OTH
Amberg-Weiden

Advanced Topics in Machine Learning

Winter Semester 2024/2025

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

Advanced Topics in Machine Learning

Overview

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Topics From Last Time: Introduction & Deep Learning Recap

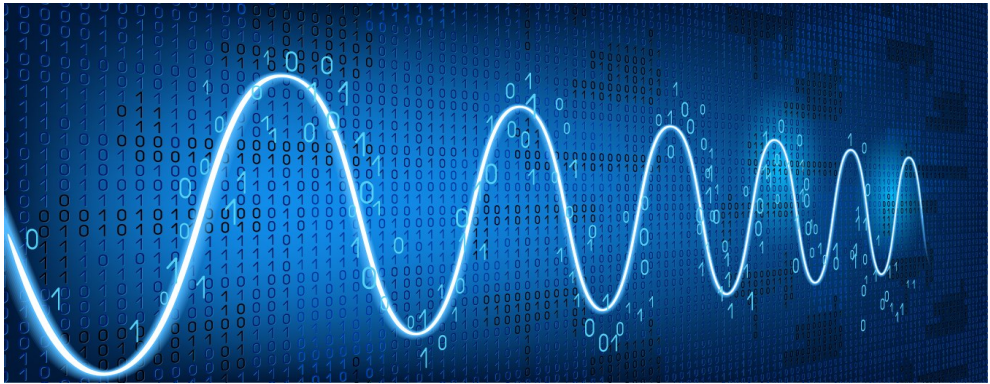
- Recurrent Neural Networks (Forward/Backward Propagation)
- Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU) Models
- Attention Mechanism
- Transformer Model

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

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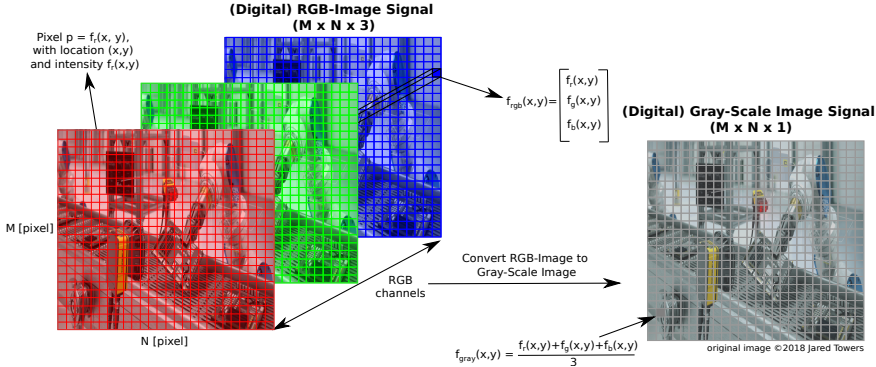
- Audio Signals: Represented as waveforms that vary over time, capturing sound. They are continuous signals (analog) or can be digitized (digital), such as in speech or music

Signal Processing

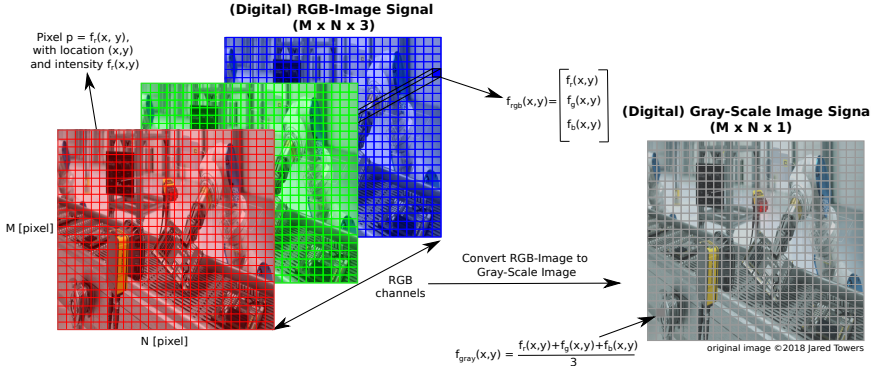
Signals – Different Types – (Digital) Image



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

Signal Processing

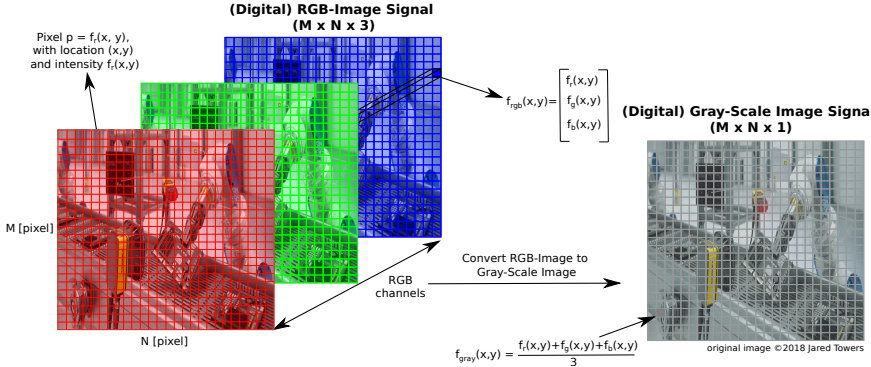
Signals – Different Types – (Digital) Image



- 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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- Mathematically it describes a function over time $s(t)$, with time t and amplitude $s(t)$

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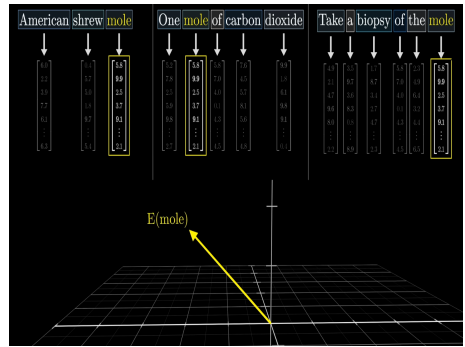
- Mathematically it describes a function over time $s(t)$, with time t and amplitude $s(t)$
- In machine (deep) learning it is also known as Time Series (data) or a continuous function comprising readings from a sensor (digitized via sampling & quantization)

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

- Text as String (sequence of words & characters)



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

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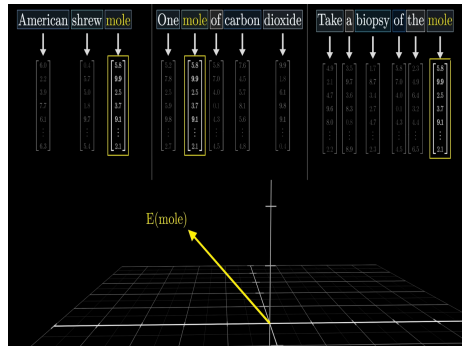
- Word Embedding describes words as numerical vectors in a continuous and multi-dimensional space



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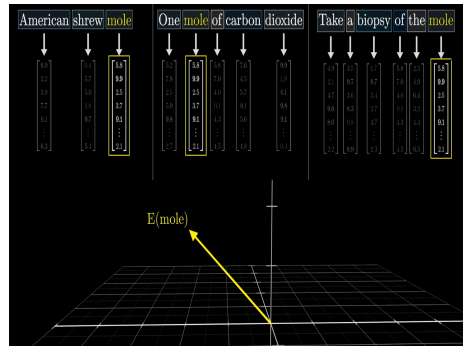

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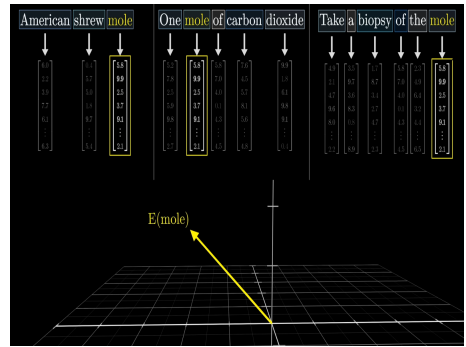
- Similarity: Dot-product ($\vec{u} \cdot \vec{v} = \sum_{i=1}^{N} u_i v_i$) $\rightarrow$ Indicator of a high similarity ($>>$) for long vectors $\rightarrow$ Cosine Similarity (only directional!)



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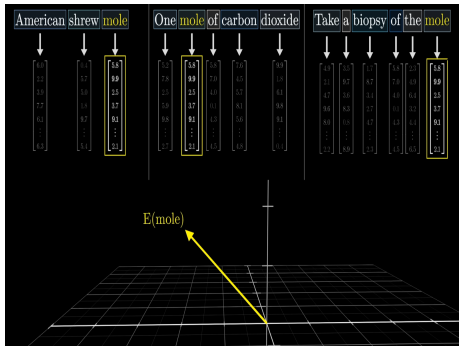
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = \frac{\vec{u}\,\vec{v}}{||\vec{u}||\,||\vec{v}||} = \frac{\sum_{i=1}^{N} u_i v_i}{\sqrt{\sum_{i=1}^{N} u_i^2}\sqrt{\sum_{i=1}^{N} v_i^2}}$
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = 1 \rightarrow$ same direction!
  - $cos(\Theta) = cos(\vec{u}, \vec{v}) = 0 \rightarrow$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



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- 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

Source: Image from https://www.lafilm.edu/blog/the-importance-of-sound/

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  - Analog: raw and unprocessed waveforms as they appear in reality

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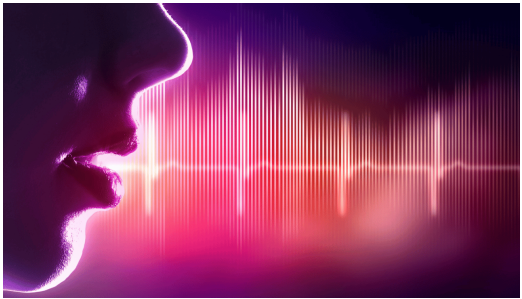
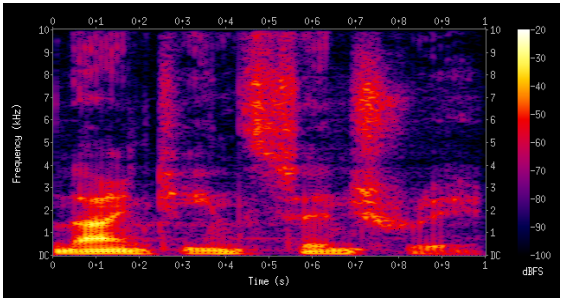
- An audio signal is a real-valued representation (analog vs. digital)
  - Analog: raw and unprocessed waveforms as they appear in reality
  - Digital: transformed and preprocessed signals for machine interpretation

