0000
0
100
200
300
400
500
600
Frequency [Hz]


RAVDESS
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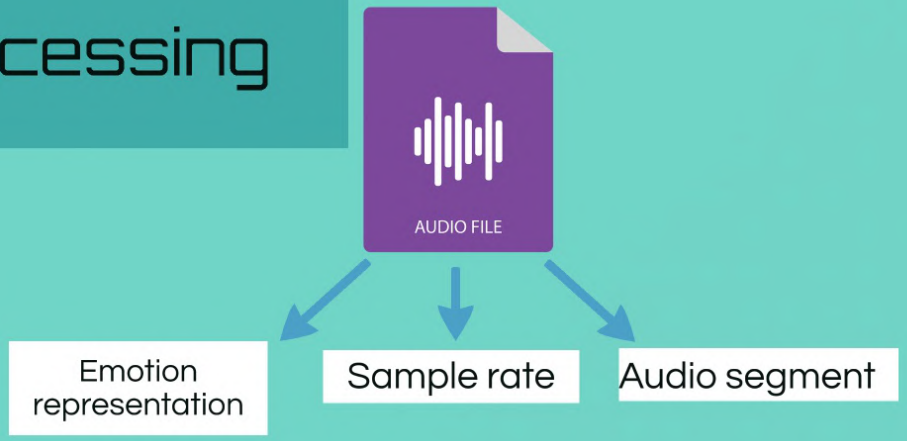
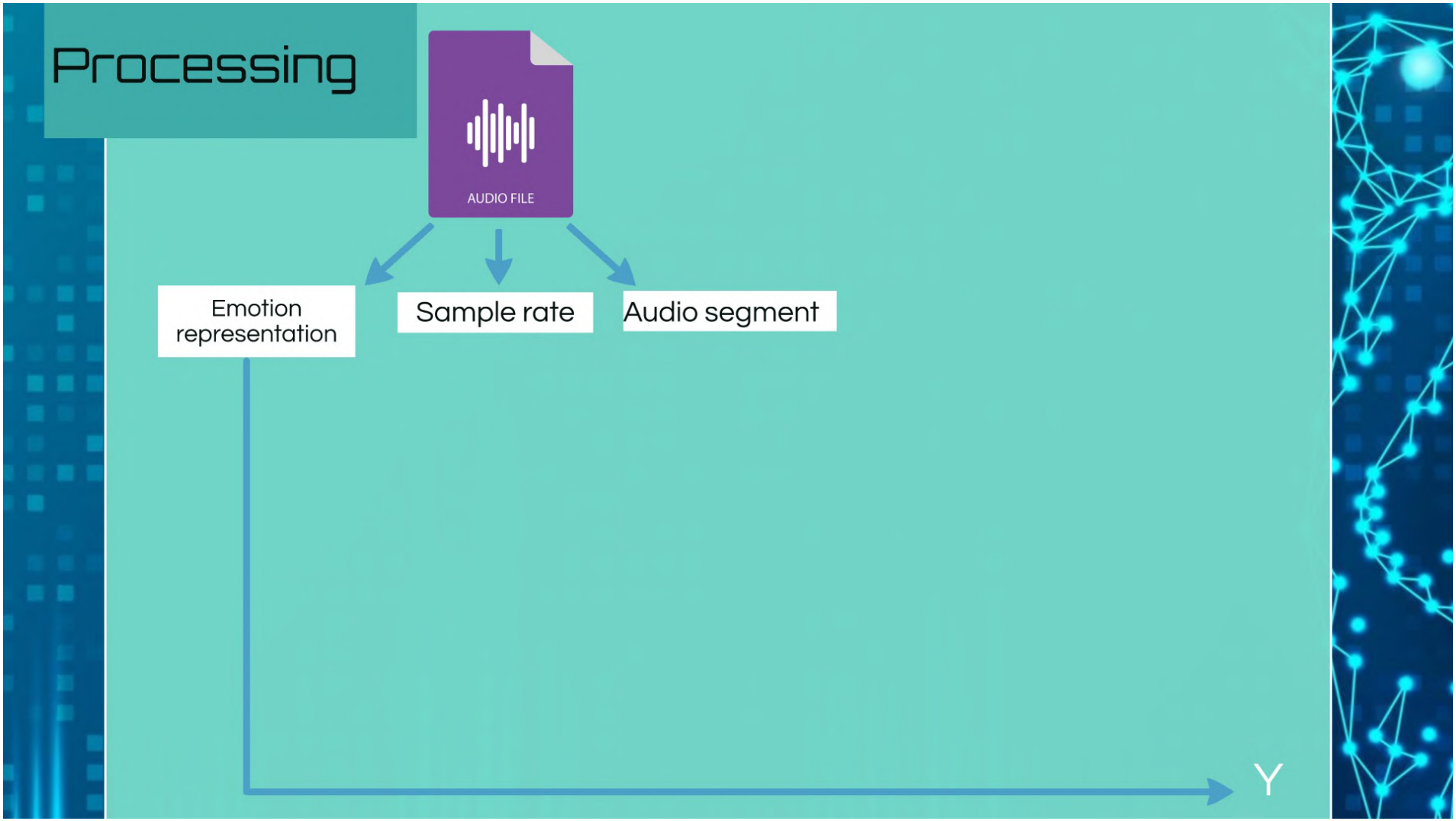
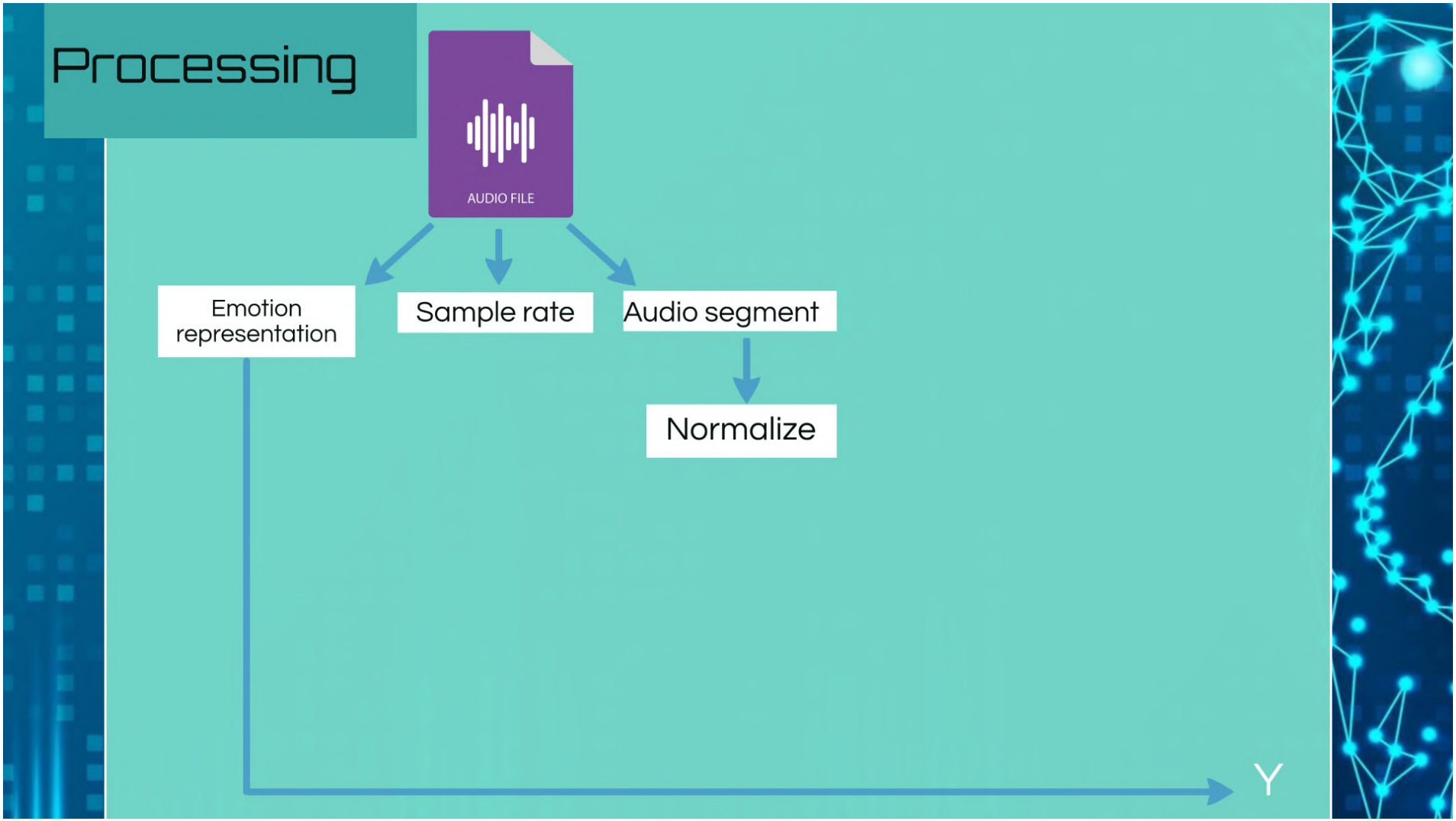
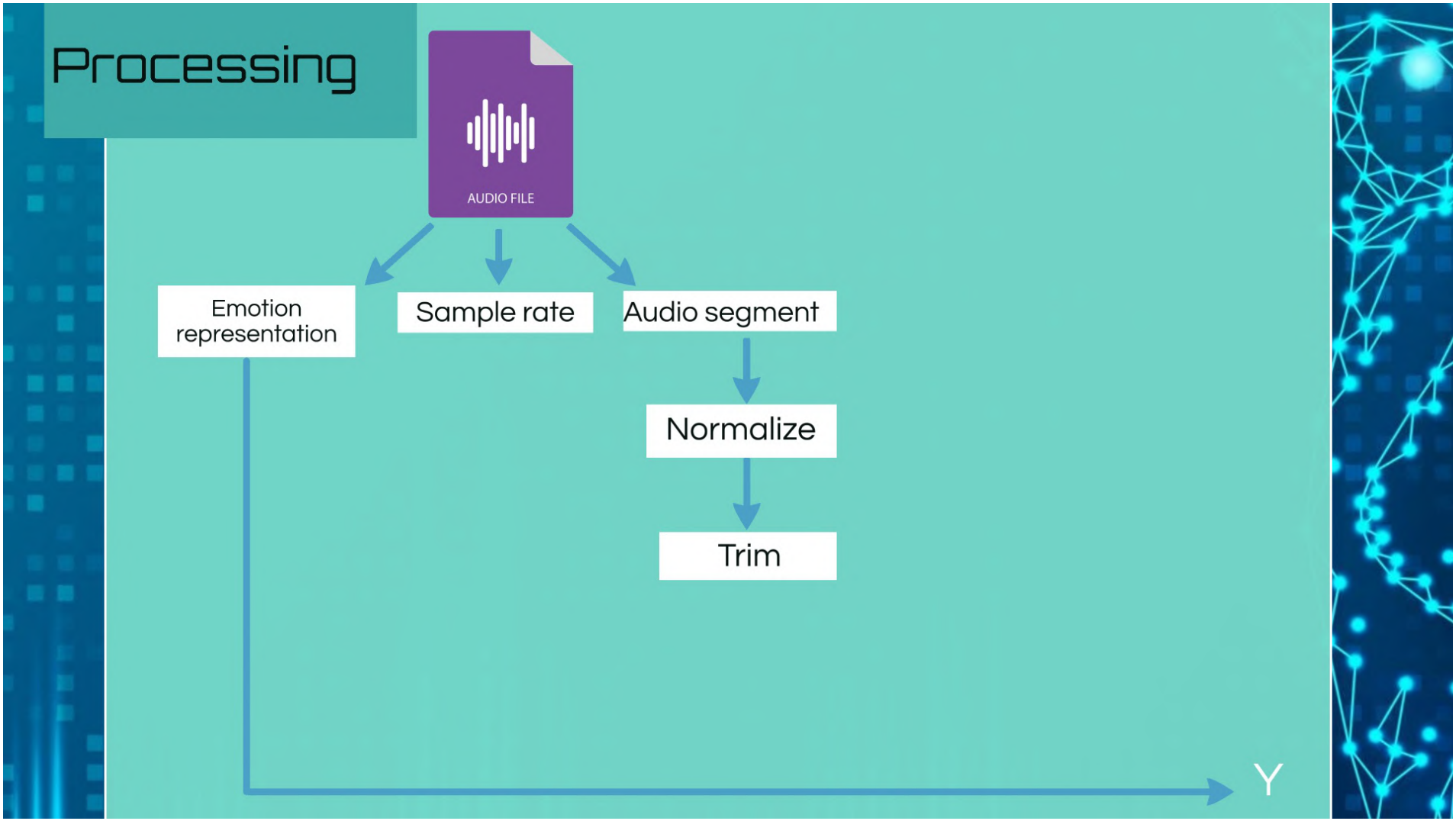
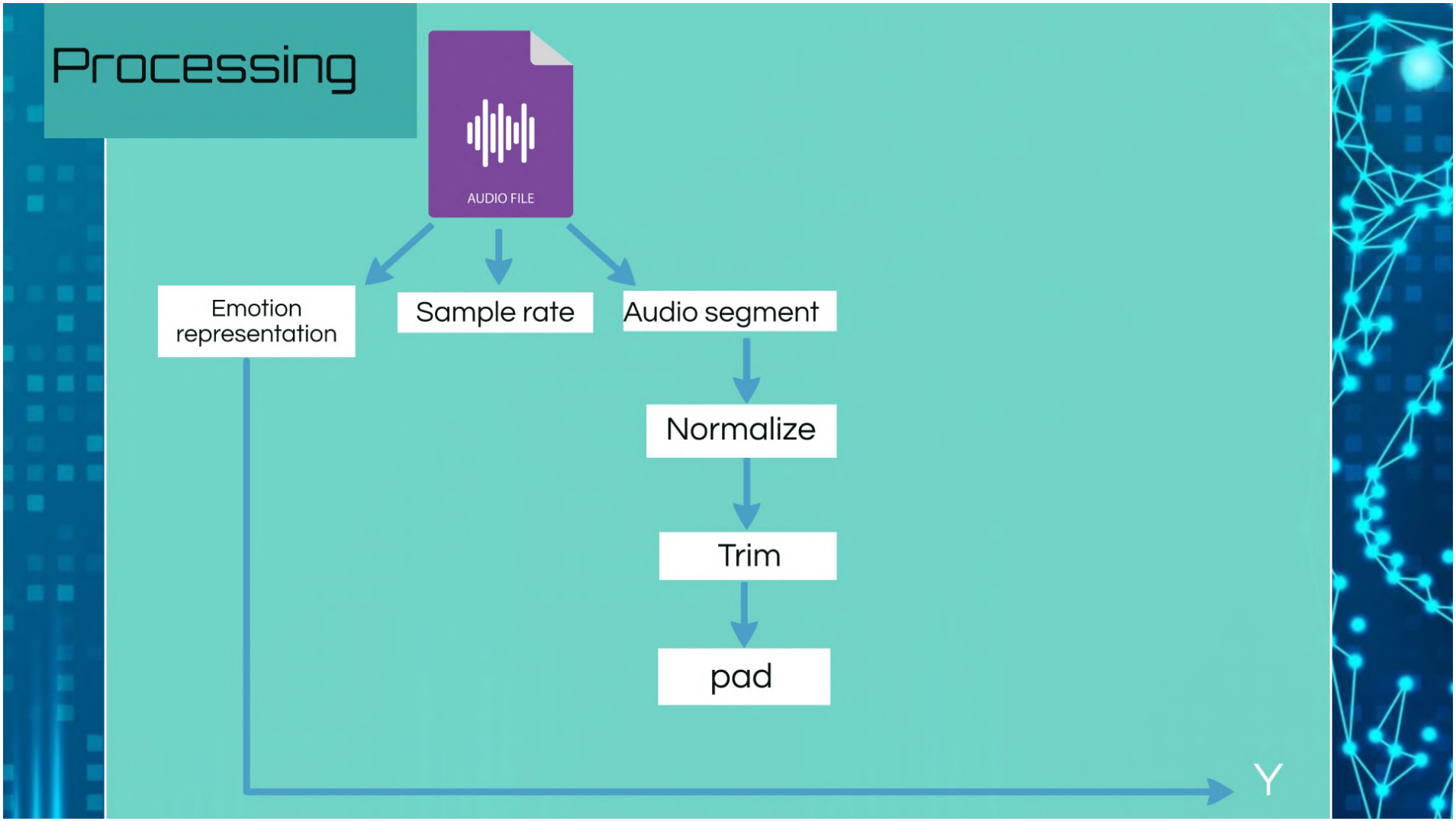
Processing

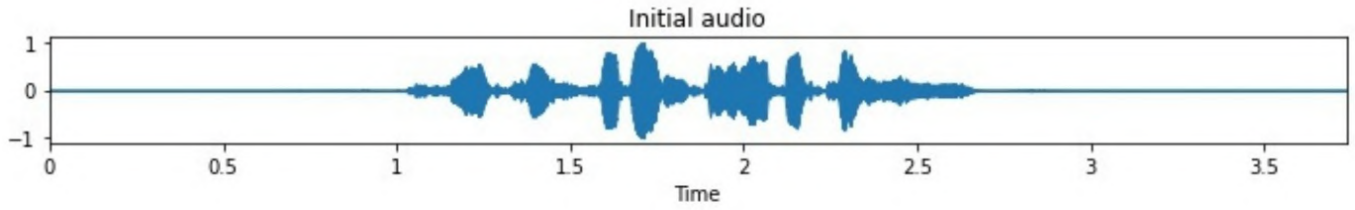

AUDIO FILE
Emotion representation
Sample rate
Audio segment

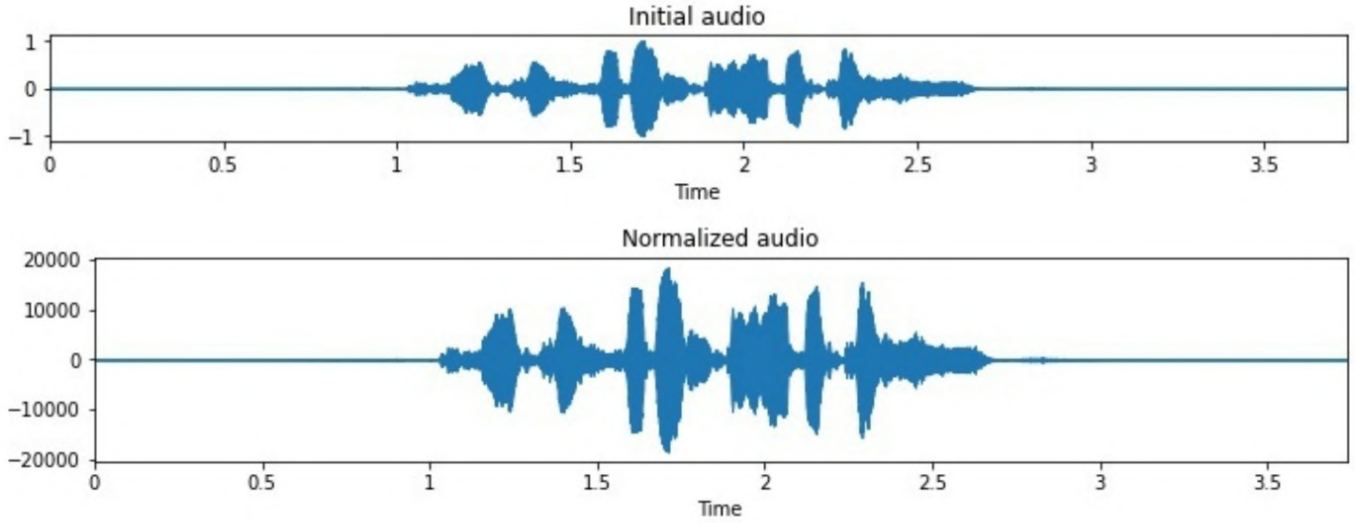

Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Y

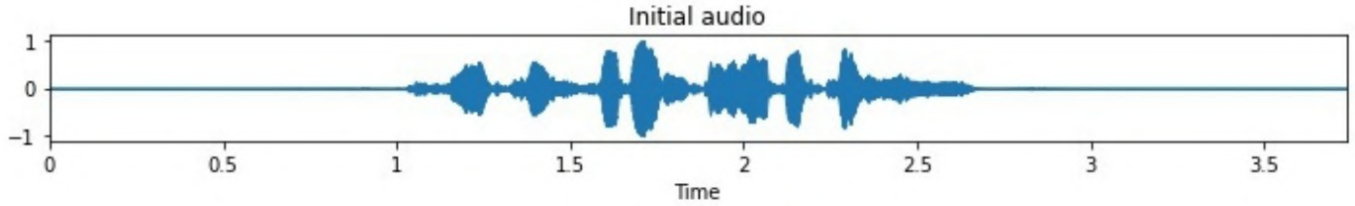

Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
Y

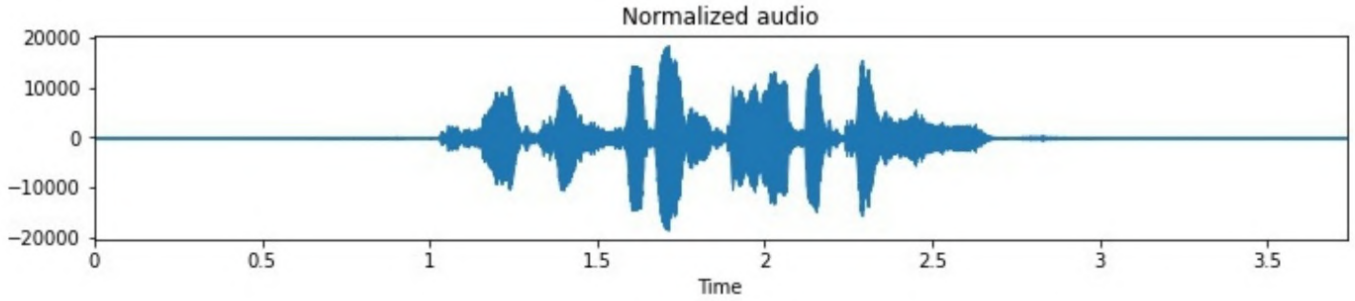

Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
Trim
Y


Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
Trim
pad
Y


Initial audio
1
0
−1
0
0.5
1
1.5
2
2.5
3
3.5
Time


Initial audio
1
0
−1
0
0.5
1
1.5
2
2.5
3
3.5
Time
Normalized audio
20000
10000
0
−10000
−20000
0
0.5
1
1.5
2
2.5
3
3.5
Time


