OTH Amberg-Weiden

Advanced Topics in Machine Learning

Winter Semester 2024/2025

Prof. Dr.-Ing. Christian Bergler | OTH Amberg-Weiden

Overview

Topics From Last Time: Introduction & Deep Learning Recap

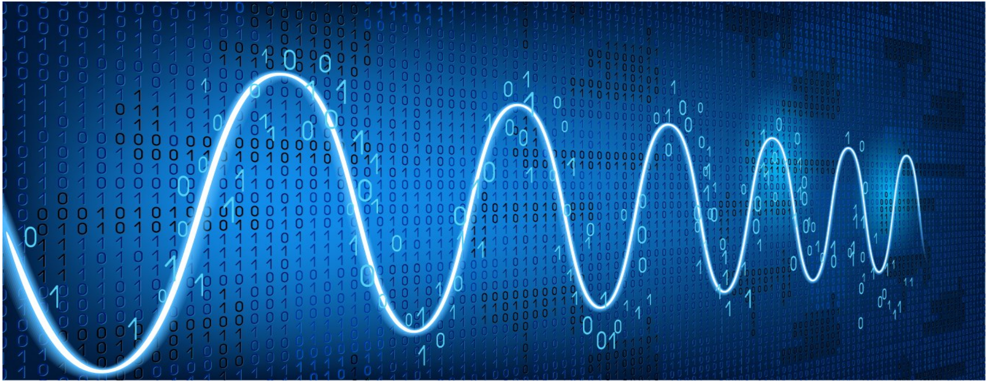
- Recurrent Neural Networks (Forward/Backward Propagation)
- Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU) Models
- Attention Mechanism
- Transformer Model

Topics of Today: Acoustic Signal Processing and Multimodal Learning

- Signals and Signal Types
- Audio Signals in Deep Learning
- Analog/Digital (A/D) Conversion (Sampling, Quantization)
- Discrete Fourier Transform (DFT)
- Short-Time Fourier Transform (STFT)
- Spectrogram
- Multimodal Learning

Signal Processing

Signals – What is it about?



- Signal: a real-world signal refers to any physical or abstract quantity, as part of different fields, considered as a function f, which conveys information about the behavior or respective state in a physical system

Source: Image taken from https://www.enclustra.com/en/design-services/digital-signal-processing/

Signal Processing

Signals – Different Fields

- Electronics & Communication: a signal refers to an electrical or electromagnetic representation of data, which can vary over time and can be classified into analog (continuous) & digital signals (discrete)

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- Natural Language Processing: signal describes patterns or features in text data which helps to identify relevant information, such as keywords, sentiment indicators, or linguistic structures

Signal Processing

Signals – Different Types

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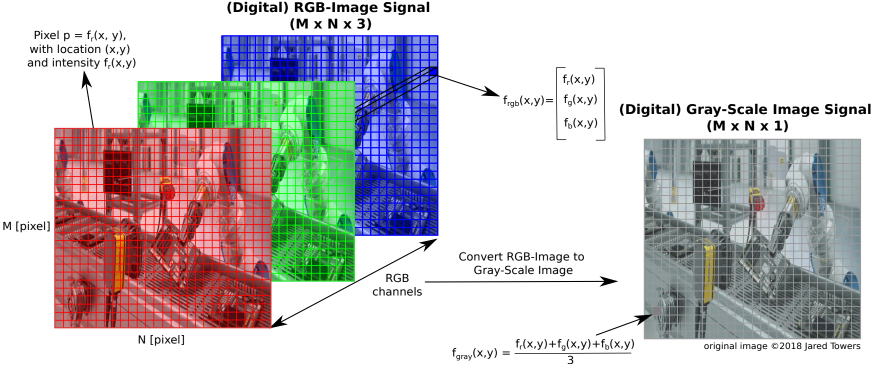
- Audio Signals: Represented as waveforms that vary over time, capturing sound. They are continuous signals (analog) or can be digitized (digital), such as in speech or music

Signal Processing

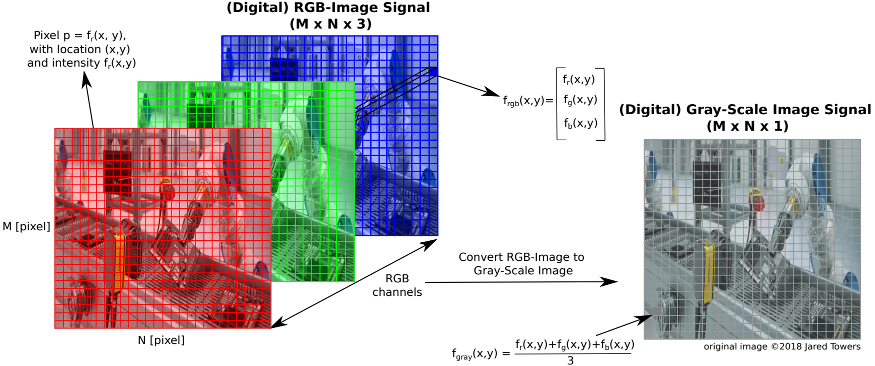
Signals – Different Types – (Digital) Image



- 2D-Representation: spatial coordinates (x, y), intensity value $f(x, y)$ (=pixel)

Signal Processing

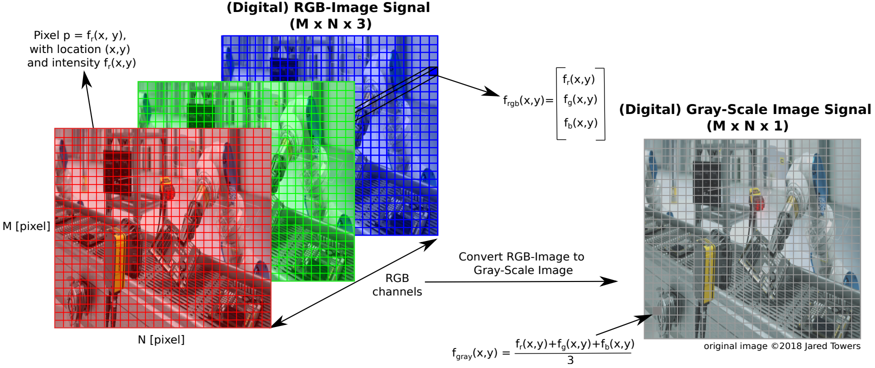
Signals – Different Types – (Digital) Image



- 2D-Representation: spatial coordinates (x, y), intensity value $f(x, y)$ (=pixel)
- $x, y \in \mathbb{Z}^2$, Gray-Scale $f(x, y) = \vec{y}_{1\times1}$ (scalar!) $= [f_g(x, y)]$, Color-Scale $f(x, y) = \vec{y}_{3\times1} = [f_r(x, y), f_g(x, y), f_b(x, y)]^T$

Signal Processing

Signals – Different Types – (Digital) Image



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- Digital RGB-Image $(M \times N \times 3)$, Gray-Scale Image $(M \times N \times 1)$

Signal Processing

Signals – Different Types – Sensor

- Sensor signals measure physical quantities like temperature, distance, light, and others

Source: Image from https://www.volersystems.com/blog/understanding-sensor-signal-conditioning-for-precise-data-acquisition

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- In machine (deep) learning it is also known as Time Series (data) or a continuous function comprising readings from a sensor (digitized via sampling & quantization)

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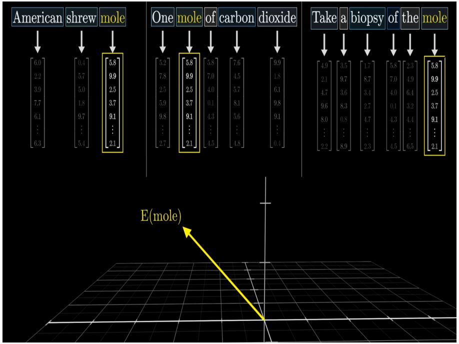
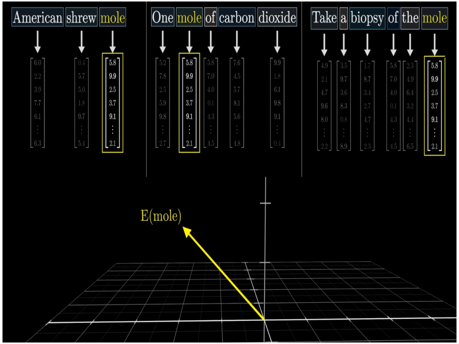


Source: Images taken from YouTube 3Brown1Blue – https://www.youtube.com/watch?v=eMlx5fFNoYc

Signal Processing

Signals – Different Types – Text

- Text as String (sequence of words & characters)
- Word Embedding describes words as numerical vectors in a continuous and multi-dimensional space



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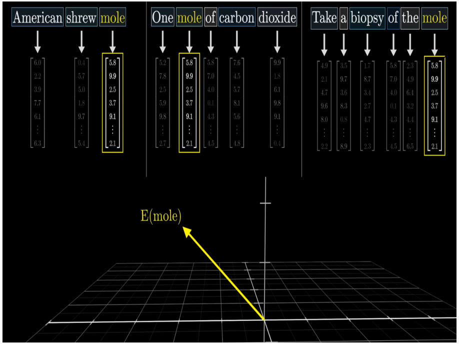

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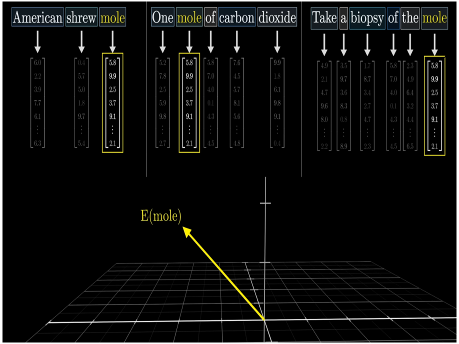
- Similarity: Dot-product ($\vec{u} \cdot \vec{v} = \sum_{i=1}^{N} u_i v_i$) $\rightarrow$ Indicator of a high similarity ($>>$) for long vectors $\rightarrow$ Cosine Similarity (only directional!)