Source: Image from https://www.lafilm.edu/blog/the-importance-of-sound/

Acoustic Signal Processing

Audio Signals (Waveform, Spectrogram)



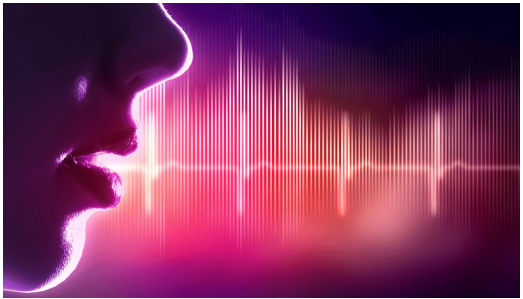


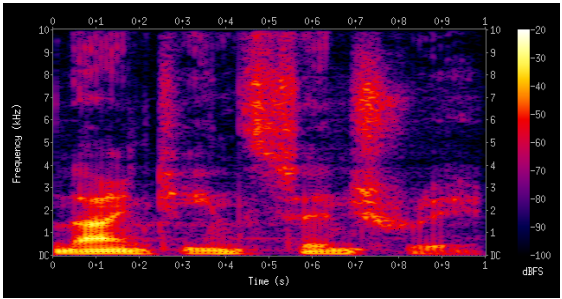
- Acoustic signal in the format of a waveform (time-domain representation of the acoustic signal with the amplitude $f(t)$ change over time t) $\rightarrow 1 \times N$ ($N =$ sampling points)

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

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)
- 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))

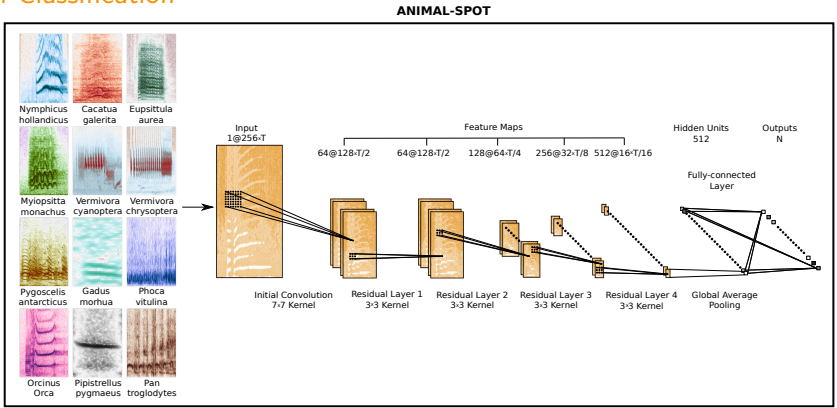
Source: https://www.levelsmusicproduction.com/blog/unleashing-the-power-of-sound-9-characteristics-of-a-sound-wave
Source: https://en.wikipedia.org/wiki/Spectrogram

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

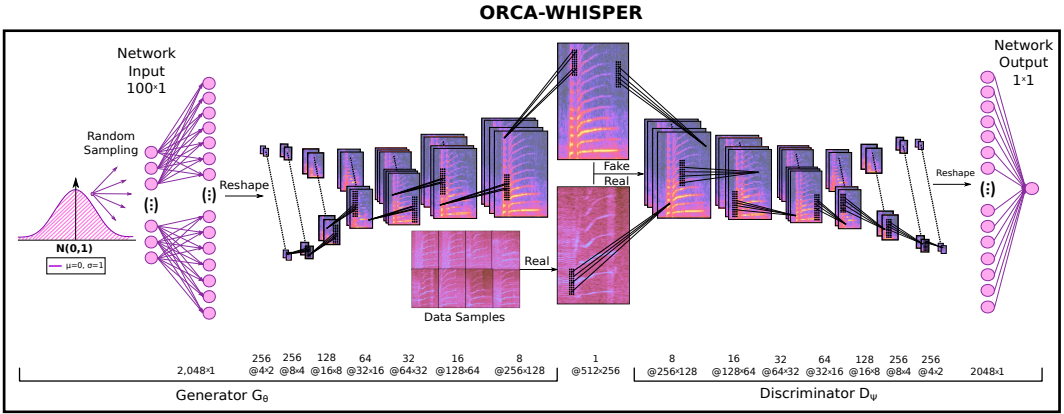
Audio Signal Classification



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

Source: Image taken from "Dissertation Christian Bergler"

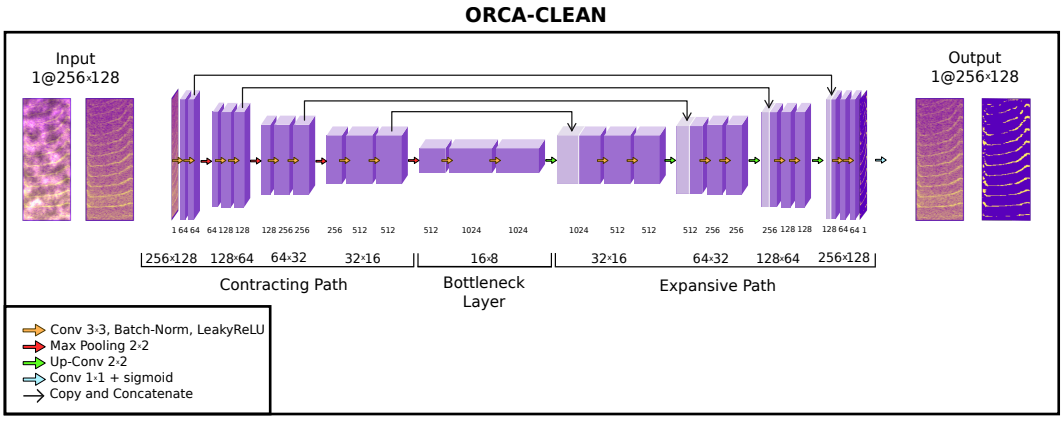
Speech Synthesis



- 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

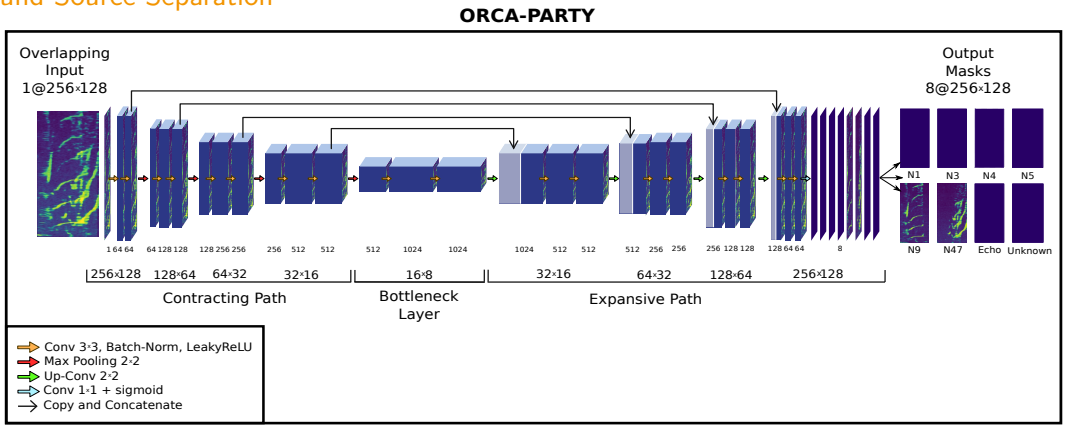
Acoustic Enhancement and Noise Reduction



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

Source: Image taken from "Dissertation Christian Bergler"

Sound Source Separation



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

Source: Image taken from “Dissertation Christian Bergler”

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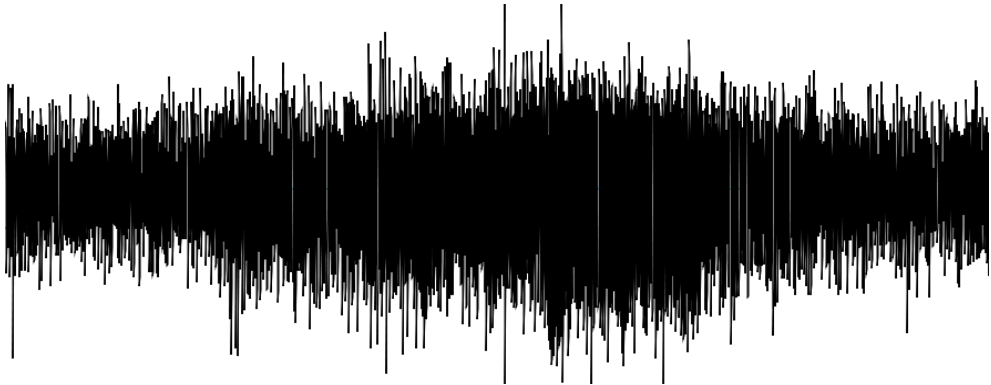
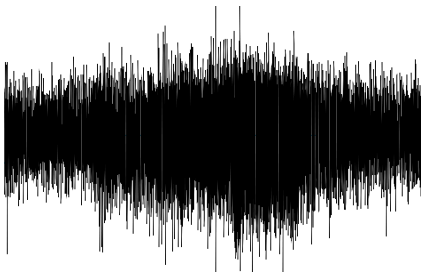
Soundwave

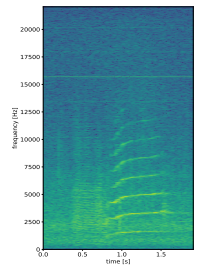


- Pure waveform (amplitude $f(t)$ over time t) is difficult to interpret!
- What are the individual components of an audio signal and how do I find patterns?

