Working with Images and Text

Reading, exploring and analyzing, feature extraction

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Image Processing

Understanding what people see

Loading and Inspecting Images

- There are many ways to read an image
  - One of the easiest is using `scikit-image`

```
from skimage.io import imread
tiger_image = imread("tiger.jpg")
```

  - Displaying the image

```
plt.imshow(tiger_image)
```

- The image is actually a matrix of pixels
  - Each pixel is an array of three values: R, G, B ∈ [0; 255]
  - Grayscale images only have one value per pixel
- Most image processing algorithms are easier to understand on grayscale images

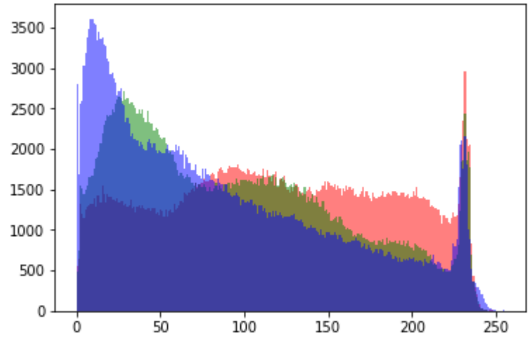
```
red = tiger_image[:, :, 0]
green = tiger_image[:, :, 1]
blue = tiger_image[:, :, 2]
```

Image Histogram

- As usual, histograms tell us how the values are distributed
  - How many dark values, how many light values
  - Maximum brightness, peaks, etc.
- Histograms need to have a single variable
  - Take each channel separately, e.g. red
  - Convert the 2D matrix to 1D array: `image.ravel()`
  - Show the histogram as usual
    - It's common to use 256 bins

```
plt.hist(red.ravel(), bins = 256, color = "red")
plt.show()
```

  - We can also plot all channels on a single histogram



Converting to Grayscale

- Sometimes working per channel is not necessary
  - We can combine all three channels and get a grayscale image
  - Simplest way: get the mean of all values

```
tiger_grayscale = np.mean(tiger_image, axis = 2)
```

  - Better way: use coefficients for each channel
    - The human eye discerns colors differently
    - We're more sensitive to green colors
    - Some formulas are given here

```
tiger_grayscale = 0.299 * red + 0.587 * green + 0.114 * blue
```

  - Depending on the image, the differences may or may not be easy to see
    - It's easiest to see the differences when we compare the histograms
- For art purposes, we can experiment with our own coefficients for combining all channels

Convolution

- Convolution kernel (filter)
  - A small, usually 3x3, matrix of numbers
- Convolution process
  - Input: image, kernel; output: new image
  - Combining the image and a kernel
    - Apply the kernel over each pixel
    - Multiply the values element-wise
    - Sum all values
    - Assign the sum to the corresponding pixel in the output image
      - Image corners are treated in different ways, not really important how

35	40	41	45	50
40	40	42	46	52
42	46	50	55	55
48	52	56	58	60
56	60	65	70	75

×

	0	1	0	
	0	0	0	
	0	0	0	

=

		42		

Convolution (2)

- The choice of kernel depends what the output image will represent
  - Some ideas here

```
from scipy.ndimage.filters import convolve
convolve(image, kernel)
```

- Example: box blur


```
box_blur_kernel = np.array([
[1, 1, 1],
[1, 1, 1],
[1, 1, 1]
]) / 9

blurred = convolve(tiger_grayscale, box_blur_kernel)
plt.imshow(tiger_grayscale[150:250, 300:400], cmap = "gray")
plt.show()
plt.imshow(blurred[150:250, 300:400], cmap = "gray")
plt.show()
```

Image Morphology

- Four main operations (see [this](#) tutorial)
  - Dilation, erosion, opening, closing
- A simple series of algorithms for image transformation
- Basic methodology
  - Choose a structuring element (e.g. 2x2 square or cross)
  - Move the element around the image
  - Apply an operation
- Input: binary image
  - Pixel values 0 and 1, not [0; 255]
    - This is called thresholding
- Output: transformed image