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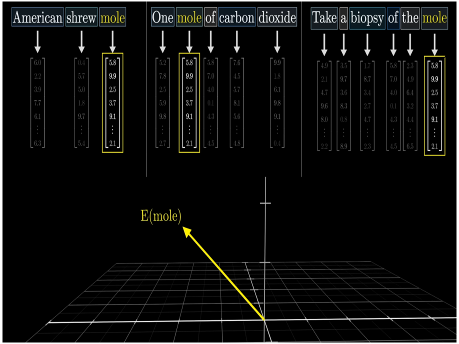
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = \frac{\vec{u}\,\vec{v}}{||\vec{u}||\;||\vec{v}||} = \frac{\sum_{i=1}^{N} u_i v_i}{\sqrt{\sum_{i=1}^{N} u_i^2}\,\sqrt{\sum_{i=1}^{N} v_i^2}}$
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = 1 \rightarrow$ same direction!
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = 0 \rightarrow$ orthogonal!
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = -1 \rightarrow$ opposite direction!



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Signal Processing

Signals – Different Types – Audio

- Acoustic signals (audio) $f(t)$ describe sound waves, which are pressure variations in the air over time t (time Series), leading to a pressure-time graph, also known as waveform

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- An audio signal is a real-valued representation (analog vs. digital)
  - Analog: raw and unprocessed waveforms as they appear in reality

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- An audio signal is a real-valued representation (analog vs. digital)
  - Analog: raw and unprocessed waveforms as they appear in reality
  - Digital: transformed and preprocessed signals for machine interpretation

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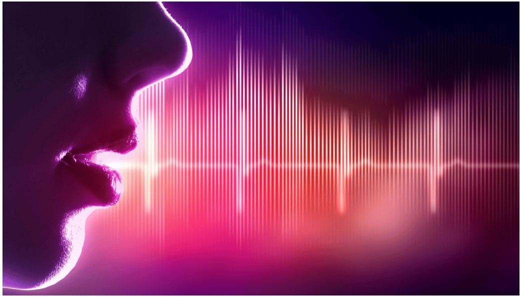
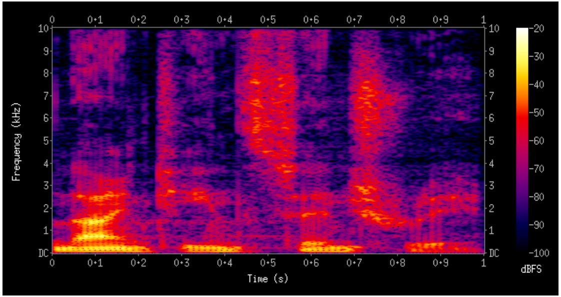
Acoustic Signal Processing

Audio Signals (Waveform, Spectrogram)





- Acoustic signal in the format of a waveform (time-domain representation of the acoustic signal with the amplitude $f(t)$ change over time t) $\rightarrow 1 \times N$ ($N =$ sampling points)

Source: https://www.levelsmusicproduction.com/blog/unleashing-the-power-of-sound-9-characteristics-of-a-sound-wave
Source: https://en.wikipedia.org/wiki/Spectrogram

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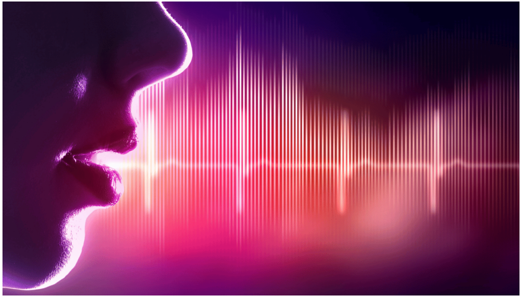

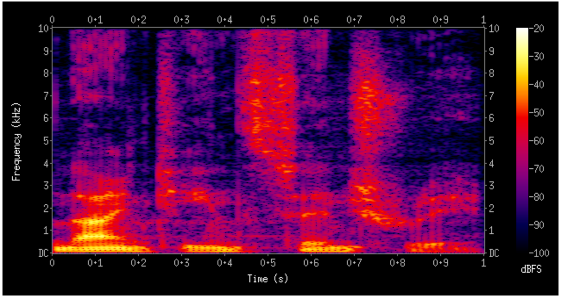

- Acoustic signal in the format of a waveform (time-domain representation of the acoustic signal with the amplitude $f(t)$ change over time t) $\rightarrow 1 \times N$ ($N =$ sampling points)
- Acoustic signal in the format of a spectrogram (time-frequency representation of the acoustic signal with the amplitude/power of the frequency $f(\omega)$ as coloring) $\rightarrow$ $T \times F \times 1$ ($T =$ time, $F =$ frequency) or complex variant ($T \times F \times 2$ (Re, Im))

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Acoustic Signal Processing

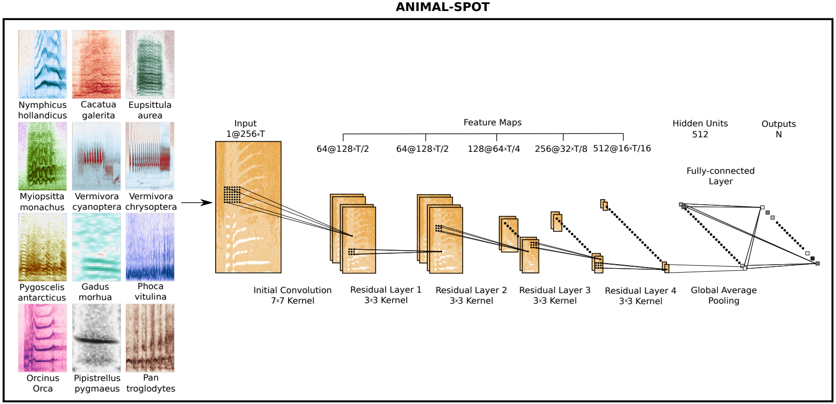
Audio Signals in Deep Learning – Applications

Automatic Speech Recognition (ASR)

- $P(W|A) = \frac{P(A|W)\ P(W)}{P(A)}$, with $P(A|W)$=Acoustic Model, $P(W)$=Language Model

Source: Image taken from https://www.iosb.fraunhofer.de/en/competences/image-exploitation/interactive-analysis-diagnosis/explainable-ai.html

Audio Signal Classification



- Acoustic event classification (speaker, emotions, sentiments, vocalization paradigms, pathology, voice activity,...)

Source: Image taken from "Dissertation Christian Bergler"

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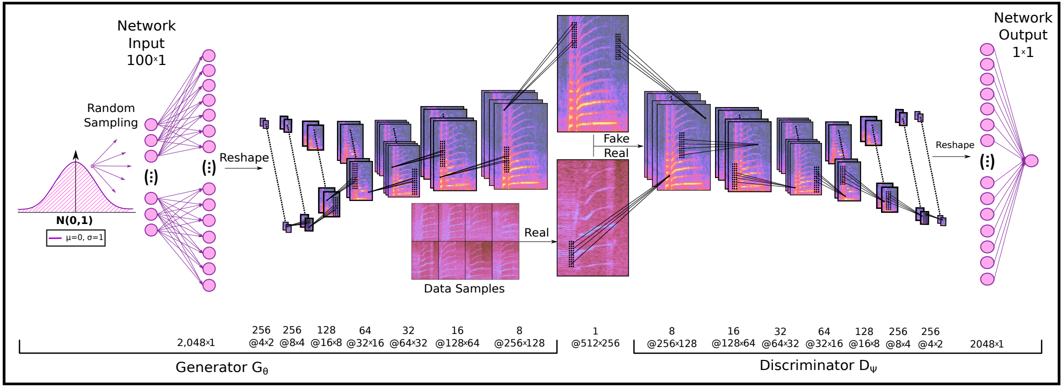
Speech Synthesis

ORCA-WHISPER



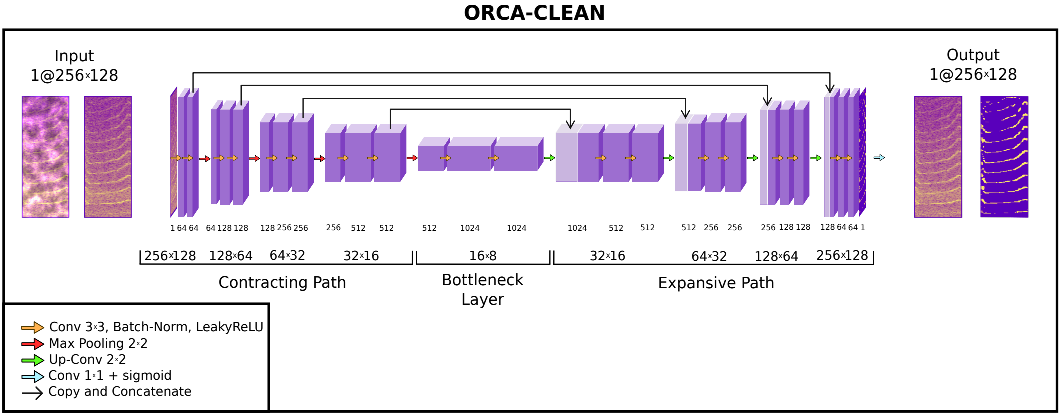
- Text-To-Speech (TTS) synthesis, voice generation (deep fakes), speech translation, ...