- 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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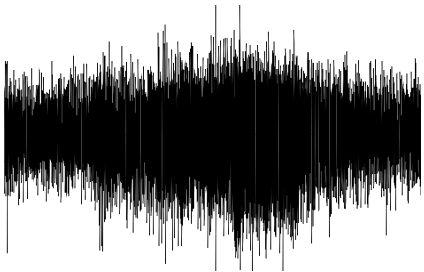
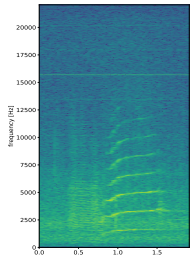


Waveform



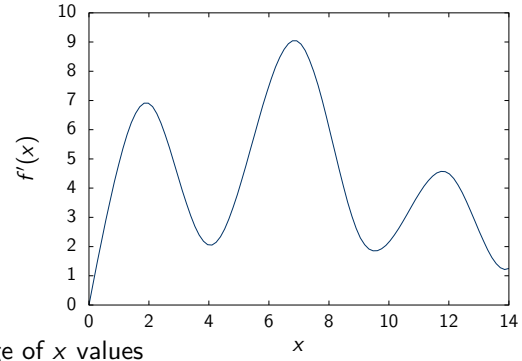
Spectrogam

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

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

Acoustic Signal Processing

Analog/Digital (A/D) Conversion



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

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

Acoustic Signal Processing

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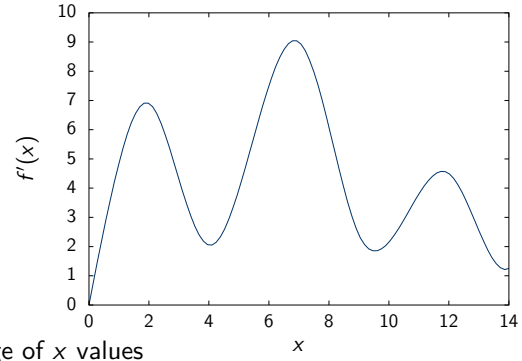
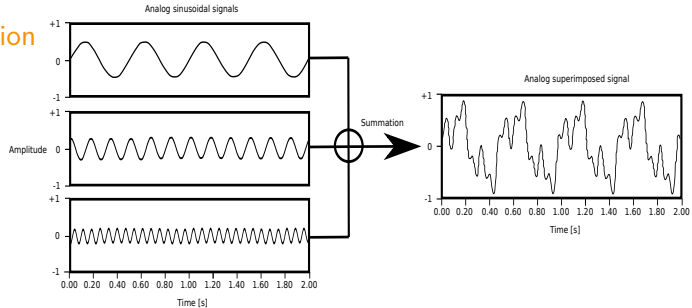


- Analog signals:
  - Continuous range of x values
  - Continuous range of amplitude/function values $f'(x)$
- Digital signals:
  - Only a finite amount of values can be stored
  - Finite number of bits (discrete values)

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

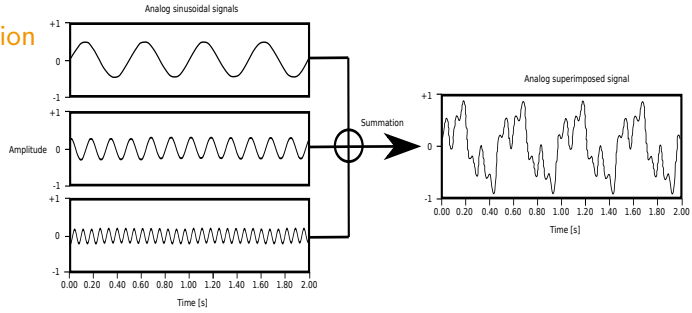
(Analog) Signal Superposition



- 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"

(Analog) Signal Superposition



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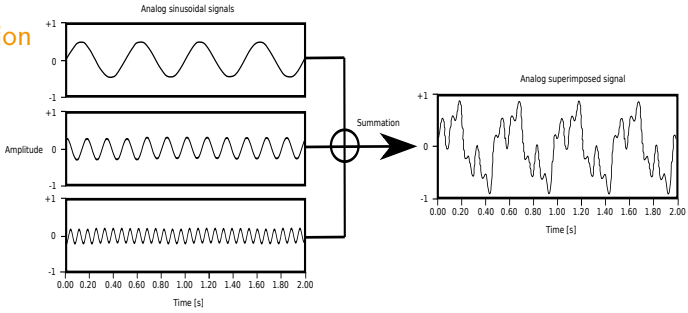
- $f(t) := A \cdot sin(2\pi(\omega t - \phi))$, with $A =$ Amplitude (loudness), $\omega =$ frequency (pitch), $\lambda = \frac{1}{\omega} =$ period (repeating!), and $\phi =$ phase

Source: Image taken from "Dissertation Christian Bergler"

(Analog) Signal Superposition

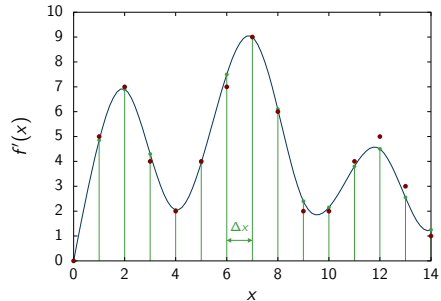


- A given signal f is considered as periodic using a period $\lambda \in \mathbb{R}_{>0}$ if $f(t) = f(t + \alpha\lambda)$, where $\alpha \in \mathbb{Z}$ for every given $t \in \mathbb{R}$
- $f(t) := A \cdot sin(2\pi(\omega t - \phi))$, with $A =$ Amplitude (loudness), $\omega =$ frequency (pitch), $\lambda = \frac{1}{\omega} =$ period (repeating!), and $\phi =$ phase
- Superposition: $(f + g)(t) := f(t) + g(t) \rightarrow$ Still periodic signal!

Source: Image taken from "Dissertation Christian Bergler"

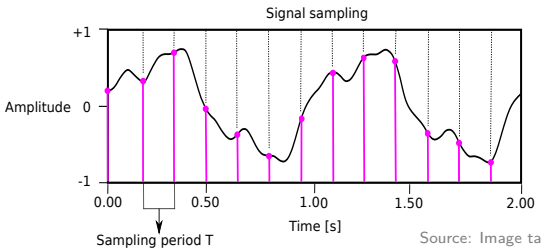
A/D Conversion (Coding) involves:

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



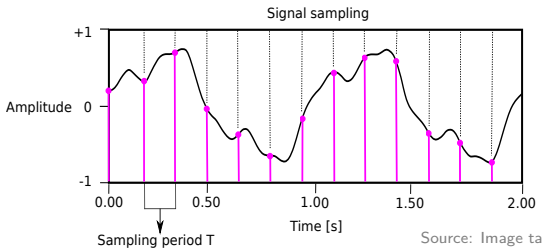
Source: Image taken from FAU-Lecture Slides "Praktikum Representation Learning" (Bergler, Christlein)

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



Source: Image taken from "Dissertation Christian Bergler"

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



Source: Image taken from "Dissertation Christian Bergler"

Acoustic Signal Processing

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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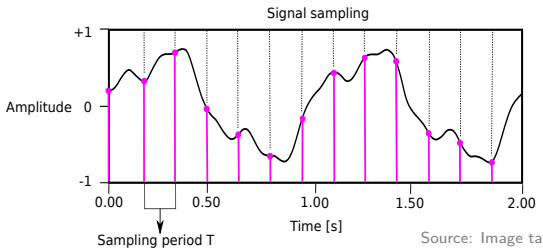

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Acoustic Signal Processing

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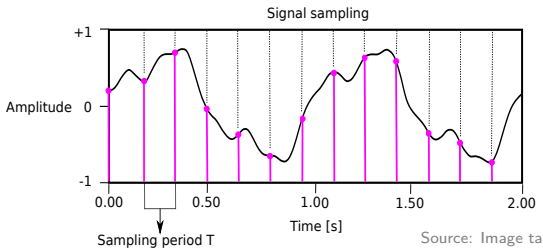

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Acoustic Signal Processing

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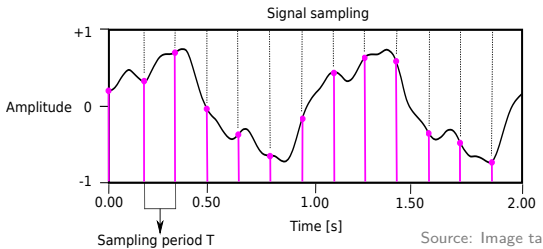
- Sampling period T, with $F_s = 1/T$ as the sampling rate
- Default: lossy conversion $\to$ discrete $x(n)$ to reconstruct continuous $f(t)$ (Aliasing!)
- Solution: Nyquist-Shannon Sampling Theorem, facilitates a perfect and lossless signal reconstruction, using: $F_s > 2 \cdot (f_{max} - f_{min})$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



Source: Image taken from "Dissertation Christian Bergler"

- 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

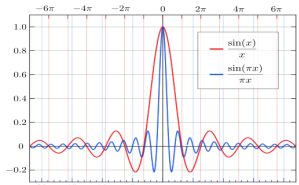
$$f_k = f(k \cdot \Delta x), \quad k = 0, \pm 1, \pm 2, \ldots$$

if the following constraint holds for the sampling interval Δx:

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

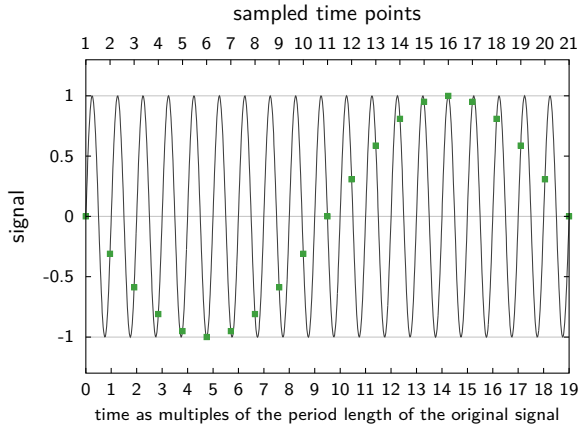
- The original signal $f(x)$ can be reconstructed precisely using the following interpolation:

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



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

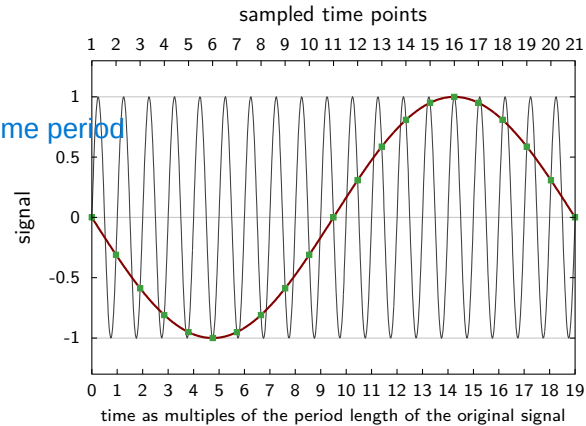
Impact of the Sampling Theorem – Undersampling (Aliasing!)



