HANDS-ON AI I

Reading, Handling and Visualization of Datasets

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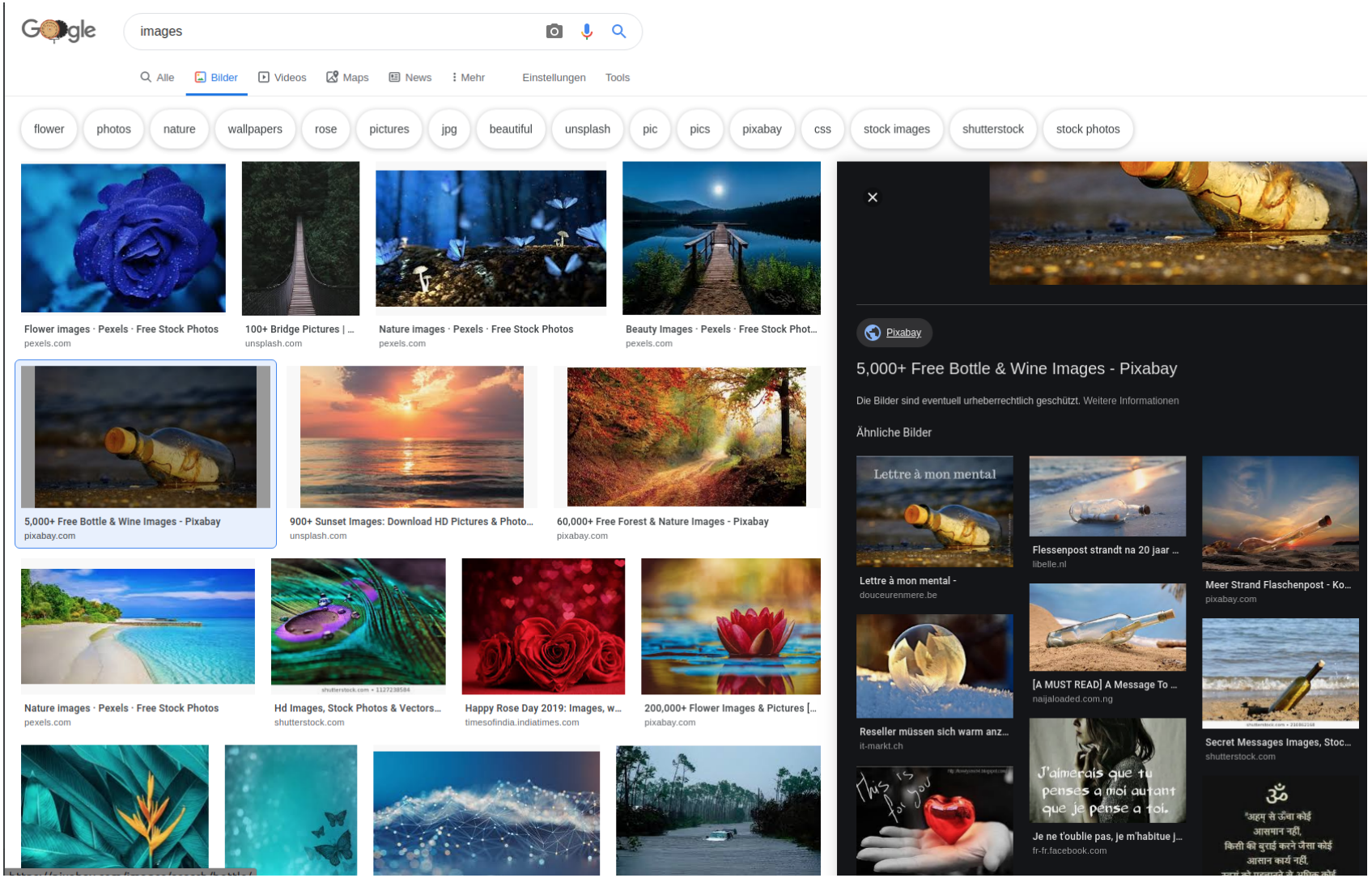
Content of Unit 2

- Second data source: images
- Third data source: sequential data
  - Sound
  - Text

Images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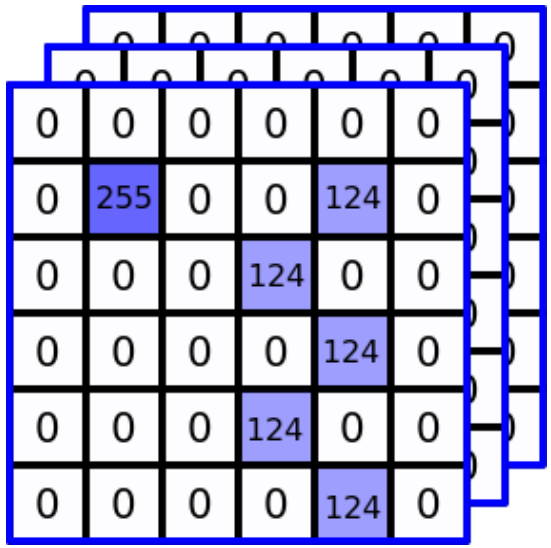
किसी को बुराई करने जैसा कोई आसान कार्य नहीं.

