Quantitative Big Imaging - Introduction

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CONTENTS

Quantitative Big Imaging ETHZ: 227-0966-00L

CHAPTER

ONE

TODAYS LECTURE

- About the course
- What is an image?
- Where do images come from?
- Science and Reproducibility
- Workflows

1.1 We need some python modules

```
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
from skimage.io import imread
from scipy.ndimage import convolve
from skimage.morphology import disk
import numpy as np
import os
```

CHAPTER

TWO

ABOUT THE COURSE

- Who are we?
- Who are you?
- What is expected?
- **Why does this class exist?**
- Collection
- Changing computing (Parallel / Cloud)
- Course outline

2.1 Who are we?

Lectures and exercises

- **Beamline scientist** at the ICON Beamline at the SINQ (Neutron Source) at Paul Scherrer Institute
  - **Lecturer** at ETH Zurich
- **Algorithm developer** Varian Medical Systems, Baden-Daettwil
- **Post Doc** at ETH Zurich, Inst for Terrestial Ecology
- **PhD** at Chalmers Institute of Technology, Sweden, Signal processing

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Exercises

- **PhD Student** in the X-Ray Microscopy Group at ETH Zurich and Swiss Light Source at Paul Scherrer Institute
- Teaching assistant

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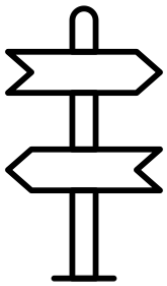
2.2 Who are you?

A wide spectrum of backgrounds		A wide range of skills
Biomedical Engineers Physicists Chemists Art History Researchers Mechanical Engineers and Computer Scientists		I think I've heard of python before I write template C++ code and hand optimize it afterwards

2.3 So how will this ever work?

Adaptive assignments

- Conceptual, graphical assignments with practical examples
  - Emphasis on chosing correct steps and understanding workflow
- Opportunities to create custom implementations, and perform more complicated analysis on larger datasets if interested
  - Emphasis on performance, customizing analysis, and scalability

CHAPTER

THREE

COURSE EXPECTATIONS

3.1 Exercises

3.2 Science Project

- Usually 1 set per lecture
- Optional (but recommended!)
- Easy - using GUIs (KNIME and ImageJ) and completing Matlab Scripts (just lecture 2)
- Advanced - Writing Python, Java, Scala, . . .
- Optional (but strongly recommended)
- Applying Techniques to answer scientific question!
- Ideally use on a topic relevant for your current project, thesis, or personal activities
- or choose from one of ours (will be online, soon)
- Present approach, analysis, and results

CHAPTER

FOUR

LITERATURE / USEFUL REFERENCES

4.1 General Material

- Jean Claude, Morphometry with R
- Online through ETHZ
- Buy it
- John C. Russ, "The Image Processing Handbook",(Boca Raton, CRC Press)
- Available online within domain ethz.ch (or proxy.ethz.ch / public VPN)
- J. Weickert, Visualization and Processing of Tensor Fields
- Online through ETHZ

4.2 Today's Material

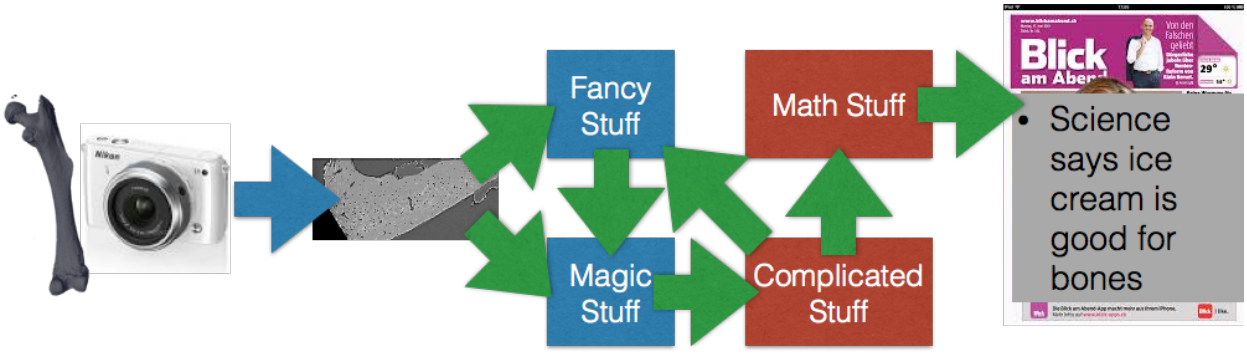
- Imaging
- ImageJ and SciJava
- Cloud Computing
- The Case for Energy-Proportional Computing _ Luiz André Barroso, Urs Hölzle, IEEE Computer, December 2007_
- Concurrency
- Reproducibility
- Trouble at the lab *Scientists like to think of science as self-correcting. To an alarming degree, it is not*
- Why is reproducible research important? *The Real Reason Reproducible Research is Important*
- Science Code Manifesto
- Reproducible Research Class @ Johns Hopkins University

4.3 Motivation - You have data!

4.3.1 Imaging experiments produce a lot of data

Gigabytes. . .
. . . or even
terabytes of data

4.4 Motivation - how to proceed?



- To understand what, why and how from the moment an image is produced until it is finished (published, used in a report, . . .)
- To learn how to go from one analysis on one image to 10, 100, or 1000 images (without working 10, 100, or 1000X harder)

4.5 High acquisition rates

- Detectors are getting bigger and faster constantly
- Todays detectors are really fast
- 2560 x 2160 images @ 1500+ times a second = 8GB/s
- Matlab / Avizo / Python / . . . are saturated after 60 seconds
- A single camera
- More information per day than Facebook
- Three times as many images per second as Instagram

4.6 Different sources of images

4.6.1 X-Ray

- SRXTM images at (>1000fps) → 8GB/s
- cSAXS diffraction patterns at 30GB/s
- Nanoscopium Beamline, 10TB/day, 10-500GB file sizes

4.6.2 Optical

- Light-sheet microscopy (see talk of Jeremy Freeman) produces images → 500MB/s
- High-speed confocal images at (>200fps) → 78Mb/s

4.6.3 Personal

- GoPro 4 Black - 60MB/s (3840 x 2160 x 30fps) for $600
- fps1000 - 400MB/s (640 x 480 x 840 fps) for $400

4.7 Motivation

1. **Experimental Design** finding the right technique, picking the right dyes and samples has stayed relatively consistent, better techniques lead to more demanding scientists.
2. **Measurements** the actual acquisition speed of the data has increased wildly due to better detectors, parallel measurement, and new higher intensity sources
3. **Management** storing, backing up, setting up databases, these processes have become easier and more automated as data magnitudes have increased
4. **Post Processing** this portion has is the most time-consuming and difficult and has seen minimal improvements over the last years