Source: Image taken from https://medium.com/@globalbizoutlook/ai-voice-generators-what-are-they-and-how-do-they-work-60e6c8067e4c

Acoustic Signal Processing

Audio Signals in Deep Learning – Applications

Acoustic Enhancement and Noise Reduction

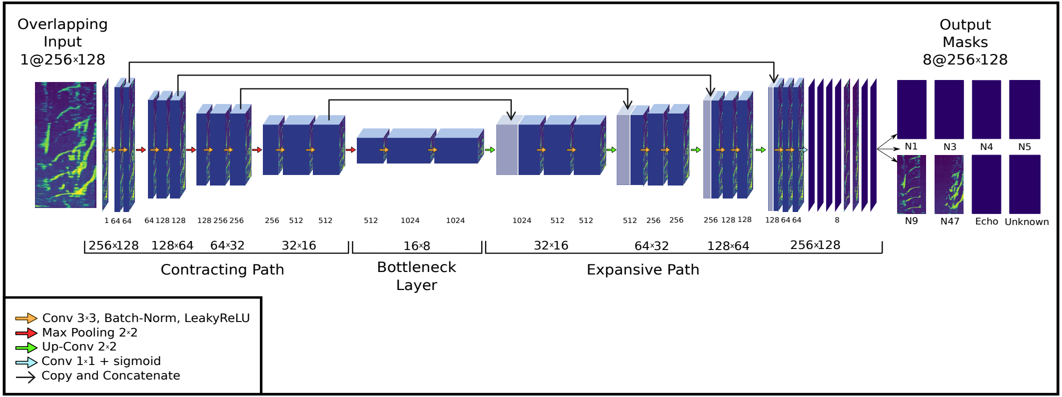


- Denoising (Noise2Noise concept, binary masking, noisy vs. clean)

Source: Image taken from "Dissertation Christian Bergler"

Sound Source Separation

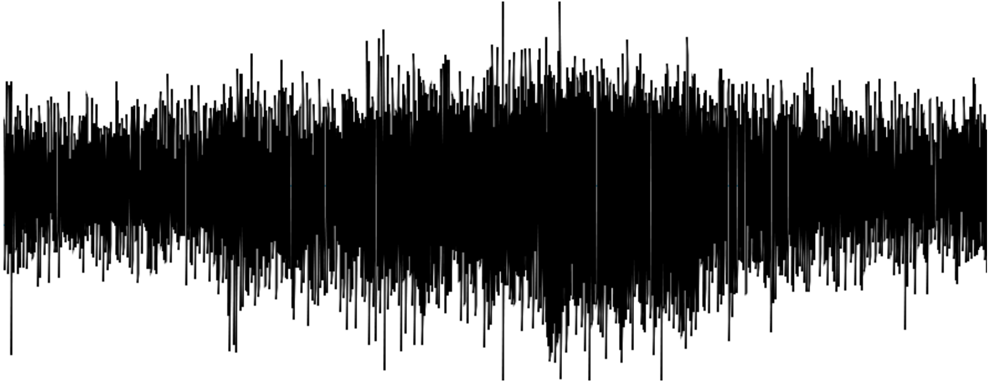
ORCA-PARTY



- Source separation, speaker separation, patter separation (“Cocktail Party Effect”)

Source: Image taken from “Dissertation Christian Bergler”

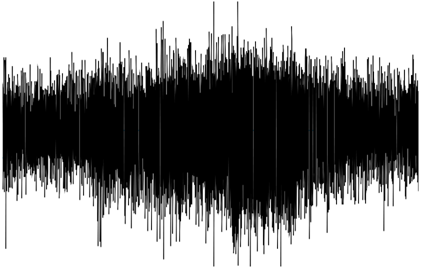
Soundwave



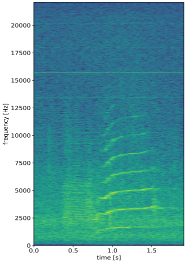
- Pure waveform (amplitude $f(t)$ over time t) is difficult to interpret!
- What are the individual components of an audio signal and how do I find patterns?

Acoustic Signal Processing
Audio Analysis

- Goal: Analysis of analog audio signals (waveform) by investigating the spectral envelope (spectrum) in order to derive the characteristic of various signals (e.g. human speech, animal sounds, etc.)



Waveform



Spectrogam

Source: Image taken from FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

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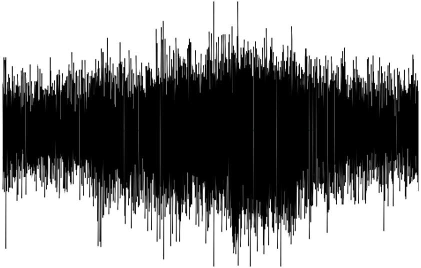

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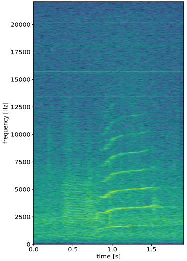

Spectrogam

- Approach: Sampling and Quantization (Digitization), Short Time Fourier Transform (STFT), Spectrogram (time and spectral visualization)

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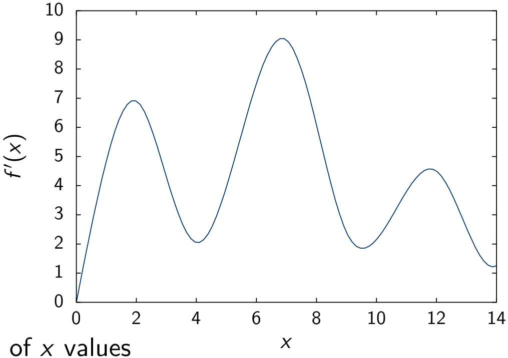
Acoustic Signal Processing

Analog/Digital (A/D) Conversion



- Analog signals:
  - Continuous range of x values
  - Continuous range of amplitude/function values $f'(x)$

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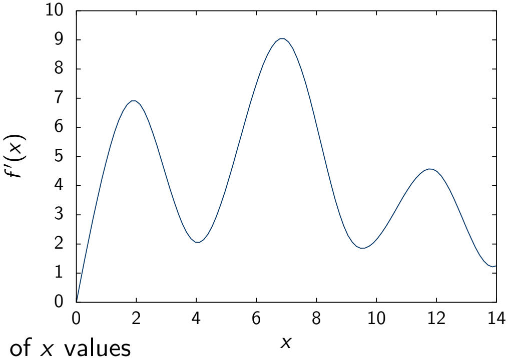
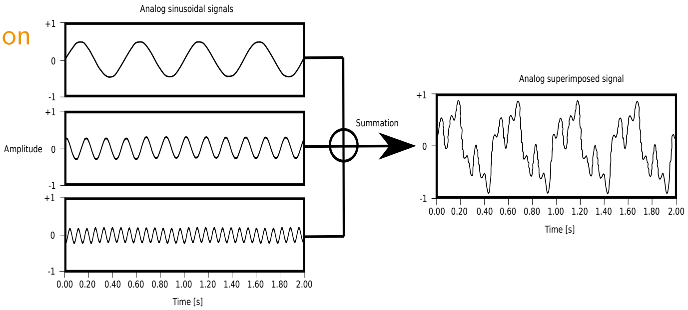


- Analog signals:
  - Continuous range of x values
  - Continuous range of amplitude/function values $f'(x)$
- Digital signals:
  - Only a finite amount of values can be stored
  - Finite number of bits (discrete values)

Source: Image taken from FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

(Analog) Signal Superposition



- A given signal f is considered as periodic using a period $\lambda \in \mathbb{R}_{>0}$ if $f(t) = f(t + \alpha\lambda)$, where $\alpha \in \mathbb{Z}$ for every given $t \in \mathbb{R}$

Source: Image taken from “Dissertation Christian Bergler”

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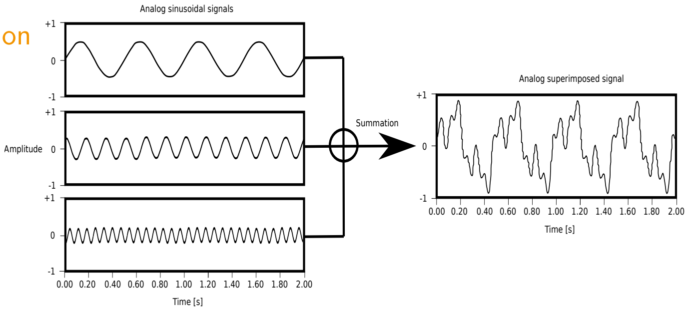

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- $f(t) := A \cdot sin(2\pi(\omega t - \phi))$, with $A =$ Amplitude (loudness), $\omega =$ frequency (pitch), $\lambda = \frac{1}{\omega} =$ period (repeating!), and $\phi =$ phase

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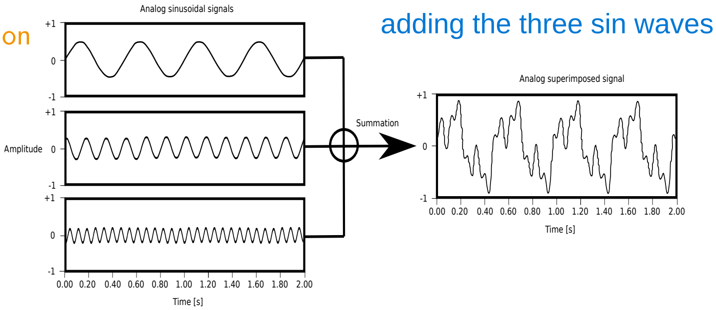

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- Superposition: $(f + g)(t) := f(t) + g(t) \rightarrow$ Still periodic signal!