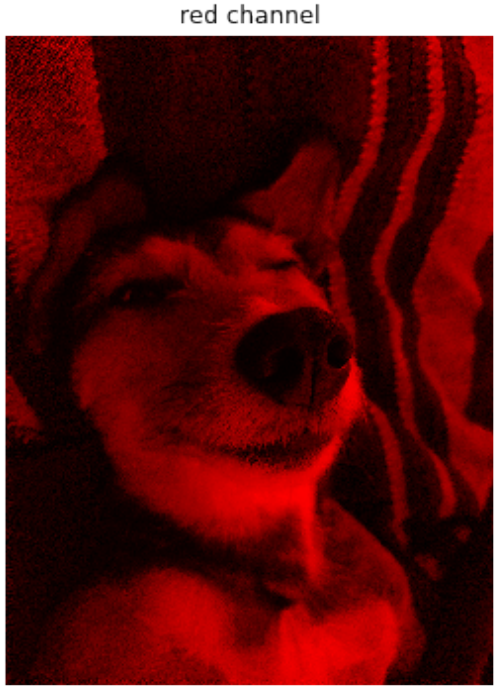
Representation of Images

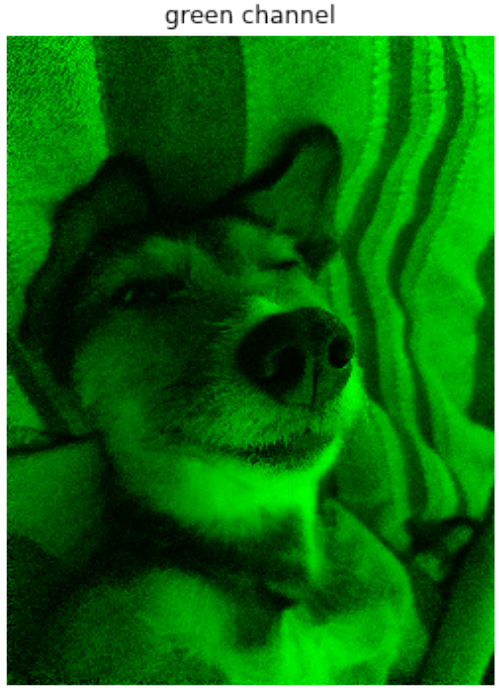
- Images are usually represented in **3 dimensions**:
  - Height
  - Length (or width)
  - Channels (often: red, green, blue)
- **Color depth** refers to the number of possible values for each channel of a pixel.
  - Color depths of **8-bit** ($2^8 = 256$ values) and **16-bit** ($2^{16} = 65536$ values) are common.
  - Higher values mean increased intensity.

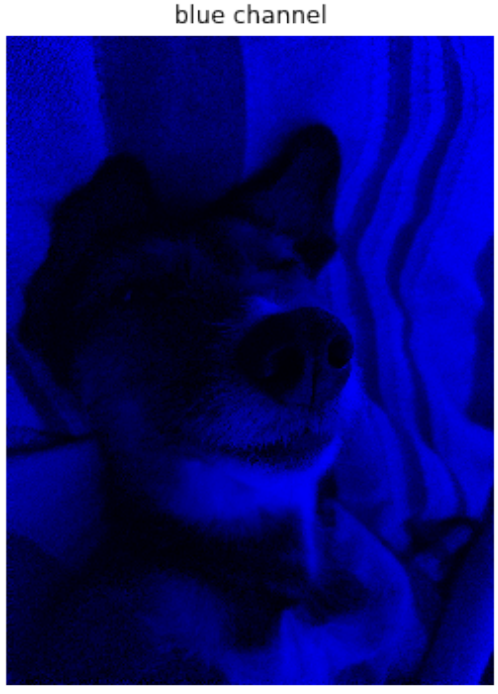


RGB Model

- The RGB (red, green, blue) model is the most important model for colored images.
- 3 channels: **red, green, blue**
- Adding up the 3 color channels results in the final image.







RGB Model

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RGBA Model

- The RGBA model uses a fourth channel: **alpha**.
- Alpha controls the transparency of the image.
- Higher values mean increased opaqueness ($\alpha = 0 \rightarrow$ fully transparent, $\alpha = \max \rightarrow$ fully opaque).

Grayscale

- Grayscale images have only **one channel representing the brightness**.
- Color images can be converted to grayscale images (different grayscale conversions exist), but not vice versa (without additional information).

Data Augmentation

- The field of **computer vision** focuses on processing and understanding images.
- Strong shift towards machine learning as **a way to understand, manipulate and even generate images**.
- Example: We “show” a machine learning model a large number of images with and without Charlie.
  - Train it to distinguish between these two groups.
  - **Augment** the images to reduce the workload of getting a lot of Charlie images.
  - Feed original and/or augmented images to our model.