Initial audio
1
0
−1
0
0.5
1
1.5
2
2.5
3
3.5
Time


Normalized audio
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10000
0
−10000
−20000
0
0.5
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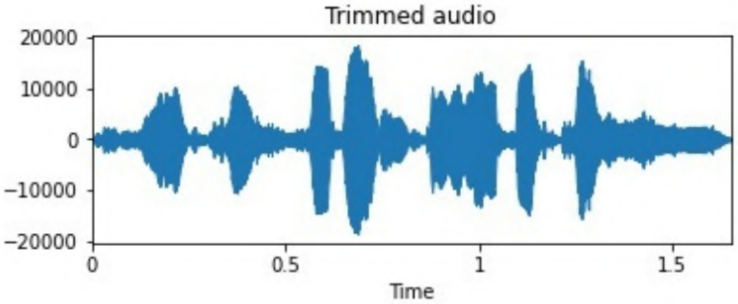
1.5
2
2.5
3
3.5
Time


Trimmed audio
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10000
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−10000
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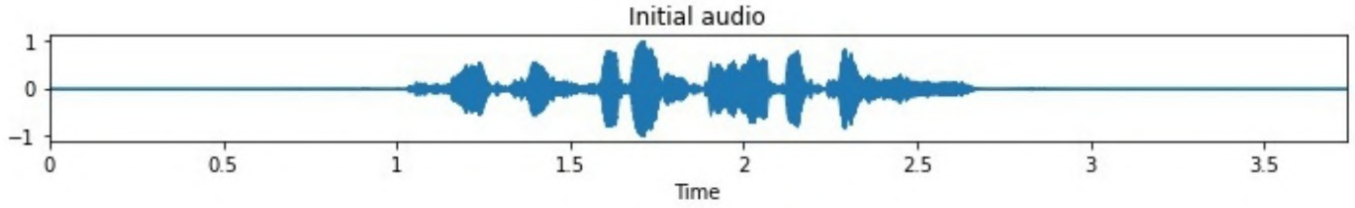
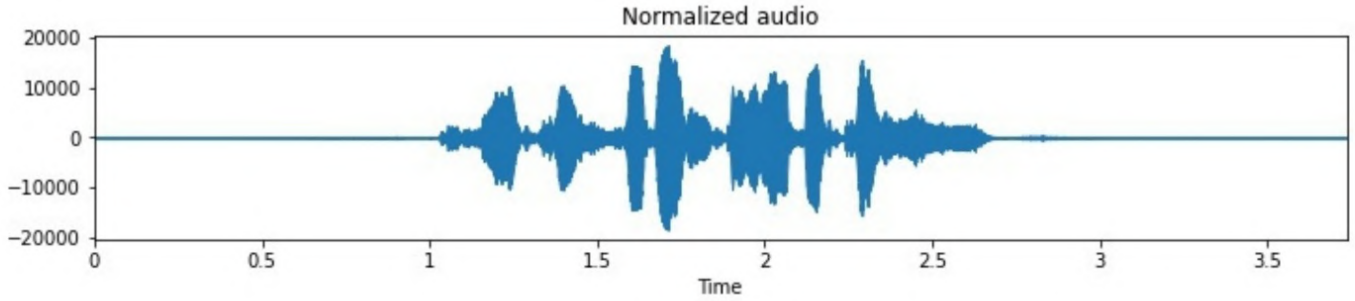
0
0.5
1
1.5
Time


Initial audio
1
0
−1
0
0.5
1
1.5
2
2.5
3
3.5
Time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3
3.5
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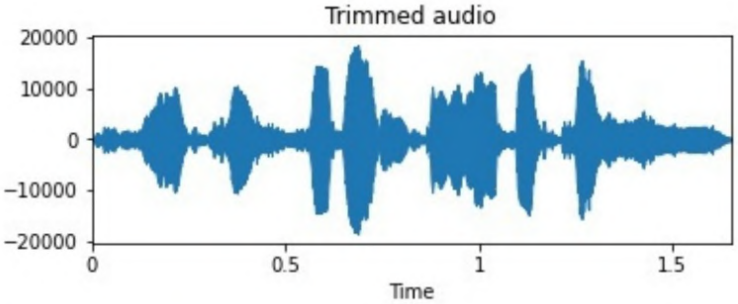
Trimmed audio
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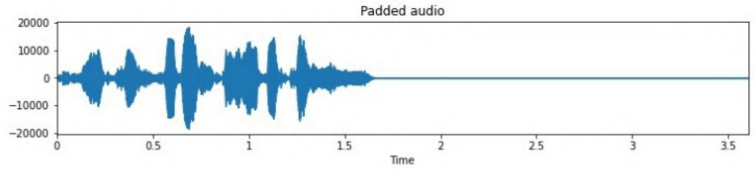
0
0.5
1
1.5
Time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0.5
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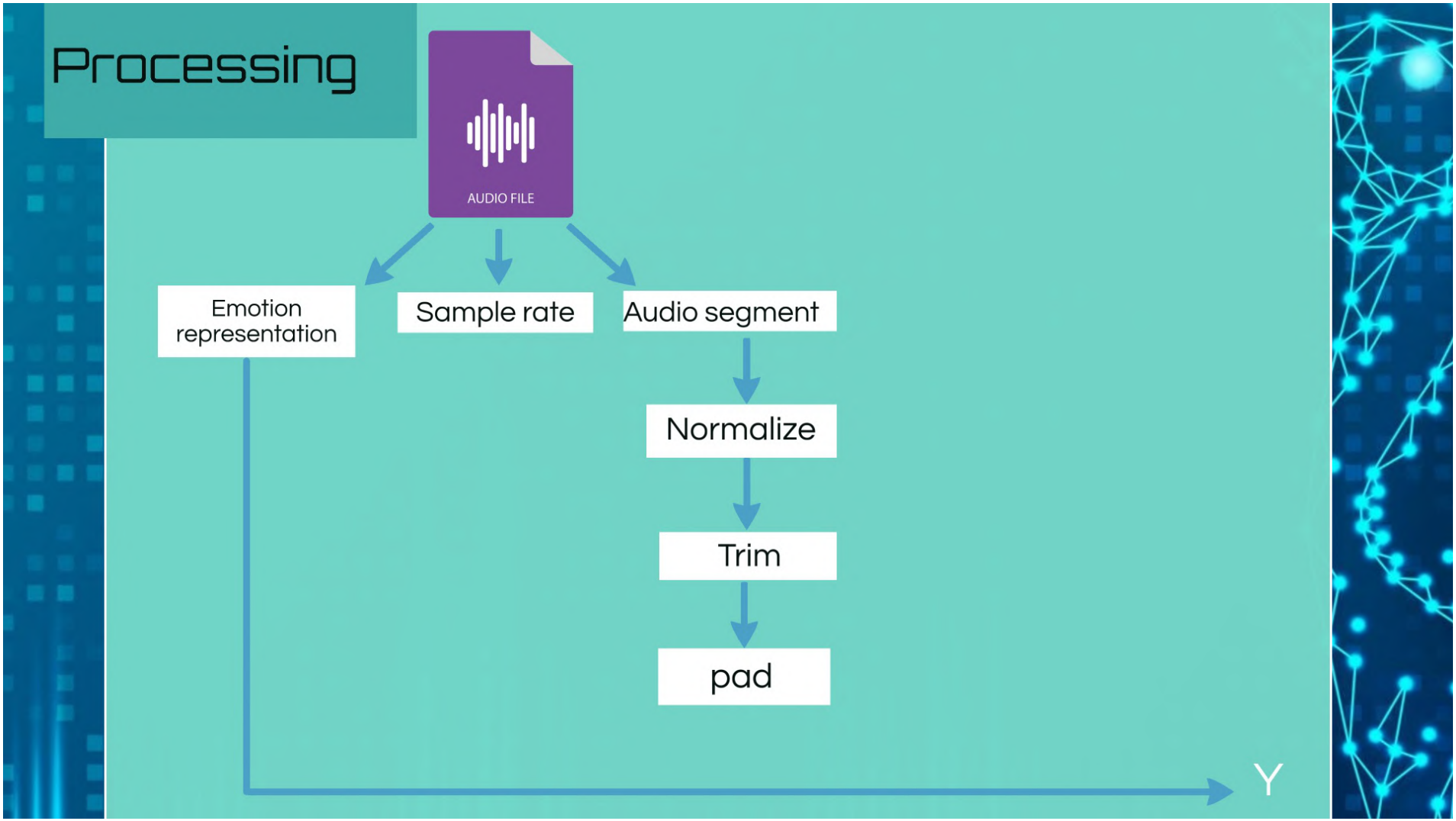
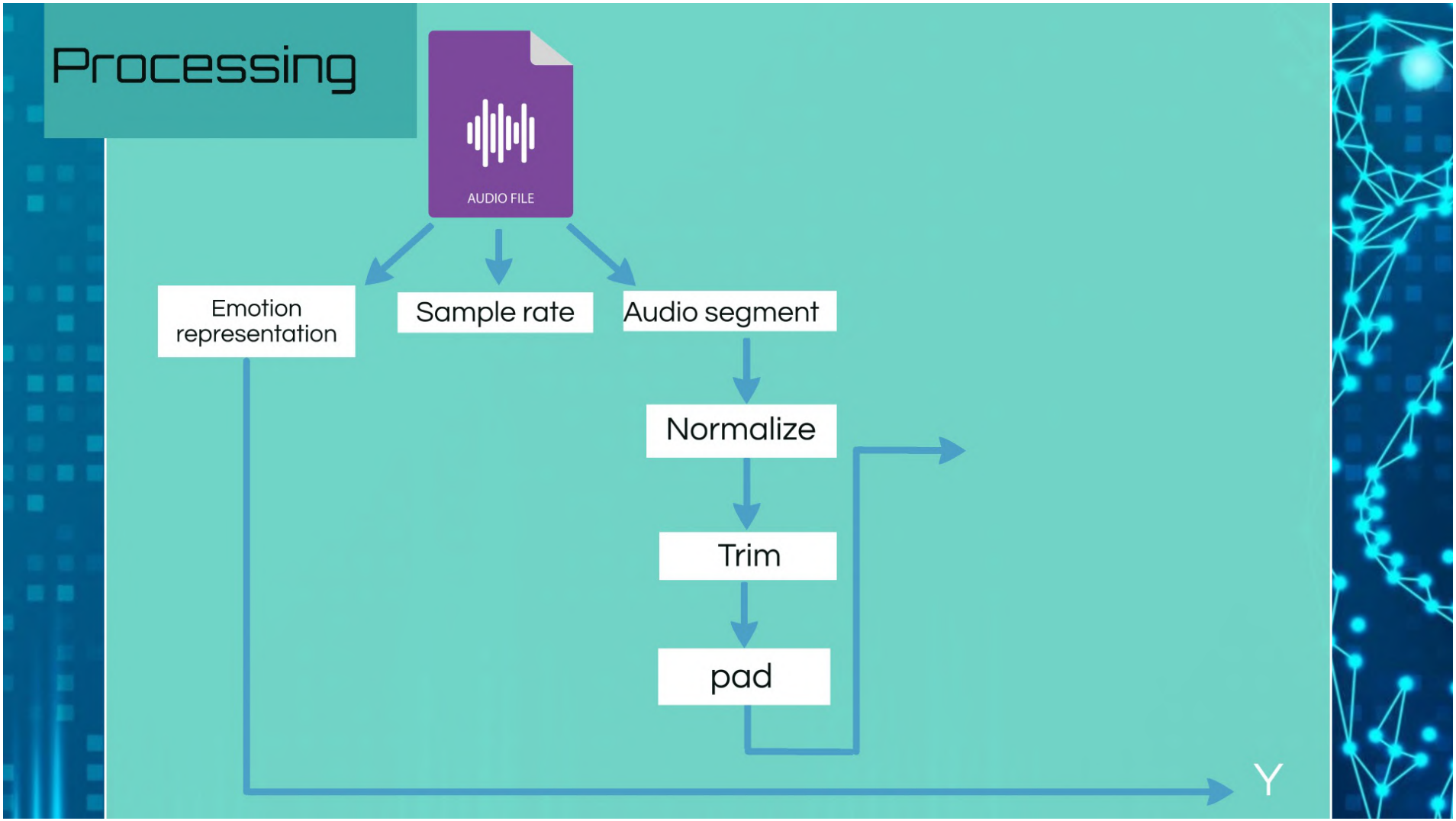
2.5
3
3.5
Time


Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
Trim
pad
Y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Sample rate
Audio segment
Normalize
Trim
pad
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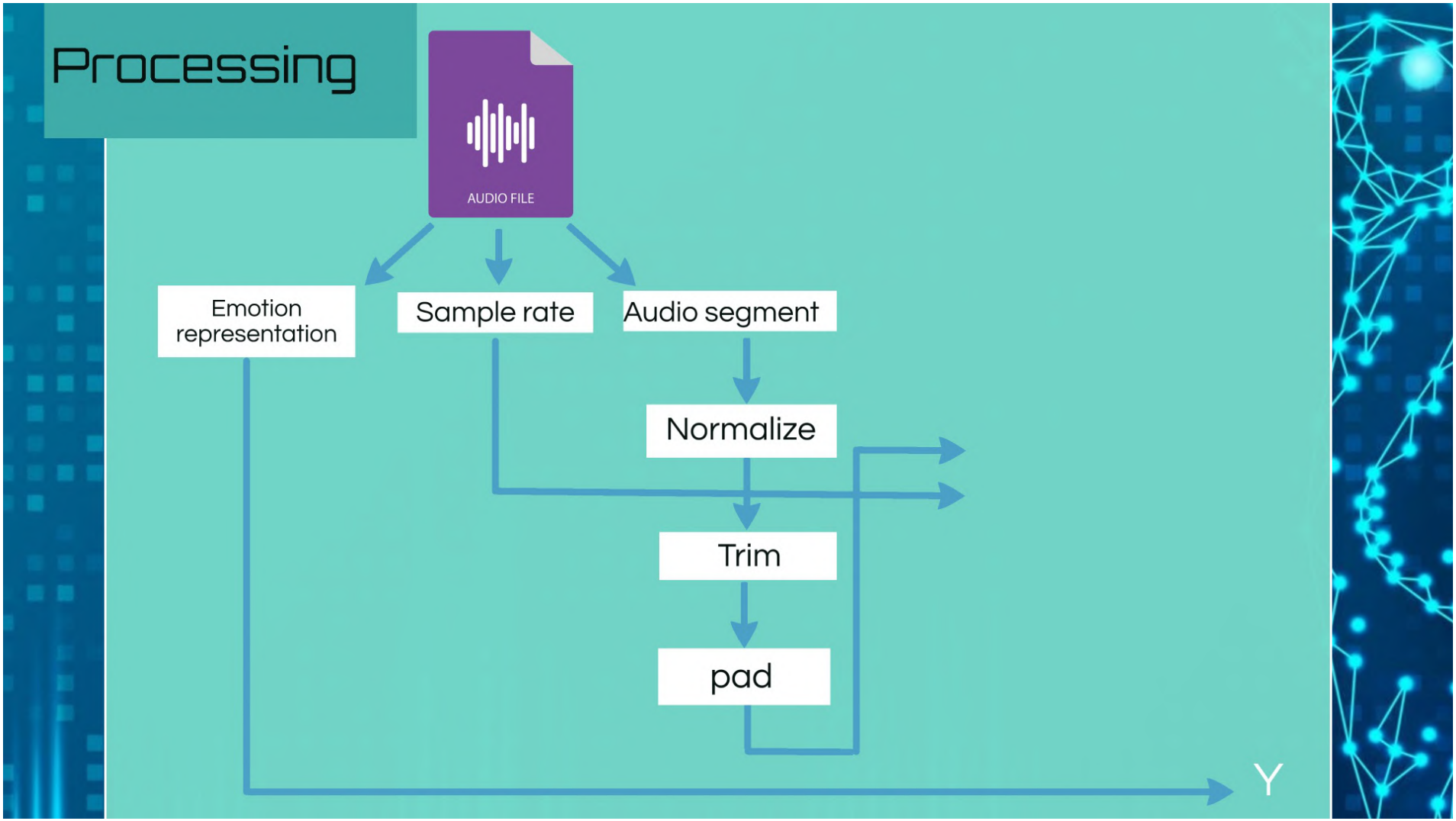
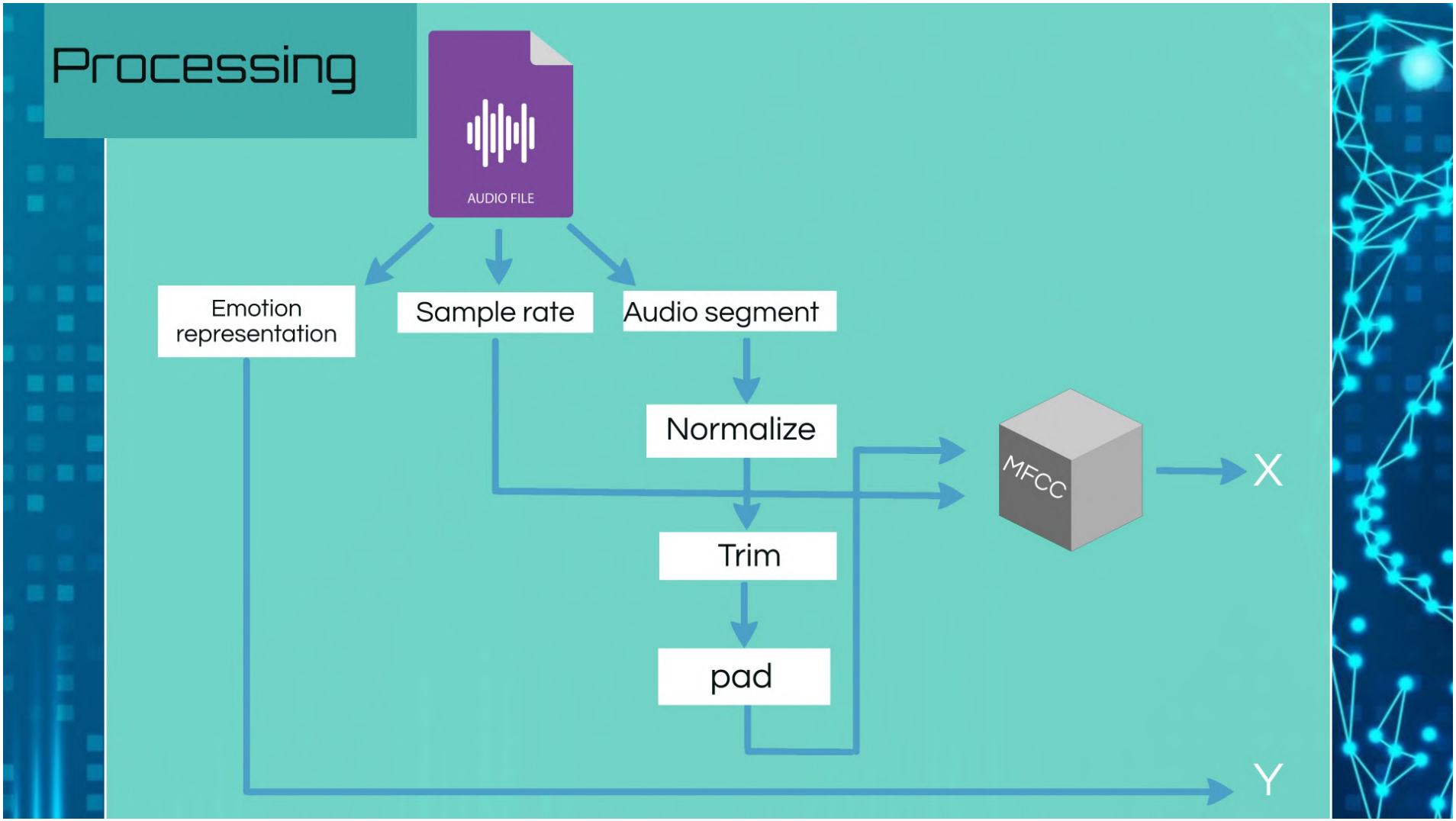
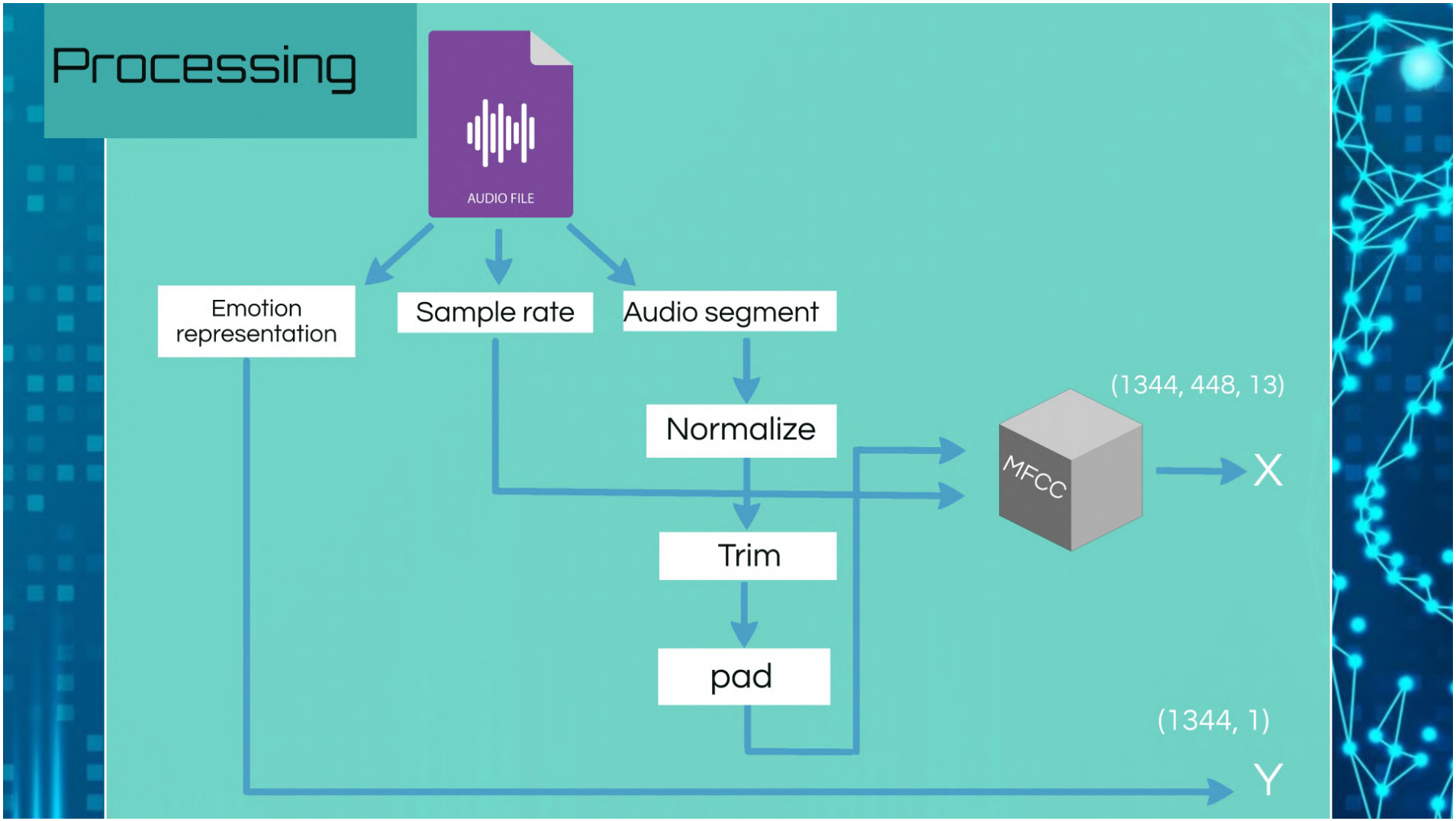

Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
Trim
pad
Y


Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
MFCC
X
Trim
pad
Y


Processing
AUDIO FILE
Emotion representation
Sample rate
Audio segment
Normalize
Trim
pad
MFCC
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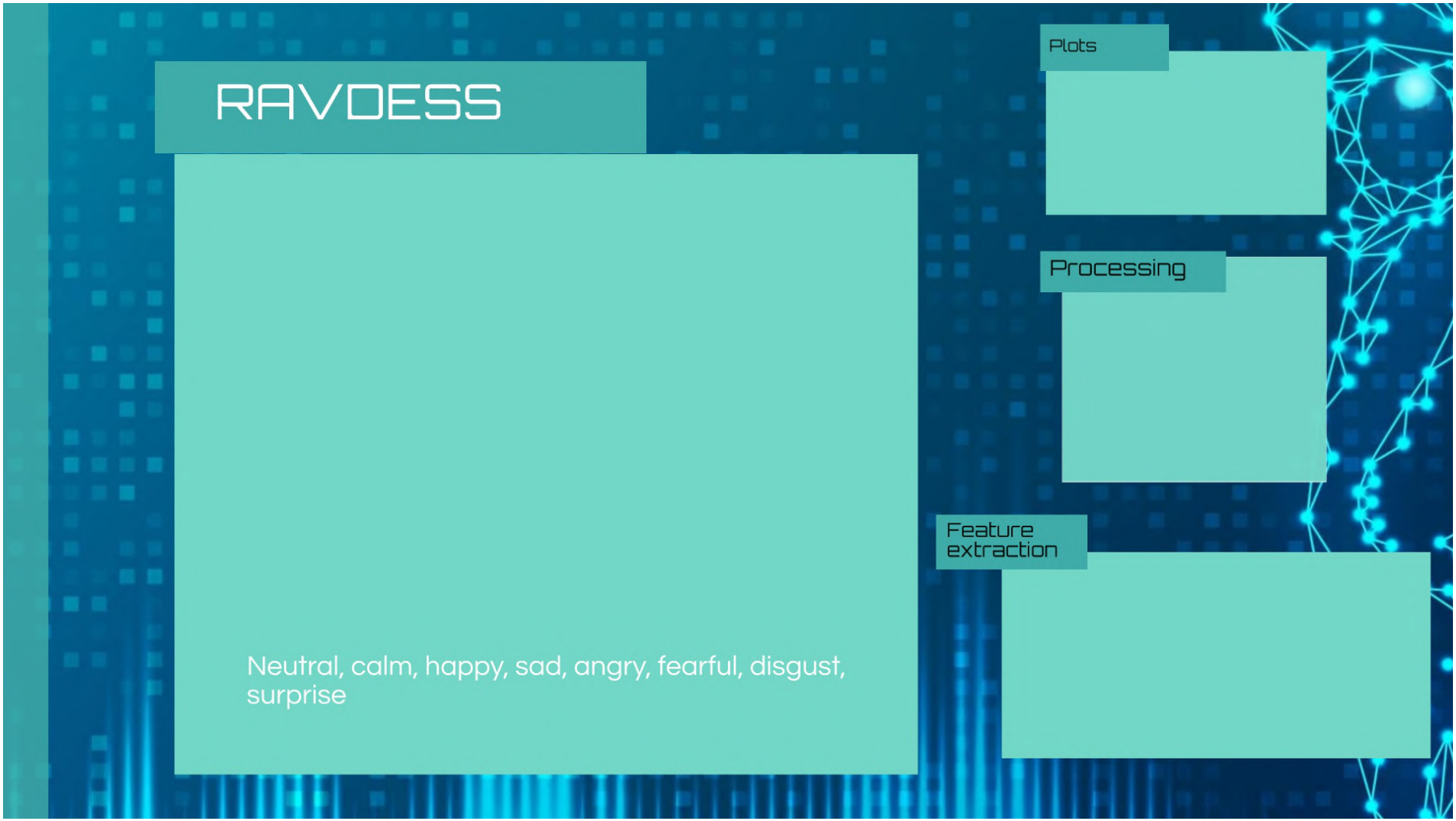
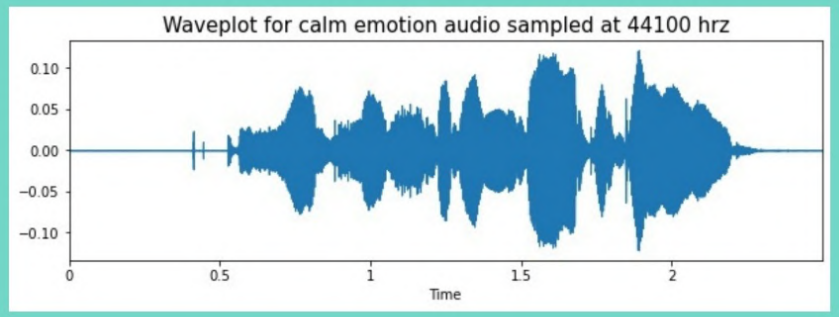
X
(1344, 1)
Y


RAVDESS
Neutral, calm, happy, sad, angry, fearful, disgust, surprise
Plots
Processing
Feature extraction

Feature extraction

Feature extraction

- Time-Domain
  - RMSE, ZCR

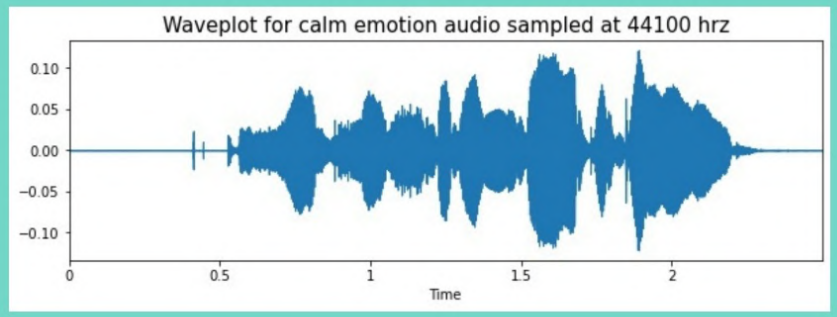


Mel-Spectrogram

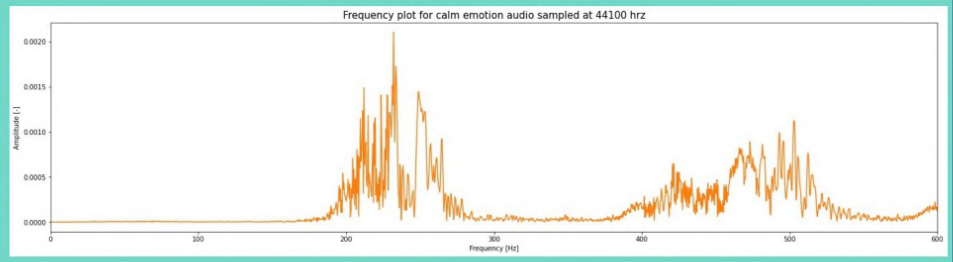
MFCC

Feature extraction

- Time-Domain
  - RMSE, ZCR



- Frequency Domain
  - Spectral Centroid



Mel-Spectrogram

MFCC

Mel Spectrogram

Mel Spectrogram

1. Extract STFT

Mel Spectrogram

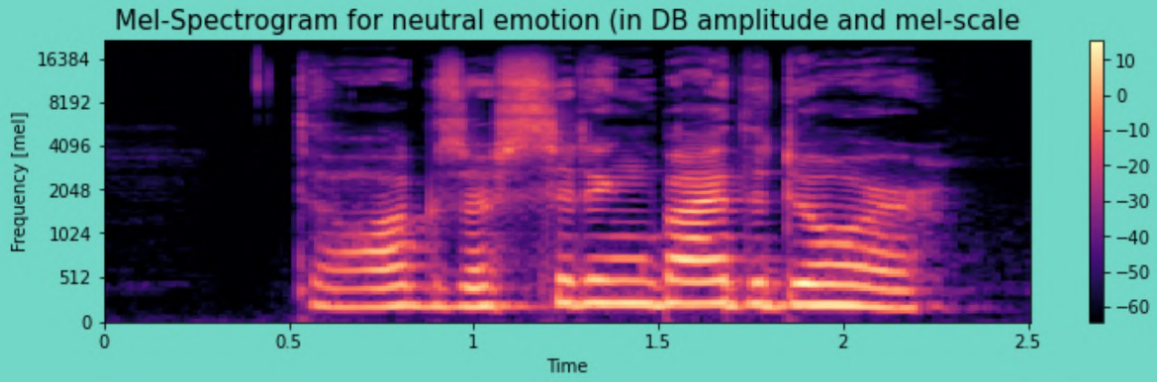
1. Extract STFT
2. Convert amplitude to DBs

Mel Spectrogram

1. Extract STFT
2. Convert amplitude to DBs
3. Convert frequencies to Mel Scale

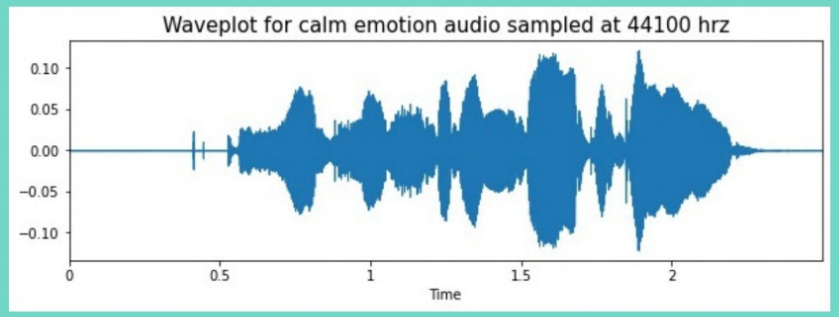
Mel Spectrogram

1. Extract STFT
2. Convert amplitude to DBs
3. Convert frequencies to Mel Scale

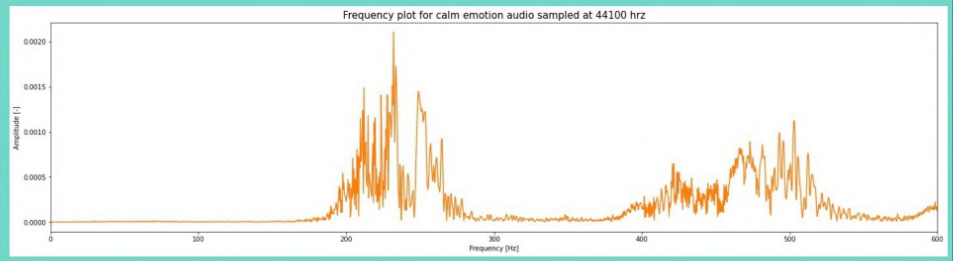


Feature extraction

- Time-Domain
  - RMSE, ZCR



- Frequency Domain
  - Spectral Centroid



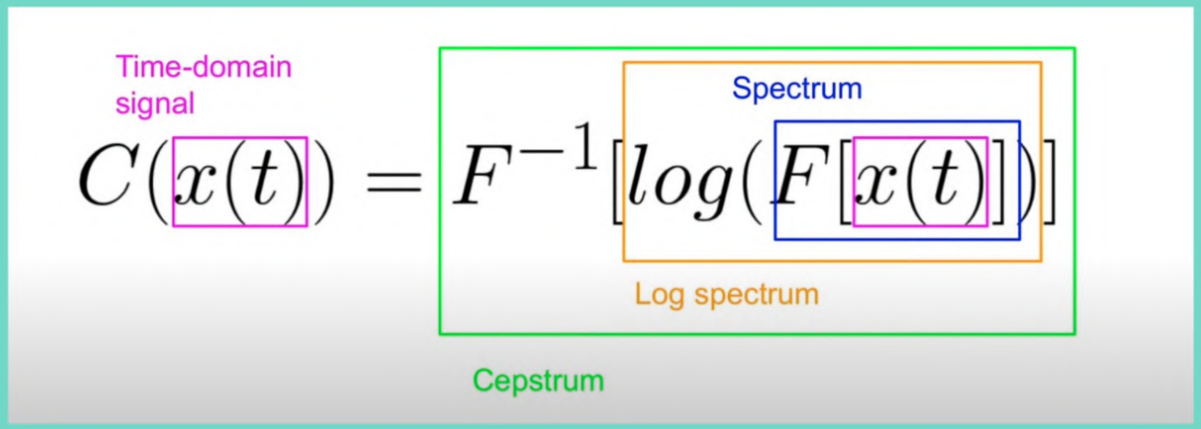
Mel-Spectrogram

MFCC

Mel-Frequecy Cepstrum Coefficients (MFCCs)

Mel-Frequecy Cepstrum Coefficients (MFCCs)