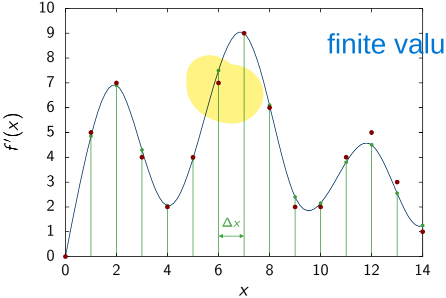
Source: Image taken from "Dissertation Christian Bergler"

Acoustic Signal Processing
Analog/Digital (A/D) Conversion

1khz means in one second we have 1000 dots to make it discreate.

A/D Conversion (Coding) involves:

1. Sampling:
   Measuring the amplitude/function values at a finite number of positions
2. Quantization:
   Representing the amplitude values by a finite number of natural numbers

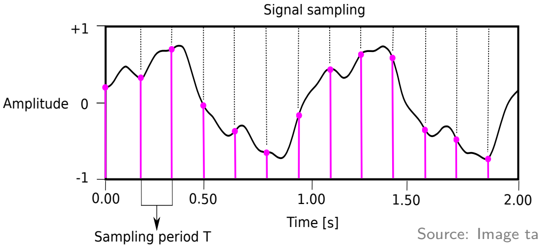


finite values of amplitude range

Source: Image taken from FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

Analog/Digital (A/D) Conversion – Sampling

- Transforming a continuous-time signal $f : \mathbb{R} \to \mathbb{R}$ to a discrete-time signal $x : \mathbb{Z} \to \mathbb{R}$



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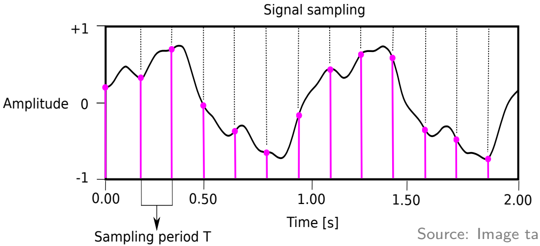
Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Sampling

- Transforming a continuous-time signal $f : \mathbb{R} \rightarrow \mathbb{R}$ to a discrete-time signal $x : \mathbb{Z} \rightarrow \mathbb{R}$
- Equidistant sampling: $x(n) := f(n \cdot T) \rightarrow x(n) = \text{sample}$



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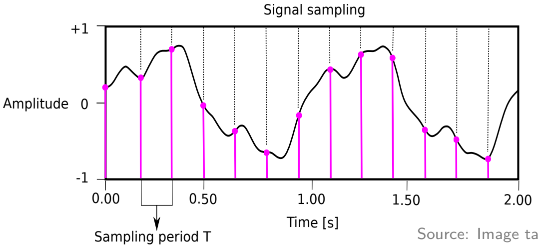
- Equidistant sampling: $x(n) := f(n \cdot T) \rightarrow x(n) = \text{sample}$
- Sampling period T, with $F_s = 1/T$ as the sampling rate



Source: Image taken from "Dissertation Christian Bergler"

- Transforming a continuous-time signal $f : \mathbb{R} \rightarrow \mathbb{R}$ to a discrete-time signal $x : \mathbb{Z} \rightarrow \mathbb{R}$
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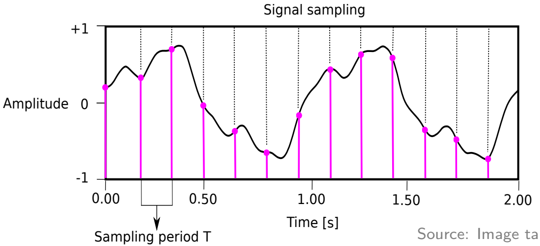

Source: Image taken from "Dissertation Christian Bergler"

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Analog/Digital (A/D) Conversion – Sampling

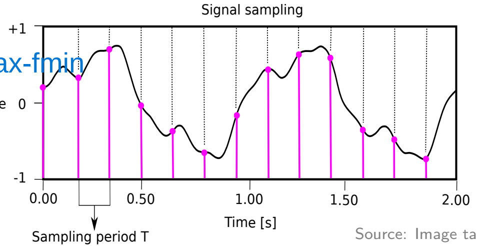
- Transforming a continuous-time signal $f : \mathbb{R} \rightarrow \mathbb{R}$ to a discrete-time signal $x : \mathbb{Z} \rightarrow \mathbb{R}$
- Equidistant sampling: $x(n) := f(n \cdot T) \rightarrow x(n) = \text{sample}$

n replaces time

- Sampling period T, with $F_s = 1/T$ as the sampling rate
- Default: lossy conversion $\rightarrow$ discrete $x(n)$ to reconstruct continuous $f(t)$ (Aliasing!)
- Solution: Nyquist-Shannon Sampling Theorem, facilitates a perfect and lossless signal reconstruction, using: $F_s > 2 \cdot (f_{max} - f_{min})$ (Nyquist-Frequency $\Omega = \frac{F_s}{2}$)

sampling rate in 2 times fmax-fmin

usually fmin is zero



humans are able to hear 22khz so we sample it with 44khz which can be devided by 2

Source: Image taken from "Dissertation Christian Bergler"

Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Nyquist-Shannon Sampling Theorem

- Let $f(x)$ be a band-limited function in the frequency range $[-B_x, B_x]$.
- Then $f(x)$ is determined completely by the samples

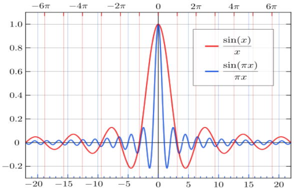
$$f_k = f(k \cdot \Delta x), \quad k = 0, \pm 1, \pm 2, \ldots$$

if the following constraint holds for the sampling interval Δx:

$$\Delta x \leq \frac{1}{2B_x} = \frac{1}{f_{sample}}, \text{with: } f_{sample} > 2 \cdot B_x$$

- The original signal $f(x)$ can be reconstructed precisely using the following interpolation:

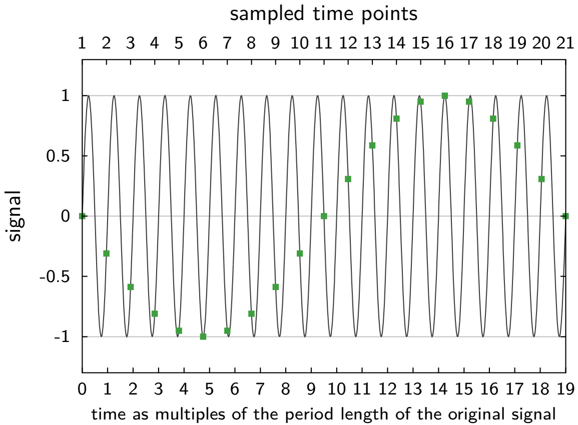
$$f(x) = \sum_{k=-\infty}^{\infty} f_k \cdot sinc\left(2\pi B_x (x - k\Delta x)\right)$$



Source: Image taken from https://en.wikipedia.org/wiki/Sinc_function, FAU-Lecture Slides “Praktikum Representation Learning” (Bergler, Christlein)

OTH Amberg-Weiden

Impact of the Sampling Theorem – Undersampling (Aliasing!)



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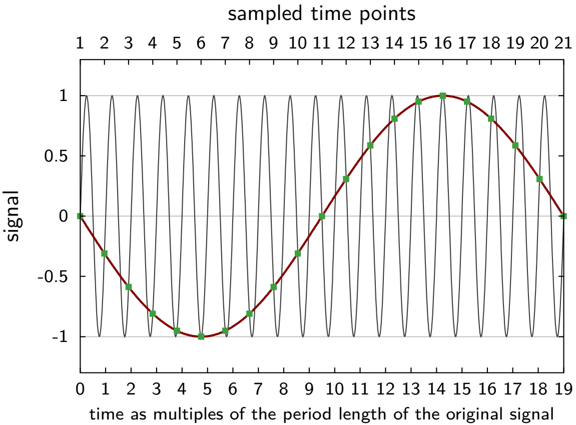
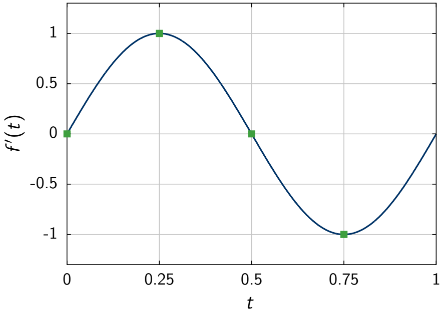


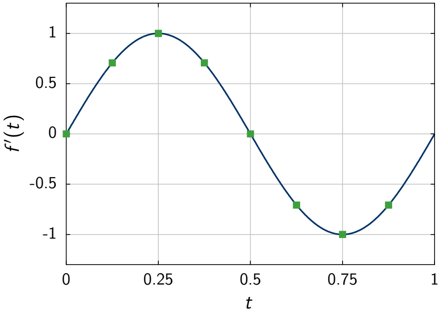
Source: FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

Impact of the Sampling Theorem – Oversampling

- Avoids aliasing, improves resolution, reduces noise
- Higher sampling rates lead to larger amounts of data!