Data Augmentation

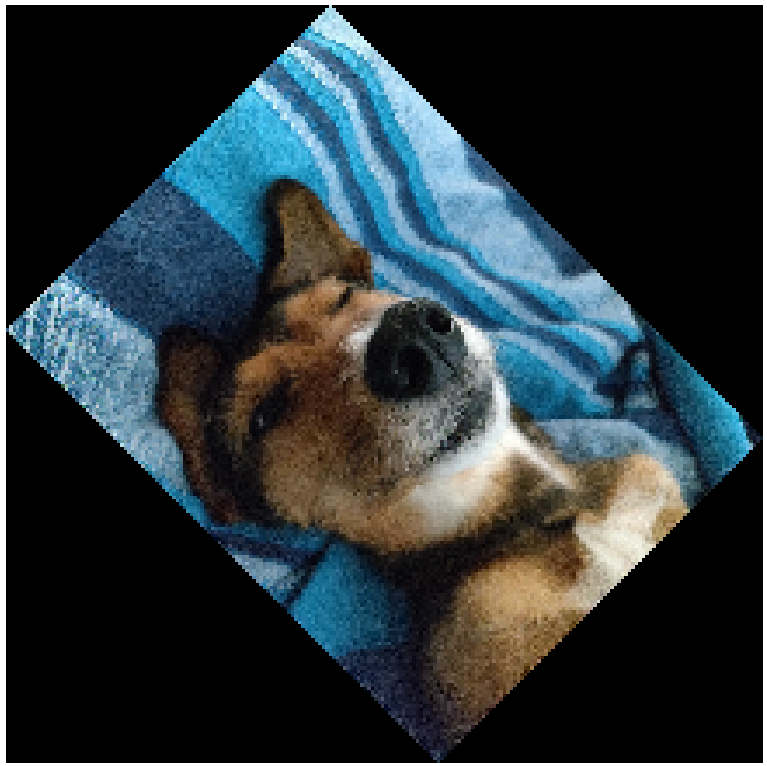
- In many cases, we can augment data artificially without collecting new real samples: Create "new" **artificial samples** by modifying existing samples.
- Pros:
  - Can increase the number of data points by a large factor with little effort (often on-the-fly).
  - Reduces overfitting, increases robustness of model (we will learn about this in a later unit).
- Cons:
  - Can introduce artifacts or change the task.
  - Heavily dependent on data, model and task.

Data Augmentation Techniques

- There exist a lot of data augmentation **techniques**.
- Some can be applied across different fields (e.g., adding noise), some are specific and only applicable in certain scenarios.
- Here are some common examples in the area of **image augmentation**:
  - Rotation
  - Flipping
  - Zooming/Cropping
  - Blurring
  - Noise
  - Input Dropout
  - Distortion Effects
  - Color Jittering
  - ...

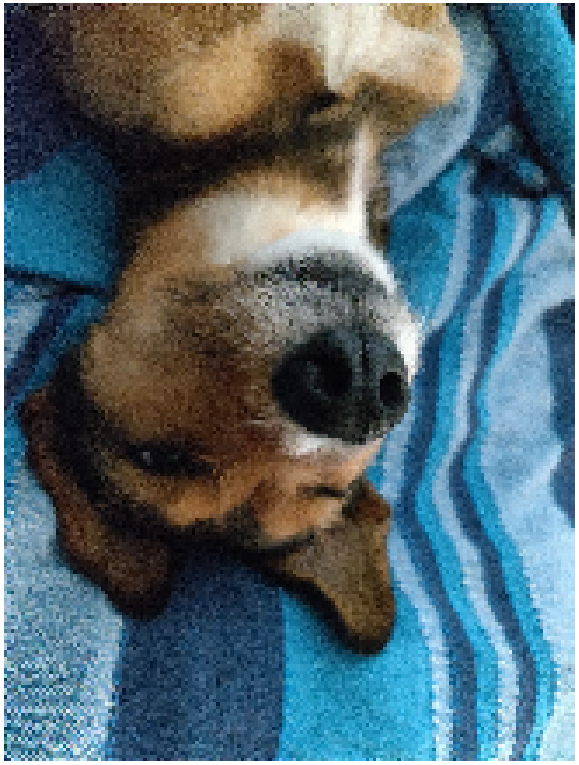
Rotation

- Rotate images around their center by a certain angle.
- It always depends on the task how much rotation is reasonable.



Flipping

- Mirroring the image across its vertical or horizontal axis.
- It depends on the task if flipping is reasonable.

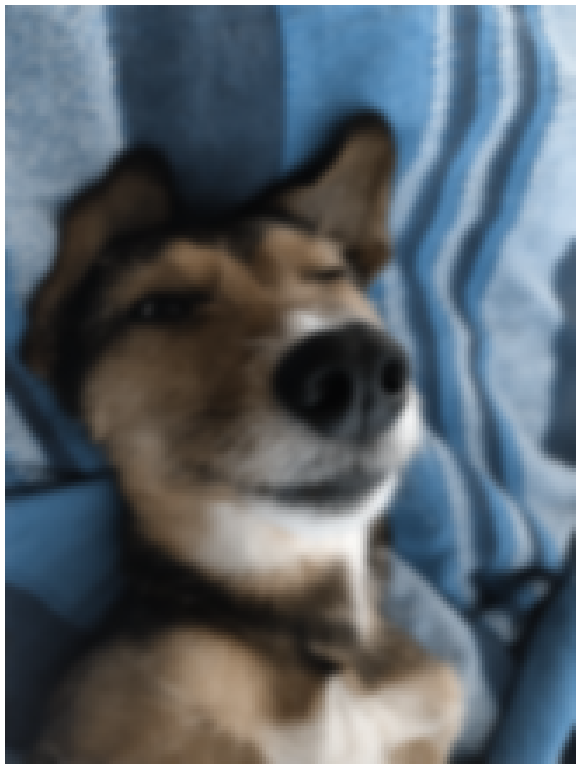


Zooming/Cropping

- Zoom into the image (different sizes of Charlie).
- Often, the same size of the image is required:
  - Selecting a smaller part and resizing it to the original resolution.