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

Impact of the Sampling Theorem – Undersampling (Aliasing!)

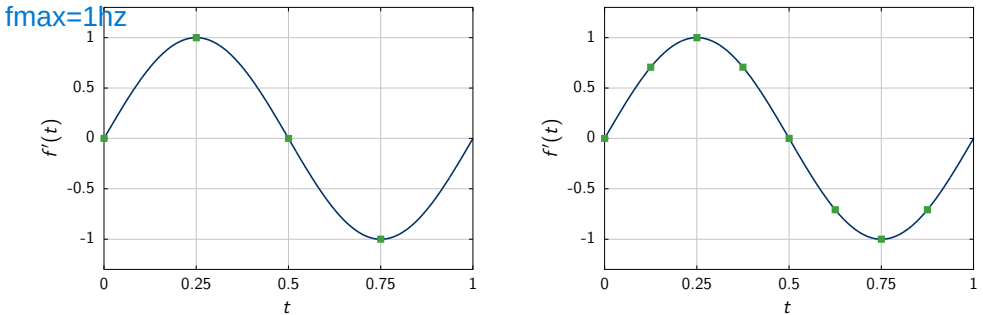
undersampling:
2 points in one time period



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)

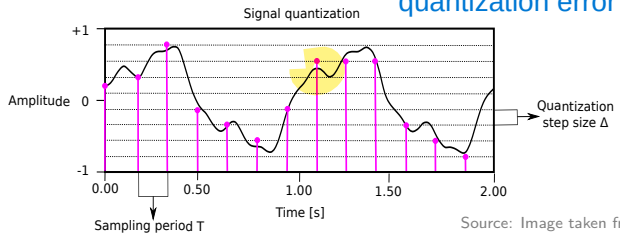
- Sampling is the discretization in time ($f : \mathbb{R} \to \mathbb{R}$ to $x : \mathbb{Z} \to \mathbb{R}$)

quantiation along y axis

more quatization step size error will be loew but the size of the file will be high

discrearization along x axis

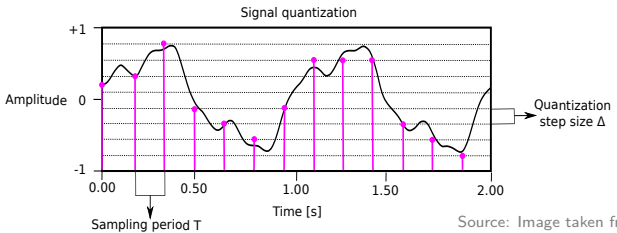
quantization error



16 bits means 2 to power 16. discreate steps

Source: Image taken from "Dissertation Christian Bergler"

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



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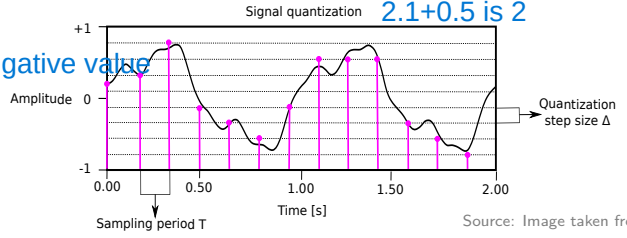
- $Q(a) \in \Gamma$, with $Q(a) := sgn(a) \cdot \Delta \cdot \lfloor \frac{|a|}{\Delta} + \frac{1}{2} \rfloor$, with $a \in \mathbb{R}$, quantization step-size Δ, $sgn(\cdot)$ as the signum function, $\lfloor \cdot \rfloor$ as real number truncation

rounding by adding 0.5

sgn(-3)= -

we round down to lower limit
2.1+0.5 is 2

its gives positive or negative value



Source: Image taken from "Dissertation Christian Bergler"

Acoustic Signal Processing

Analog/Digital (A/D) Conversion – Quantization

- Sampling is the discretization in time ($f : \mathbb{R} \to \mathbb{R}$ to $x : \mathbb{Z} \to \mathbb{R}$)
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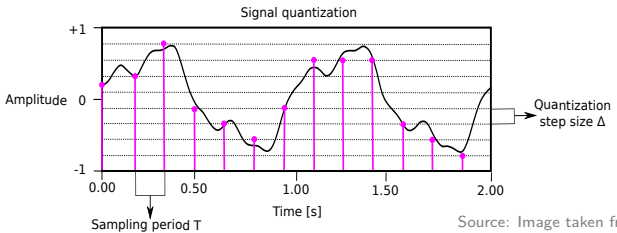
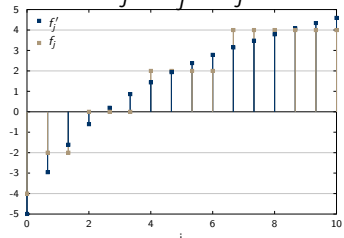
- $Q(a) \in \Gamma$, with $Q(a) := sgn(a) \cdot \Delta \cdot \lfloor \frac{|a|}{\Delta} + \frac{1}{2} \rfloor$, with $a \in \mathbb{R}$, quantization step-size Δ, $sgn(\cdot)$ as the signum function, $\lfloor \cdot \rfloor$ as real number truncation
- Lossy operation: different amplitudes $a \in \mathbb{R}$ are mapped to the same discrete value $Q(a)$, known as Quantization Error!



Source: Image taken from "Dissertation Christian Bergler"

- 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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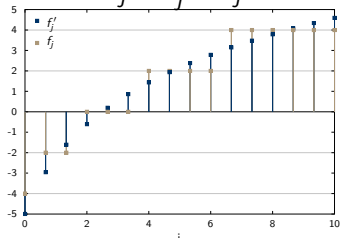

- Smaller quantization steps Δ lead to an increase in resolution, less errors, and significantly higher number of required bits for encoding
- Usually impossible to reconstruct the original analog waveform, however, fulfilling the Nyquist-Shannon Theorem with adequate sampling rates, together with a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

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

- 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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- Identify all underlying and important frequency components ω of a given signal $f(t)$

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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)!

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

OTH Amberg-Weiden

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wnkN is a matrix

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

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

integrals are sums

n is sample

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

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

we did summations as we discretise our signal

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

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

k rows and n columns but k=n

when k is o or n is zero we get e to power of zero

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

XK

WN

different position of the sin wave

XN

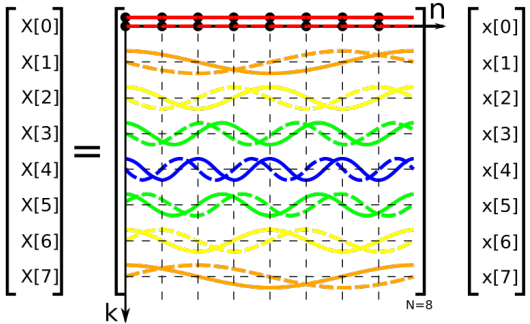
$$\begin{bmatrix} X[0] \\ X[1] \\ X[2] \\ X[3] \\ \vdots \\ X[N-1] \end{bmatrix}_{N\times 1} = \begin{bmatrix} 1 & 1 & 1 & 1 & \dots & 1 \\ 1 & W_N^1 & W_N^2 & W_N^3 & \dots & W_N^{N-1} \\ 1 & W_N^2 & W_N^4 & W_N^6 & \dots & W_N^{2(N-1)} \\ 1 & W_N^3 & W_N^6 & W_N^9 & \dots & W_N^{3(N-1)} \\ \vdots &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

frequency bin

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

Acoustic Signal Processing

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



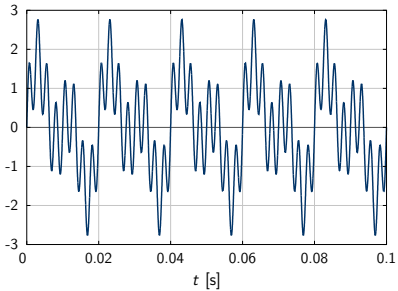
- Each row refers to a particular frequency component $W_N^{nk} = e^{-\frac{2\pi ink}{N}} = e^{-2\pi i\omega n}$
- Diagonal symmetric due to complex conjugate elements (negative frequencies), which are discarded, so only the first $\lfloor N/2 + 1 \rfloor$ frequency bins are required
- Signal oscillating with a similar/same specific frequency component $\omega = \frac{k}{K}$ when its linear projection (weighted sum over time) is strong (large absolute value!)