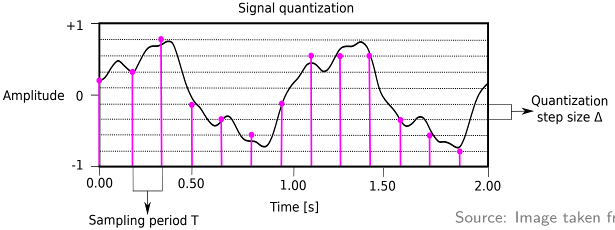
(a) $f_s = 4 \cdot f_{max}$



(b) $f_s = 8 \cdot f_{max}$

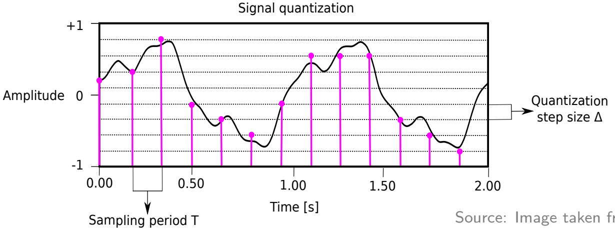
Source: FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

- Sampling is the discretization in time ($f : \mathbb{R} \rightarrow \mathbb{R}$ to $x : \mathbb{Z} \rightarrow \mathbb{R}$)



Source: Image taken from "Dissertation Christian Bergler"

- Sampling is the discretization in time ($f : \mathbb{R} \rightarrow \mathbb{R}$ to $x : \mathbb{Z} \rightarrow \mathbb{R}$)
- Quantization is the discretization process of the continuous amplitude values $a \in \mathbb{R}$ converted via Q: $\mathbb{R} \rightarrow \Gamma$, with the discrete set $\Gamma \subset \mathbb{R}$



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Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Quantization

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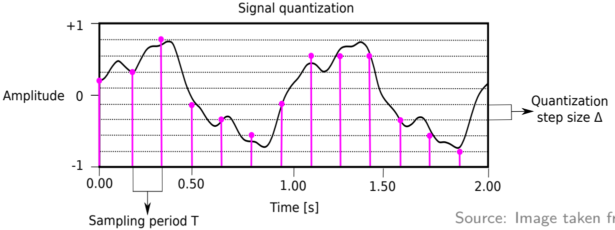
- $Q(a) \in \Gamma$, with $Q(a) := sgn(a) \cdot \Delta \cdot \lfloor \frac{|a|}{\Delta} + \frac{1}{2} \rfloor$, with $a \in \mathbb{R}$, quantization step-size Δ, $sgn(\cdot)$ as the signum function, $\lfloor \cdot \rfloor$ as real number truncation



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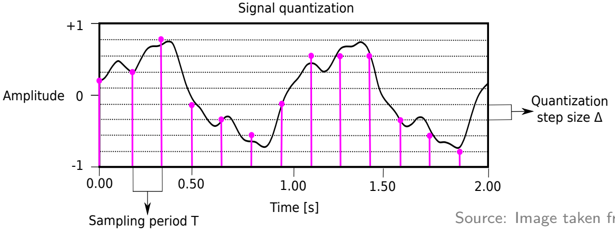
- Lossy operation: different amplitudes $a \in \mathbb{R}$ are mapped to the same discrete value $Q(a)$, known as Quantization Error!

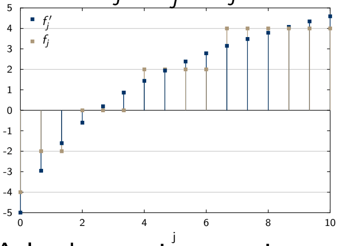


Source: Image taken from "Dissertation Christian Bergler"

Analog/Digital (A/D) Conversion – Quantization

- Quantization error n_j between real value f'_j and discretized value f_j:

$$n_j = f'_j - f_j$$



- Smaller quantization steps Δ lead to an increase in resolution, less errors, and significantly higher number of required bits for encoding

Source: Image taken from FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

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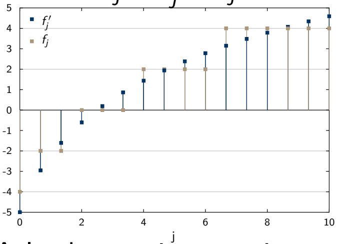
$$n_j = f_j' - f_j$$



- Smaller quantization steps Δ lead to an increase in resolution, less errors, and significantly higher number of required bits for encoding
- Usually impossible to reconstruct the original analog waveform, however, fulfilling the Nyquist-Shannon Theorem with adequate sampling rates, together with a sufficiently high quantization resolution, reconstructs the original perceptually free!

Source: Image taken from FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Discrete Fourier Transform

- The Fourier analysis can be considered as the inverse process of decomposing an analog and periodic (stationary) audio signal $f(t)$ into its weighted components of superimposed elementary and periodic sinusoidal functions: $f(t) \rightarrow DFT \rightarrow \hat{f}(\omega)$

Source: FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein) & "Dissertation Christian Bergler"

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- Continuous Fourier Transform:

$$\hat{f}(\omega) = \int_{t \in \mathbb{R}} f(t) e^{-2\pi i \omega t} dt = \int_{t \in \mathbb{R}} f(t) \cos(-2\pi\omega t) dt + i \int_{t \in \mathbb{R}} f(t) \sin(-2\pi\omega t) dt$$

- However: Digitized signals need a discrete version $\rightarrow$ Discrete Fourier Transform (DFT)!

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$$X[k] \stackrel{\text{def}}{=} \sum_{n=0}^{N-1} x[n] \cdot \mathrm{e}^{-\frac{2\pi i n k}{N}} = \sum_{n=0}^{N-1} x[n] \cdot \mathrm{W}_N^{nk}, \text{ with } W_N = \mathrm{e}^{-\frac{2\pi i}{N}}$$

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with $X[k] \in \mathbb{C}$ (Re/Im), n = sample index, $K \in \mathbb{N}$ = fixed number of frequency bins, $k \in \mathbb{N}$ = frequency index, typical $K = N$, frequency resolution $\omega = \frac{k}{N=K}$

Source: FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein) & "Dissertation Christian Bergler"

DFT – Matrix-Vector Product

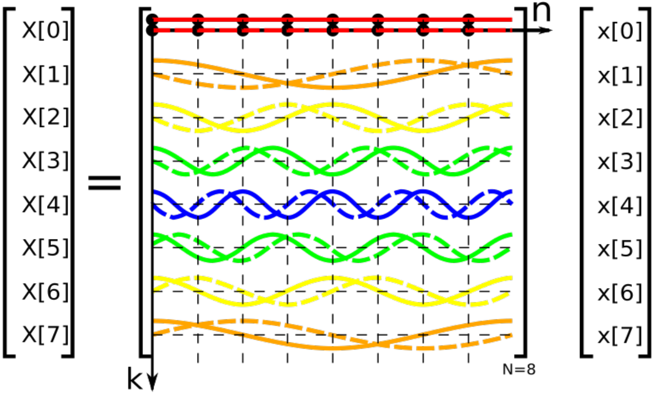
$$X[k] \overset{\text{def}}{=} \sum_{n=0}^{N-1} x[n] \cdot \mathrm{e}^{-\frac{2\pi ink}{N}} = \sum_{n=0}^{N-1} x[n] \cdot \mathrm{W}_N^{nk}, \text{ with } W_N = \mathrm{e}^{-\frac{2\pi i}{N}}$$

$$\begin{bmatrix} X[0] \\ X[1] \\ X[2] \\ X[3] \\ \vdots \\ X[N-1] \end{bmatrix}_{N\times 1} = \begin{bmatrix} 1 & 1 & 1 & 1 & \dots & 1 \\ 1 & W_N^1 & W_N^2 & W_N^3 & \dots & W_N^{N-1} \\ 1 & W_N^2 & W_N^4 & W_N^6 & \dots & W_N^{2(N-1)} \\ 1 & W_N^3 & W_N^6 & W_N^9 & \dots & W_N^{3(N-1)} \\ \vdots & & & & & \\ 1 & W_N^{(N-1)} & W_N^{2(N-1)} & W_N^{3(N-1)} & \dots & W_N^{(N-1)(N-1)} \end{bmatrix}_{N\times N} \begin{bmatrix} x[0] \\ x[1] \\ x[2] \\ x[3] \\ \vdots \\ x[N-1] \end{bmatrix}_{N\times 1}$$

Source: FAU-Lecture Slides “Praktikum Representation Learning” (Bergler, Christlein) & “Dissertation Christian Bergler”

Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Discrete Fourier Transform

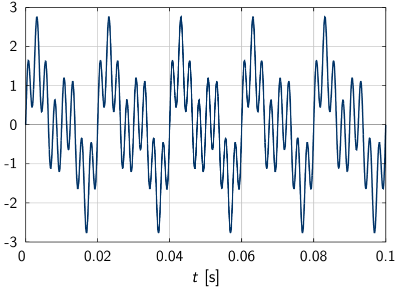


- Each row refers to a particular frequency component $W_N^{nk} = e^{-\frac{2\pi ink}{N}} = e^{-2\pi i\omega n}$
- Diagonal symmetric due to complex conjugate elements (negative frequencies), which are discarded, so only the first $\lfloor N/2+1 \rfloor$ frequency bins are required