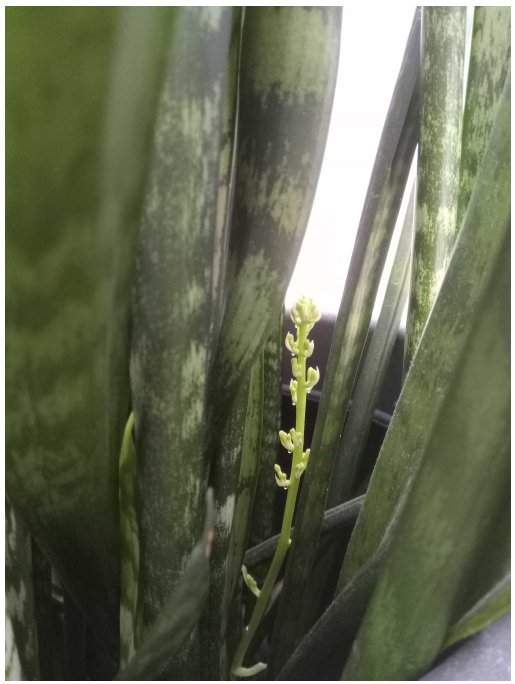
Blurring

- Usually not all images are super sharp.
  - Blurred images help the machine learning model to detect blurred Charlies as well.
- Gaussian blurring is most common blurring technique.



Noise

- Add random noise such that input feature values (pixels) are still plausible.
- Noise strength can be parameterized.



original

light noise

heavy noise

Input Dropout

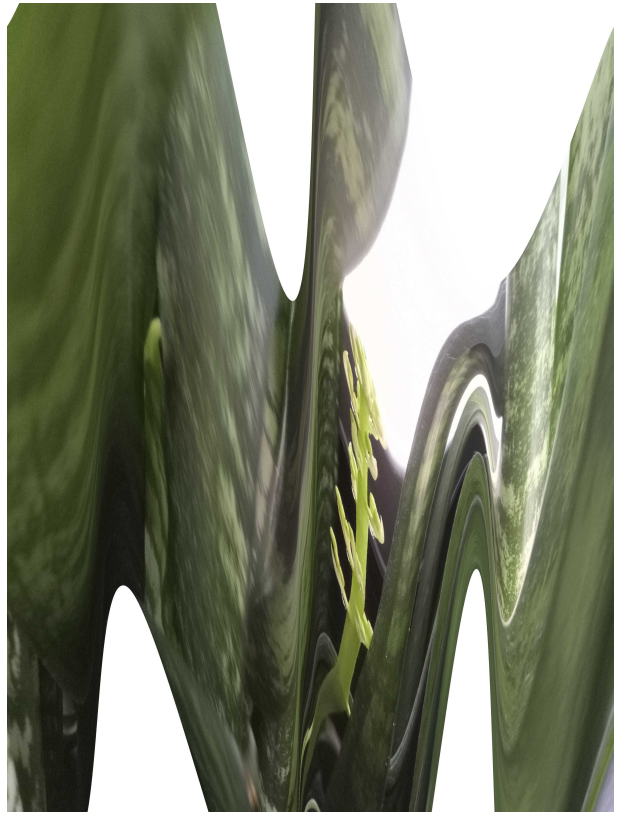
- Temporarily remove input features to mimic data errors or hidden image content.
- Different dropout techniques exist, e.g., removing individual R, G or B values, or even entire (adjacent/neighboring) pixels over all channels.

dropout random values

adjacent pixels

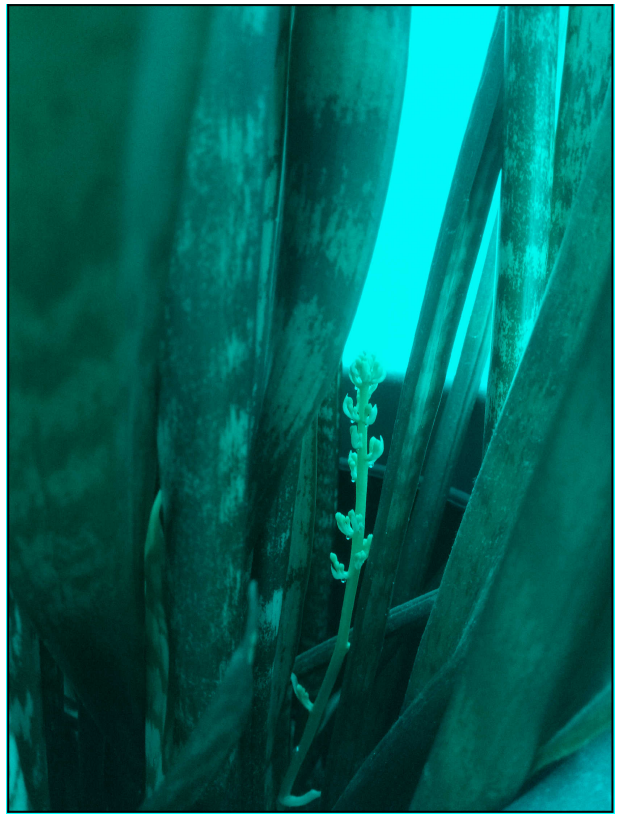
Distortion Effects

- Warp image using, e.g., lens-distortion-like effects.