Cepstrum



Visualize

Speech Generation

Cepstrum and Speech

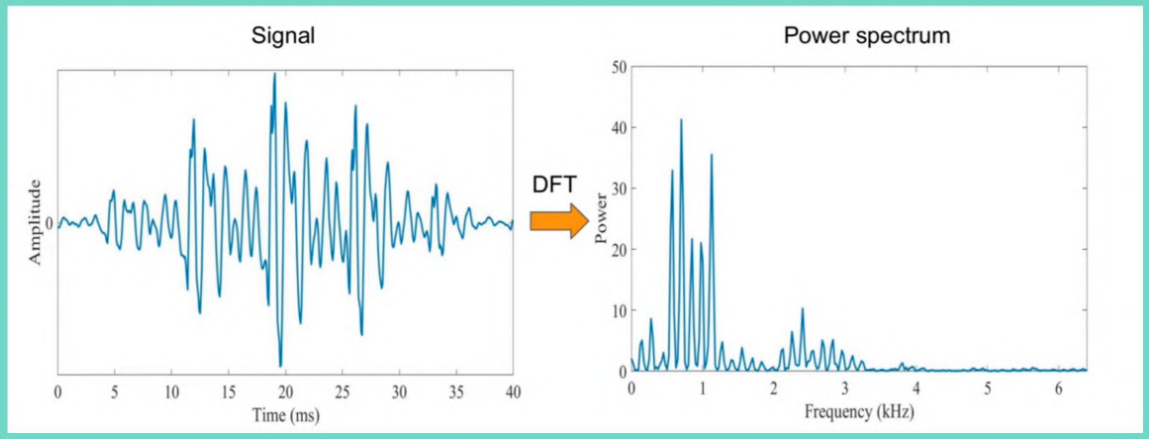
Compute

$$C(x(t)) = F^{-1}[log(F[x(t)])]$$

$$C(x(t)) = F^{-1}[log(F[x(t)])]$$

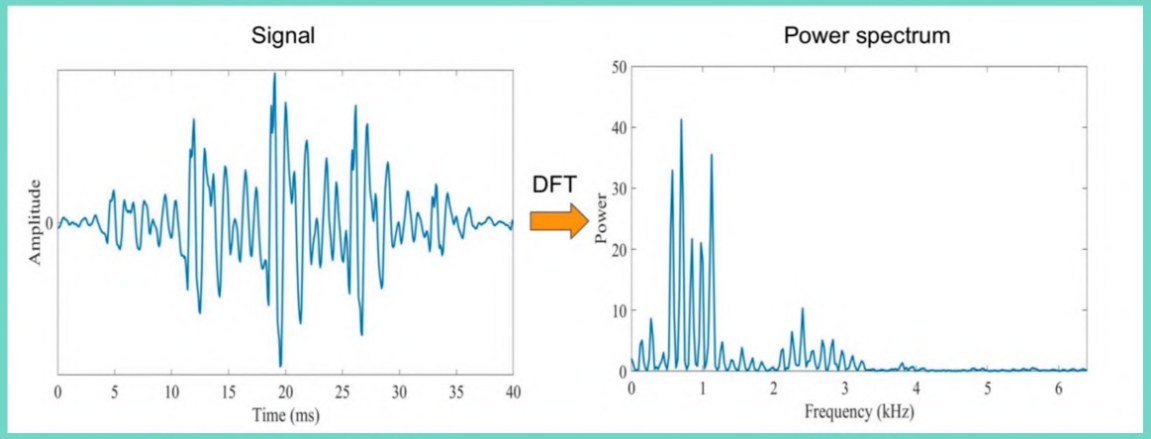
$x(t)$

$F[x(t)]$

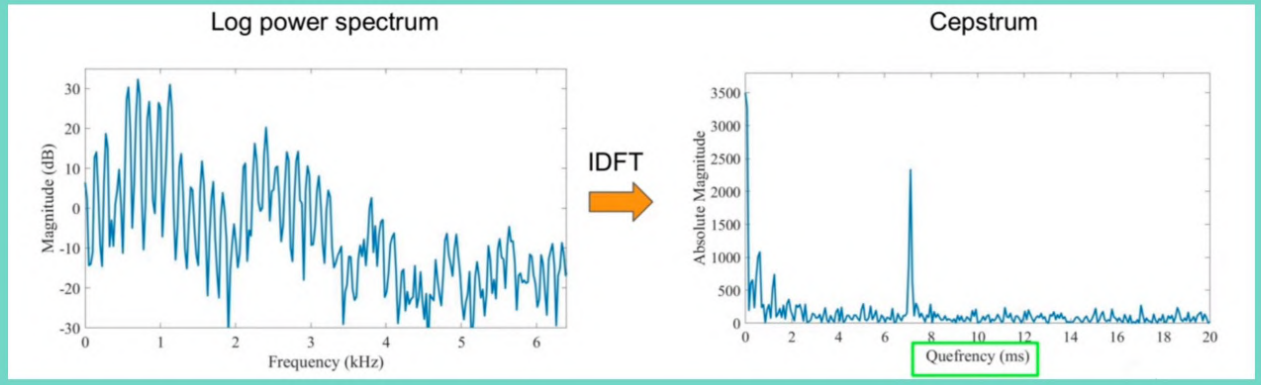


$$C(x(t)) = F^{-1}[log(F[x(t)])]$$

$x(t)$ $F[x(t)]$



$log(F[x(t)])$ F^{-1}



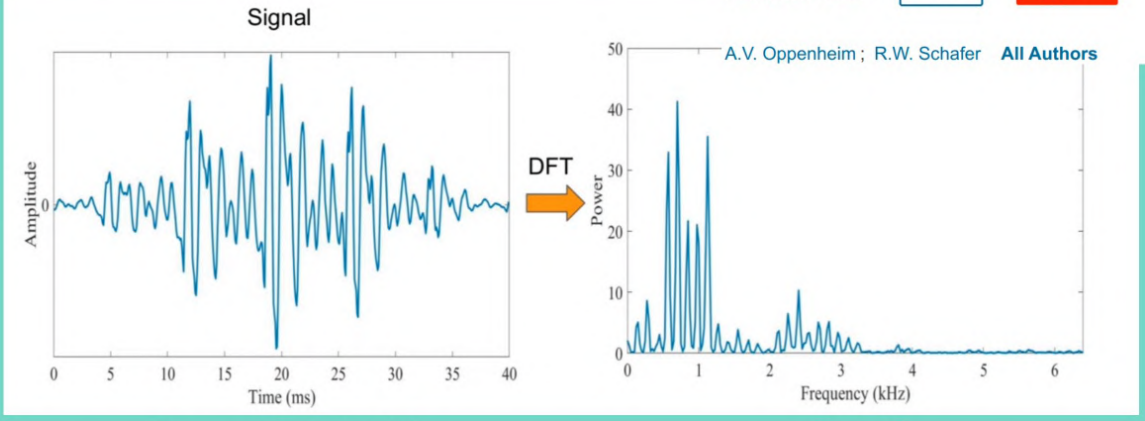
$$C(x(t)) = F^{-1}[log(F[x(t)])]$$

$x(t)$

From frequency to quefrency: a history of the cepstrum

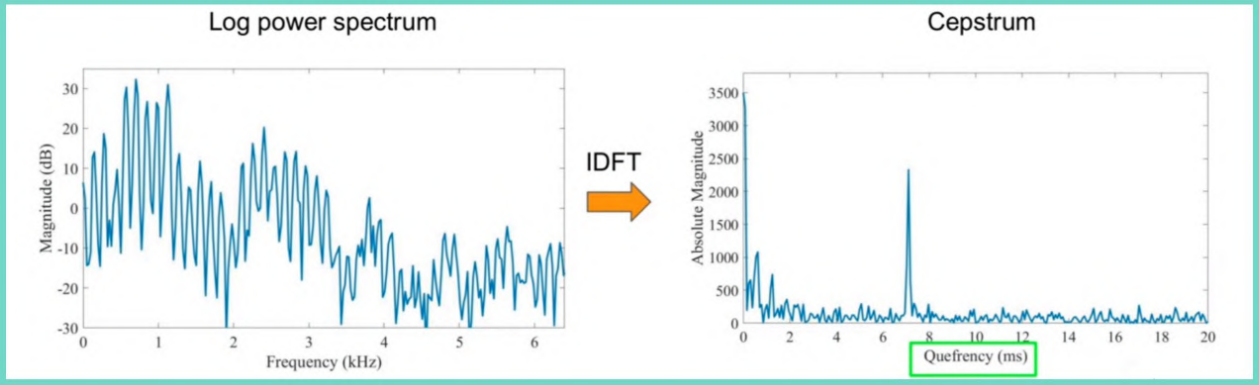
Publisher: IEEE | Cite This | PDF

A.V. Oppenheim ; R.W. Schafer All Authors



$log(F[x(t)])$

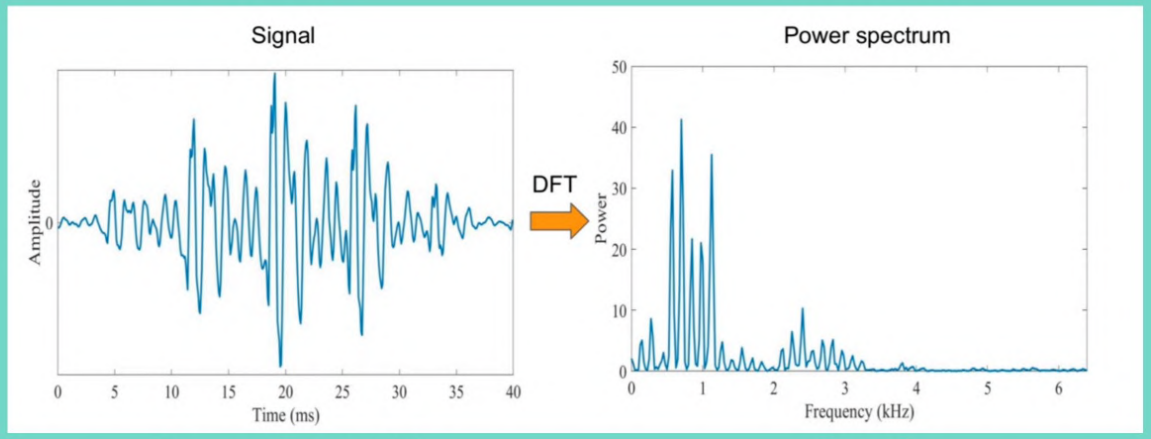
F^{-1}



$$C(x(t)) = F^{-1}[log(F[x(t)])]$$

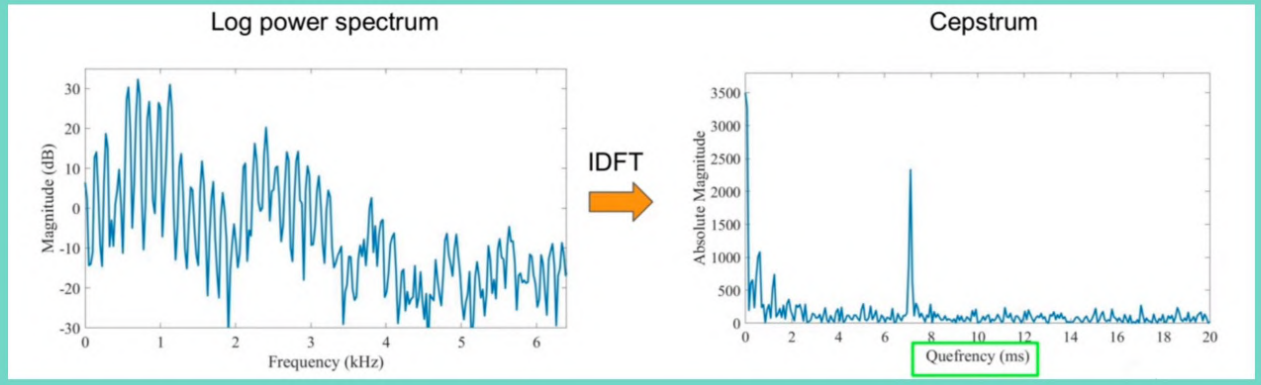
$x(t)$

$F[x(t)]$



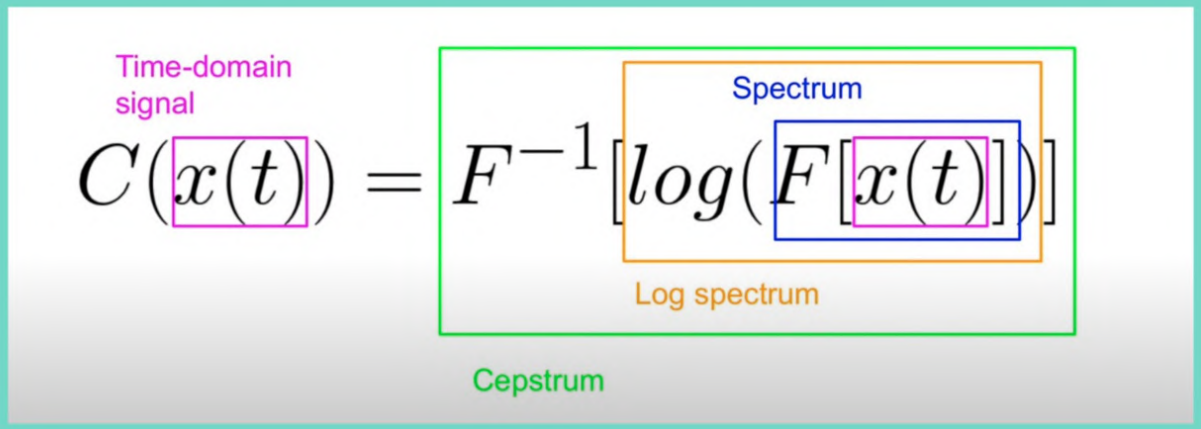
$log(F[x(t)])$

F^{-1}



Mel-Frequecy Cepstrum Coefficients (MFCCs)

Cepstrum

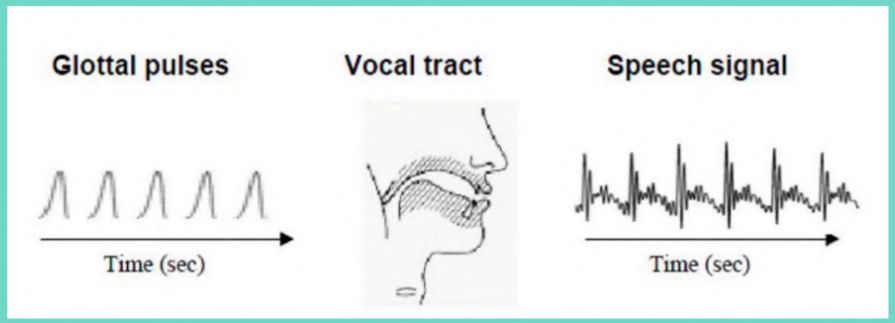


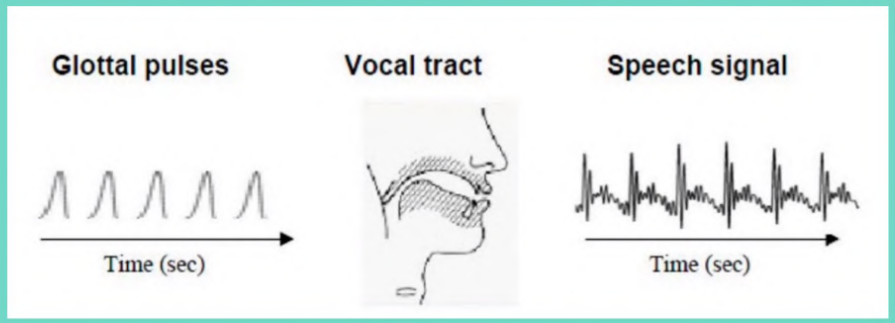
Visualize

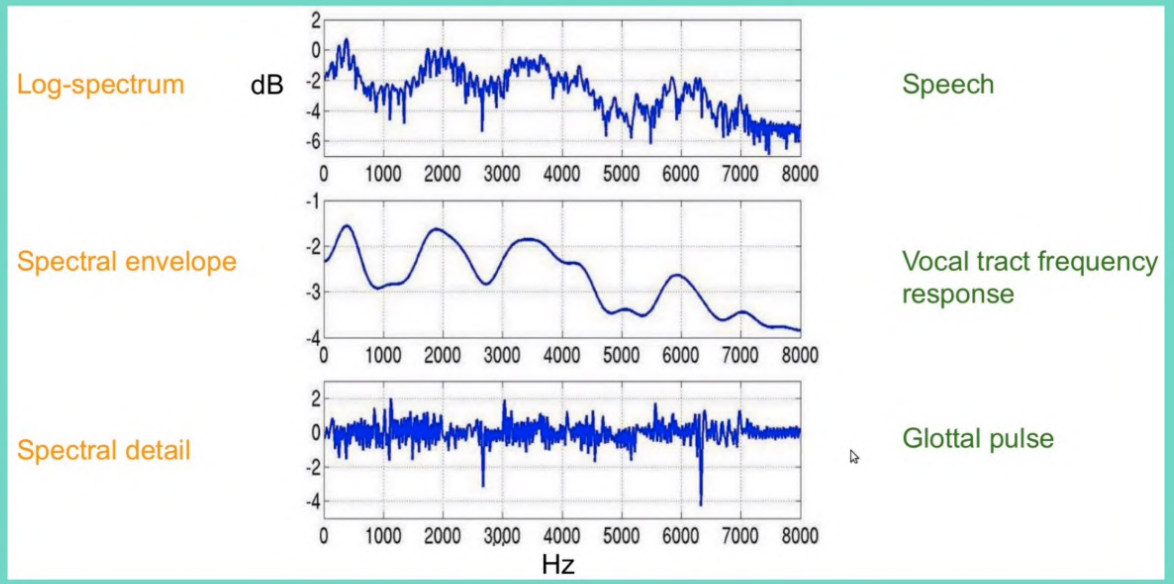
Speech Generation

Cepstrum and Speech

Compute

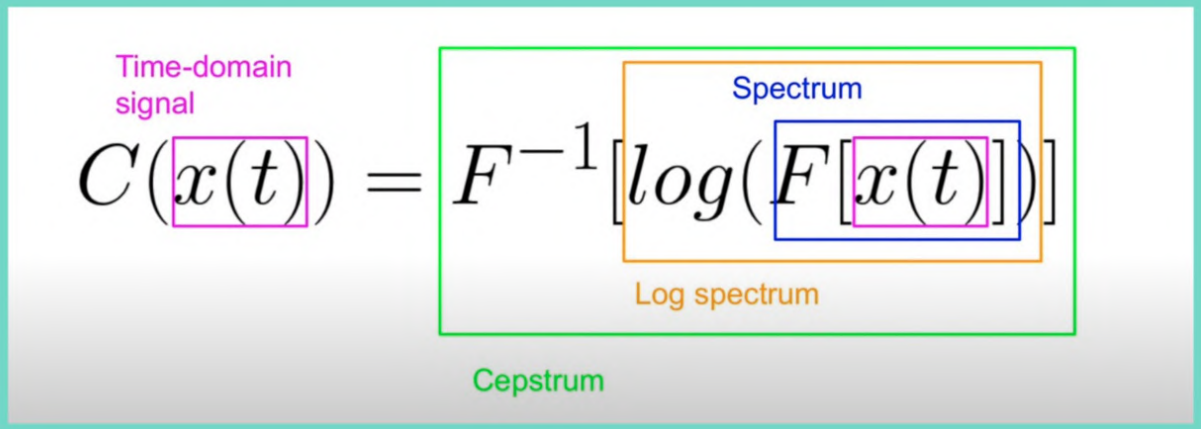

Glottal pulses
Vocal tract
Speech signal
Time (sec)
Time (sec)


Glottal pulses
Vocal tract
Speech signal
Time (sec)
Time (sec)


Log-spectrum
dB
Spectral envelope
Spectral detail
Hz
Speech
Vocal tract frequency response
Glottal pulse

Mel-Frequecy Cepstrum Coefficients (MFCCs)