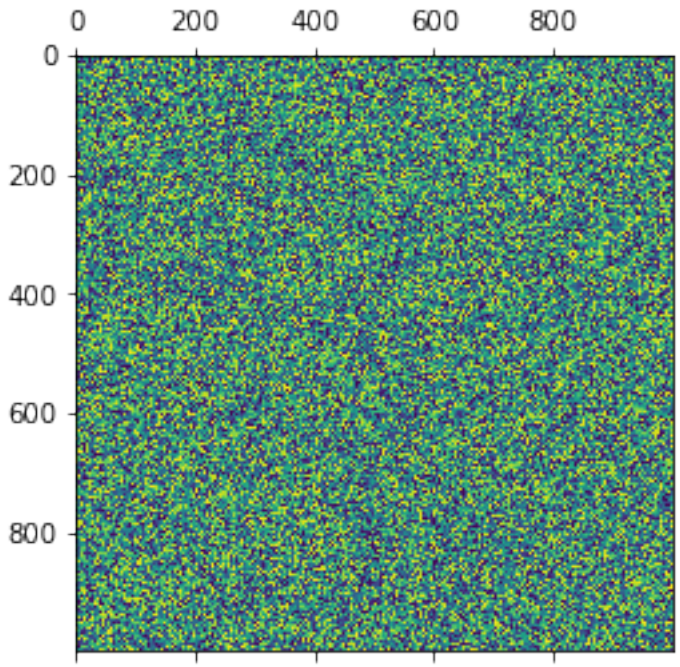
4.8 How is time used during the experiment life cycle?

4.9 So... how much is a TB, really?

If **you** looked at one 1000 x 1000 sized image

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np

plt.matshow(np.random.uniform(size = (1000, 1000)),
            cmap = 'viridis');
```



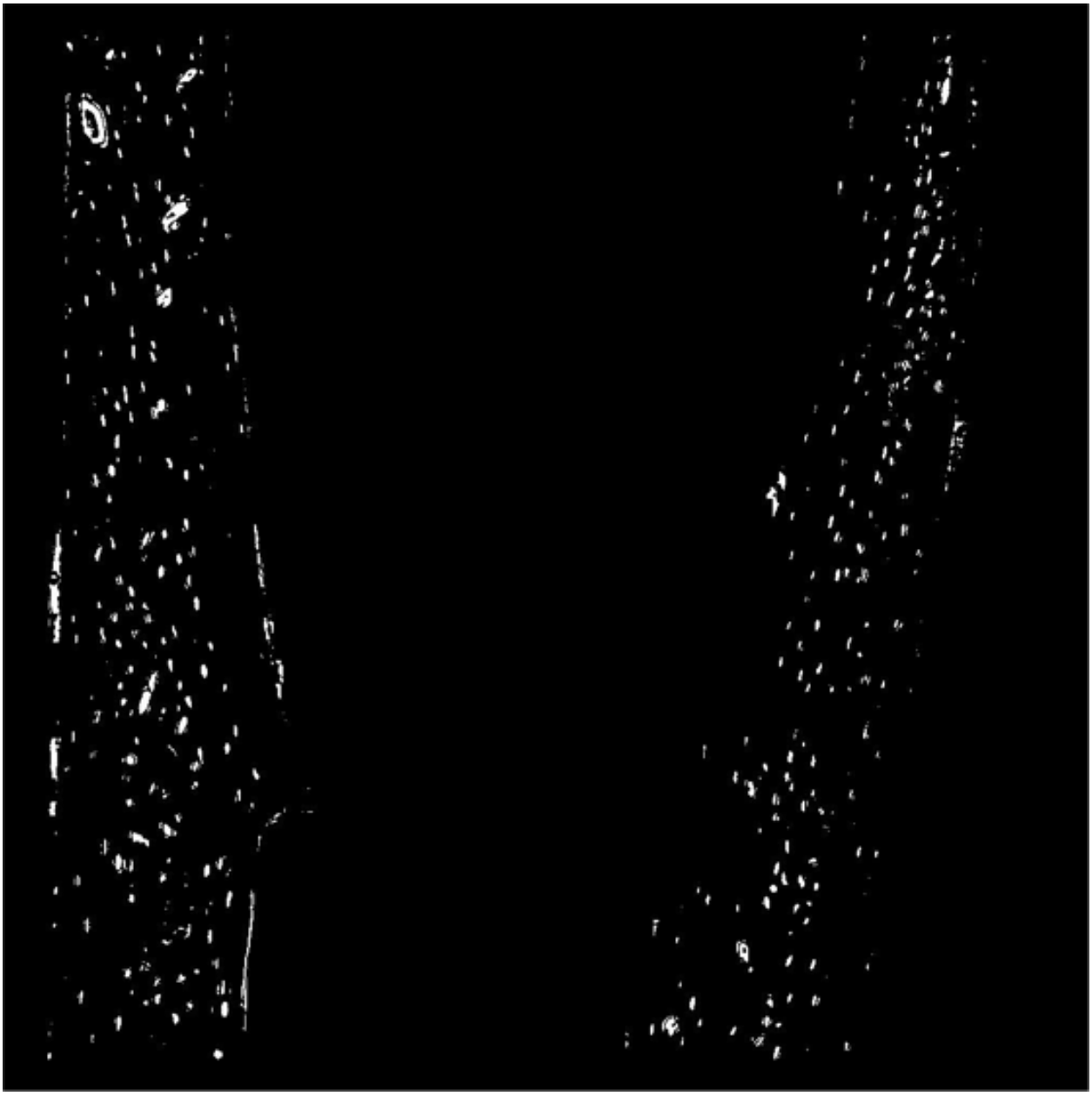
every second, it would take you

```
# assuming 16 bit images and a 'metric' terabyte
time_per_tb=1e12/(1000*1000*16/8) / (60*60)
print("%04.1f hours to view a terabyte" % (time_per_tb))
```