Color Jittering

- Modify color channels, brightness, hue, saturation or value.



Some Notes on Data Augmentation

- Very useful to get more data without having to explicitly "collect" it from the source.
- Increases variation and thereby allows for a better generalization.
- **Careless augmentations** can actually have a **negative impact**. Example:
  - Extreme zoom on Charlie's nose.
  - Only black pixels remain with no resemblance of Charlie whatsoever.
  - Training a machine learning model with this input (while still saying this is Charlie) will yield worse results.
- Data augmentation is typical in image processing but not restricted to it.
  - Example: Add random noise to time series signal.

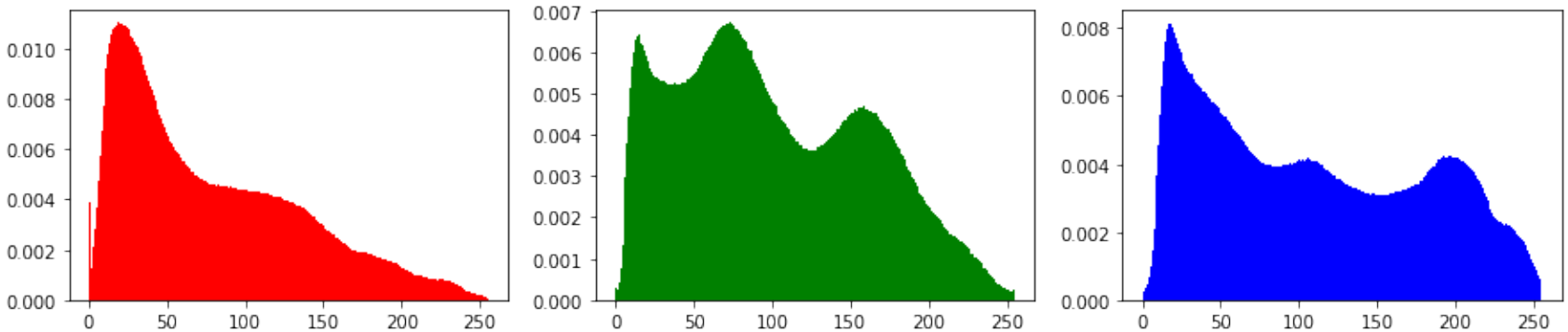
Image Segmentation

- A common problem in computer vision is to mark an object within an image, e.g., a dog with some background.

- We segment the image into **object** and **no object**: **image segmentation**.
- Wide field of research.

Simple Solution to Segment Charlie

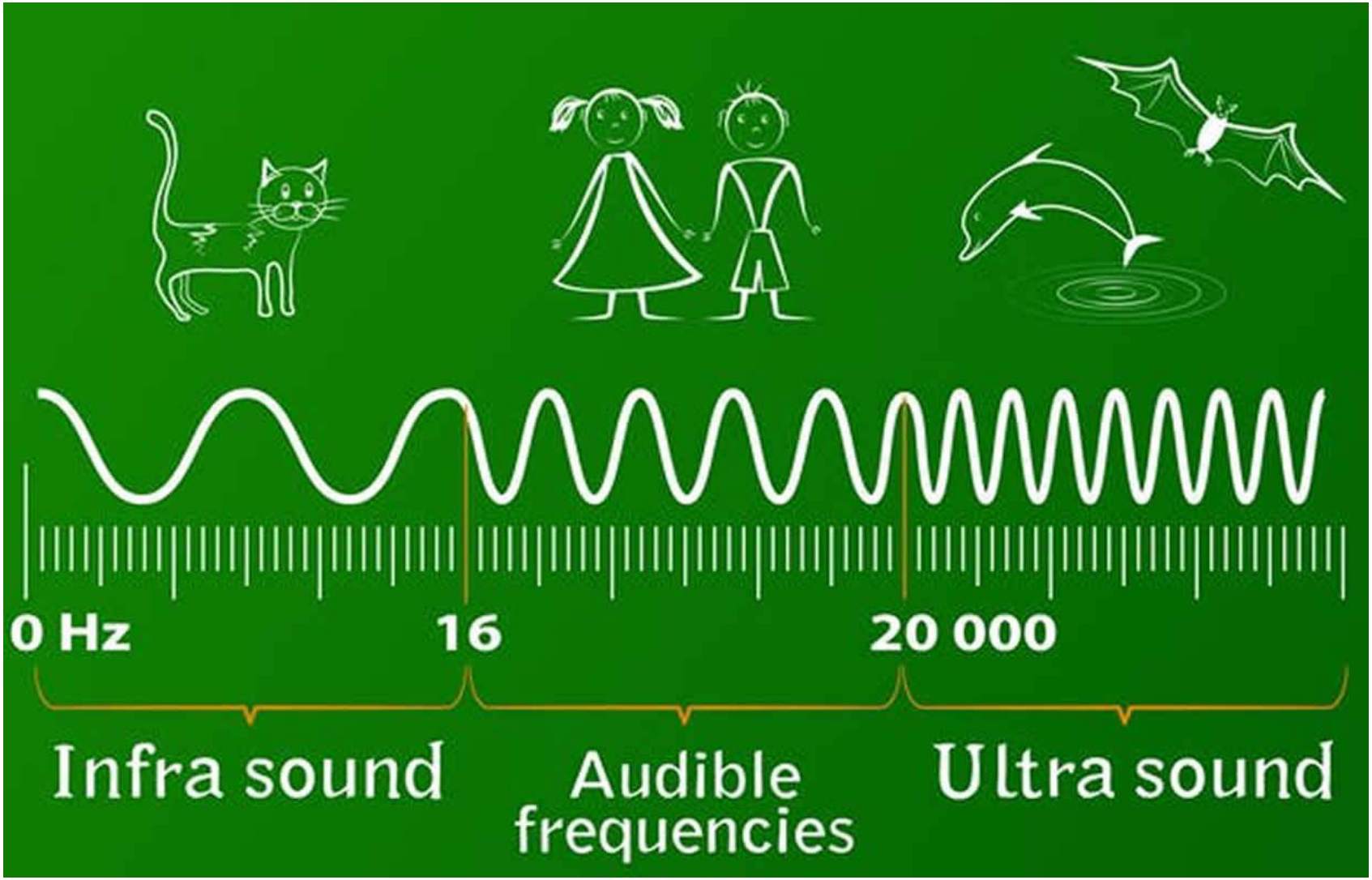
- Occurance of individual color values of an image.
- Pixels with RGB values ranging from 0 to 255.
- Setting thresholds to segment between Charlie and background.