Cepstrum



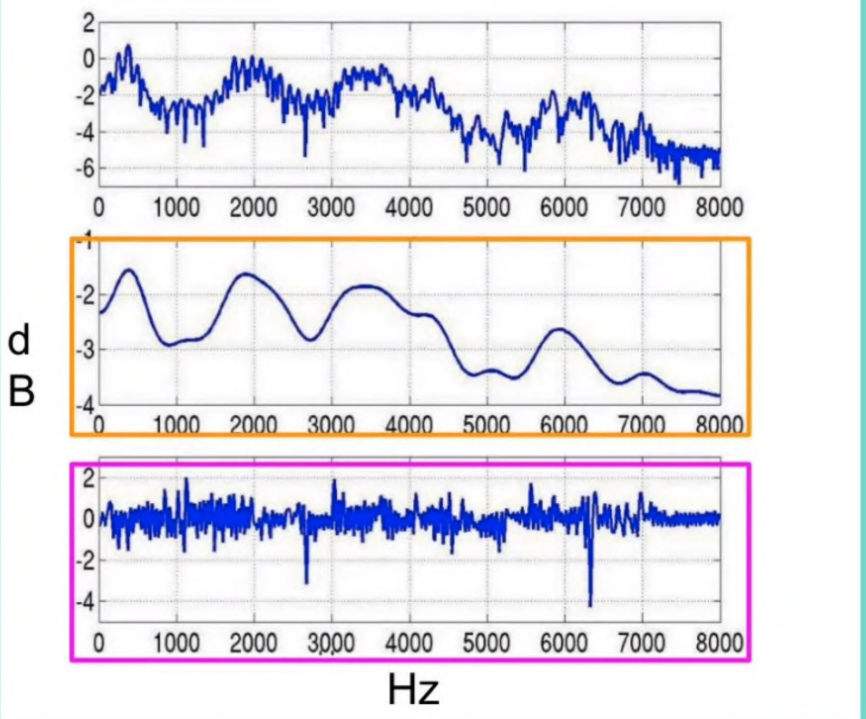
Visualize

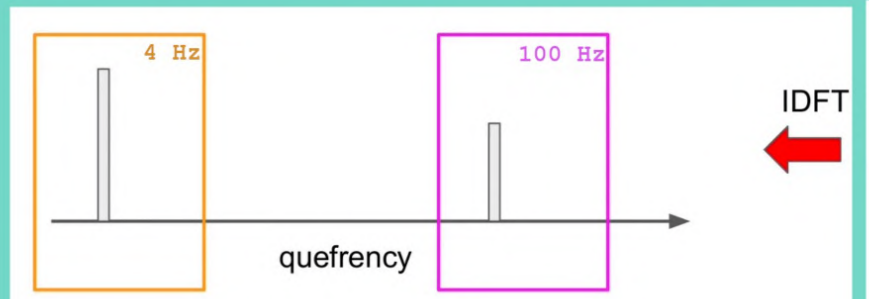
Speech Generation

Cepstrum and Speech

Compute

$$log(X(t)) = log(E(t)) + log(H(t))$$

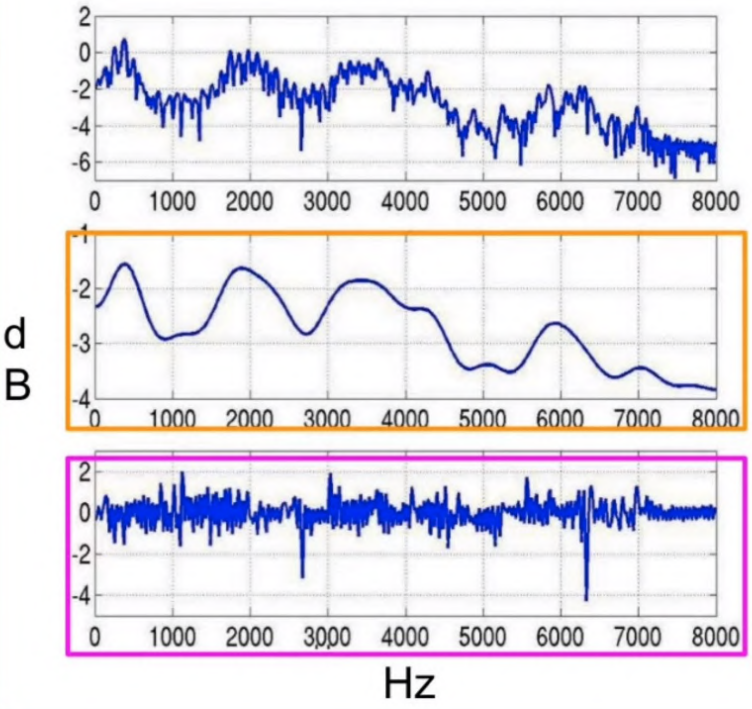




IDFT

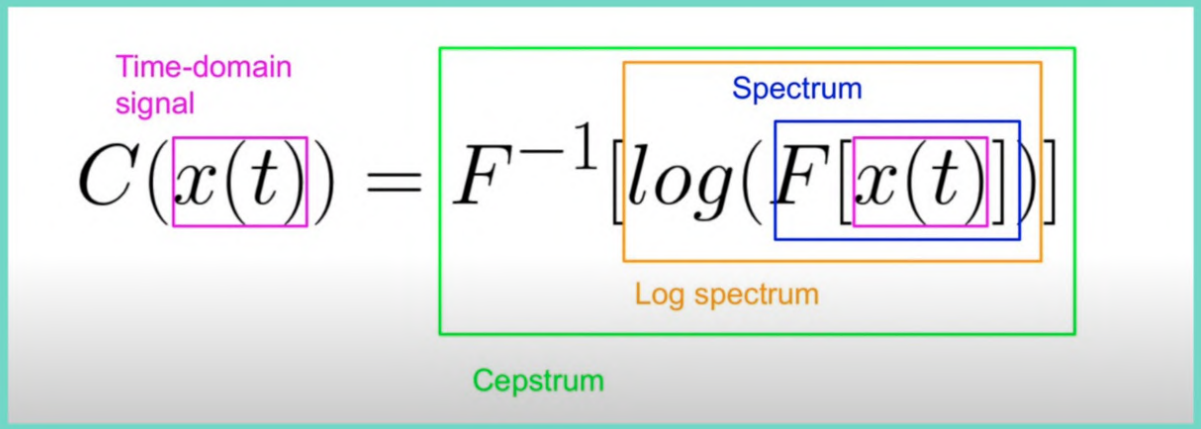
$$X(t) = E(t) \cdot H(t)$$

$$log(X(t)) = log(E(t)) + log(H(t))$$



Mel-Frequecy Cepstrum Coefficients (MFCCs)

Cepstrum

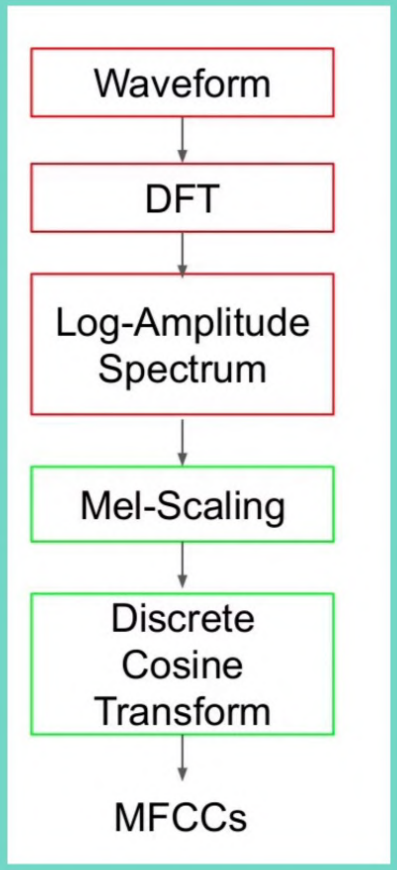


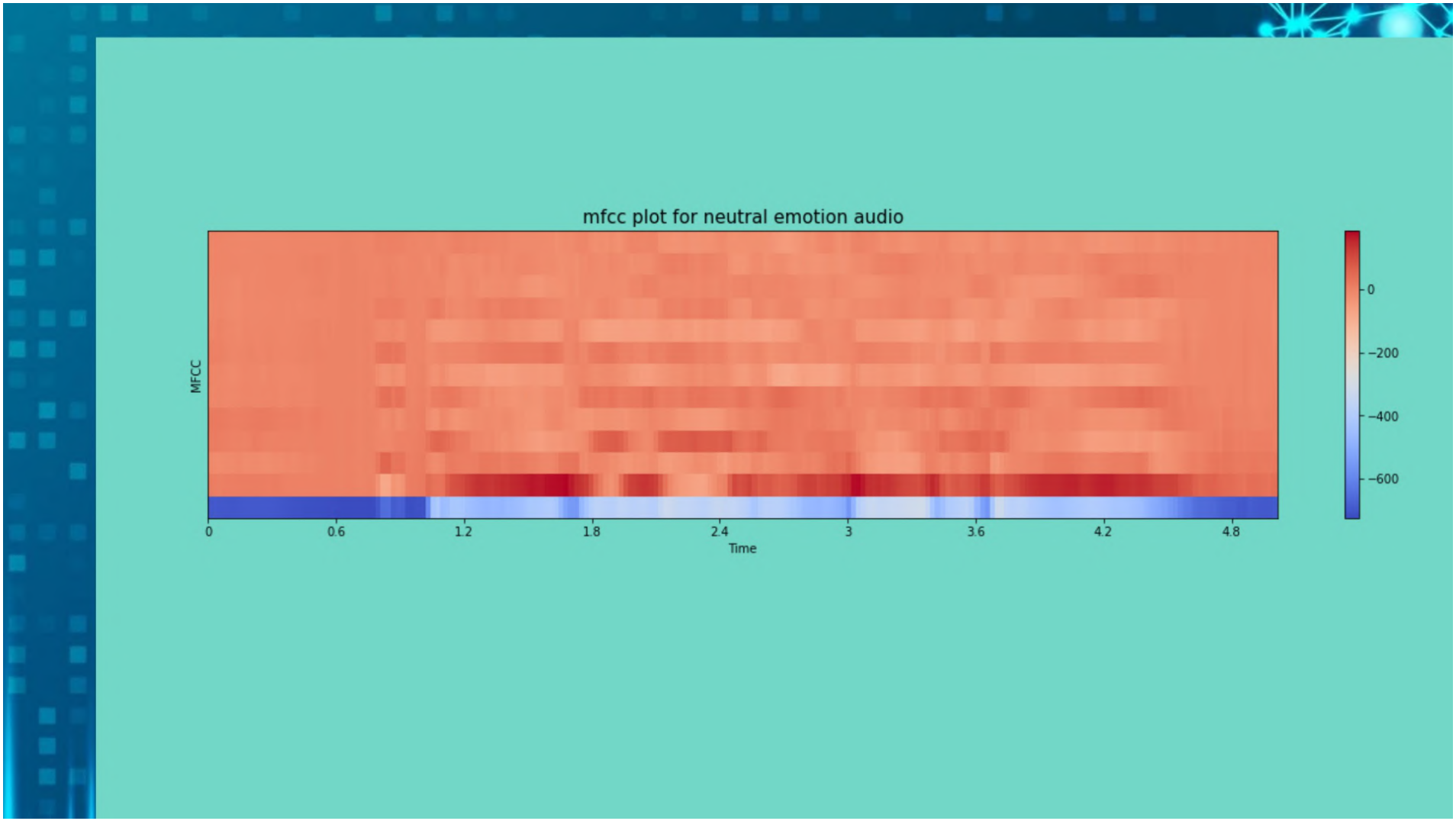
Visualize

Speech Generation

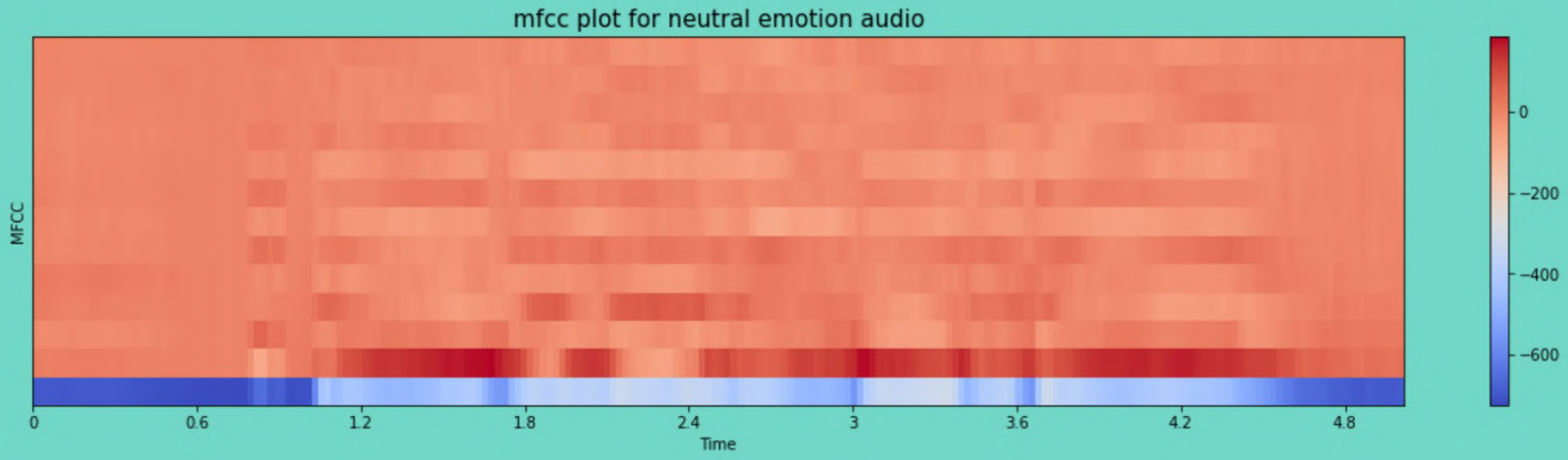
Cepstrum and Speech

Compute


Waveform
DFT
Log-Amplitude Spectrum
Mel-Scaling
Discrete Cosine Transform
MFCCs

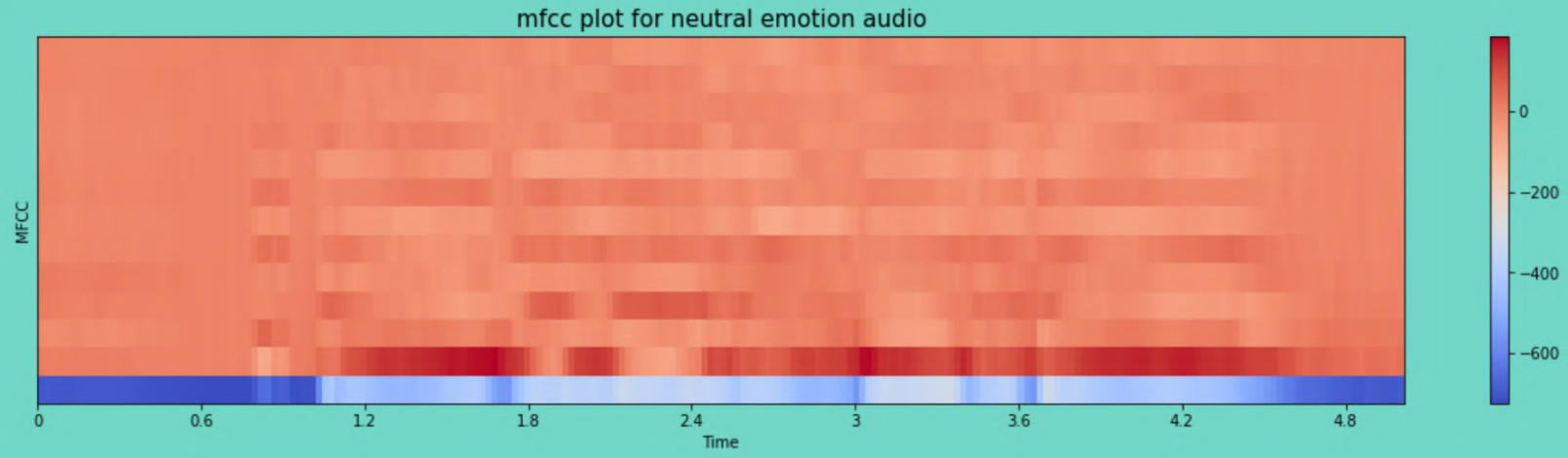

mfcc plot for neutral emotion audio
MFCC
Time
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
0
−200
−400
−600

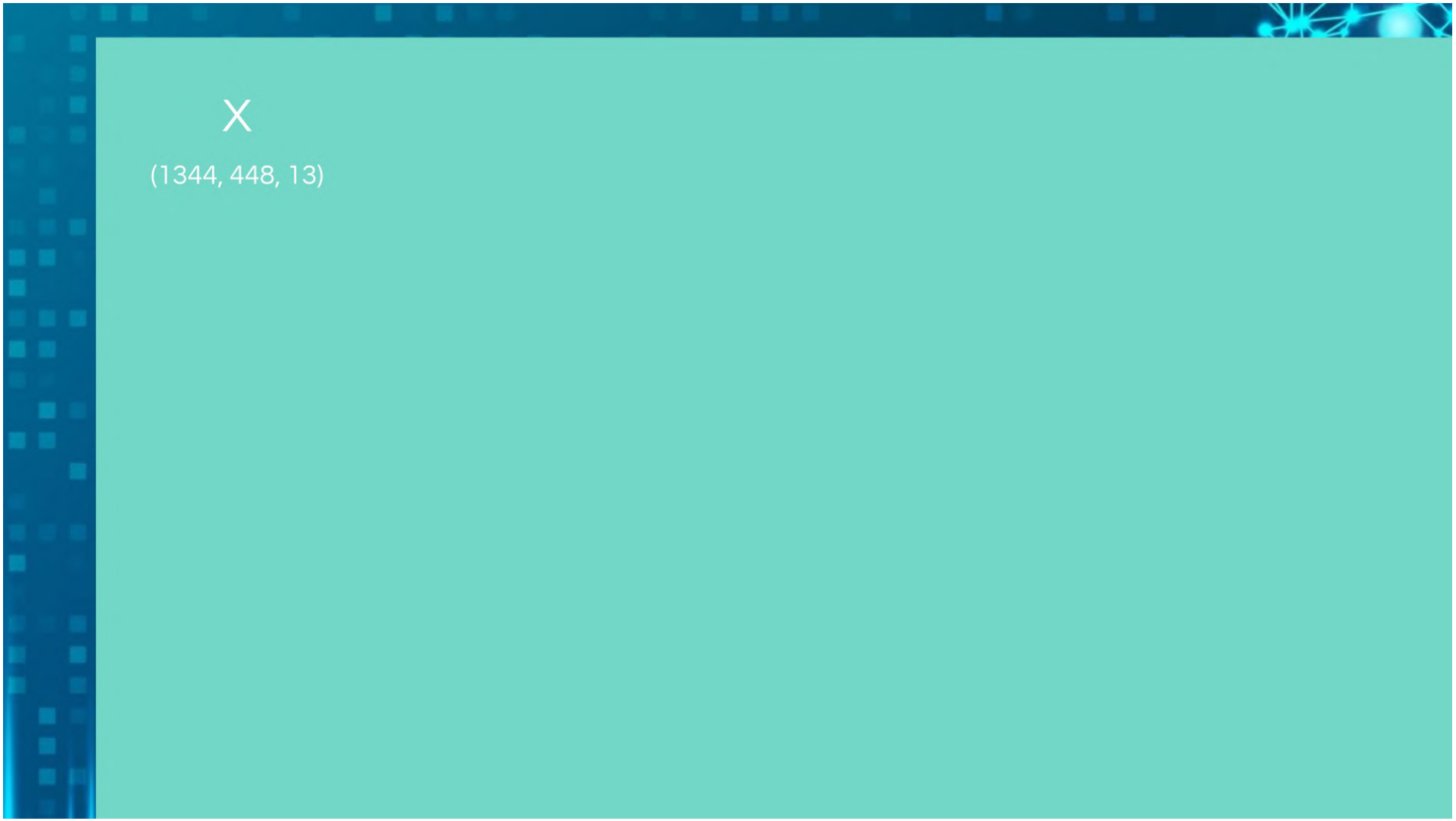
X


mfcc plot for neutral emotion audio
MFCC
Time
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
0
−200
−400
−600