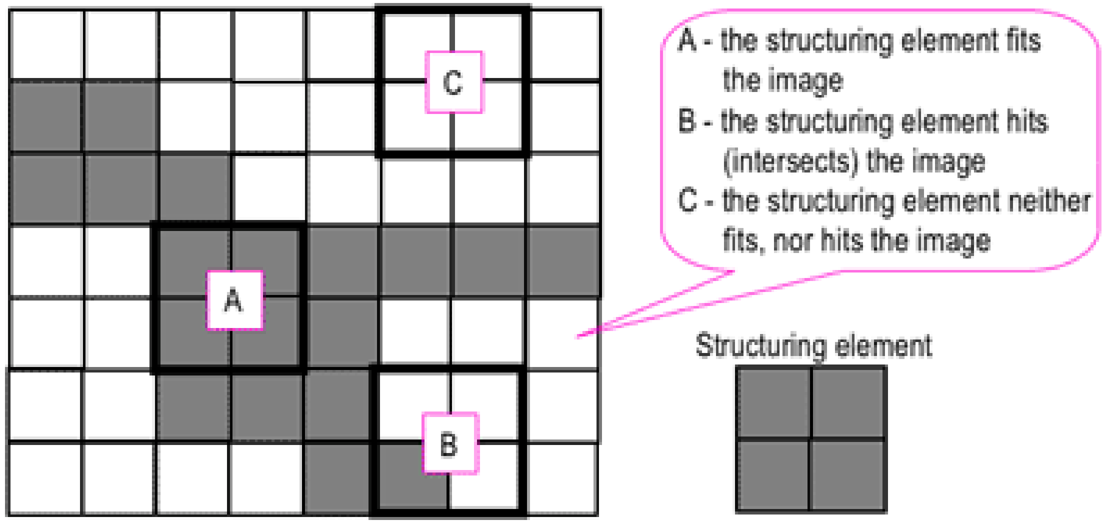
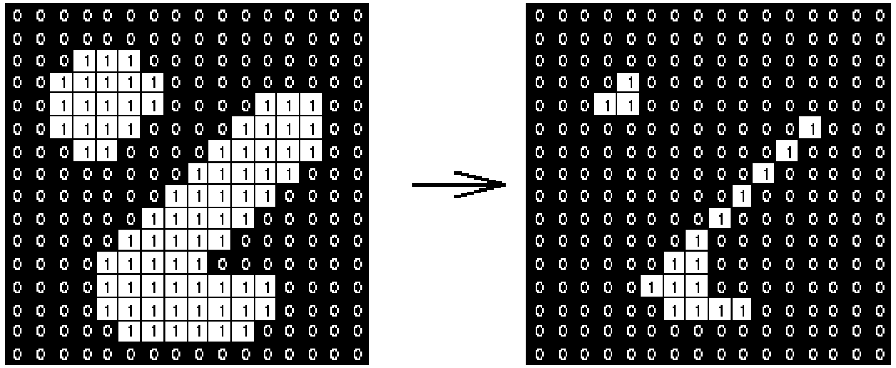


Image Morphology (2)

- First get all values inside the structuring element
- **Erosion:** replace all values with the min value
  - Strips away a layer of pixels
  - Holes become larger
  - Small regions are eliminated



- **Dilation:** replace all values with the max value
  - Adds a layer of pixels
  - Gaps become smaller
  - Small gaps are filled in

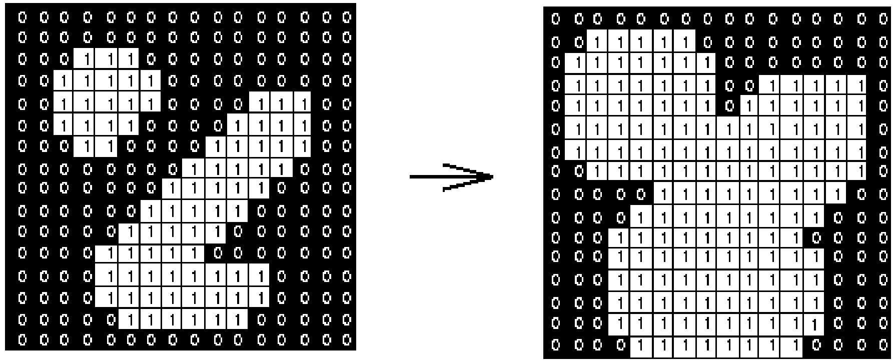
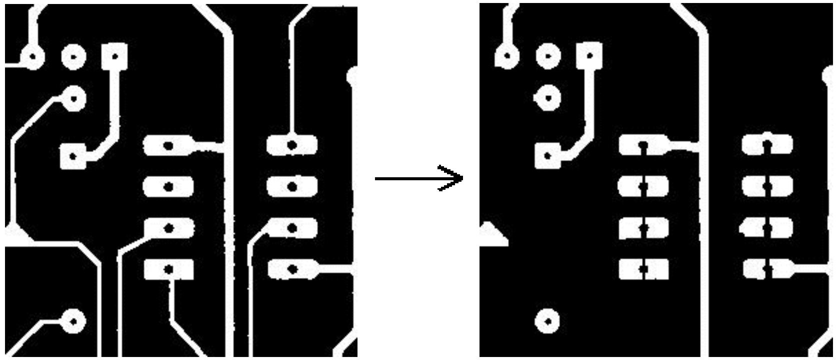
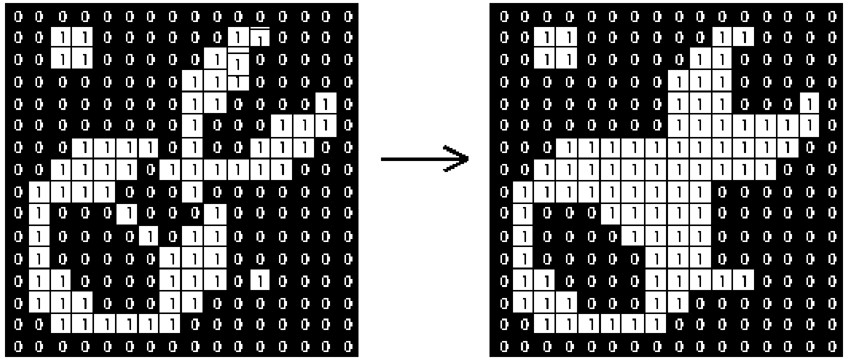


