COMP 204

Introduction to image analysis with scikit-image
(part two)

Yue Li
based on slides from Mathieu Blanchette, Christopher J.F. Cameron and Carlos G. Oliver
Outline

Assignment 5

Image compression by matrix decomposition (very brief)

Brief survey on image denoising and inpainting

Image processing (caveat & review from last lecture)

Image blurring

Edge detection
Assignment 5 posted
open Jupyter Notebook
Principal Component Analysis (PCA) (background to A5)

Flatten images

\[ X_{\text{train}} \]

\[ Z \]

\[ W_{\text{train}} \]

7500 features

10 PCs

7500 features

\[ X_{\text{test}} \]

\[ Z_{\text{test}} \]

\[ W_{\text{train}} \]

7500 features

10 PCs

7500 features

Flatten images

Reduced data

Image basis (learned from the training data)

Flatten images

Reduced test data

Image basis (fixed from training data)
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Image compression by matrix decomposition

Original image

Filter

Basis

\[ X \approx W \cdot H \]

\[ K < \min(\text{width, height}) \]

2.4 million pixels

100 components \( 1200 \cdot 100 + 100 \cdot 2000 = 320k \)

(7.5 times smaller than the original image!)
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import NMF
import skimage.io as io

# read image into memory
image = io.imread("monkey.jpg")

image_imputed = image.copy()

k = 100
Ws = np.zeros((image.shape[0], k, 3))
Hs = np.zeros((k, image.shape[1], 3))

for c in range(3):
    print(c)
    model = NMF(n_components=k, init='random', random_state=0)
    image_imputed[:, :, c] = image[:, :, c]
    W = model.fit_transform(image[:, :, c])
    H = model.components_
    image_imputed[:, :, c] = np.dot(W, H)
    Ws[:, :, c] = W
    Hs[:, :, c] = H
Reconstructed image (lossy de-compression)
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Image restoration

http://scikit-image.org/docs/dev/auto_examples/filters/plot_restoration.html
Image denoising

noisy

non-local means
(slow)

non-local means
(slow, using $\sigma_{est}$)

original
(noise free)

non-local means
(fast)

non-local means
(fast, using $\sigma_{est}$)

http://scikit-image.org/docs/dev/auto_examples/filters/plot_nonlocal_means.html
Image inpainting

Original image

Defected image

Mask

Inpainted image

http://scikit-image.org/docs/dev/auto_examples/filters/plot_inpaint.html
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What’s an image in Python? (recap)

An image is stored as a NumPy ndarray (n-dimensional array).

- ndarrays are easier and more efficient than using 2-dimensional lists as we’ve seen before.

A color image with $R$ rows and $C$ columns is

- represented as a 3-dimensional ndarray of dimensions $R \times C \times 3$
- element at position $(i,j)$ of the array corresponds to the RGB value at row $i$ and column $j$
- each pixel is represented by 3 numbers, each between 0 and 255: Red, Green, Blue
Flipping the image up side down (recap)

How to turn flip an image up side down?

to
def upsidedown_wrong1(image):
    n_row, n_col = image.shape[0:2]
    for i in range(0,int(n_row/2)):
        for j in range(0,n_col):
            image[i,j] = image[n_row-i-1,j]
    return image

What went wrong?
The top half of the image is replaced by the bottom half of the image
def upsidedown_wrong2(image):
    n_row, n_col = image.shape[0:2]
    for i in range(0,int(n_row/2)):
        for j in range(0,n_col):
            t = image[i,j]
            image[i,j] = image[n_row-i-1,j]
            image[n_row-i-1, j] = t
    return image
Still incorrect
What went wrong in attempt 2?

```
t = image[i,j]
image[i,j] = image[n_row-i-1,j]
image[n_row-i-1, j] = t
```

`t` refers to the same memory locations (RGB values) as `image[i,j]`.

When we change `image[i,j]` (on line 20), the values pointed by `t` is also changed!