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

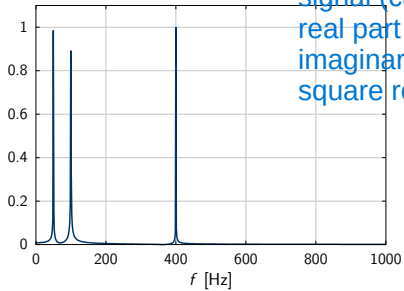
DFT – Periodic Signal

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

length is the amplitude of the signal (calculated by real part and imaginary part square root)



(a) waveform

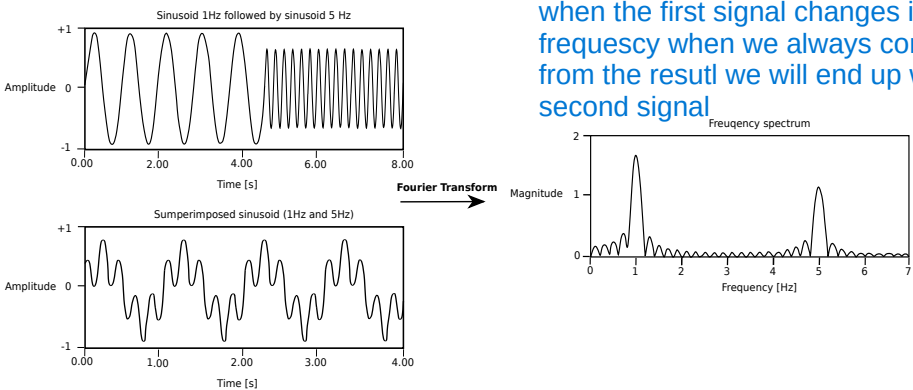


(b) Fourier spectrum (amplitudes)

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

DFT – Non-Periodic Signal

loss of information here is the time when the first signal changes its frequescy when we always come back from the resutl we will end up with second signal



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

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

- DFT is only meaningful/reasonable for periodic (stationary) signals

Source: "Dissertation Christian Bergler"

Acoustic Signal Processing

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

- DFT is only meaningful/reasonable for periodic (stationary) signals
- However, real-world signals are mostly time varying, characterized by a changing and non-stationary/-periodic frequency information → No periodicity over longer periods (e.g. speech, music, ...)

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Acoustic Signal Processing

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Solution

- Consider very short time segments (windows) and step-by-step compute DFT

Source: "Dissertation Christian Bergler"

Acoustic Signal Processing

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

- DFT is only meaningful/reasonable for periodic (stationary) signals
- However, real-world signals are mostly time varying, characterized by a changing and non-stationary/-periodic frequency information → No periodicity over longer periods (e.g. speech, music, ...)
- Fourier transform across the whole temporal context extracts the entire frequency information, however, without maintaining the knowledge at which specific point in time a certain frequency exactly occurs

Solution

- Consider very short time segments (windows) and step-by-step compute DFT
- Short-time analysis maintains both: time information when frequencies appear and periodicity, since short temporal segments of real signals are quasi-stationary (implicite assumption: periodic continuation of the window)

Source: "Dissertation Christian Bergler"

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- Algorithmen: Short-Time Fourier Transform (STFT)

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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H ia hop size

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x is orignial w is windown signal

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)

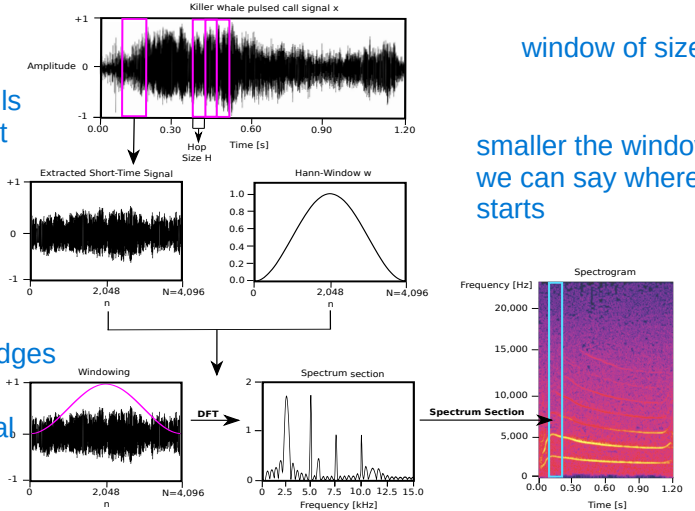
(2048,512,2)

2 is the two channels becasue of real part and imaginary part

2048 is time along x axis, 512 is frequency along y axis

smoothing the edges

windowed signal



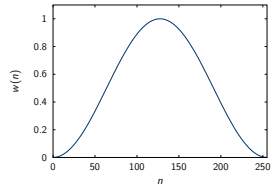
window of size n

smaller the window more precisely we can say where the frequeny starts

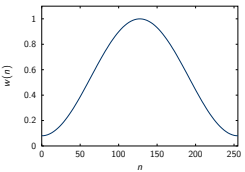
one slice is a vector of n points in a spectro gram which is used before multiplied with matrix

Source: "Dissertation Christian Bergler"

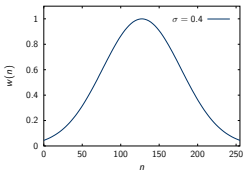
Window Function w



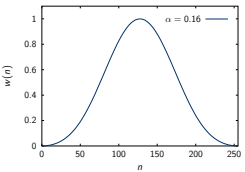
(a) Hann



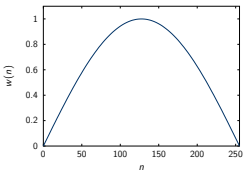
(b) Hamming



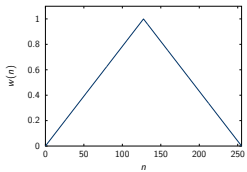
(c) Gauss



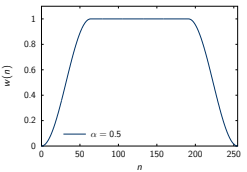
(d) Blackman



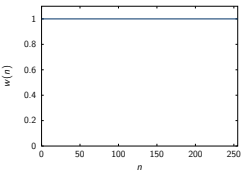
(e) Cosine



(f) Bartlett



(g) Tukey



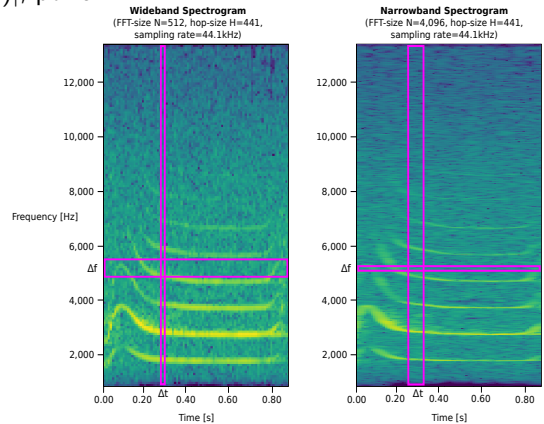
(h) Rectangle

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

Acoustic Signal Processing

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

- Spectrogram: complex $X(k, m)$, magnitude $|X(k, m)|$, power $|X(k, m)|^2$, log-scaled, with specific filter-banks



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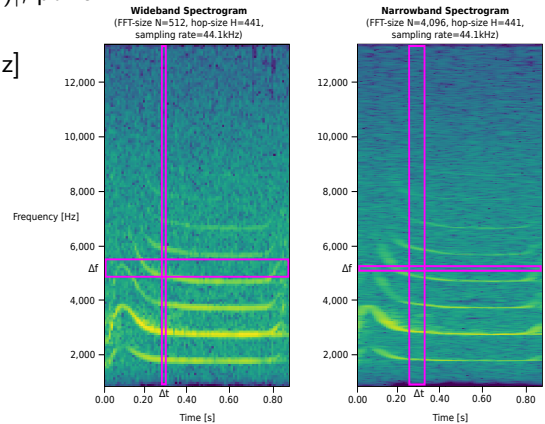

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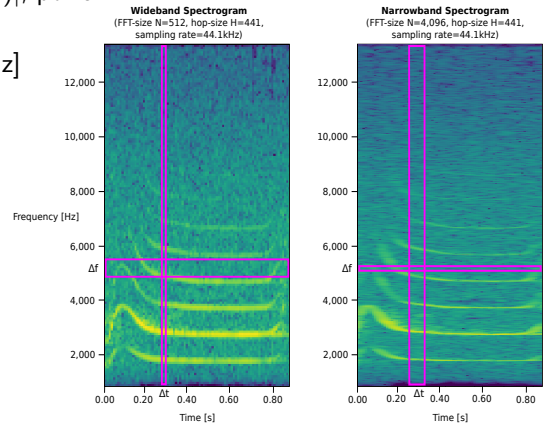

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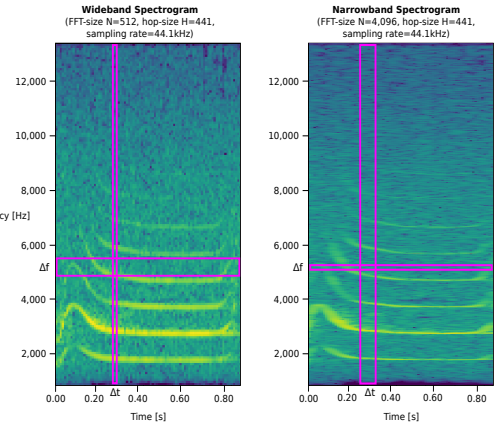

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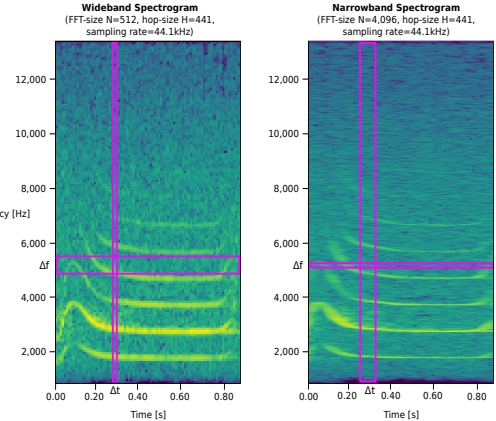
window size is thr power of 2