Image Morphology (3)

- **Opening:** erosion followed by dilation
  - Pixels which survived erosion are restored to their original size
  - Opens up a gap between two objects connected by thin bridges



- **Closing:** dilation followed by erosion
  - Fills in holes in the regions while keeping the initial region sizes



Text Processing

Understanding what people write

Text Data

- Documents, written in plain text
  - News, tweets, blog posts, poems, books, legal documents, etc.
  - May also be auto-generated (i.e. server logs)
- Objective
  - Preprocess the text data so that it's structured
    - Algorithms can analyze a table of numbers, not plain text
      - This is especially true for machine learning algorithms
- Applications
  - Sentiment analysis
  - Grouping texts – similar topics, similar authors
  - Classification (e.g. spam / fake news prevention)
  - Text summarizing, etc.

Character Frequencies

- Reading is simple: open the file, read it, close it

```
text = ""
with open("alice.txt", "r", encoding = "utf-8") as f:
    text = f.read()
print(len(text))
```

- A string is a collection of characters
  - There are several ways to count them, the easiest being by using a library: collections.Counter

```
from collections import Counter
char_counter = Counter(text)
```

  - Most common characters ([“etaoin shrdlu”])

```
char_counter.most_common(20)
```

  - Similarly, most common words: split by all non-word characters

```
import re
word_counter = Counter(re.split("\W+", text))
```

Preparing Text Data

- Before we start working with the text, we have to "normalize“ and clean up the messy data
  - Remove all non-letter characters
    - Numbers, punctuation, whitespace, etc.
    - If needed, apply additional rules, e.g. if we're looking at tweets, **@mention** means a username and we may want to get rid of it
  - Transform all characters to lowercase
  - Remove "stopwords"
    - Words that are too frequent in all documents and don't contain much information such as "the", "a", "is", etc.
  - Perform stemming
    - Extract the stems of all words, e.g. "connected", "connection", "connecting" should all point to "connect"

Stopwords and Stemming: NLTK

- NLTK is a library for working with natural language
  - Contains all frequently used algorithms and corpora
  - Installation: as usual, using conda: `conda install nltk`
- Getting and removing stopwords
  - Download the words first

```
import nltk
nltk.download("stopwords")
from nltk.corpus import stopwords
stop = set(stopwords.words("english"))
sentence = "this is a foo bar sentence"
print([w for w in sentence.lower().split() if w not in stop])
```

- Stemming – Porter's algorithm (includes many "manual" rules)

```
from nltk.stem.porter import *
stemmer = PorterStemmer()
words = ["caresses", "flies", "dies", "seizing", "itemization",
"sensational", "traditional", "reference", "plotted"]
print([stemmer.stem(w) for w in words])
```

TF – IDF

- **T**erm **f**requency – **i**nverse **d**ocument **f**requency
  - A common method to preprocess the text

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

N = total number of documents

  - High score: rare, specific words
    - Hypothesis: these may be better related to the topic
    - Note: This may also include misspelled words and / or names
  - Low score: words that occur in nearly all documents

Using TF – IDF

- Read the "20 newsgroups" dataset

```
from sklearn.datasets import fetch_20newsgroups
# Download only some categories to speed up the process
newsgroups = fetch_20newsgroups()
```

- Initialize the algorithm (docs) and compute the matrix

```
tfidf = TfidfVectorizer(input = "content", analyzer = "word",
    ngram_range = (1, 4), min_df = 0, stop_words = stop, sublinear_tf = True)
tfidf_matrix = tfidf.fit_transform(newsgroups.data)
```

- Get all feature names

```
feature_names = tfidf.get_feature_names()
```

- Get the IDF for each word / n-gram in one document

```
doc = 0 # Change the index to view another document
feature_index = tfidf_matrix[doc, :].nonzero()[1]
tfidf_scores = zip(feature_index, [tfidf_matrix[doc, x] for x in feature_index])
for w, s in [(feature_names[i], s) for (i, s) in tfidf_scores]:
    print(w, s)
```

Summary

- Image processing
  - Reading, exploring, manipulation
  - Convolution
  - Image morphology
- Text processing
  - Text preparation
  - Frequency analysis
  - TF-IDF

Questions?