So this is not swapping the two pixels: `image[n_row-i-1,j]` remains unchanged.
t and \( \text{image}[i,j] \) refers to the same memory address

\[ t = \text{image}[i,j] \]
data1 in memory A is replaced by data2 in memory B

t = \text{image}[i,j]

\text{image}[i,j] = \text{image}[n\_\text{row}-i-1,j]
Replacing data2 in memory B with data 2 in memory A

t = image[i,j]

image[i,j] = image[n_row-i-1,j]

image[n_row-i-1,j] = t

image[n_row-i-1,j] → data2
Memory address B

image[i,j] → data2
Memory address A

t
Correct way to do it (pay attention to line 25)

```python
def upsidedown_correct1(image):
    n_row, n_col = image.shape[0:2]
    for i in range(0,int(n_row/2)):
        for j in range(0,n_col):
            t = image[i,j].copy()
            image[i,j] = image[n_row-i-1,j]
            image[n_row-i-1, j] = t
    return image
```
t and image[i,j] refers to the *different* memory address

t = image[i,j].copy

image[i,j] → data1
Memory address A

t → data1
Memory address B

image[n_row-i-1,j] → data2
Memory address C
data1 in memory A is replaced by data2 in memory B

t = image[i,j].copy
image[i,j] = image[n_row-i-1,j]
Replacing data2 in memory B with data 2 in memory A

\[
t = \text{image}[i,j].\text{copy}
\]

\[
\text{image}[i,j] = \text{image}[n\_row-i-1,j]
\]

\[
\text{image}[n\_row-i-1,j] = t
\]
Correct output image
Another correct way to do it (pay attention to line 35)

```python
def upsidedown_correct2(image):
    n_row, n_col = image.shape[0:2]
    for i in range(0,int(n_row/2)):
        for j in range(0,n_col):
            for c in range(3):
                t = image[i,j,c]  # a float value
                image[i,j,c] = image[n_row-i-1,j,c]
                image[n_row-i-1, j, c] = t
    return image
```

A new variable with a float value will be stored in a separate memory location. For a simpler example,

```python
>>> a = 1
>>> b = a
>>> a = 3
>>> print(b)  # 1
```
A couple of more correct ways to do it

def upsidedown_correct3(image):
    return image[::-1, :]
    # image[::-1, :] reverse rows
    # image[::, ::-1] reverse columns

def upsidedown_correct4(image):
    return np.flip(image, 0)
    # axis=0 flip vertically;
    # axis=1 flip horizontally
Outline

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Brief survey on image denoising and inpainting

Image processing (caveat & review from last lecture)

Image blurring

Edge detection
Blurring an image

Goal: Reduce the resolution of an image by blurring it, e.g. to reduce fine-level ”noise” (unwanted details).

We may also want to place emphasis on certain area of the image (e.g., “portrait mode” on an iPhone camera)
Blurring an image

Blurring is achieved by replacing each pixel by the average value of the pixels in a small window centered on it.

Example, window of size 5:

Original image

<table>
<thead>
<tr>
<th>5 3 5 6 3 0 0 0 0 0</th>
<th>0 0 0 0 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 4 3 5 2 0 0 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>5 5 5 2 4 0 0 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>3 7 6 3 8 0 0 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>8 9 3 5 7 12 0 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>9 7 3 5 6 2 0 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>5 3 5 6 3 2 0 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>5 6 5 7 9 9 2 0 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>5 7 3 6 7 2 3 3 0 0</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>5 5 6 7 9 8 7 4 0 0</td>
<td>0 0 0 0 0</td>
</tr>
</tbody>
</table>