```
138.9 hours to view a terabyte
```

4.10 Overwhelmed scientist

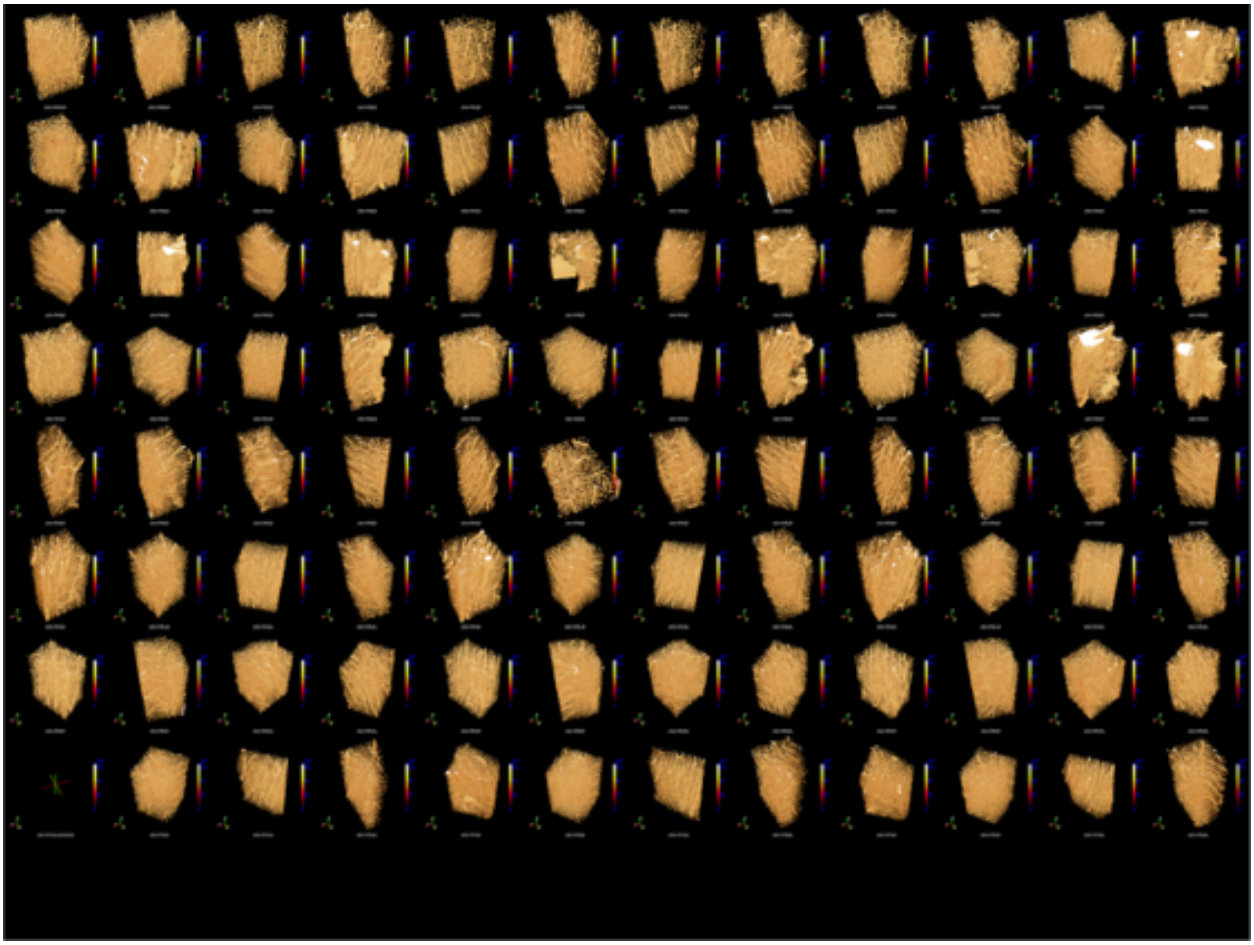
- Count how many cells are in the bone slice
- Ignore the ones that are ‘too big’ or shaped ‘strangely’
- Are there more on the right side or left side?
- Are the ones on the right or left bigger, top or bottom?



4.11 More overwhelmed

4.11.1 Many samples are needed

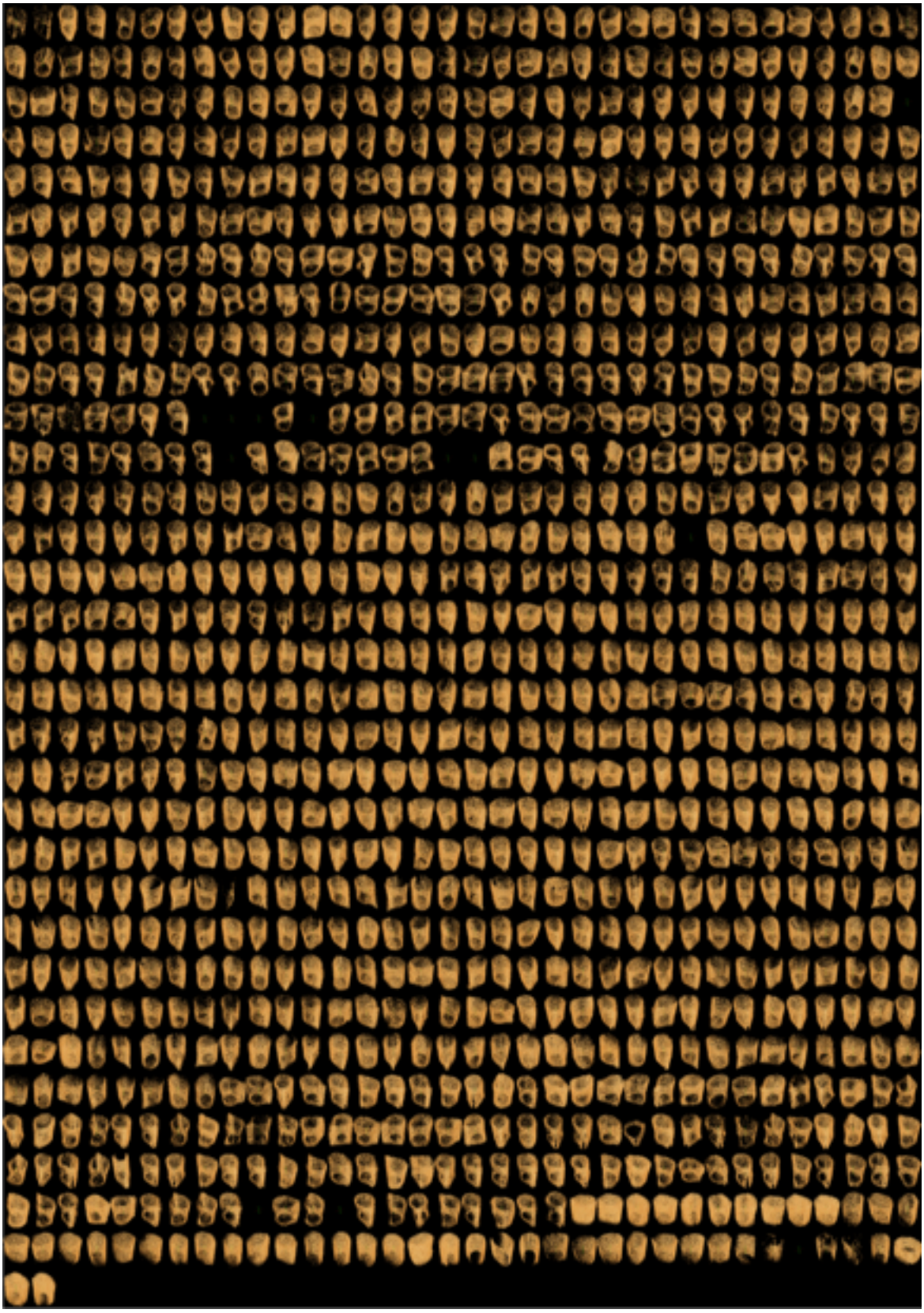
- Do it all over again for 96 more samples
- this time in 3D with 2000 slices instead of just one!



4.12 Bring on the pain

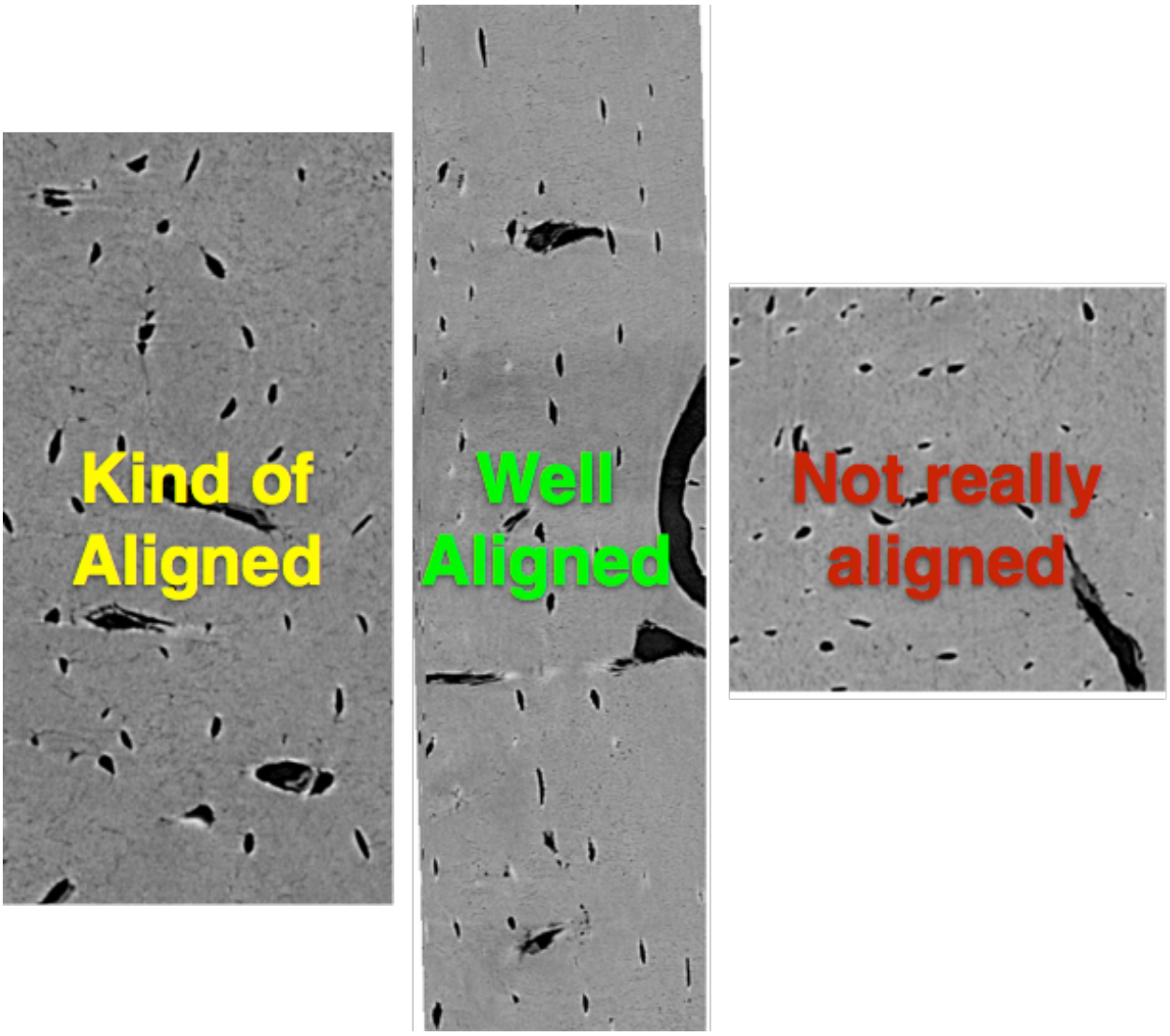
4.12.1 Great variations in the population

- Now again with 1090 samples!
- How to measure?
- How to analyze?



4.13 It gets better

- Those metrics were quantitative and could be easily visually extracted from the images
- What happens if you have *softer* metrics



- How aligned are these cells?
- Is the group on the left more or less aligned than the right?
- errr?

4.14 Dynamic Information

- How many bubbles are here?
- How fast are they moving?
- Do they all move the same speed?
- Do bigger bubbles move faster?
- Do bubbles near the edge move slower?
- Are they rearranging?

4.15 Course Overview

Topic	Date	Title	Description
Introduction	25th February	Introduction and Workflows	Basic overview of the course, introduction to . . .
Data	5th March	Image Enhancement	Overview of what techniques are available for . . .
	March	Ground Truth: Building and Augmenting Datasets	Examples of large datasets, how they were buil. . .
Segmentation	March	Basic Segmentation, Discrete Binary Structures	How to convert images into structures, startin. . .