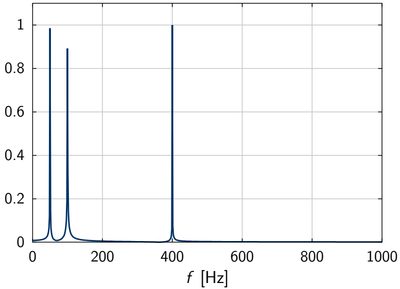
Source: Image taken from https://en.wikipedia.org/wiki/DFT_matrix

DFT – Periodic Signal

- Example: Summation of three different sinusodial function frequencies
- $f_1 = 50\,\text{Hz},\ f_2 = 100\,\text{Hz},\ f_3 = 400\,\text{Hz}$
- $f(t) = \sin(2\pi \cdot 50 \cdot t) + \sin(2\pi \cdot 100 \cdot t) + \sin(2\pi \cdot 400 \cdot t)$



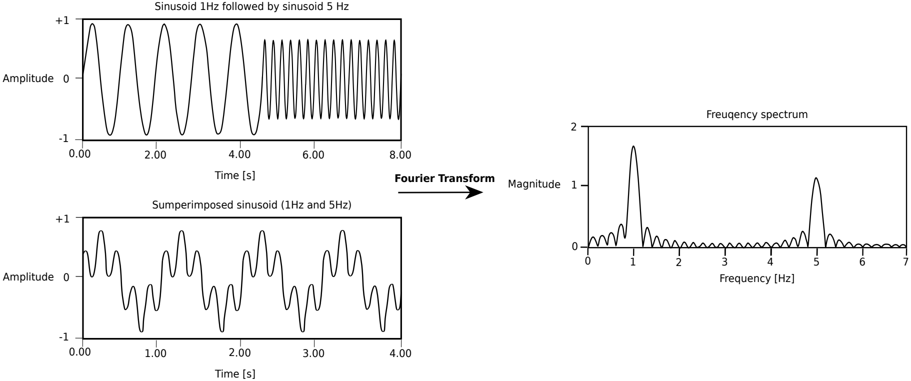
(a) waveform



(b) Fourier spectrum (amplitudes)

Source: FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

DFT – Non-Periodic Signal



- Same DFT-output for both input signals (→ DFT looses information about the temporal occurrence of a certain frequency) → How to handle real-world signals???

Source: FAU-Lecture Slides “Praktikum Representation Learning” (Bergler, Christlein) & “Dissertation Christian Bergler”

Analog/Digital (A/D) Conversion – DFT – Periodic VS. Non-Periodic Signal

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Source: "Dissertation Christian Bergler"

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Source: "Dissertation Christian Bergler"

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Acoustic Signal Processing

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Source: “Dissertation Christian Bergler”

The STFT Algorithm

1. Extraction of a short-time audio excerpt from the original input signal according to the chosen FFT window-size N

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$$w(n) := \begin{cases} \epsilon - (1-\epsilon) \cdot \cos(\frac{2\pi n}{N}) & \text{with } 0 \leq n \leq N-1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

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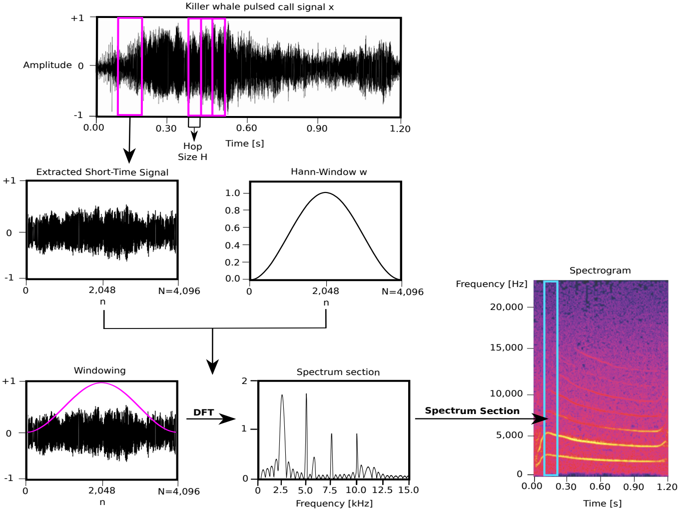
5. Move the analysis window by the chosen hop-size H and repeat the entire procedure

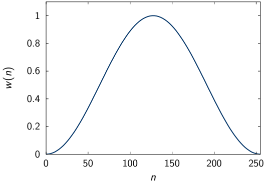
Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Short-Time Fourier Transform (STFT)

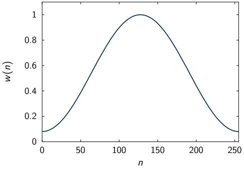


Source: "Dissertation Christian Bergler"

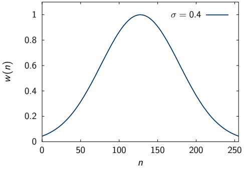
Window Function w



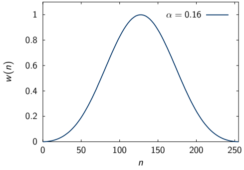
(a) Hann



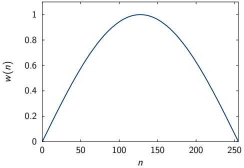
(b) Hamming



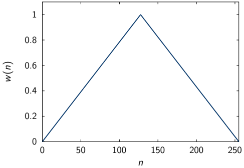
(c) Gauss



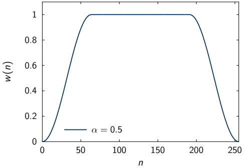
(d) Blackman



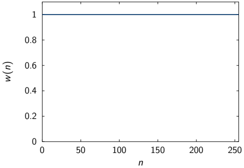
(e) Cosine



(f) Bartlett



(g) Tukey



(h) Rectangle

Source: FAU-Lecture Slides “Praktikum Representation Learning” (Bergler, Christlein)

Analog/Digital (A/D) Conversion – Spectrogram (Narrow vs. Wide)

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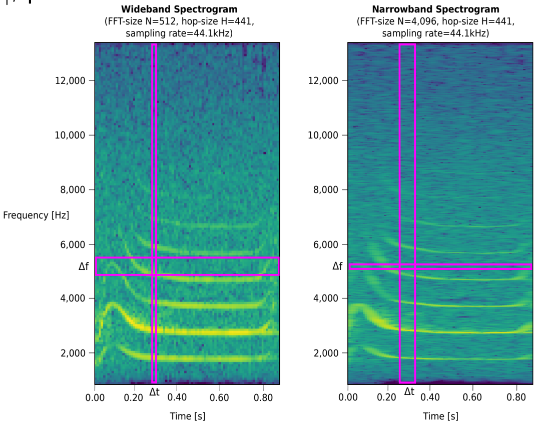

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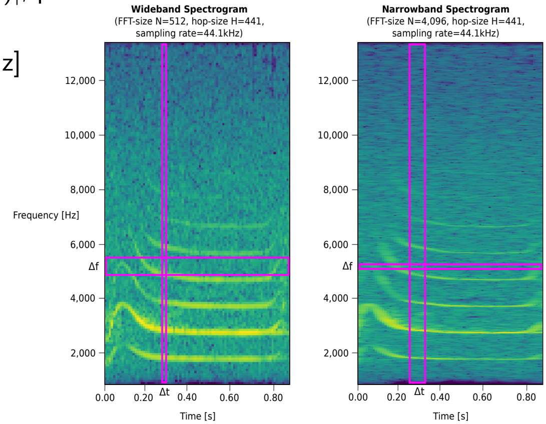

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Acoustic Signal Processing

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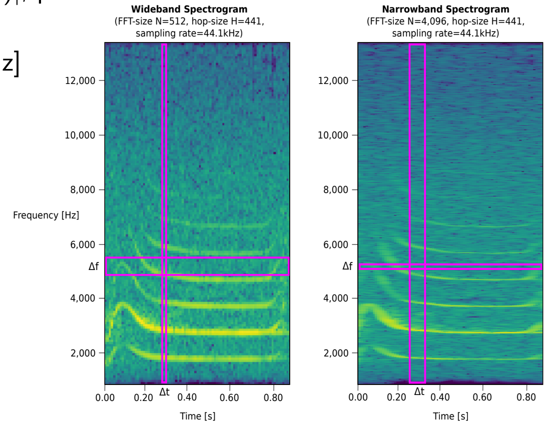

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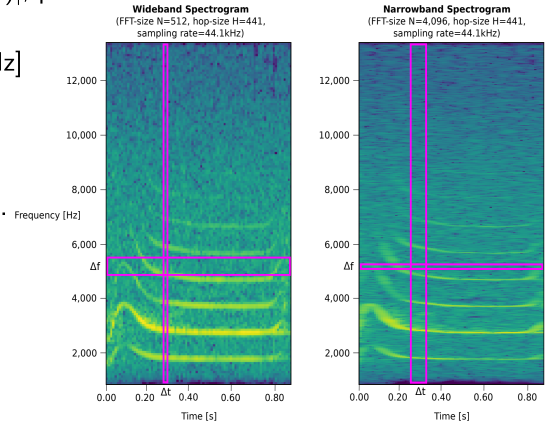

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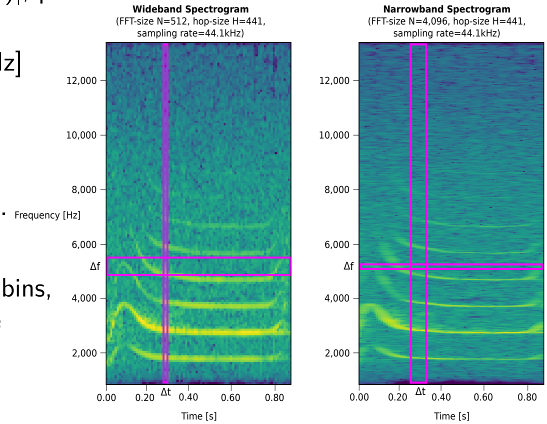