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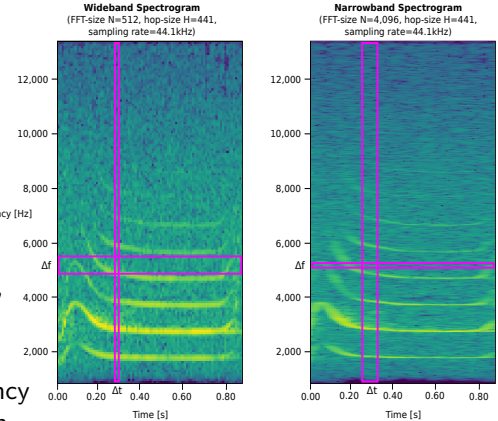
- Narrowband: larger time windows N, increase in frequency bins, narrows the spectral content represented in one bin, improves frequency resolution deteriorates time resolution



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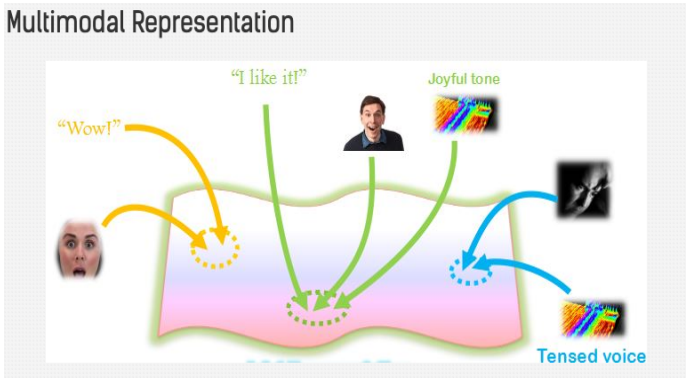
Multimodal Learning

What is it about?

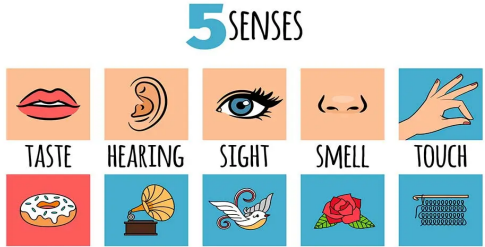


- Multimodal Learning is a learning paradigm in the field of deep learning, using various data modalities, such as text, audio, sensor signals, and images/videos within a single learning concept at the same time!

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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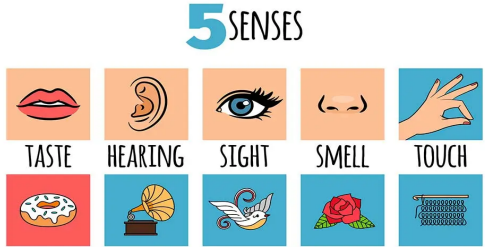

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- Humans have access to five senses – sight, hearing, touch, taste, and smell – not just to collect information, but also to understand and interpret the environment around us

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Multimodal Learning

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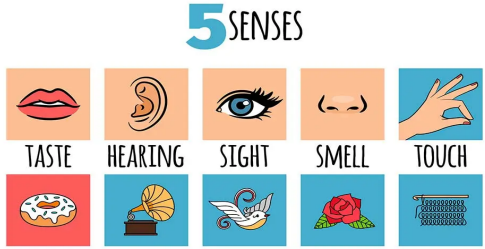

- The core idea of deep learning was to design algorithms trying to mimic the human brain (neurons, layers, deep structures, ...)
- Humans have access to five senses – sight, hearing, touch, taste, and smell – not just to collect information, but also to understand and interpret the environment around 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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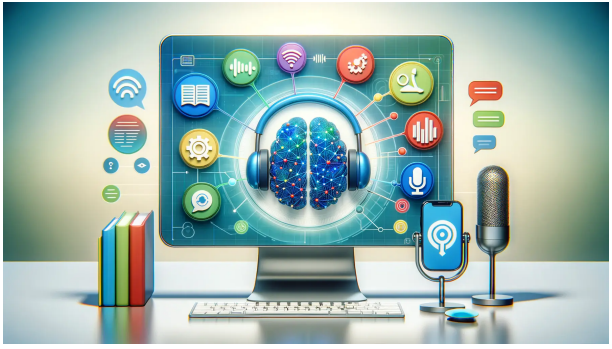


- The integration of multiple modalities allows a model to leverage complementary information, handle missing data from one source by relying on another, provide more comprehensive insights, and improves model generalization!
- Real-world data and applications are very often multimodal!

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

Text-Image VS. Image-Text Retrieval

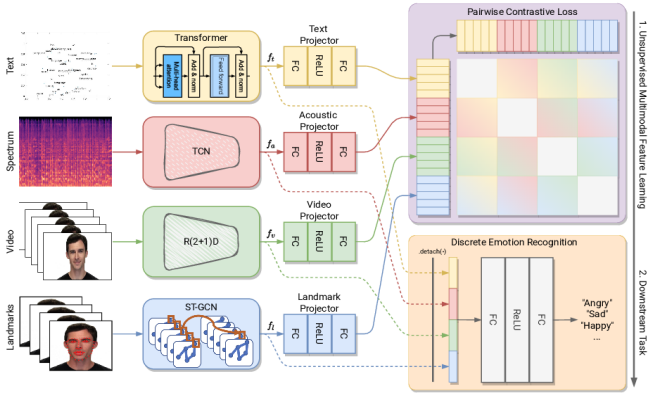
- For a given image, find related text, or vice versa, which is particularly useful in any kind of search engines

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



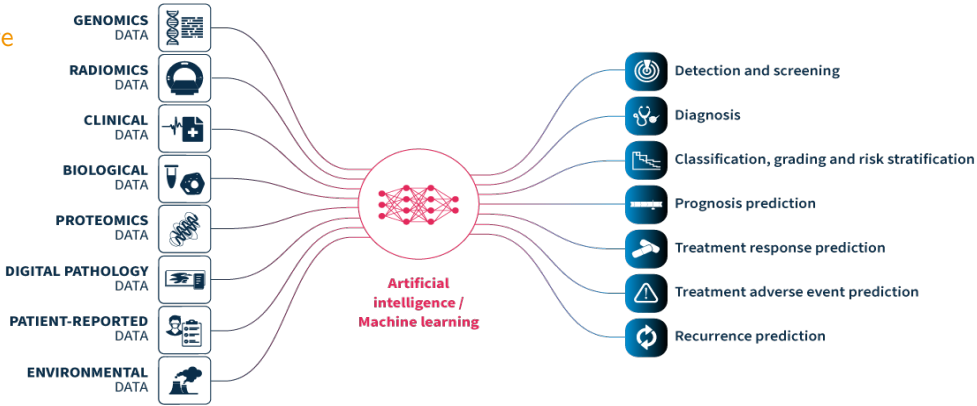
- Modern systems use video (facial expressions), audio (voice tone), and textual data (spoken words) to specifiy emotions of a person more accurately
- Further: LipSync and textual models in ASR Systems (Vision + Speech + Text)

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

Multimodal Learning

Real-World Applications – Computer Vision/Text/Audio

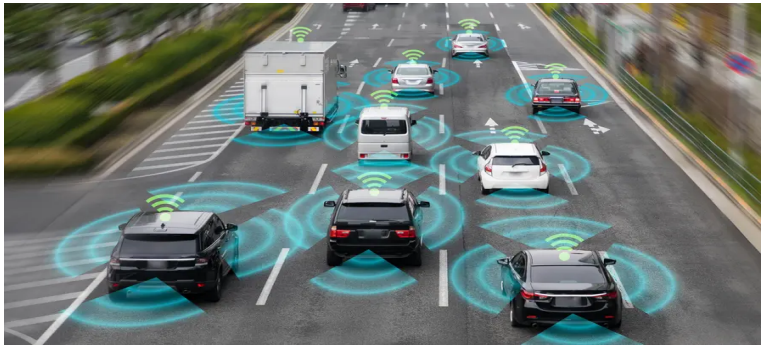
Healthcare



- 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/

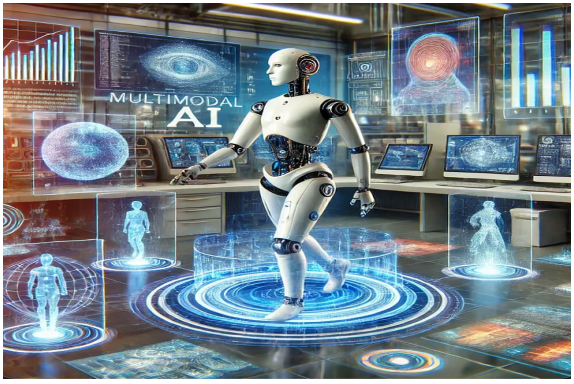
Autonomous Driving



- 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

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

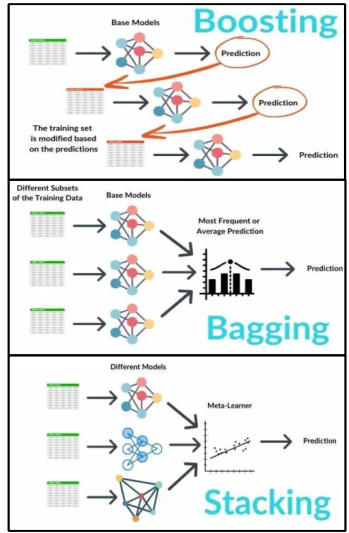
Source: Image from https://squoraishee.medium.com/multimodal-machine-learning-a-deep-dive-bc4f25f6a63b

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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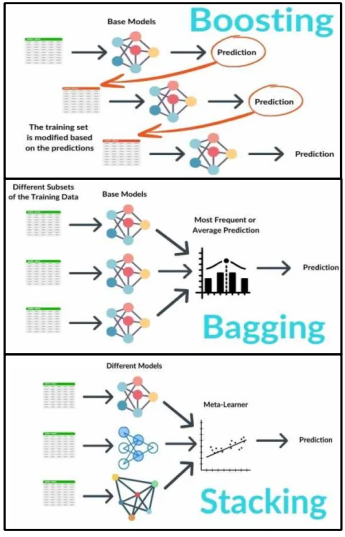
- Bagging – Training multiple model instances of the same algorithm w.r.t. different training subsets (final prediction, obtained by averaging or majority vote)