	19th March	Advanced Segmentation	More advanced techniques for extracting struct. . .
	26th March	Supervised Problems and Segmentation	More advanced techniques for extracting struct. . .
Analysis	2nd April	Analyzing Single Objects, Shape, and Texture	The analysis and characterization of single st. . .
	9th April	Analyzing Complex Objects and Distributions	What techniques are available to analyze more . . .
	16th April	Dynamic Experiments	Performing tracking and registration in dynami. . .
Big Imaging	23rd April	Statistics, Prediction, and Reproducibility	Making a statistical analysis from quantified . . .
	30th April	Guest Lectures	How Roche does Microscopy at Scale with High C. . .
	7th May	Scaling Up / Big Data	Performing large scale analyses on clusters an. . .
Wrapping up	14th May	Project Presentations	You present your projects

4.16 Projects

- A small image processing project
- Can be related to you Master or PhD project
- You will get input and ideas for your own projects
- You will get hands on experience on the techniques you learn here
- Can be used as discussion base for your exam

CHAPTER

FIVE

IMAGES

5.1 An introduction to images

CHAPTER

SIX

WHAT IS AN IMAGE?

A very abstract definition:

- **A pairing between spatial information (position)**
- **and some other kind of information (value).**

In most cases this is a 2- or 3-dimensional position (x,y,z coordinates) and a numeric value (intensity)

6.1 Image sampling

- Continuous
- No boundaries
- Discrete levels
- Limited extent

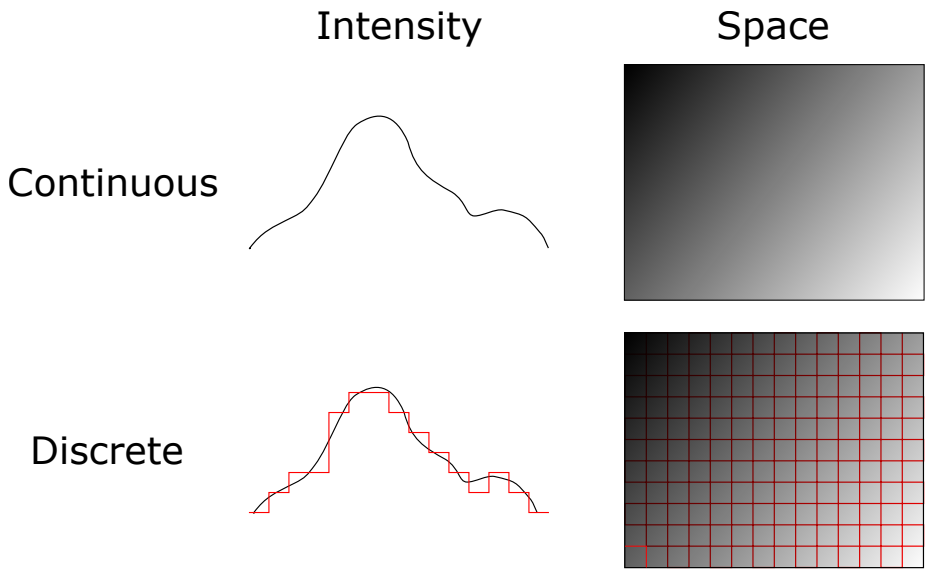
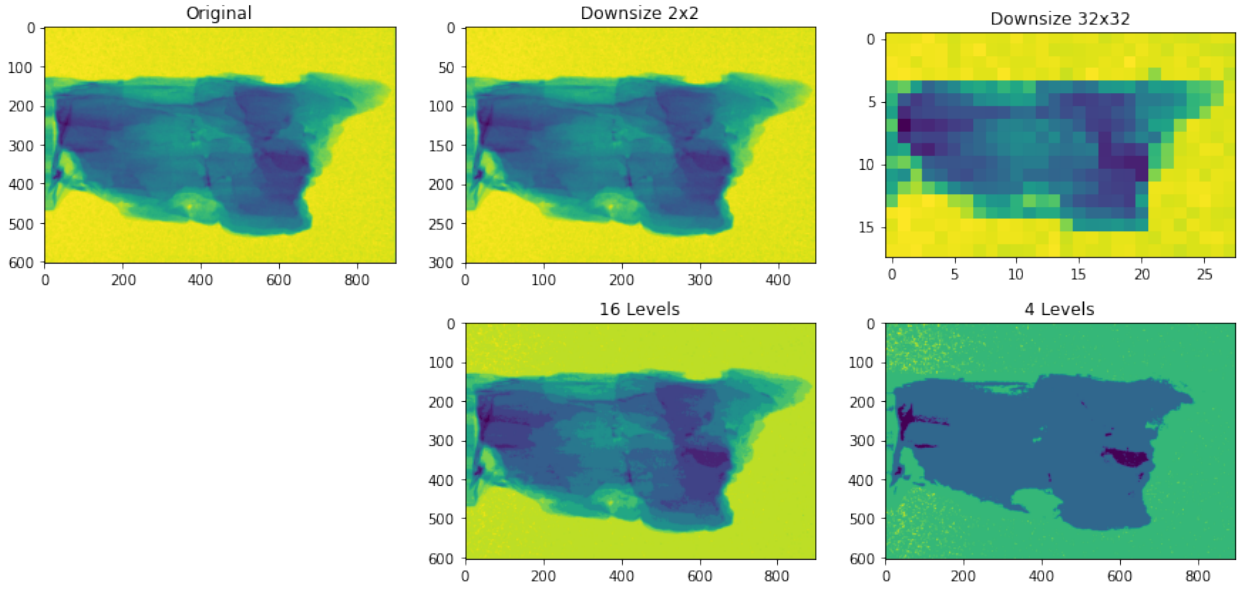


Fig. 6.1: The real world is sampled into discrete images with limited extent.