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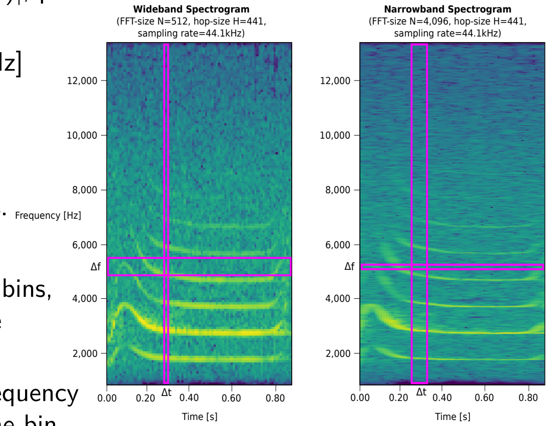
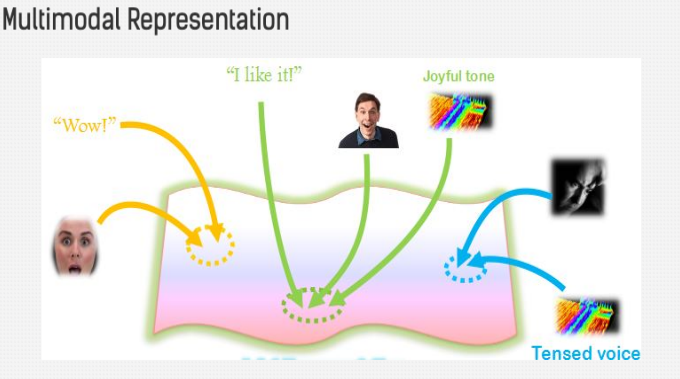
- Narrowband: larger time windows N, increase in frequency bins, narrows the spectral content represented in one bin, improves frequency resolution deteriorates time resolution



Source: FAU-Lecture Slides “Praktikum Representation Learning” (Bergler, Christlein) & “Dissertation Christian Bergler”

Multimodal Learning

What is it about?

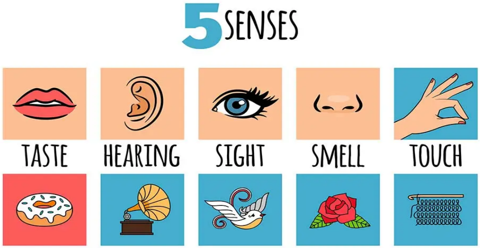


- Multimodal Learning is a learning paradigm in the field of deep learning, using various data modalities, such as text, audio, sensor signals, and images/videos within a single learning concept at the same time!

Source: Image taken from https://vinija.ai/multimodal/challenges/

Multimodal Learning

Why?



- The core idea of deep learning was to design algorithms trying to mimic the human brain (neurons, layers, deep structures, ...)

Source: Image taken from https://www.kdnuggets.com/2023/03/multimodal-models-explained.html

Multimodal Learning

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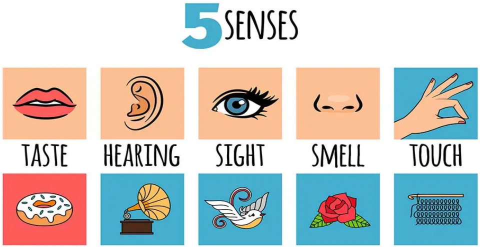

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- Humans have access to five senses – sight, hearing, touch, taste, and smell – not just to collect information, but also to understand and interpret the environment around us

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Multimodal Learning

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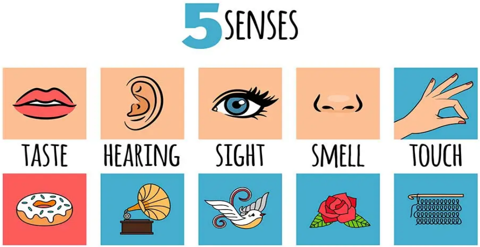

- The core idea of deep learning was to design algorithms trying to mimic the human brain (neurons, layers, deep structures, ...)
- Humans have access to five senses – sight, hearing, touch, taste, and smell – not just to collect information, but also to understand and interpret the environment around us
- Making use of diverse information sources at the same time it is possible to derive a better and more complete understanding of the underlying purpose/data/task, unlock new and deeper insights

Source: Image taken from https://www.kdnuggets.com/2023/03/multimodal-models-explained.html

Multimodal Learning

Transfer to Deep Learning!

- The integration of multiple modalities allows a model to leverage complementary information, handle missing data from one source by relying on another, provide more comprehensive insights, and improves model generalization!

Source: Image taken from https://618media.com/en/blog/the-multimodal-capabilities-of-chatgpt-4/

Multimodal Learning

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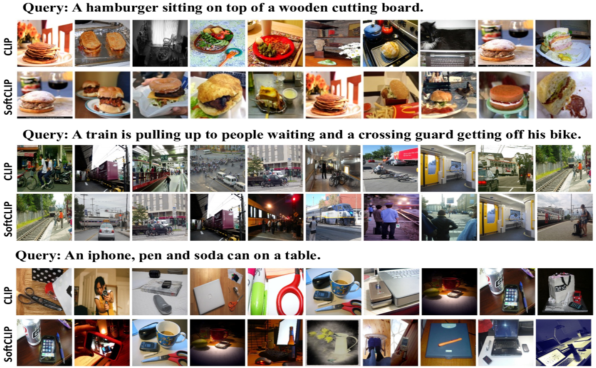
- The integration of multiple modalities allows a model to leverage complementary information, handle missing data from one source by relying on another, provide more comprehensive insights, and improves model generalization!
- Real-world data and applications are very often multimodal!

Source: Image taken from https://618media.com/en/blog/the-multimodal-capabilities-of-chatgpt-4/

Multimodal Learning

Real-World Applications – Computer Vision/NLP

Text-Image VS. Image-Text Retrieval



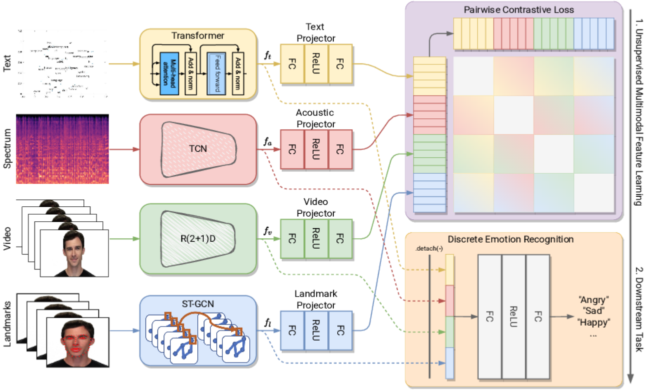
- For a given image, find related text, or vice versa, which is particularly useful in any kind of search engines

Source: Ìmage from Gao et al. "SoftCLIP: Softer Cross-modal Alignment Makes CLIP Stronger"

Multimodal Learning

Real-World Applications – Computer Vision/Audio/NLP

Emotion Recognition



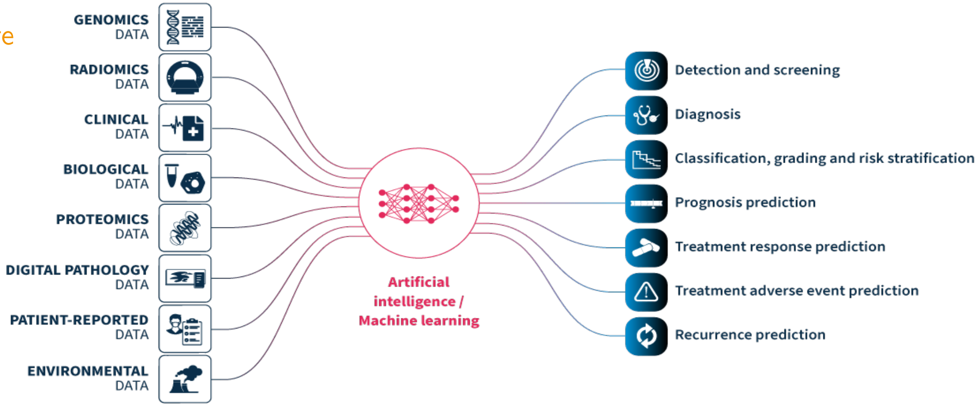
- Modern systems use video (facial expressions), audio (voice tone), and textual data (spoken words) to specifiy emotions of a person more accurately
- Further: LipSync and textual models in ASR Systems (Vision + Speech + Text)

Source: Image from Franceschini et al., "Multimodal Emotion Recognition with Modality-Pairwise Unsupervised Contrastive Loss"

Multimodal Learning

Real-World Applications – Computer Vision/Text/Audio

Healthcare



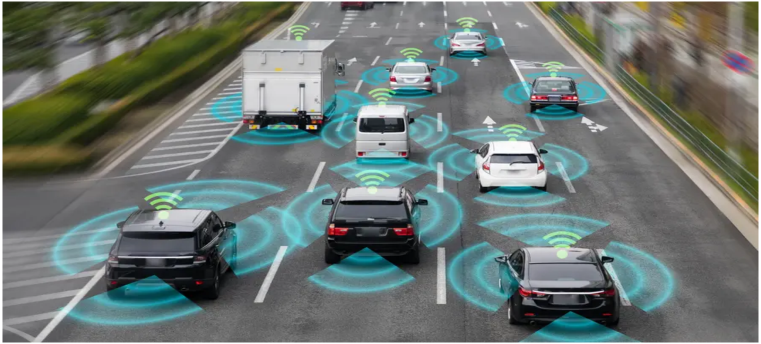
- Using multimodal data such as clinical & patient data, radiomics, biological data, environmental data, etc., in order to gain much deeper insights to the human biology & medical conditions