Sequences

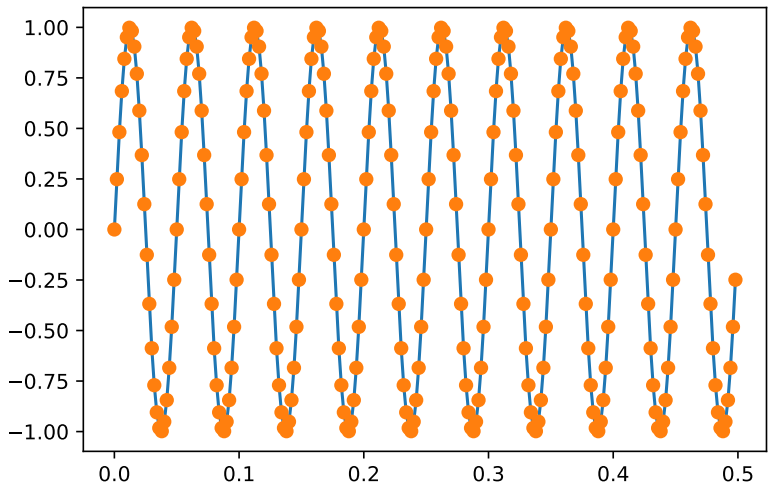
- A **sequence** is a type of data where the order of the values matters: $(a_1, a_2, a_3, a_4, \ldots, a_n)$
- Some examples:
  - Text
  - Sound (or time series in general)
  - Strictly speaking: images (order of pixels is essential)
  - ...

Sequences: Sound



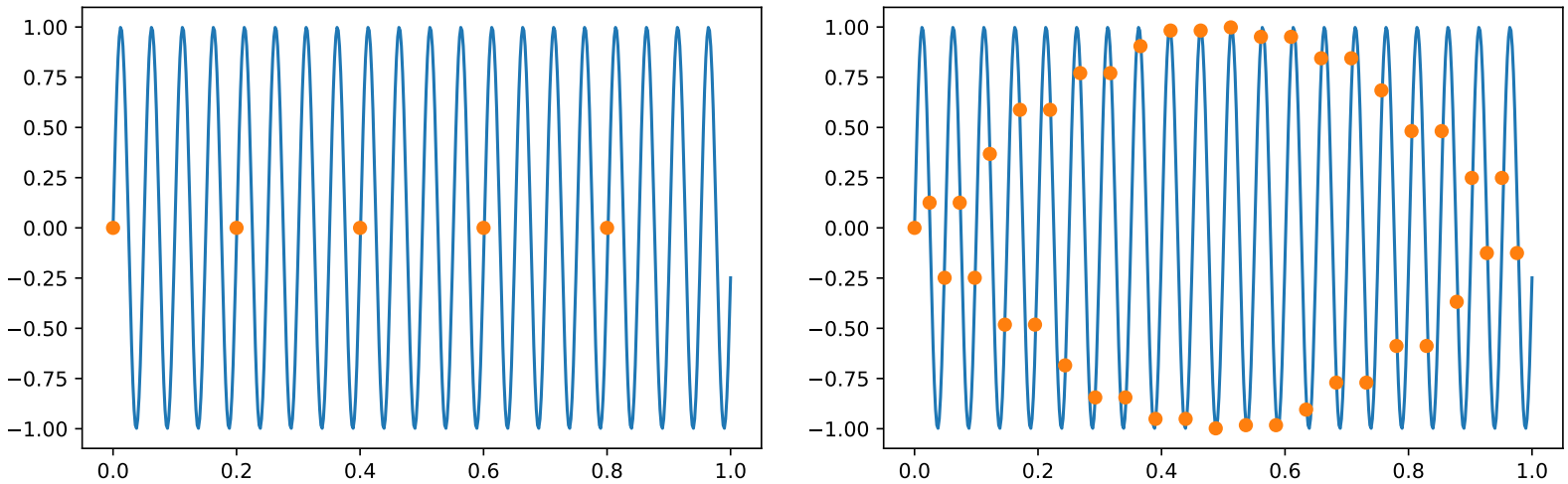
Continuous Signal

- Sound waves are a continuous signal.
- In physics, the **sound frequency** is measured in Hertz (Hz).
- In data analysis, the **sampling rate** from the continuous signal (per second) is also measured in Hz.
  - For example, a sampling rate of 48 kHz means retrieving 48000 samples per second.