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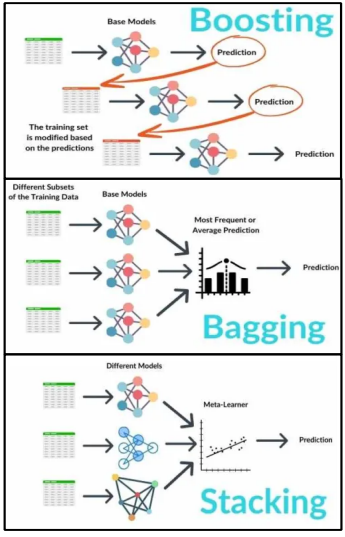
- Boosting – Sequence of models, while each subsequent model corrects the mistakes made by the previous ones (Adaptive Boosting, Gradient Boosting Machines, ...)
- Bagging – Training multiple model instances of the same algorithm w.r.t. different training subsets (final prediction, obtained by averaging or majority vote)
- Stacking – Training multiple diverse base models and combine the predictions using another meta-model, weighting the base-model output for final prediction



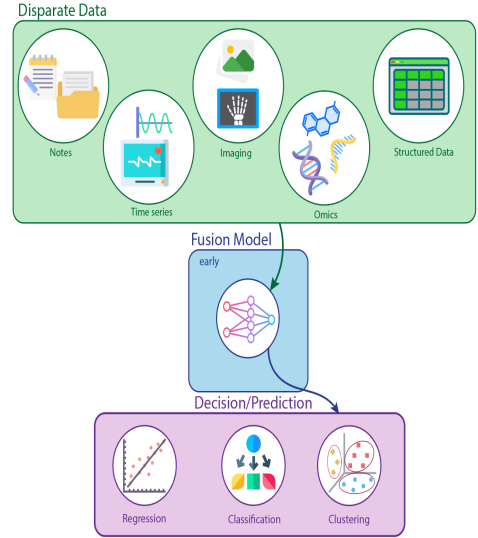
Source: https://spotintelligence.com/2024/03/18/bagging-boosting-stacking/

Multimodal Learning

Combining Models VS. Multimodal Learning

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



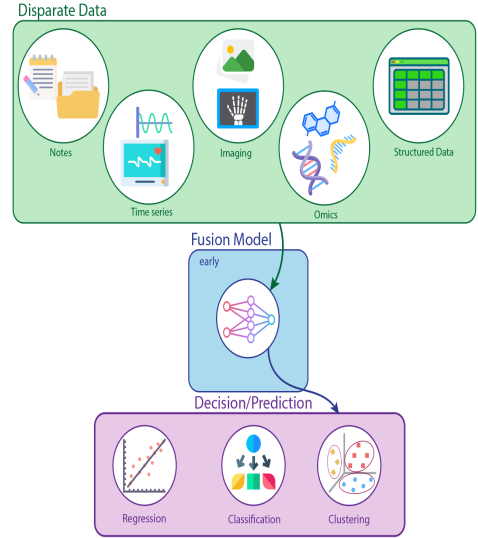
Source: https://pub.towardsai.net/multimodal-machine-learning-data-fusion-d1d8776e2cb0

Multimodal Learning

Combining Models VS. Multimodal Learning

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

- 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

Multimodal Learning

Fusion and Learning Principles

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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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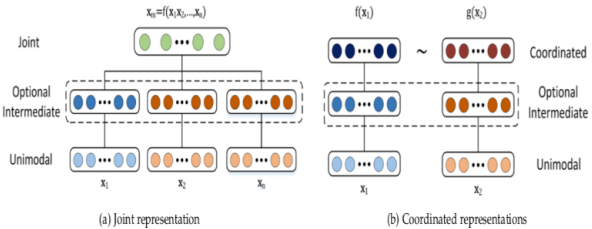
Cross-Modal Learning

- 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!)

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

Challenges

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Multimodal Learning

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Multimodal Learning

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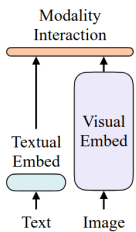
- Interpretability: challenges in understanding how decisions are made when combining multiple modalities

Multimodal Learning

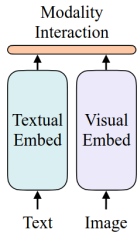
Architectural Paradigms

- (a) Uneven Disentangled
- (b) Even Disentangled
- (c) Uneven Entangled
- (d) Even Entangled

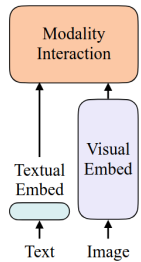
  Namings: VE = Visuel Embedder, TE = Textual Embedder, MI = Modality Interaction



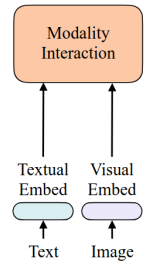
(a) VE > TE > MI



(b) VE = TE > MI



(c) VE > MI > TE



(d) MI > VE = TE

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Multimodal Learning

Source: Image from Wonjae Kim et al., ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision

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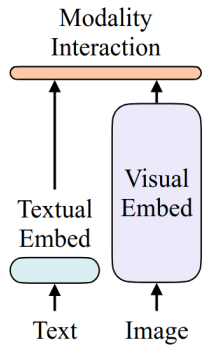
Uneven Disentangled

- Uneven: Imbalance in treatment/focus of visual & textual embeddings (prioritization!) regarding model size
- Disentangled: Visual & textual embeddings are processed separately in different model parts (no significant interaction during feature extraction), with each modality having its own path (later interaction possible!)
- Heavy visual embedder, light textual embedder and weak modality interaction (“>”, “<” = Focus!)
- For example: VSE++ → VE = VGG-19/ResNet-152, TE = RNN-based LM, MI = inner product



(a) VE > TE > MI

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, “Advanced Deep Learning” – Multimodal Learning
Source: Faghri et al.: “VSE++: Improving Visual-Semantic Embeddings with Hard Negatives”
Source: Image from Wonjae Kim et al., “ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision”

Even Disentangled

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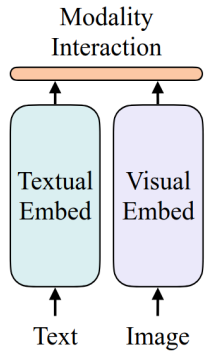
- Disentangled: Visual & textual embeddings are processed separately in different model parts (no significant interaction during feature extraction), with each modality having its own path (later interaction possible!)
- Heavy VE, heavy TE, and weak MI
- For example: CLIP (Contrastive Language-Image Pretraining) → VE = Vision Transformer, TE = Transformer, MI = Scaled pairwise cosine similarities



(b) VE = TE > MI

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Radford et al., "Learning Transferable Visual Models From Natural Language Supervision"
Source: Image from Wonjae Kim et al., "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision"

CLIP (Even Disentangled)

- Model Training:

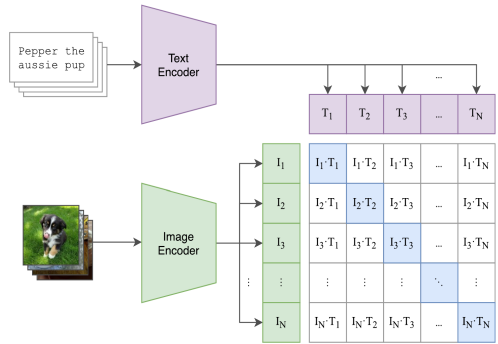
  1. Get sequences from both encoders (visual + textual embeddings)

  2. Apply symmetric contrastive loss (Normalized Temperature-scaled Cross-Entropy Loss) with cosine similarity $< v, u >= \frac{v^T u}{||v|| \cdot ||u||}$

  3. $\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \ell_i^{(T \to I)} + \ell_i^{(I \to T)}$, with:

$$\ell_i^{(T \to I)} = -log \frac{exp(<T_i, I_i>/\tau)}{\sum_{k=1}^{N} exp(<T_i, I_k>)/\tau}$$

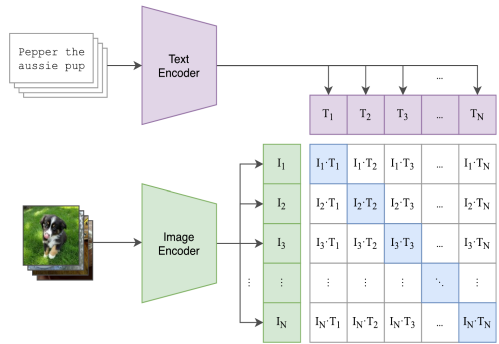
$$\ell_i^{(I \to T)} = -log \frac{exp(<I_i, T_i>/\tau)}{\sum_{k=1}^{N} exp(<I_i, T_{,k}>)/\tau}$$



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Radford et al., "Learning Transferable Visual Models From Natural Language Supervision"

CLIP (Even Disentangled)

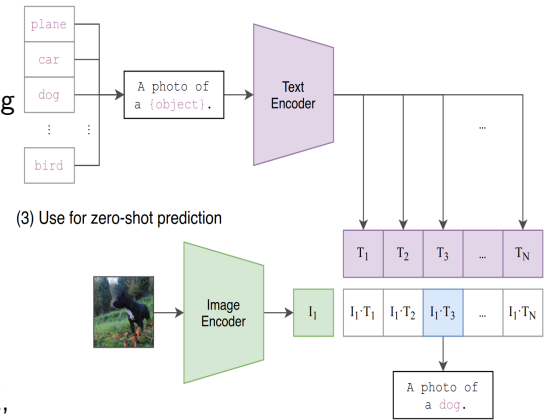
- Similar to an attention layer ($KQ^T = IT^T$) the raw similarity scores (logits) are computed
- The temperature parameter τ (learnable!) is used to scale the logits
- If $\tau = 1 \rightarrow$ Softmax!
- If $\tau << 1$ the differences between similar image/text vs. text/image pairs is better highlighted (hard negatives!)
- If $\tau >> 1$ it smooths the distribution, reducing the pair-wise contrast focus on overall similarities
- Bidirectional alignment is forced due to symmetry



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Radford et al., "Learning Transferable Visual Models From Natural Language Supervision"

CLIP (Even Disentangled)

- Zero-Shot Prediction:
  1. Encode class names as potential text pairing
  2. Use for image-based zero-shot prediction
- CLIP Summary:
  1. Excellent general performance
  2. Especially for zero-shot scenarios
  3. Unable to solve difficult tasks
  4. Standard module combining image + text modalities for many generative models (Dall·E, StableDiffusion, etc.)