Blurred image

Average

| 3 |

Original image

<table>
<thead>
<tr>
<th>5 3 5 6 3 0 0 0 0 0</th>
<th>0 0 0 0 0</th>
</tr>
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<tbody>
<tr>
<td>3 4 3 5 2 0 0 0 0 0</td>
<td>0 0 0 0 0</td>
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</tr>
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</tr>
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</tr>
<tr>
<td>5 5 6 7 9 8 7 4 0 0</td>
<td>0 0 0 0 0</td>
</tr>
</tbody>
</table>
def blur(image, filter_size):
    n_row, n_col, colors = image.shape
    blurred_image = np.zeros( (n_row, n_col, colors),
                      dtype=np.uint8)
    half_size=int(filter_size/2)
    for i in range(n_row):
        for j in range(n_col):
            # define the boundaries of window around (i,j)
            bot=max(0,i-half_size)
            top=min(i+half_size,n_row)
            left=max(0,j-half_size)
            right=min(n_col,j+half_size)

            # calculate average of RGB values in window
            blurred_image[i,j] = \
                image[bot:top, left:right, :
                      :].max(axis=(0,1))

    return blurred_image

means(axis=(0,1)) takes an average over dimension 0 (rows) and dimension 1 (columns) but not dimension 2 (RGB). This means that we get back a 1d array containing the average red, green, and blue values in window.
Window size = 5
Window size = 21
Window size = 101
Running time issues

Note: When our window size is large (say 101), blurring the image is slow (> 1 minute). Why?

► Our image is 674 × 1200 pixels (∼0.8 million pixels)
► For each pixel in the image, we need to calculate the average of the 101 × 101 pixels around it, and for each of the three colors!
► The total number of operations is proportional to 674 × 1200 × 101 × 101 = 25 Billion operations!
► It takes ∼5 minutes to run

SkImage has many built-in blurring functions (called filters) with faster implementations:
The one equivalent to your purpose is:
More filters are here:
http://scikit-image.org/docs/dev/api/skimage.filters.html
It is much faster than the nested for loop version

This takes less than a second!

```python
#from scipy import ndimage
blurred_image = ndimage.uniform_filter(image,
size=(101, 101, 1))
# plt.imshow(blurred_image)
# plt.show()
# io.imsave("car_blur101_uniform_filter.jpg", blurred_image)
```

A lots of numerical tricks went into the function (beyond the scope of this class)
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Edge detection
Goal: Identify regions of the image that contain sharp changes in colors/intensities.
Why? Useful for
- delineating objects (image segmentation)
- recognizing them (object recognition)
- etc.
Edge detection
Edge detection
Edge detection

What’s an edge in an image?

Vertical edge at row $i$:

- $\text{image}[i - 1, j]$ is very different from $\text{image}[i + 1, j]$

Horizontal edge at column $j$:

- $\text{image}[i, j - 1]$ is very different from $\text{image}[i, j + 1]$

Idea: To determine if an RGB pixel $(i, j)$ belongs to an edge:

For each color $\in \{R, G, B\}$:

- $L_x[\text{color}] = \text{image}[i, j - 1, \text{color}] - \text{image}[i, j + 1, \text{color}]$
- $L_y[\text{color}] = \text{image}[i - 1, j, \text{color}] - \text{image}[i + 1, j, \text{color}]$
- $\text{edge}_\text{image}[i, j, \text{color}] = \sqrt{L_x[\text{color}]^2 + L_y[\text{color}]^2}$
def detect_edges(image):
    n_row, n_col, colors = image.shape
    edge_image = np.zeros((n_row,n_col,3), dtype=np.uint8)
    for i in range(1,n_row-1):
        for j in range(1,n_col-1):
            for c in range(3):
                # conversion to int needed to accommodate
                # for potentially negative values
                d_r=int(image[i-1,j,c])-int(image[i+1,j,c])
                d_c=int(image[i,j-1,c])-int(image[i,j+1,c])
                gradient = math.sqrt(d_r**2+d_c**2)
                # limit value to 255
                edge_image[i,j,c]=np.uint8(min(255,gradient))
    return edge_image
Edge detection on monkey image

Not so great if our goal is to find the monkey in the image!
Blurring + Edge detection

To smooth out fine details like leaves:
Start by blurring the image, then apply edge detection.
Analysis of microscopy images
Edge detection
Edge detection

Skimage has many edge detection algorithms:
http://scikit-image.org/docs/0.5/auto_examples/plot_canny.html