Low Sampling Rates

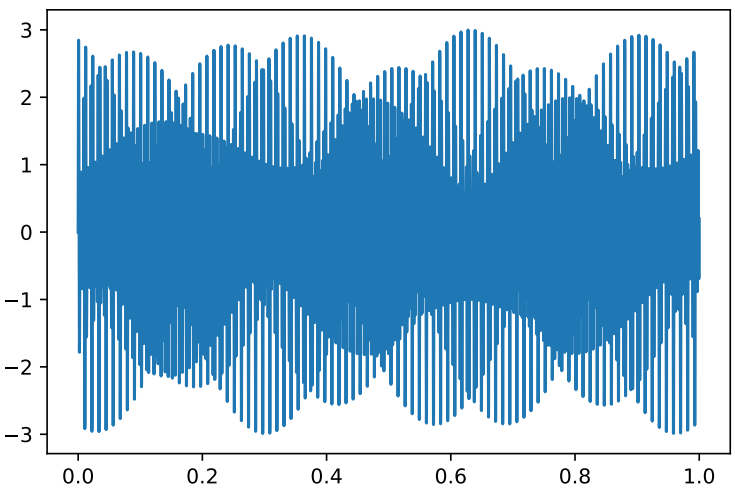
- If the sampling rate is too low, it is not possible to exactly reconstruct the signal.
- **Nyquist-Shannon theorem**: A signal is completely determined by a series of points that are $< \frac{1}{2f}$ seconds apart (f is the highest frequency in the signal), or in other words, the sampling rate f_s must be $> 2f$.

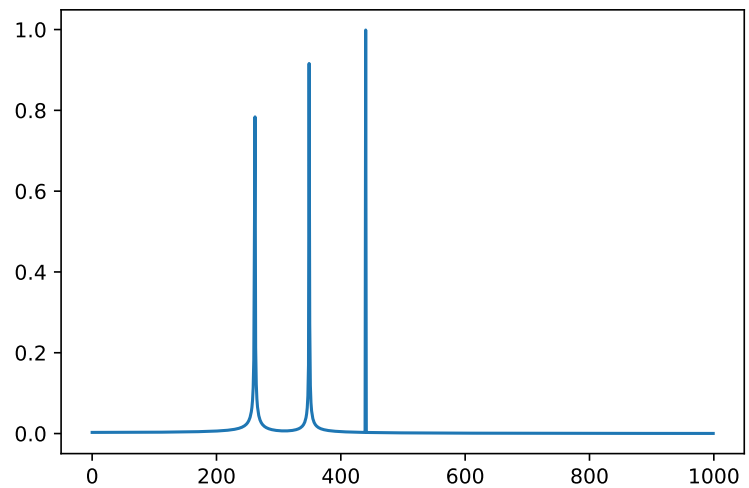


- Higher sampling rates mean higher audio quality.

Fourier Transformation

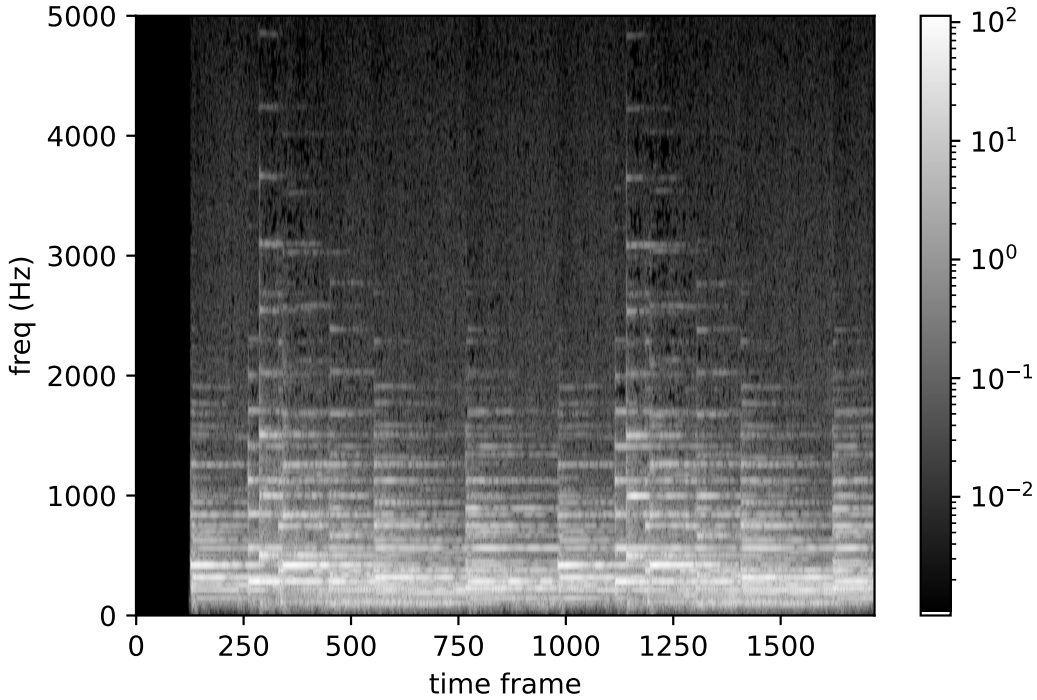
- The **Fourier transformation decomposes a signal** (a function of time) **into its constituent frequencies** (a spectrum).
- The Fourier transformation is not limited to functions of time, but the domain of the original function is commonly referred to as the **time domain** (example left image).
- The domain of the results is typically called the **frequency domain** (example right image).