```
import numpy as np
import matplotlib.pyplot as plt
from skimage.transform import resize

img=np.load('../../common/data/wood.npy');
plt.figure(figsize=[15,7])
plt.subplot(2,3,1); plt.imshow(img); plt.title('Original')
downsize =  2; plt.subplot(2,3,2); plt.imshow(resize(img,(img.shape[0] // downsize,␣
↪img.shape[1] // downsize), anti_aliasing=False)); plt.title('Downsize {0}x{0}'.
↪format(downsize))
downsize = 32; plt.subplot(2,3,3); plt.imshow(resize(img,(img.shape[0] // downsize,␣
↪img.shape[1] // downsize),anti_aliasing=False)); plt.title('Downsize {0}x{0}'.
↪format(downsize))
levels   = 16; plt.subplot(2,3,5); plt.imshow(np.floor(img*levels)); plt.title('{0}␣
↪Levels'.format(levels));
levels   = 4 ; plt.subplot(2,3,6); plt.imshow(np.floor(img*levels)); plt.title('{0}␣
↪Levels'.format(levels));
```



CHAPTER

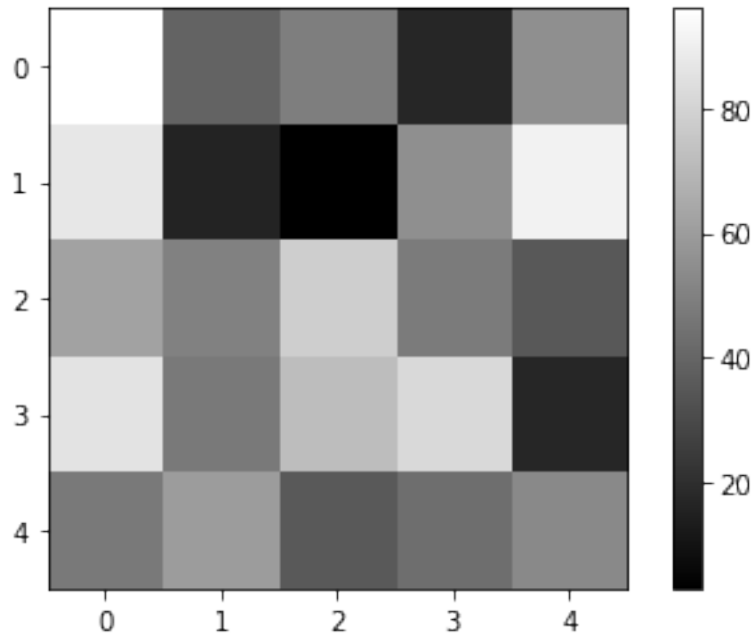
SEVEN

LET'S CREATE A SMALL IMAGE