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Uneven Entangled

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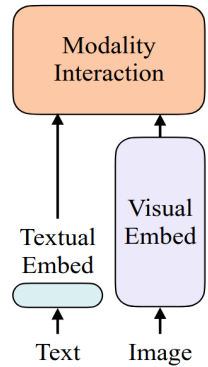
- Entangled: Visual and textual embeddings are combined earlier and processed together (entangled), allowing for cross-modal interaction during model processing
- Heavy VE, light TE, and strong MI
- For example: ViLBERT (Vision-and-Language BERT) $\rightarrow$ VE = Pre-trained Faster R-CNN (ResNet-101 backbone), TE = Transformer, MI = Transformer



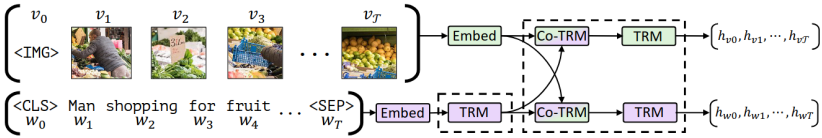
(c) VE > MI > TE

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Jiasen Lu et al.: "ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks"
Source: Image from Wonjae Kim et al., "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision"

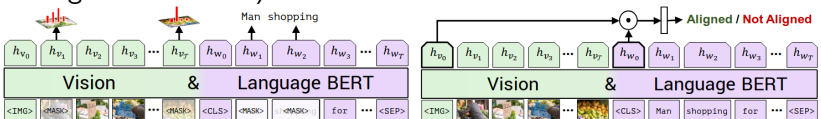
Multimodal Learning

Architectural Paradigms

ViLBERT



- Two parallel streams for visual & linguistic processing, through novel co-attentional transformer layers (allowing variable depths for each modality, while enabling sparse interaction through co-attention)



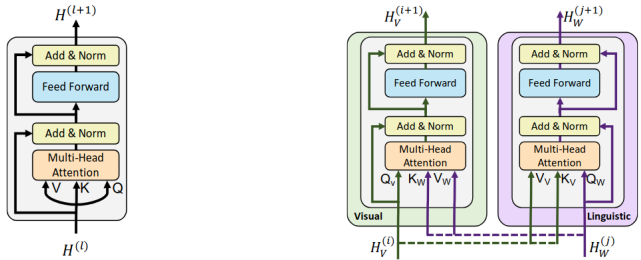
(a) Masked multi-modal learning (b) Multi-modal alignment prediction

- Reconstruction: masked multi-modal learning, the model must reconstruct image region categories, words for masked inputs
- Alignment Prediction: predict whether or not the caption describes the image content

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Jiasen Lu et al., ViLBERT: "Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks"

ViLBERT – Standard Encoder Transformer Block VS. Co-Attention Transformer Layer

- Transformer-based co-attention mechanism, exchanging key-value pairs as part of a multi-headed attention,
- Allowing vision-attended language features being incorporated into visual representations (vice versa)



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Source: Image from Jiasen Lu et al., ViLBERT: "Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks"

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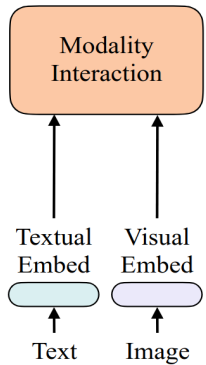
- Entangled: Visual and textual embeddings are combined earlier and processed together (entangled), allowing for cross-modal interaction during model processing
- Light VE, light TE, and strong MI
- For example: ViLT (Vision-and-Language BERT) → VE = Linear projection of flattened patches, TE = Tokenization, MI = Transformer



(d) MI > VE = TE

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
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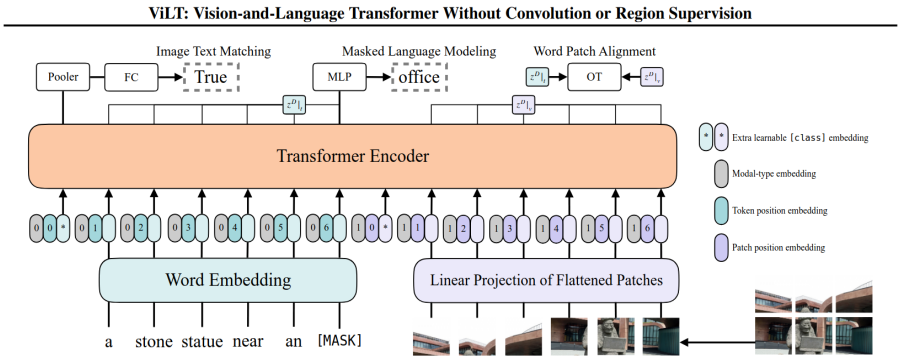
Multimodal Learning

Architectural Paradigms

ViLT



- Image Text Matching – Randomly replace input image with another, add fully-connected layers to classify pairs, masked language modeling with whole word masking, word patch alignment

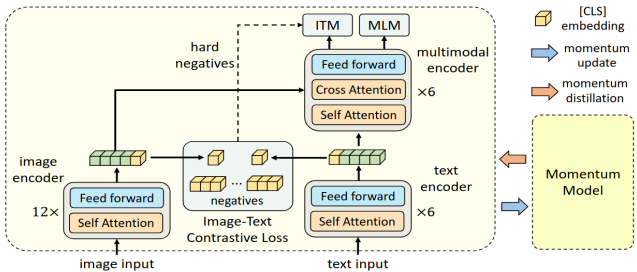
Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Wonjae Kim et al., "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision"

Multimodal Learning

Improvements in Architectural Designs

What is important?

- Vision Transformer strong modality interaction, image augmentation, liage-text contrastive loss, masked language modeling loss, Image text matching loss
- Approach: Align Before Fuse, Vision and Language Representation Learning with Momentum Distillation



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Junnan Li, et al., "Align before Fuse: Vision and Language Representation Learning with Momentum Distillation"

Multimodal Learning

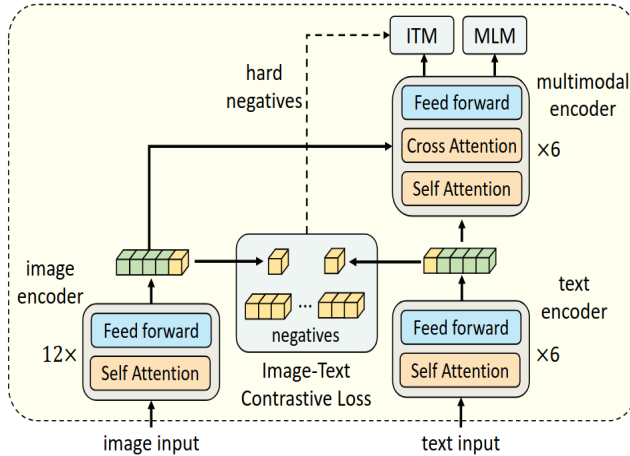
Improvements in Architectural Designs

Architecture

- Visual encoder: 12-layer vision transformer ViT-B/16
- Textual encoder: 6 layers of transformer
- Modality interaction: 6 layers of transformer
- Modality interaction through cross-attention layers

Main Objectives

- Image-text contrastive loss (ITC)
- Masked language modeling (MLM)
- Image-text matching (ITM)



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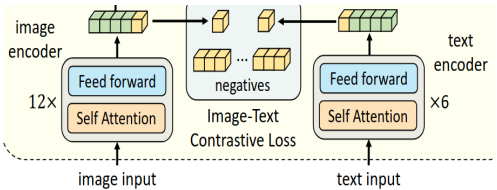
Source: Image from Junnan Li, et al., "Align before Fuse: Vision and Language Representation Learning with Momentum Distillation"

Image-Text Contrastive (ITC) Loss

- Core idea: Align unimodal embeddings before fusing them
- Take class tokens from outputs of both encoders
- Project and normalize class tokens
- Queue of recent inputs (He et al., "Momentum Contrast for Unsupervised Visual Representation Learning") for negative samples
- Cosine similarity between positive and negative pairs
- Calculate ITC loss (cross entropy)



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Junnan Li, et al., "Align before Fuse: Vision and Language Representation Learning with Momentum Distillation"

Multimodal Learning

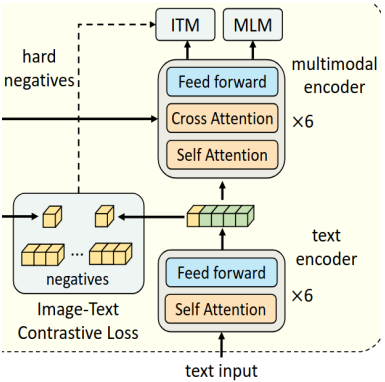
Improvements in Architectural Designs

Masked Language Modeling (MLM)

- Core idea: Enforce alignment throughout encoder
- Classification of multimodal embedding as matched vs. non-matched
- Hard negative sampling: Sample the negative pairs according to similarity from all ITC negative samples

Image-Text Matching (ITM)

- Core idea: Self-supervised pretraining
- Input tokens replaced by [MASK] with 15 % probability
- Joint image + text representation used for BERT-like masked prediction



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, "Advanced Deep Learning" – Multimodal Learning
Source: Image from Junnan Li, et al., "Align before Fuse: Vision and Language Representation Learning with Momentum Distillation"

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