Spectrogram

- Spectrograms are visual **representations of the variation of the frequencies over time**:
  - This can be done by computing a spectrum for the first few milliseconds (time frame), another one for the next, etc.
  - Stitching these spectra together, we obtain a spectrogram.
  - It tells how much energy (=gray value) is in the signal at each time frame and frequency bin (=pixel).



Sequences: Text

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Natural Language Processing (NLP)

- NLP is a subfield of:
  - Computer science
  - Linguistics
  - Deep Learning
- Challenges in NLP involve:
  - Speech recognition
  - Language understanding
  - Language generation
  - Language translation
- Nowadays, NLP is strongly driven by modern **Deep Learning** methods. We will learn more about this in Hands-on AI II.

Text as Categorical Data – Theory

- Normally, text can be considered qualitative data without mathematical meaning.
- Mathematical operations (e.g., $\sum$ or comparisons such as “less than”) do not make sense.
- Example: “Dog”, “Rat”, “Cat”

Text as Categorical Data – Practice

- Assume we consider n different categories ($= n$ different words), which we can also call **vocabulary** or **dictionary**.
- We could represent each category as an integer value:
  - Requires n different integer values, one for each category.
  - Example: "Dog"$= 0$, "Rat"$= 1$, "Cat"$= 2$
- Problem:
  - We would introduce new (probably false) information.
  - Example: In our ranking, "Dog" $<$ "Rat" and "Rat" $\cdot 2 =$ "Cat".

  $\rightarrow$ Not suitable for us.

Text as Categorical Data – Practice

- Solution: Represent a categorical feature as **one-hot-encoded** binary vector $\boldsymbol{v} = (v_1, \ldots, v_n)$:
  - Categorical data with n different values is enumerated from $1 \ldots n$ given a **fixed order**.[1]
  - $v_i = 1$ if category i is true, otherwise $v_i = 0$.
  - Each element in the vector represents one category $\rightarrow$ no false information![2]
- Example:
  - Possible values: “Dog”, “Rat”, “Cat” ($n = 3$)
  - Sample is “Dog” $\rightarrow \boldsymbol{v} = (1, 0, 0)$
  - Sample is “Cat” $\rightarrow \boldsymbol{v} = (0, 0, 1)$

[1] The order itself is not important, just that it is fixed.

[2] Only applies if information about order in feature vector is not used.

One-Hot Encoding Example

- Vocabulary with $n = 7$ and the following fixed order:

Word	an	awesome	cat	Charlie	dog	is	rat
Position	1	2	3	4	5	6	7

- Recall: For each word, we have a vector of size n where all numbers are zero but the element representing a specific word is set to 1.
- Example one-hot-encoded word “awesome” (position $= 2 \rightarrow v_2 = 1$, all other $v_i = 0$):
  $\boldsymbol{v}_{\text{awesome}} = (0, 1, 0, 0, 0, 0, 0)$

One-Hot Encoding Example

- Entire one-hot encoded vocabulary:

	an	awesome	cat	Charlie	dog	is	rat
an	1	0	0	0	0	0	0
awesome	0	1	0	0	0	0	0
cat	0	0	1	0	0	0	0
Charlie	0	0	0	1	0	0	0
dog	0	0	0	0	1	0	0
is	0	0	0	0	0	1	0
rat	0	0	0	0	0	0	1

Word Embedding

- Problem: For large vocabularies, the usage of one-hot encoding is not ideal. For example, a vocabulary size of $n = 30\,000$ would yield vectors of the same size ($= 30\,000$ dimensional feature vectors)!
- **Word embedding**: Represent each word by a much smaller vector but with real numbers.
- Ideally, a word embedding captures additional information compared to a simple encoding, e.g., (semantic) similarities between words.
- How to get a "good" embedding?
  - Not straightforward.
  - Often learned from a big corpus of words (in Hands-on AI II, we will actually learn an embedding ourselves).
  - Prelearned embeddings exist.

Downprojection of Word Embedding

- As always, visualizing our data can help in gaining insights.
- While embeddings are typically much smaller than simple encodings (e.g., 300 features per vector), this is still too much to visualize.
- Solution: **Reduce dimensionality** to **downproject** the embedding.
- If the embedding incorporates similarities, the downprojection of embedded words enables us to identify those.

Downprojection of Word Embedding