X

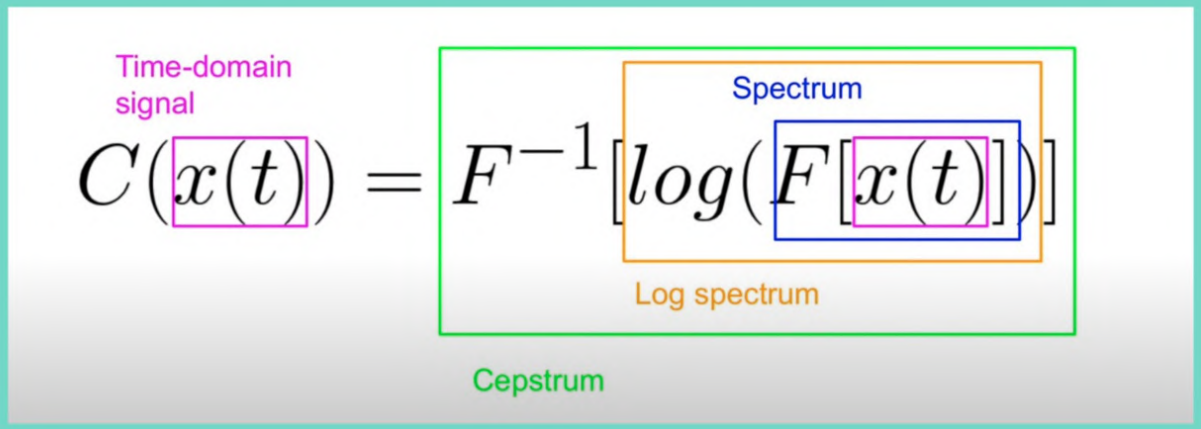
(1344, 448, 13)


mfcc plot for neutral emotion audio
MFCC
0
0.6
1.2
1.8
2.4
3
3.6
4.2
4.8
Time
0
−200
−400
−600


X
(1344, 448, 13)

Mel-Frequecy Cepstrum Coefficients (MFCCs)

Cepstrum



Visualize

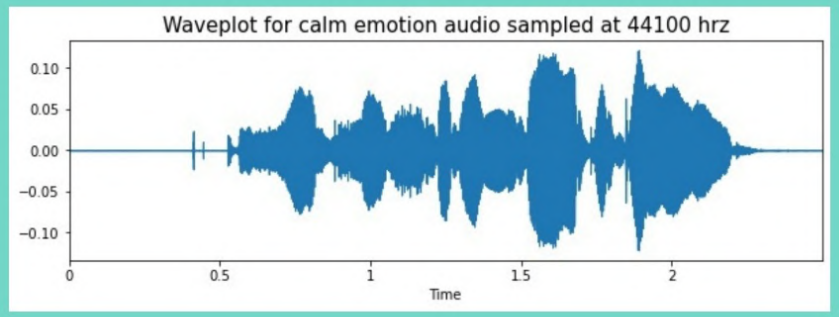
Speech Generation

Cepstrum and Speech

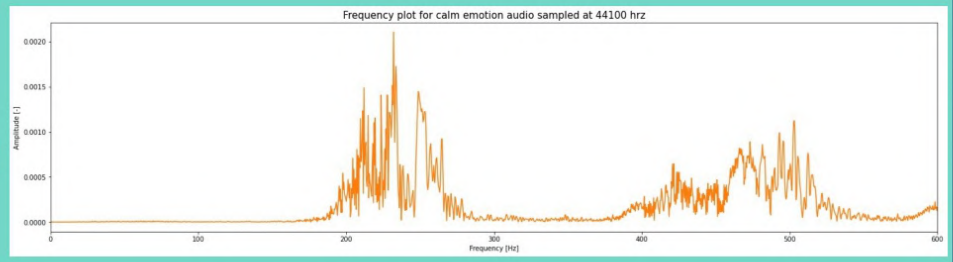
Compute

Feature extraction

- Time-Domain
  - RMSE, ZCR

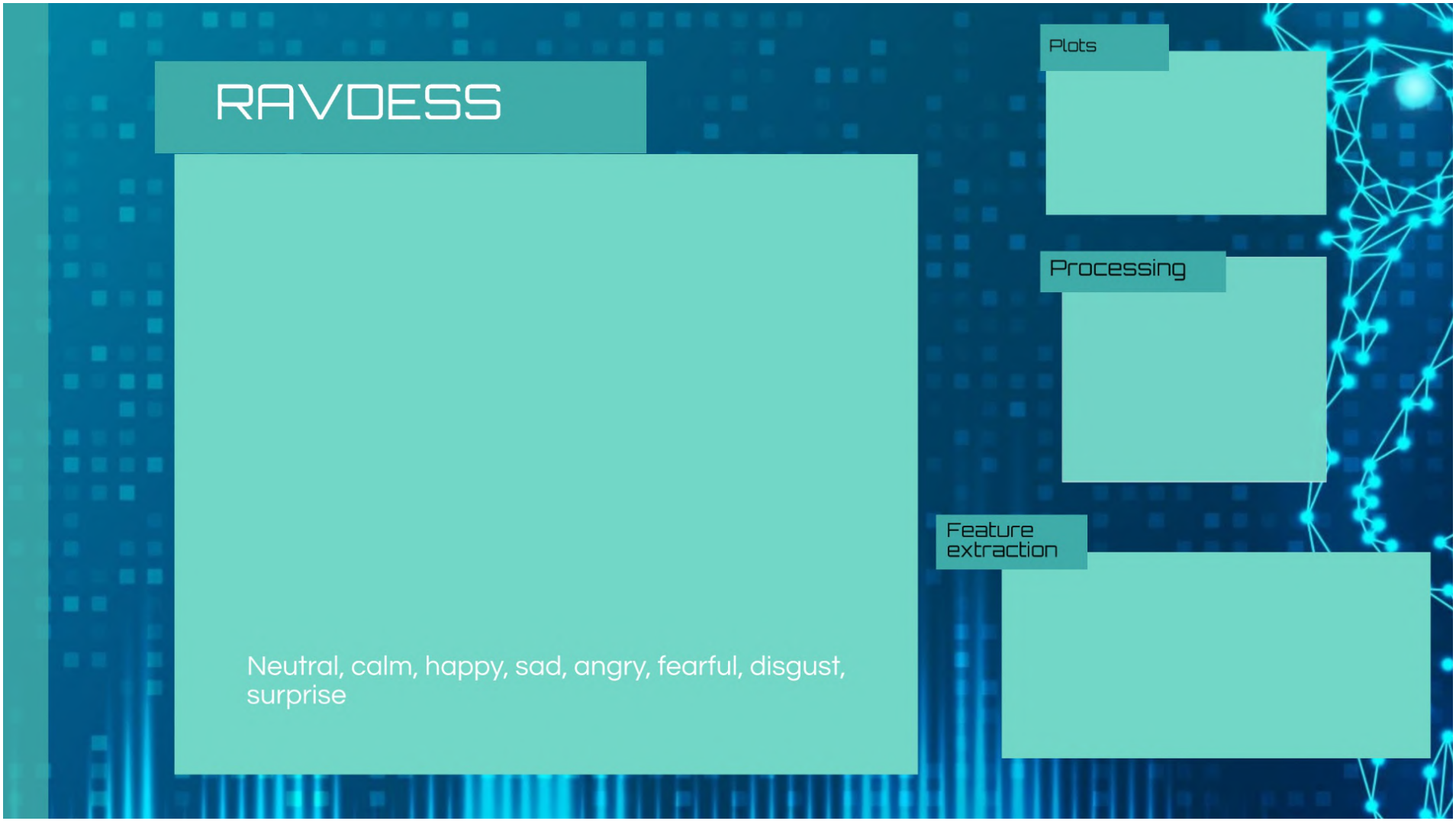


- Frequency Domain
  - Spectral Centroid



Mel-Spectrogram

MFCC


RAVDESS
Neutral, calm, happy, sad, angry, fearful, disgust, surprise
Plots
Processing
Feature extraction

Introduction

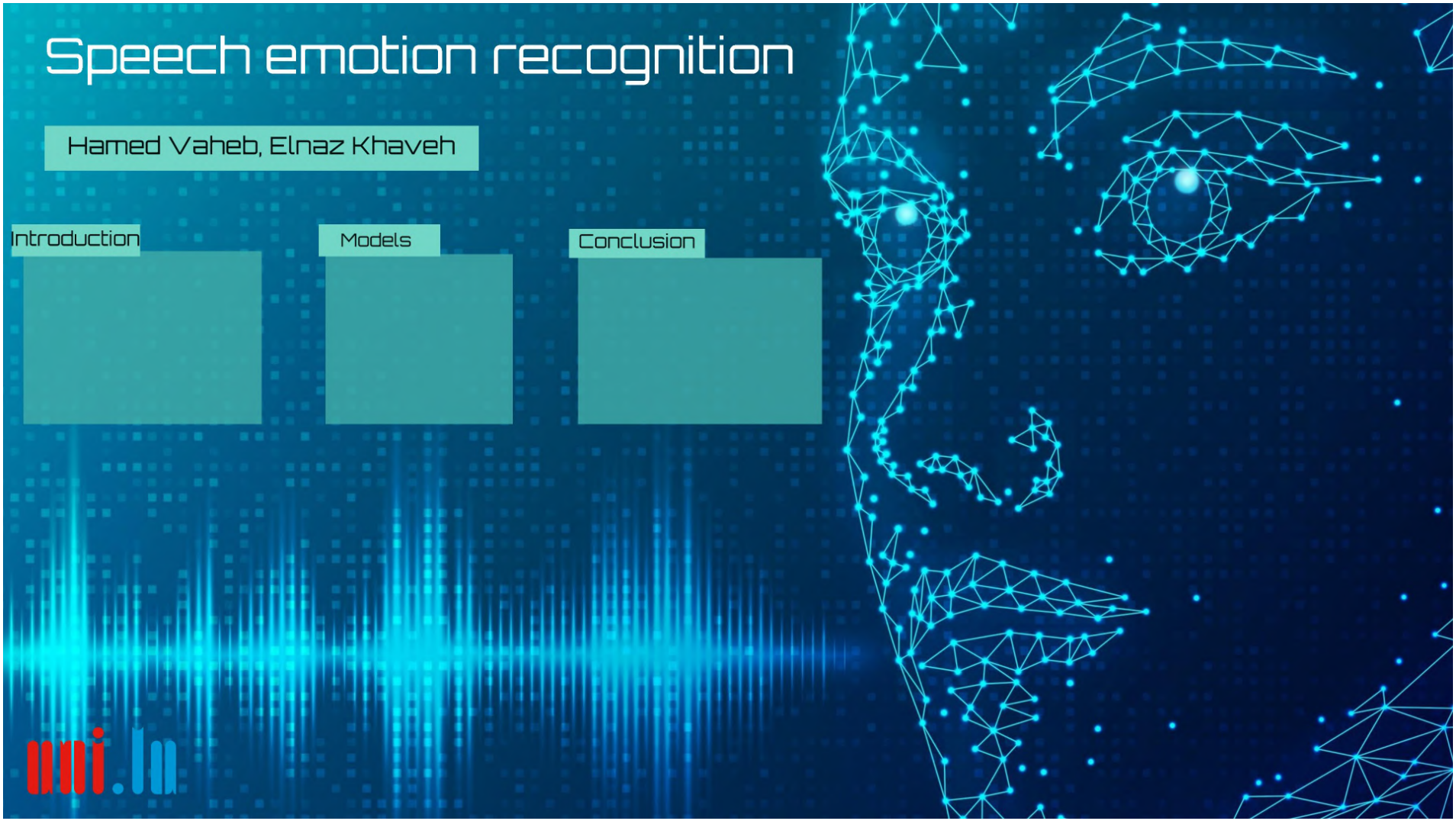
Importance:


The Evolution of Human Vocal Emotion
Gregory A. Bryant
First Published June 24, 2020 | Research Article
https://doi.org/10.1177/1754073920930791
Article information

- The most natural way to express ourselves
- Influence over judgement
  - "go home!"
- Human-computer interaction (HCI)
  - Personal Assistants
  - Next Generation AI

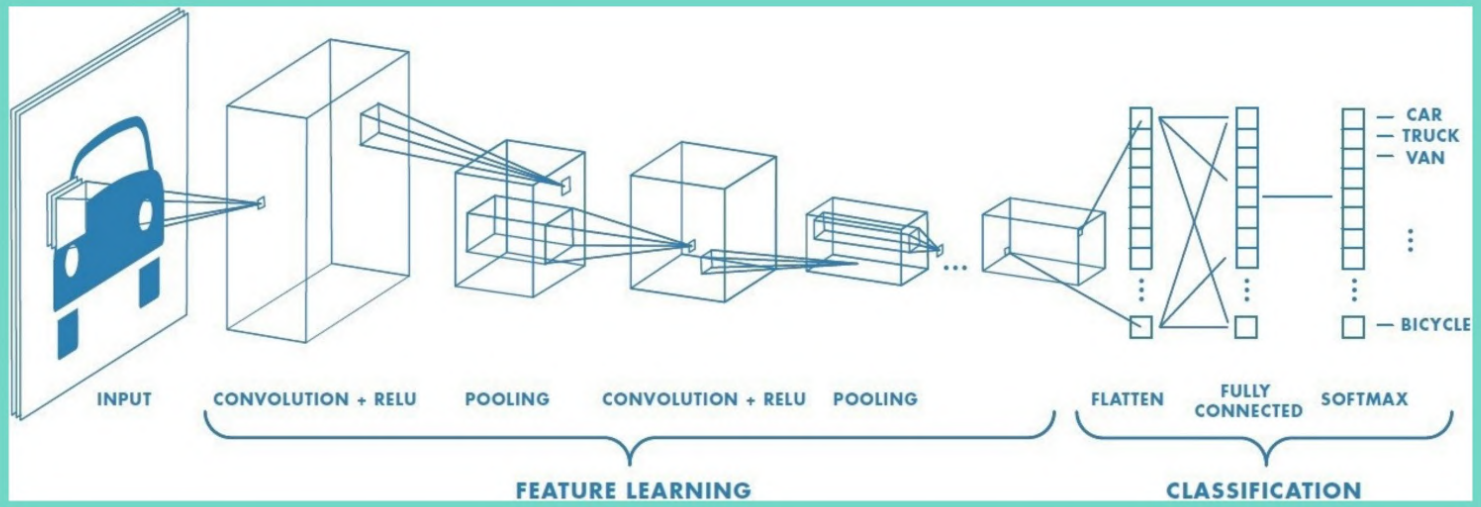
Applications

Data set

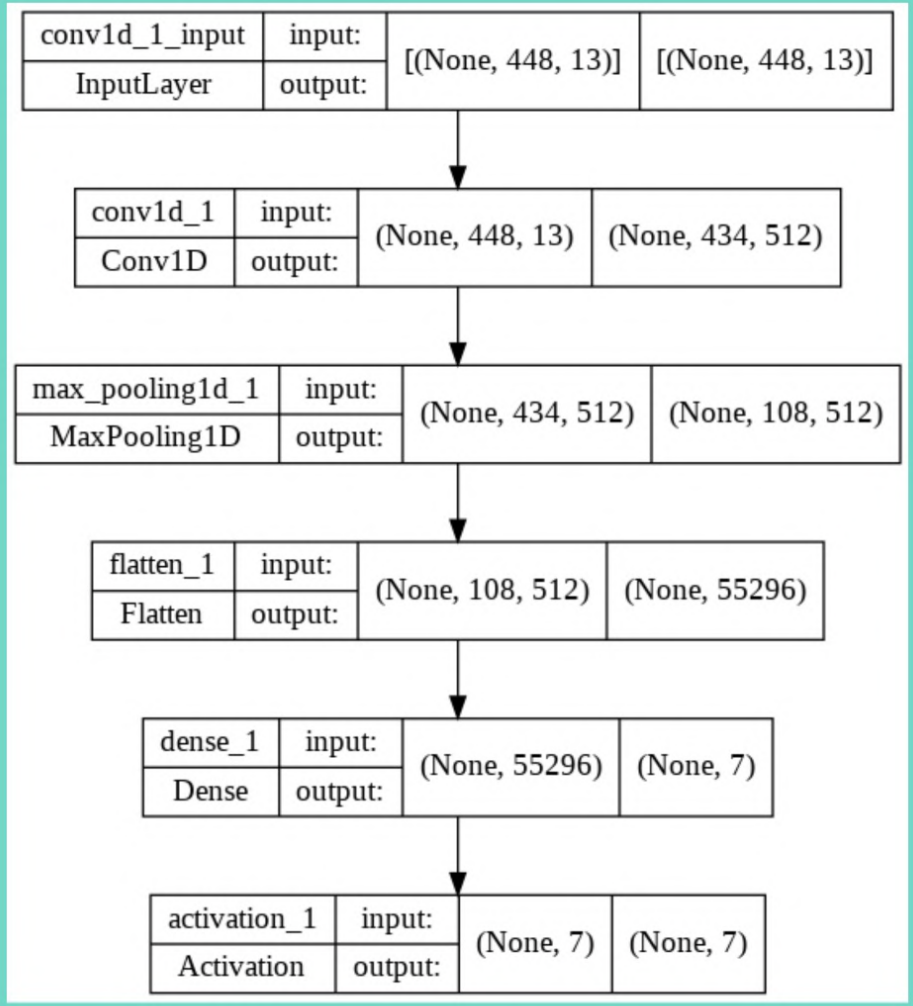

Speech emotion recognition
Hamed Vaheb, Elnaz Khaveh
Introduction
Models
Conclusion