```
import numpy as np
basic_image = np.random.choice(range(100), size = (5,5))
xx, yy = np.meshgrid(range(basic_image.shape[1]), range(basic_image.shape[0]))
image_df = pd.DataFrame(dict(x = xx.ravel(),
                  y = yy.ravel(),
                  Intensity = basic_image.ravel()))
image_df[['x', 'y', 'Intensity']].head(5)
```

```
   x  y  Intensity
0  0  0         96
1  1  0         39
2  2  0         49
3  3  0         17
4  4  0         55
```

```
import matplotlib.pyplot as plt
plt.imshow(basic_image, cmap = 'gray')
plt.colorbar();
```



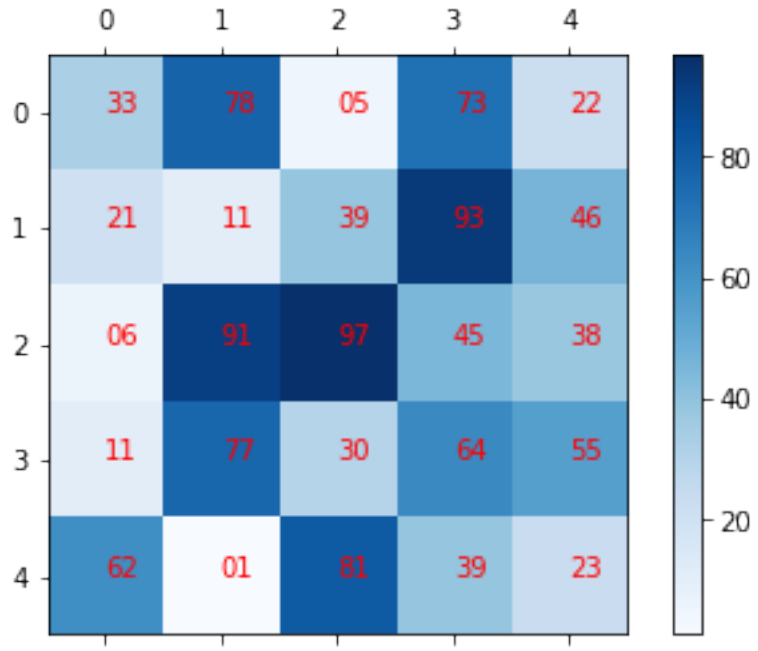
7.1 2D Intensity Images

The next step is to apply a color map (also called lookup table, LUT) to the image

- so it is a bit more exciting
- some features are easier to detect Rogowitz et al. 1996

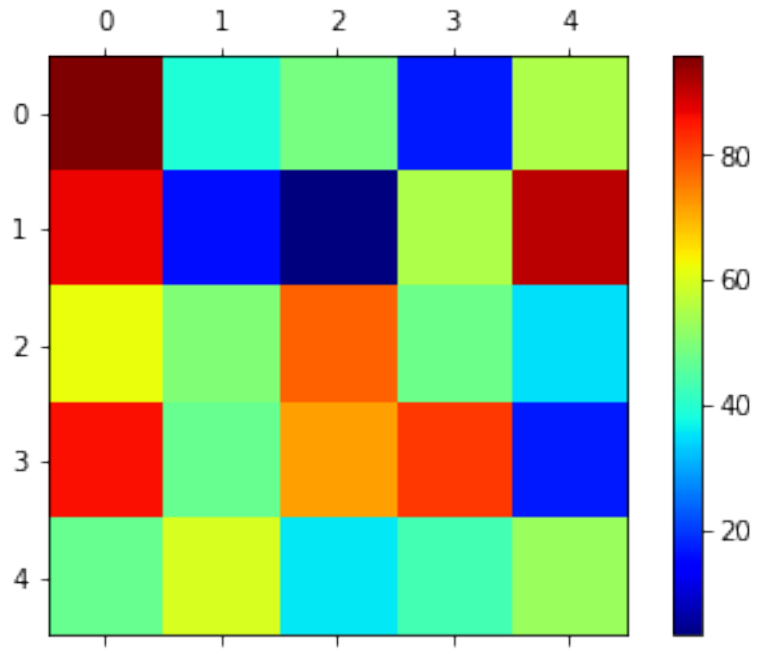
```
fig, ax1 = plt.subplots(1,1)
plot_image = ax1.matshow(basic_image, cmap = 'Blues')
plt.colorbar(plot_image)

for _, c_row in image_df.iterrows():
    ax1.text(c_row['x'], c_row['y'], s = '%02d' % c_row['Intensity'], fontdict =␣
↪dict(color = 'r'))
```



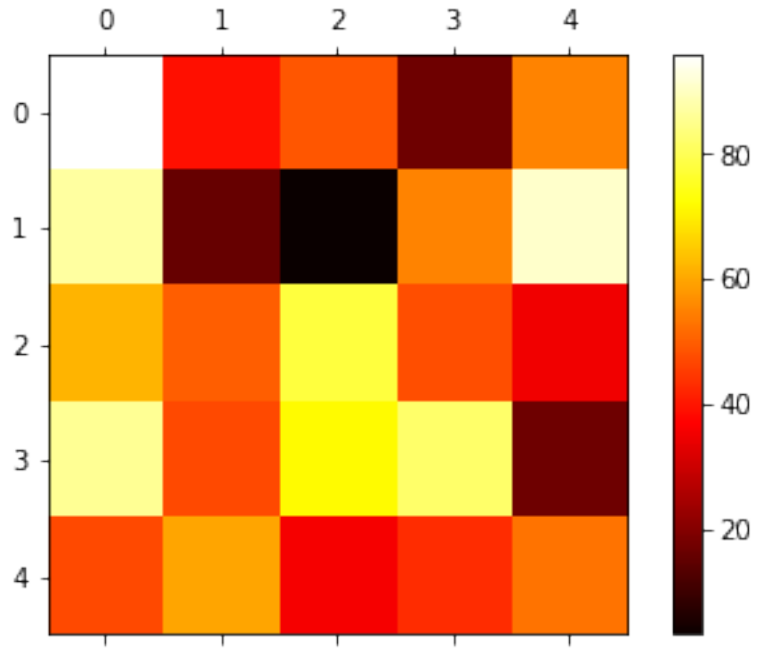
Color maps can be arbitrarily defined based on how we would like to visualize the information in the image