Source: Image from https://www.sophiagenetics.com/science-hub/the-power-of-multimodal-data-driven-medicine/

Multimodal Learning

Real-World Applications – Computer Vision/Text/Audio

Autonomous Driving



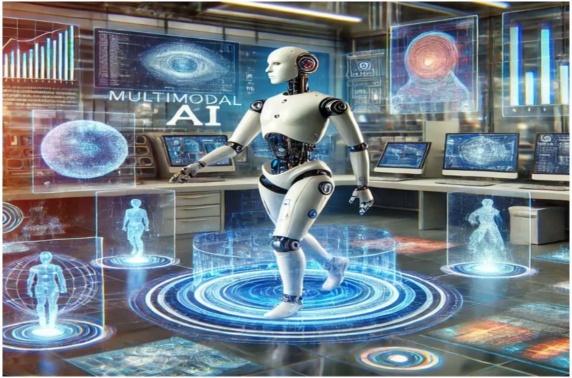
- Multiple sensor data (camera, radar, LIDAR, GPS, ...), together with audio cues (alerts, navigation, status updates, ...), to better understand the environment & to handle the respective traffic situations accordingly

Source: Image from https://www.topgear.com/car%20news/what-are-sae-levels-autonomous-driving-uk

Multimodal Learning

Real-World Applications – Computer Vision/Text/Audio

Human-Robot Interaction (Humanoid Systems)



- Intelligent Humanoid Systems: robots can interpret speech, facial expressions, gestures, and body posture to understand and interact with a human being in a very natural way

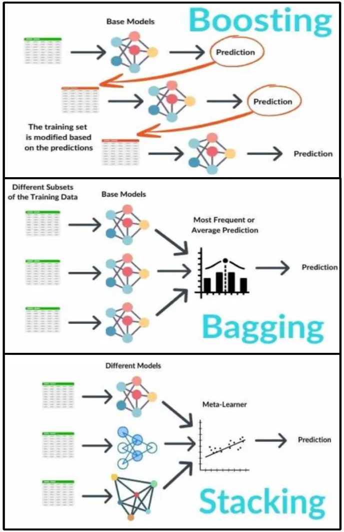
Source: Image from https://squoraishee.medium.com/multimodal-machine-learning-a-deep-dive-bc4f25f6a63b

Multimodal Learning

Combining Models VS. Multimodal Learning

Combining Models

- Combination of several individual (basic) models to improve performance & robustness, following the principle "together we are stronger"
- Boosting – Sequence of models, while each subsequent model corrects the mistakes made by the previous ones (Adaptive Boosting, Gradient Boosting Machines, ...)



Source: https://spotintelligence.com/2024/03/18/bagging-boosting-stacking/

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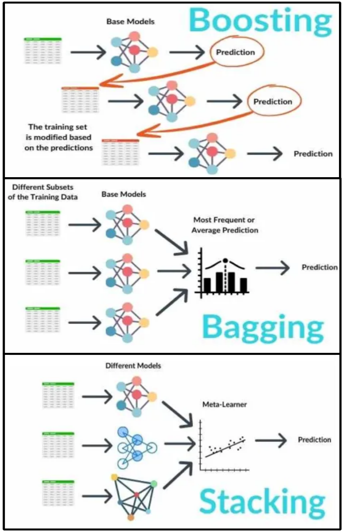

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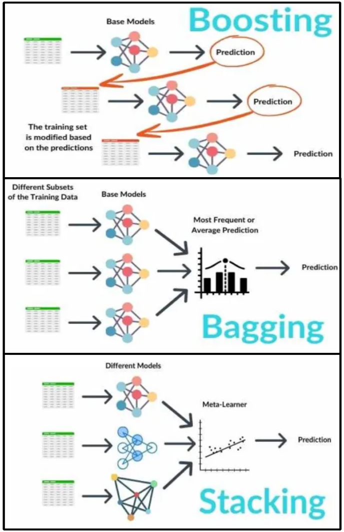
- Stacking – Training multiple diverse base models and combine the predictions using another meta-model, weighting the base-model output for final prediction



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Multimodal Learning

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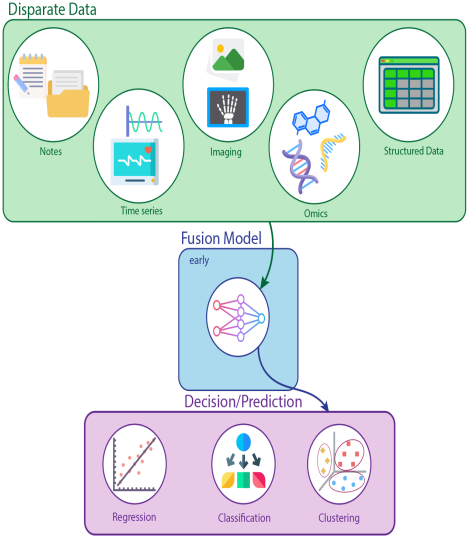


Source: https://pub.towardsai.net/multimodal-machine-learning-data-fusion-d1d8776e2cb0

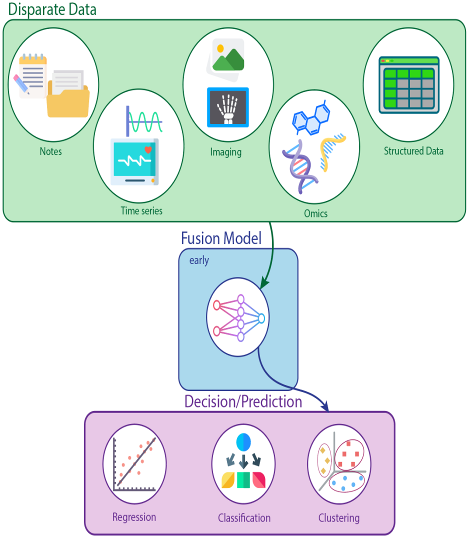
Multimodal Learning

Combining Models VS. Multimodal Learning

OTH Amberg-Weiden

Multimodal Learning

- Combining models: trained independently, while the final prediction is made by combining the outputs, especially helpful when individual models have complementary strengths and weaknesses
- Multimodal: goal is to combine & merge information from various data modalities to improve the performance on a given task
  - Early Fusion (Feature-Level Fusion)
  - Late Fusion (Decision-Level Fusion)
  - Hybrid Fusion (Mixture between Early & Late)
  - Cross-Modal Learning
  - Joint Representation Learning



Source: https://pub.towardsai.net/multimodal-machine-learning-data-fusion-d1d8776e2cb0

Multimodal Learning

Fusion and Learning Principles

General: Fusion-based approaches perform an encoding of different modalities into a common representation space, where individual feature embeddings are fused to create a single modality-invariant feature representation, capturing all the semantic knowledge

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- Early Fusion (decision-level fusion): Separately extracted features from different modalities are combined (concatenation/merging) at the input level
- Pro: Model learns similarities, correlations, interactions between the multimodal features
- Con: High-dimensional feature data $\rightarrow$ Computational complexity

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Late Fusion

- Each data modality is processed separately using stand-alone models, while the final predictions are combined at decision level (averaging, voting, weighted combination, ...)
- Pro: data modality-specific models, easier to handle different data characteristics
- Con: do not learn how data modality-specific features interact

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Hybrid Fusion

- Combines concepts of both – early and late fusion approaches – by merging data at intermediate stages
- Separate feature learning/extraction and downstream fusion at an intermediate layer
- aiming to combine the strengths of both feature- and decision-level fusion (modality-specific features plus cross-modality feature interactions)
- Pro: balance between computational efficiency and ability to learn feature connections
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Cross-Modal Learning

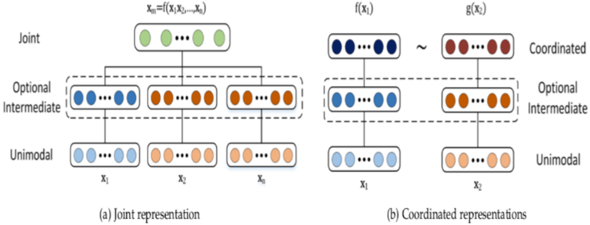
- Learning and transferring information from one data modality to another (e.g. image captioning, text-to-image synthesis, ...)
- Goal: identifying and understanding the connection and correlation between various data modalities ($\rightarrow$ Know-How Transfer!)

Multimodal Learning

Fusion and Learning Principles

Joint Representation Learning

- Unified feature space for all the different modalities
- Fuse information, while capturing & understanding complementary modality information
- Better generalization due to significantly larger knowledge access of multiple modalities



- Coordinated representations projects all the modalities (usually severe differences in characteristics) to its own space, while being coordinated over a constraint

Multimodal Learning

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- Interpretability: challenges in understanding how decisions are made when combining multiple modalities

Further Questions?

https://www.oth-aw.de/hochschule/ueber-uns/personen/bergler-christian/

Source: https://emekaboris.medium.com/the-intuition-behind-100-days-of-data-science-code-c98402cdc92c