Models
CNN
RNN
Results

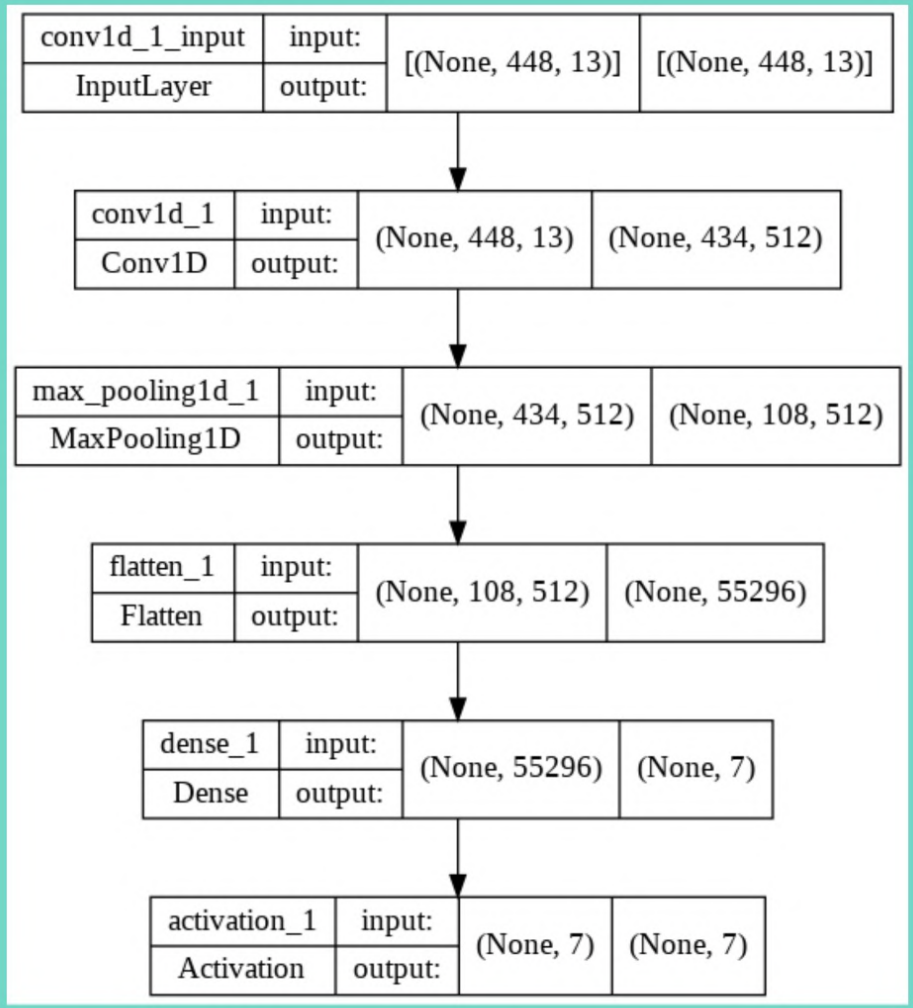
CNN



architecture

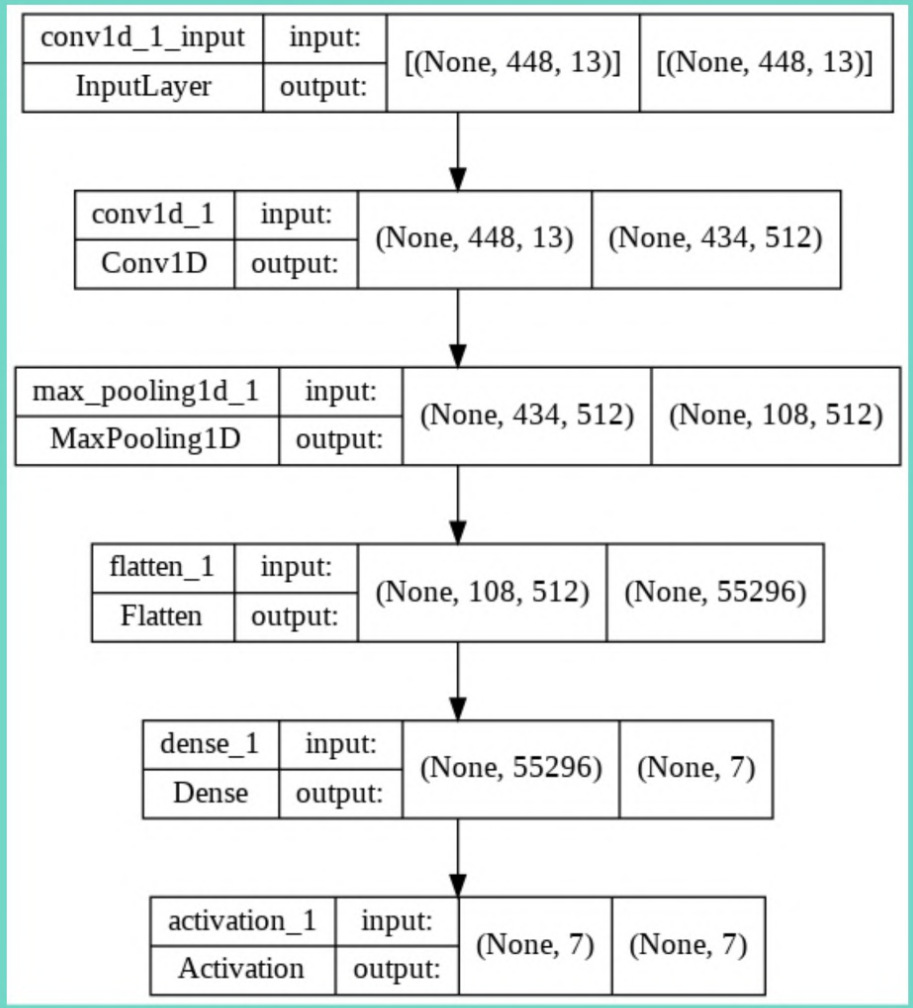

conv1d_1_input
InputLayer
input:
output:
[(None, 448, 13)]
[(None, 448, 13)]
conv1d_1
Conv1D
input:
output:
(None, 448, 13)
(None, 434, 512)
max_pooling1d_1
MaxPooling1D
input:
output:
(None, 434, 512)
(None, 108, 512)
flatten_1
Flatten
input:
output:
(None, 108, 512)
(None, 55296)
dense_1
Dense
input:
output:
(None, 55296)
(None, 7)
activation_1
Activation
input:
output:
(None, 7)
(None, 7)

X

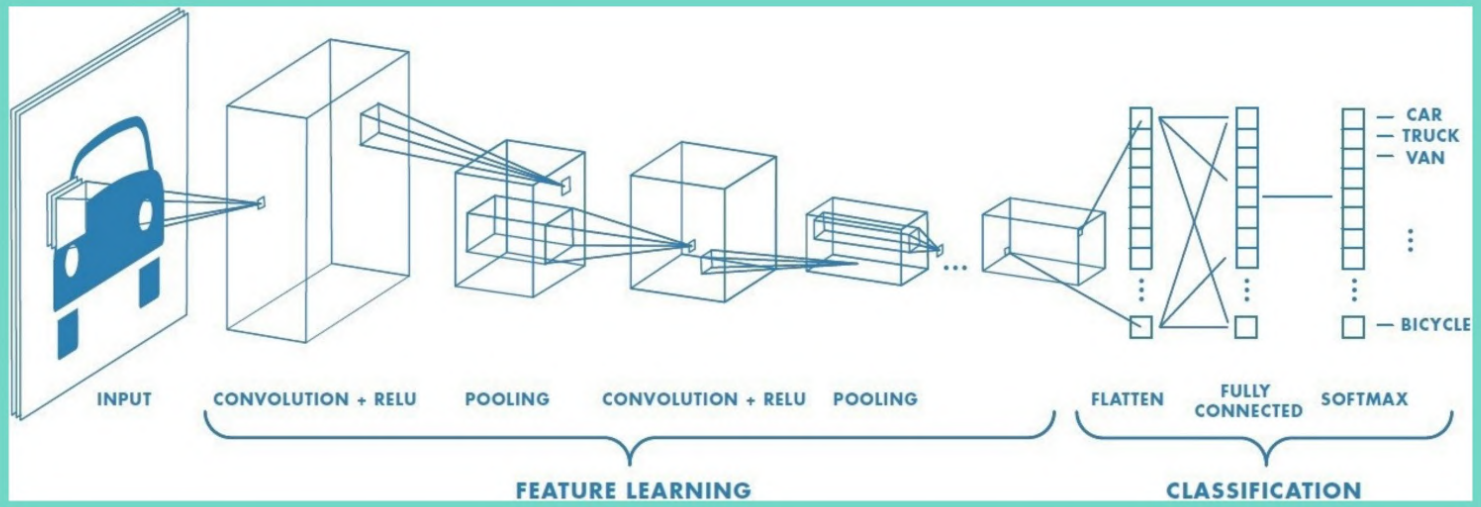

conv1d_1_input
input:
InputLayer
output:
[(None, 448, 13)]
[(None, 448, 13)]
conv1d_1
input:
Conv1D
output:
(None, 448, 13)
(None, 434, 512)
max_pooling1d_1
input:
MaxPooling1D
output:
(None, 434, 512)
(None, 108, 512)
flatten_1
input:
Flatten
output:
(None, 108, 512)
(None, 55296)
dense_1
input:
Dense
output:
(None, 55296)
(None, 7)
activation_1
input:
Activation
output:
(None, 7)
(None, 7)

X

(1344, 448, 13)


conv1d_1_input
InputLayer
input:
output:
[(None, 448, 13)]
[(None, 448, 13)]
conv1d_1
Conv1D
input:
output:
(None, 448, 13)
(None, 434, 512)
max_pooling1d_1
MaxPooling1D
input:
output:
(None, 434, 512)
(None, 108, 512)
flatten_1
Flatten
input:
output:
(None, 108, 512)
(None, 55296)
dense_1
Dense
input:
output:
(None, 55296)
(None, 7)
activation_1
Activation
input:
output:
(None, 7)
(None, 7)

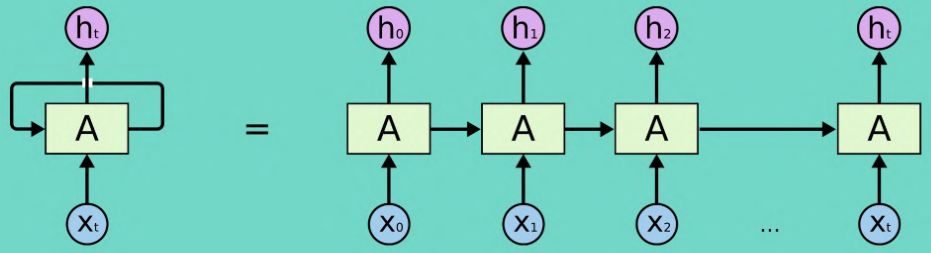
CNN



architecture


Models
CNN
RNN
Results

RNN



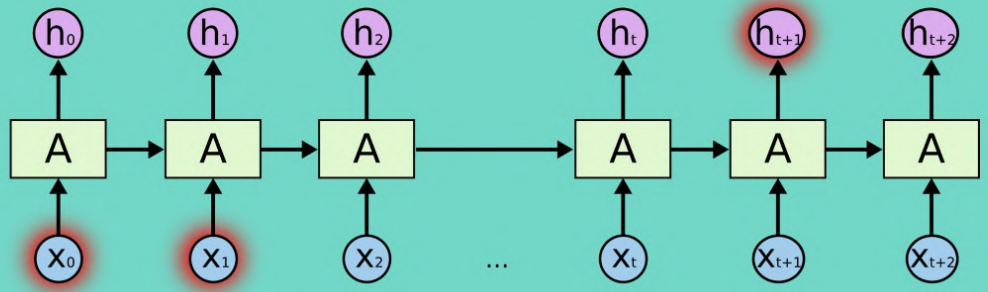
GRU

architecture

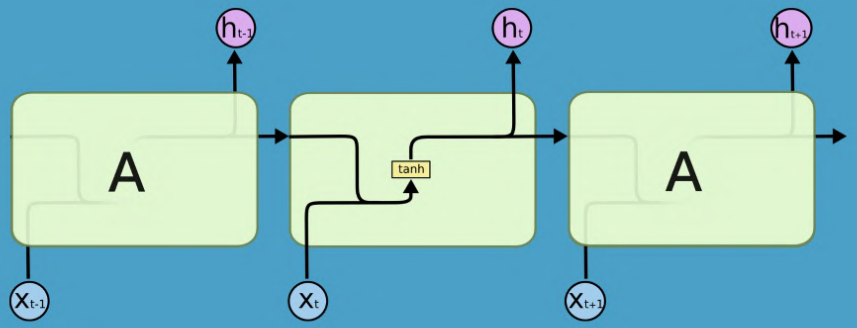

RNN
GRU
architecture

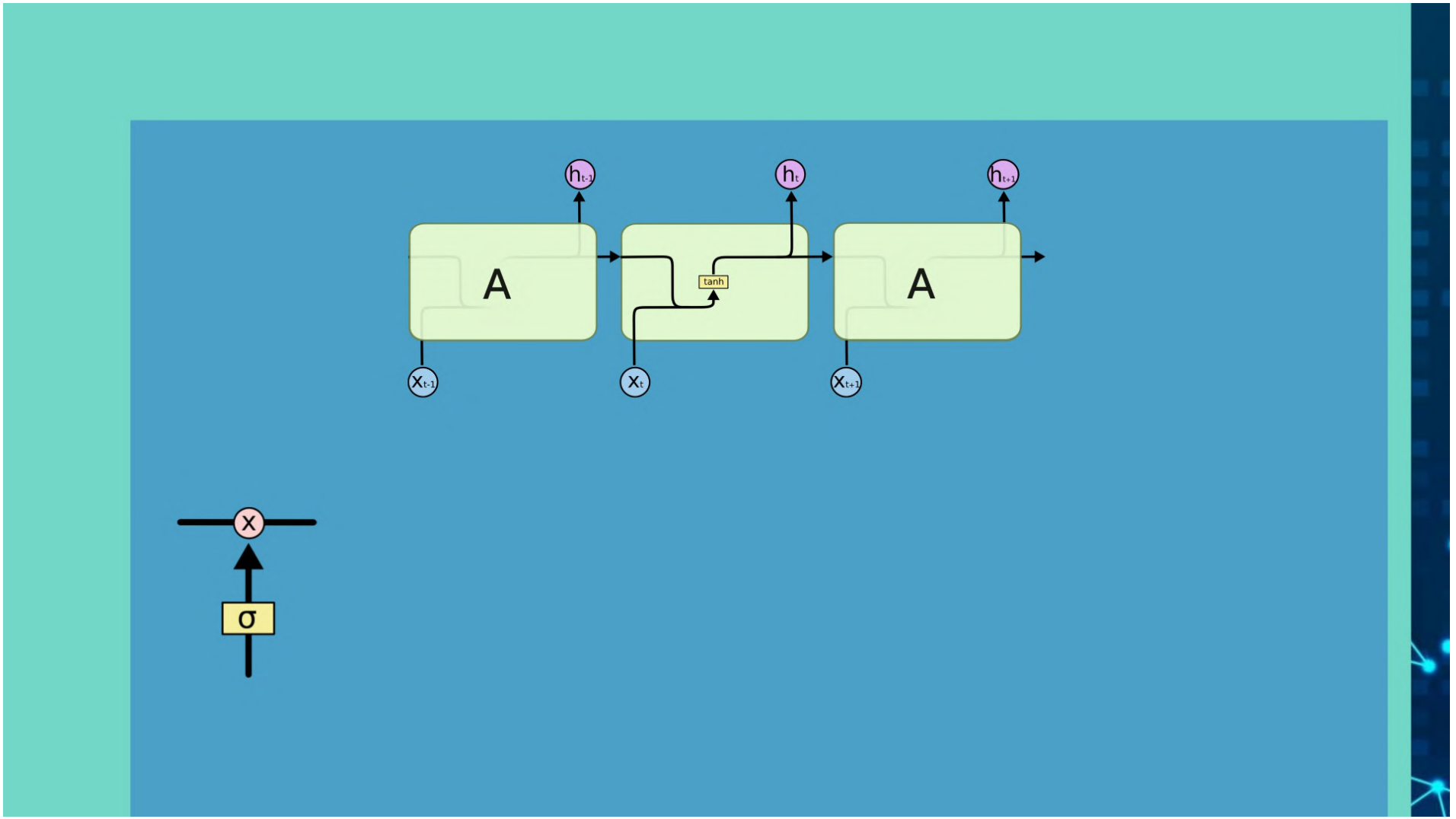
RNN

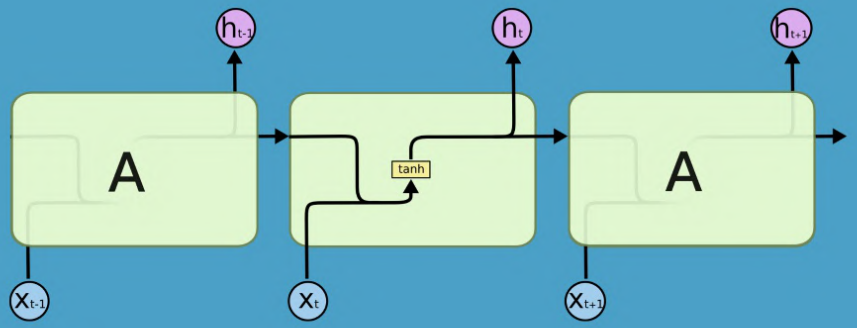
GRU

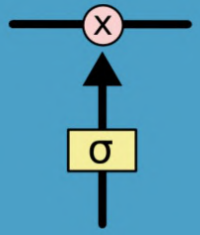


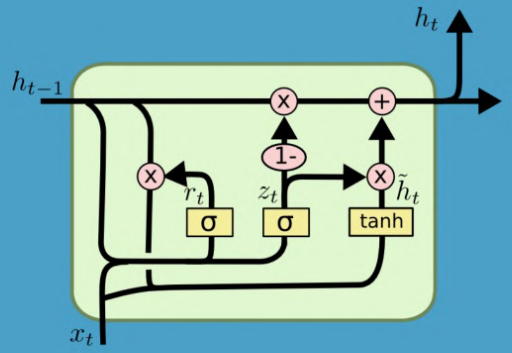
architecture


h_{t-1}
h_t
h_{t+1}
A
tanh
A
x_{t-1}
x_t
x_{t+1}


h_{t-1}
h_t
h_{t+1}
A
tanh
A
x_{t-1}
x_t
x_{t+1}
x
σ







$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

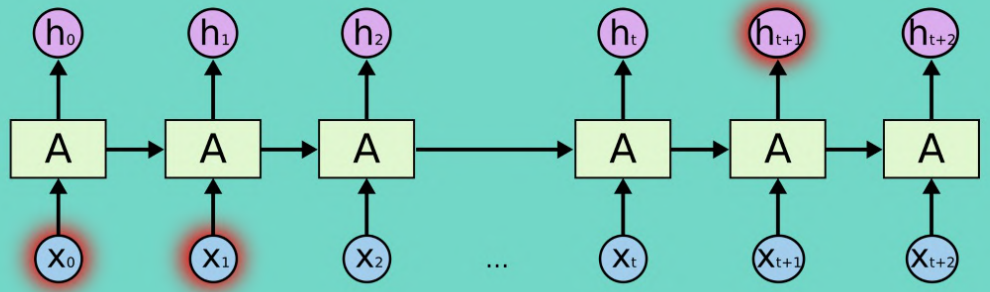
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

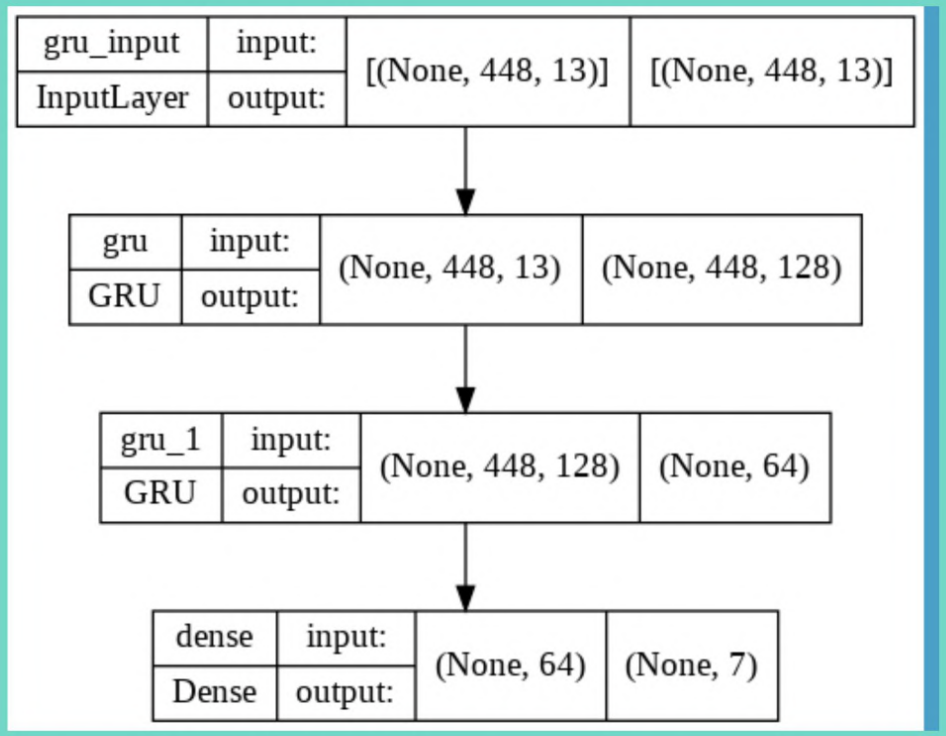
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