```
fig, ax1 = plt.subplots(1,1)
plot_image = ax1.matshow(basic_image, cmap = 'jet')
plt.colorbar(plot_image);
```




```
fig, ax1 = plt.subplots(1,1)

plot_image = ax1.matshow(basic_image, cmap = 'hot')
plt.colorbar(plot_image);
```



7.2 Lookup Tables

Formally a lookup table is a function which $f(\text{Intensity}) \rightarrow \text{Color}$

7.2.1 Matplotlib's color maps

```
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from matplotlib import cm
#from colorspacious import cspace_converter
from collections import OrderedDict
cmaps = OrderedDict()
cmaps['Perceptually Uniform Sequential'] = [
            'viridis', 'plasma', 'inferno', 'magma', 'cividis']

cmaps['Sequential'] = [
            'Greys', 'Purples', 'Blues', 'Greens', 'Oranges', 'Reds',
            'YlOrBr', 'YlOrRd', 'OrRd', 'PuRd', 'RdPu', 'BuPu',
            'GnBu', 'PuBu', 'YlGnBu', 'PuBuGn', 'BuGn', 'YlGn']

cmaps['Sequential (2)'] = [
            'binary', 'gist_yarg', 'gist_gray', 'gray', 'bone', 'pink',
            'spring', 'summer', 'autumn', 'winter', 'cool', 'Wistia',
            'hot', 'afmhot', 'gist_heat', 'copper']

cmaps['Diverging'] = [
            'PiYG', 'PRGn', 'BrBG', 'PuOr', 'RdGy', 'RdBu',
            'RdYlBu', 'RdYlGn', 'Spectral', 'coolwarm', 'bwr', 'seismic']

cmaps['Cyclic'] = ['twilight', 'twilight_shifted', 'hsv']

cmaps['Qualitative'] = ['Pastel1', 'Pastel2', 'Paired', 'Accent',
                        'Dark2', 'Set1', 'Set2', 'Set3',
                        'tab10', 'tab20', 'tab20b', 'tab20c']

cmaps['Miscellaneous'] = [
            'flag', 'prism', 'ocean', 'gist_earth', 'terrain', 'gist_stern',
            'gnuplot', 'gnuplot2', 'CMRmap', 'cubehelix', 'brg',
            'gist_rainbow', 'rainbow', 'jet', 'nipy_spectral', 'gist_ncar']


nrows = max(len(cmap_list) for cmap_category, cmap_list in cmaps.items())


gradient = np.linspace(0, 1, 256)
gradient = np.vstack((gradient, gradient))


def plot_color_gradients(cmap_category, cmap_list, nrows):
    fig, axes = plt.subplots(nrows=nrows)
    fig.subplots_adjust(top=0.95, bottom=0.01, left=0.2, right=0.99)
    axes[0].set_title(cmap_category + ' colormaps', fontsize=14)