RNN

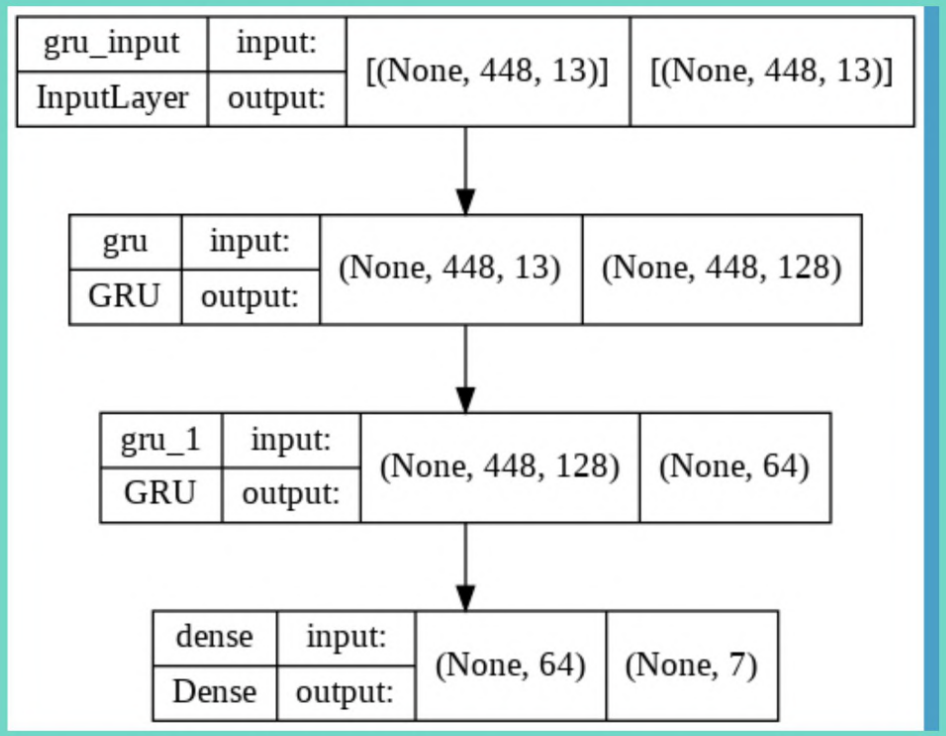
GRU



architecture


gru_input
InputLayer
input:
output:
[(None, 448, 13)]
[(None, 448, 13)]
gru
GRU
input:
output:
(None, 448, 13)
(None, 448, 128)
gru_1
GRU
input:
output:
(None, 448, 128)
(None, 64)
dense
Dense
input:
output:
(None, 64)
(None, 7)

X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Dense
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output:
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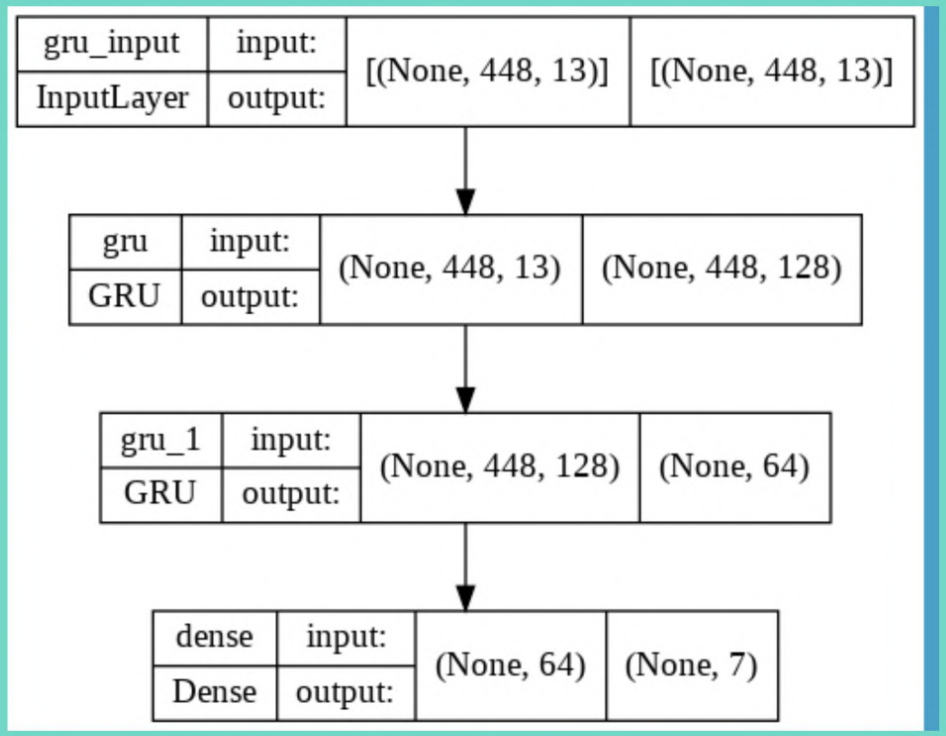
(None, 7)

X

(1344, 448, 13)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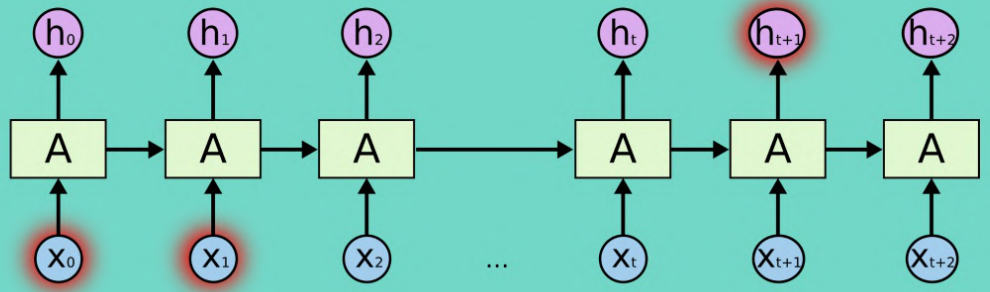
RNN

GRU

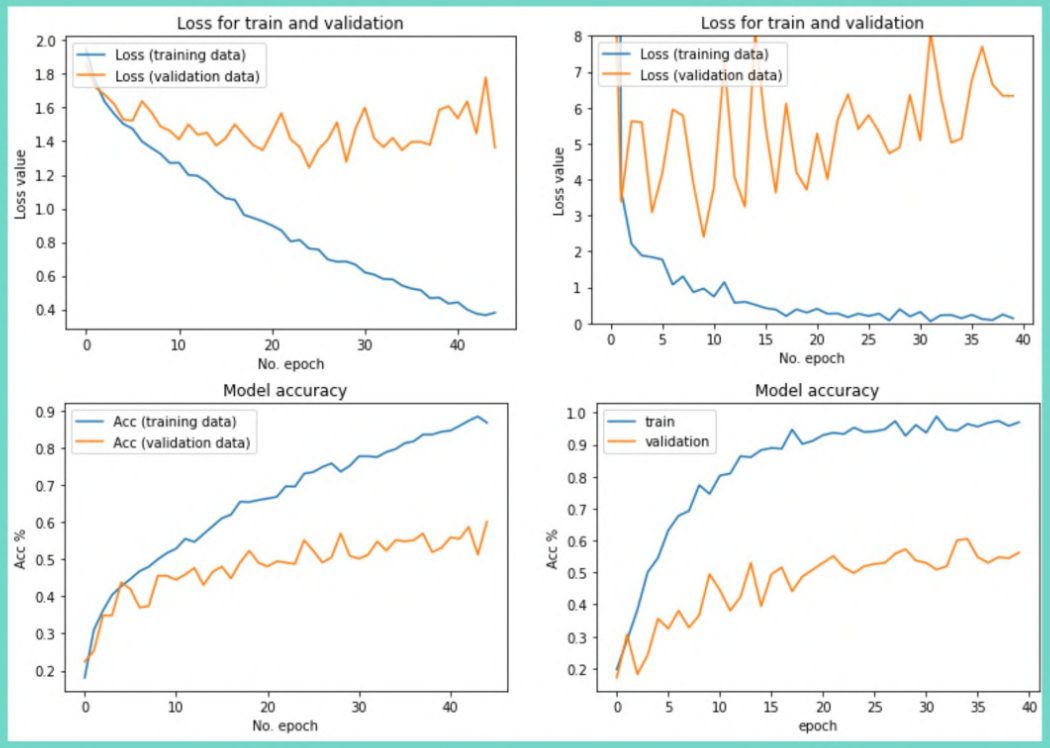


architecture


Models
CNN
RNN
Results


Compare the results
Loss-accuracy
Table
Confusion matrix

RNN CNN


Loss for train and validation
Loss (training data)
Loss (validation data)
Loss value
No. epoch
Loss for train and validation
Loss (training data)
Loss (validation data)
Loss value
No. epoch
Model accuracy
Acc (training data)
Acc (validation data)
Acc %
No. epoch
Model accuracy
train
validation
Acc %
epoch


Compare the results
Loss-accuracy
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Confusion matrix

	RNN	CNN
Accuracy	60%	61%
Precision	63%	64%
Recall	62%	62%
F1 score	61%	60%
loss	1.39	6.58

The training time for RNN: 18 minutes

The training time for CNN: 3 minutes


Compare the results
Loss-accuracy
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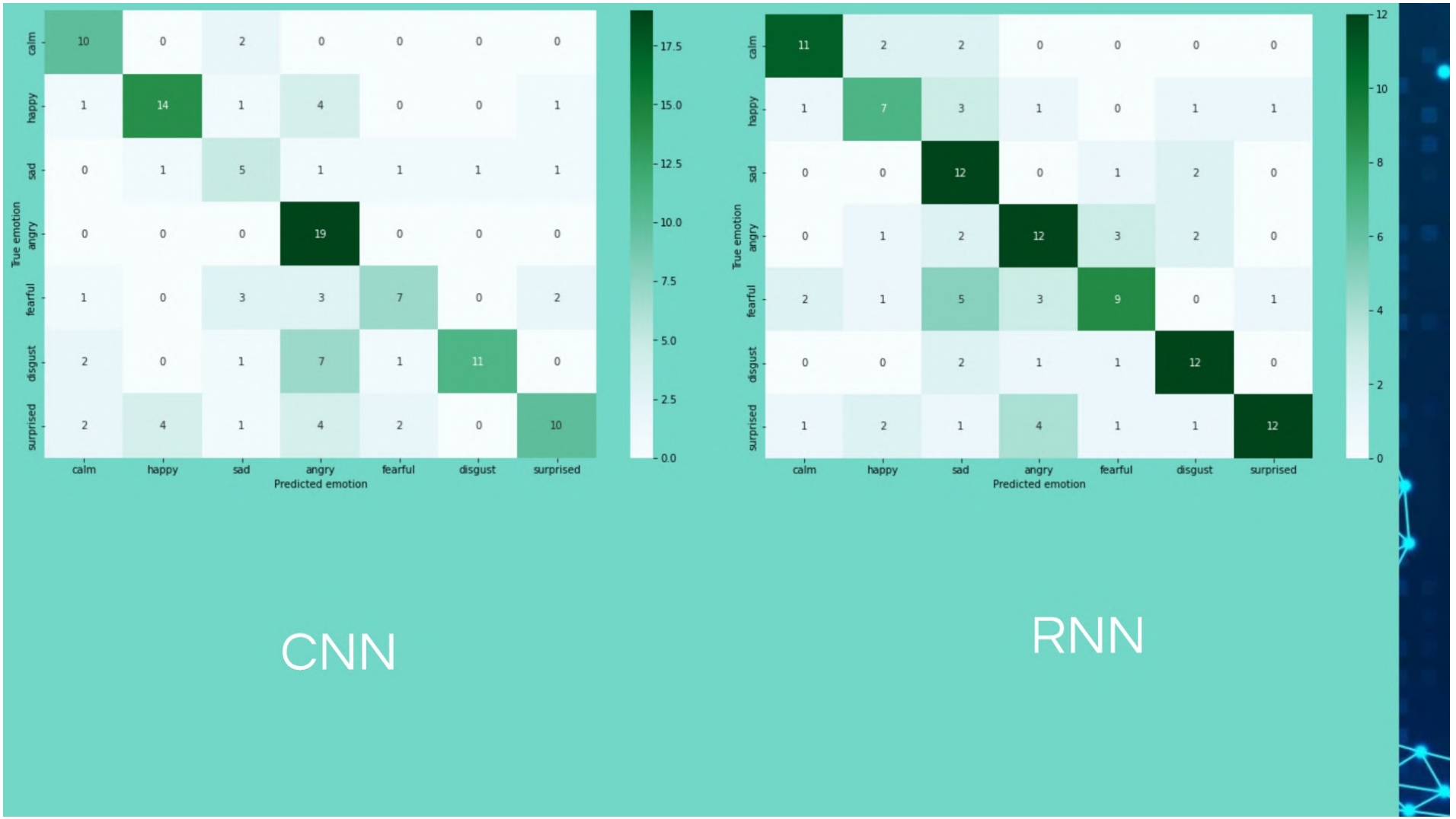
True emotion
calm
happy
sad
angry
fearful
disgust
surprised
Predicted emotion
CNN
RNN


Compare the results
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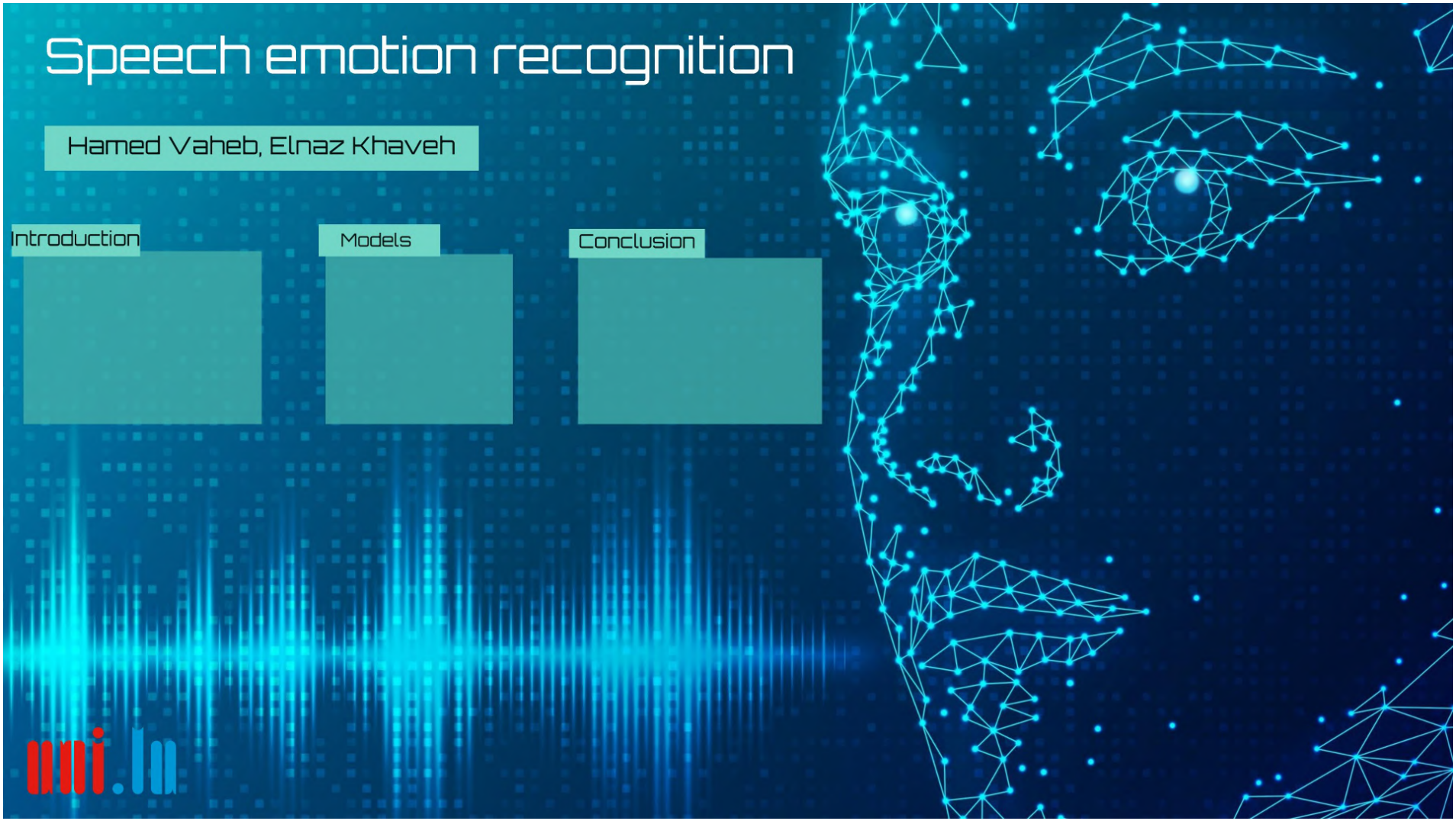
Models
CNN
RNN
Results


Speech emotion recognition
Hamed Vaheb, Elnaz Khaveh
Introduction
Models
Conclusion

Conclusion

- CNN and RNN perform almost the same
- Time complexity of CNN is slightly better
- MFCC was the most determinant feature

Future work

Future work

- Real-time
- continuous representation of emotions
- Small data set
- hyper-parameter
- ensemble

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https://github.com/berserkhmdvhb/Project-SER

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Thanks for your attention !

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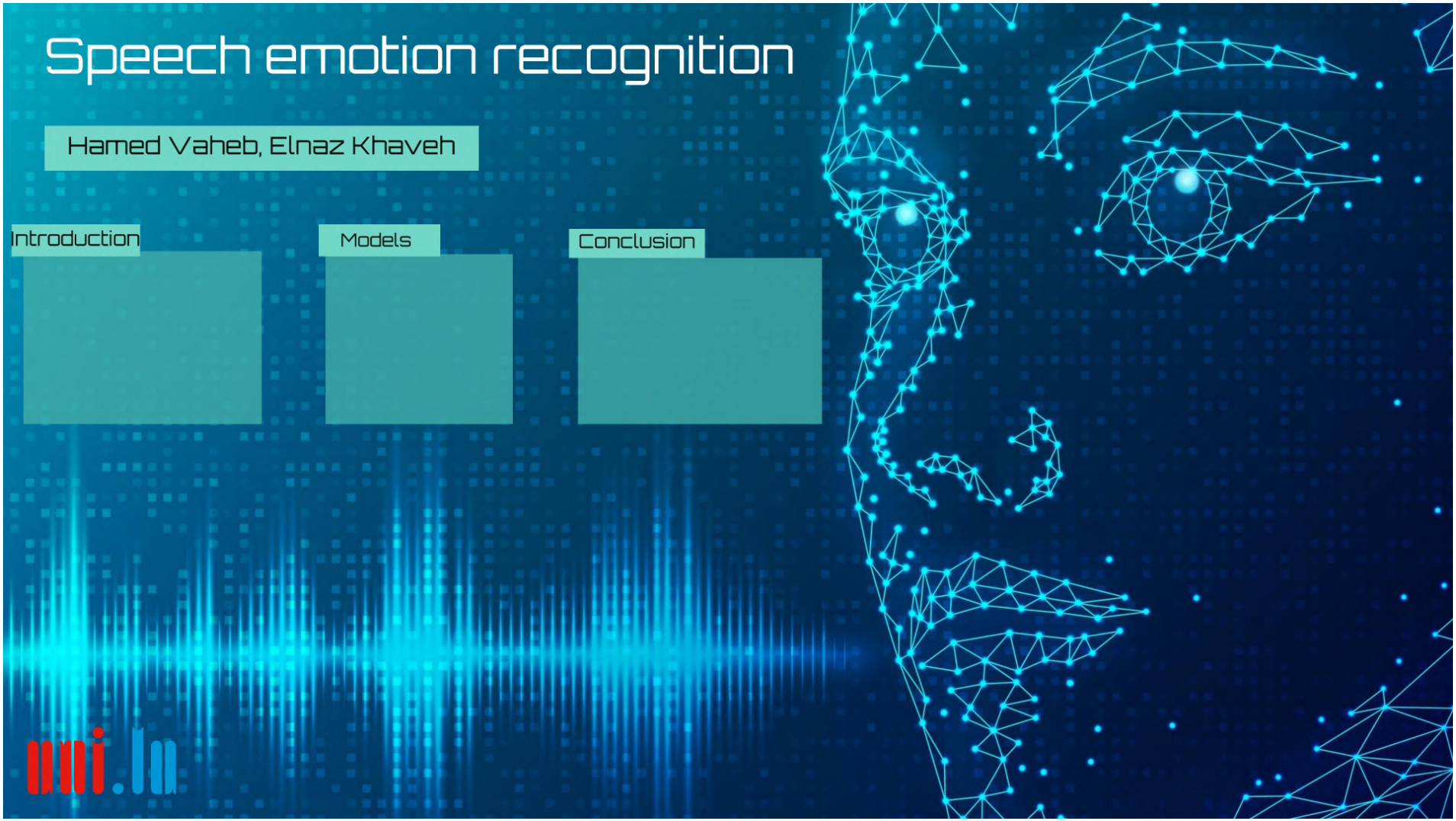
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