    for ax, name in zip(axes, cmap_list):
```

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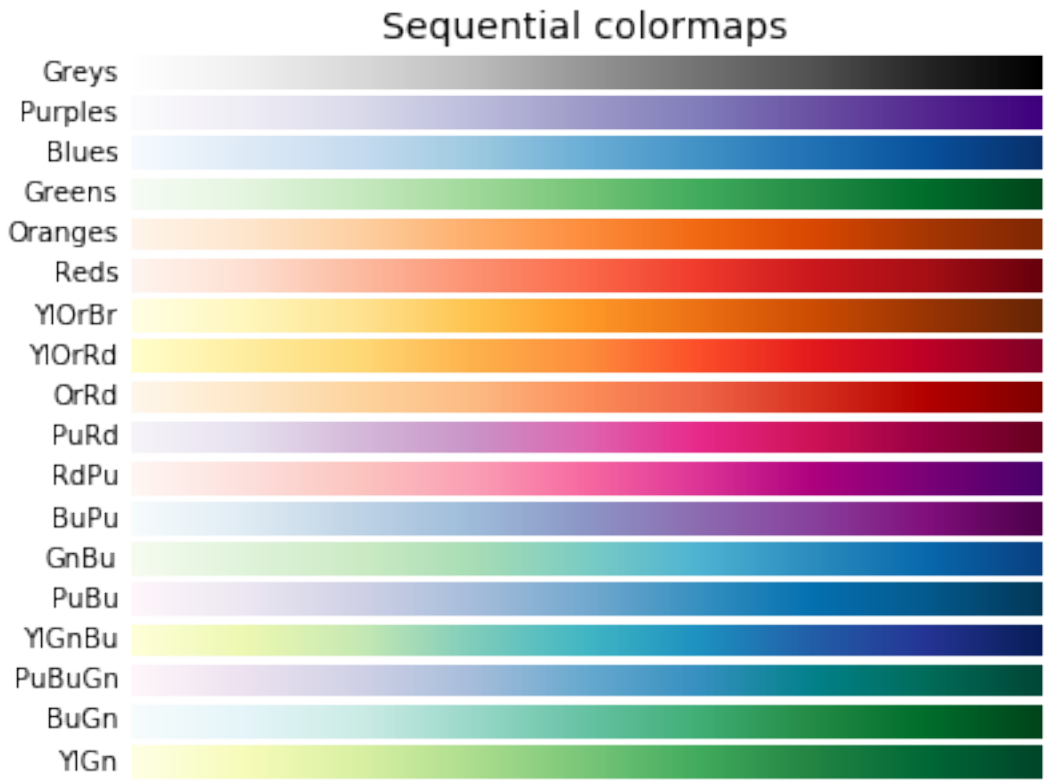
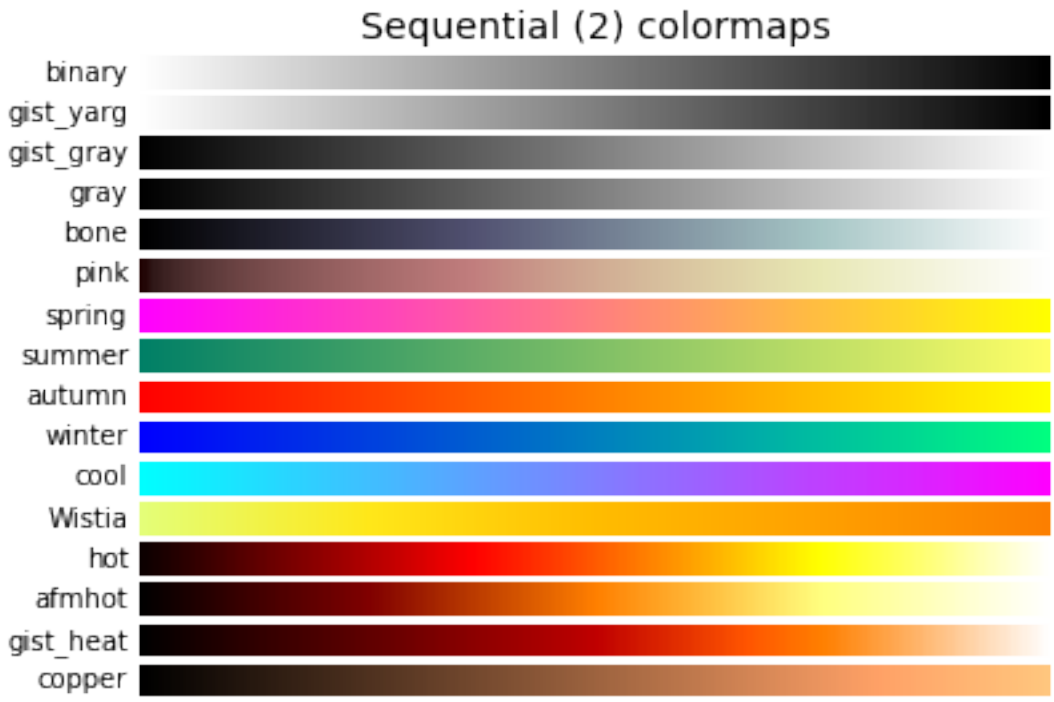
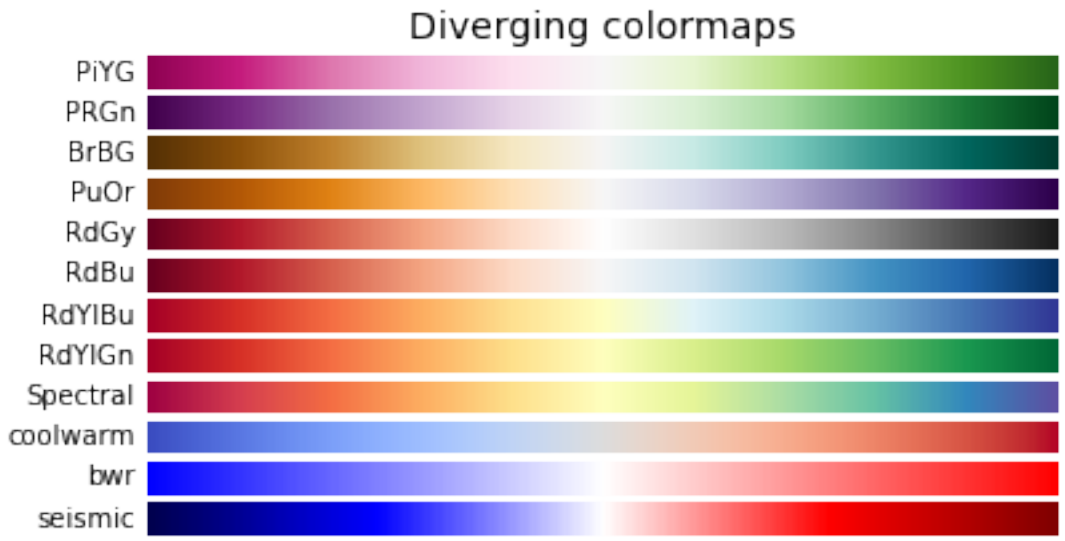
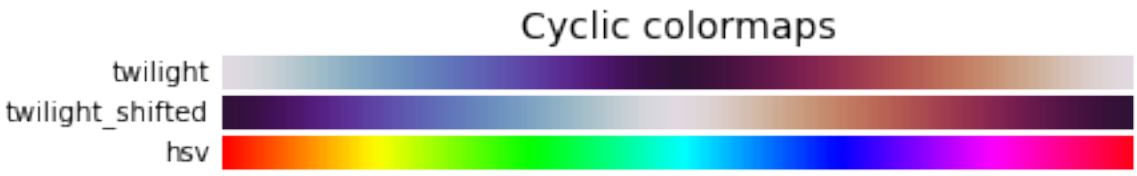
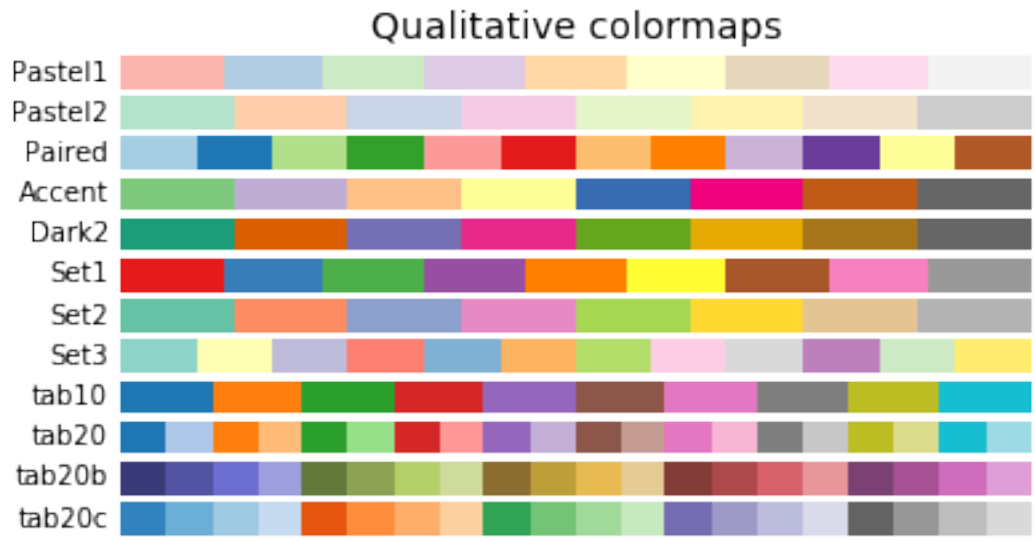
```
        ax.imshow(gradient, aspect='auto', cmap=plt.get_cmap(name))
        pos = list(ax.get_position().bounds)
        x_text = pos[0] - 0.01
        y_text = pos[1] + pos[3]/2.
        fig.text(x_text, y_text, name, va='center', ha='right', fontsize=10)

    # Turn off *all* ticks & spines, not just the ones with colormaps.
    for ax in axes:
        ax.set_axis_off()


for cmap_category, cmap_list in cmaps.items():
    plot_color_gradients(cmap_category, cmap_list, nrows)
```

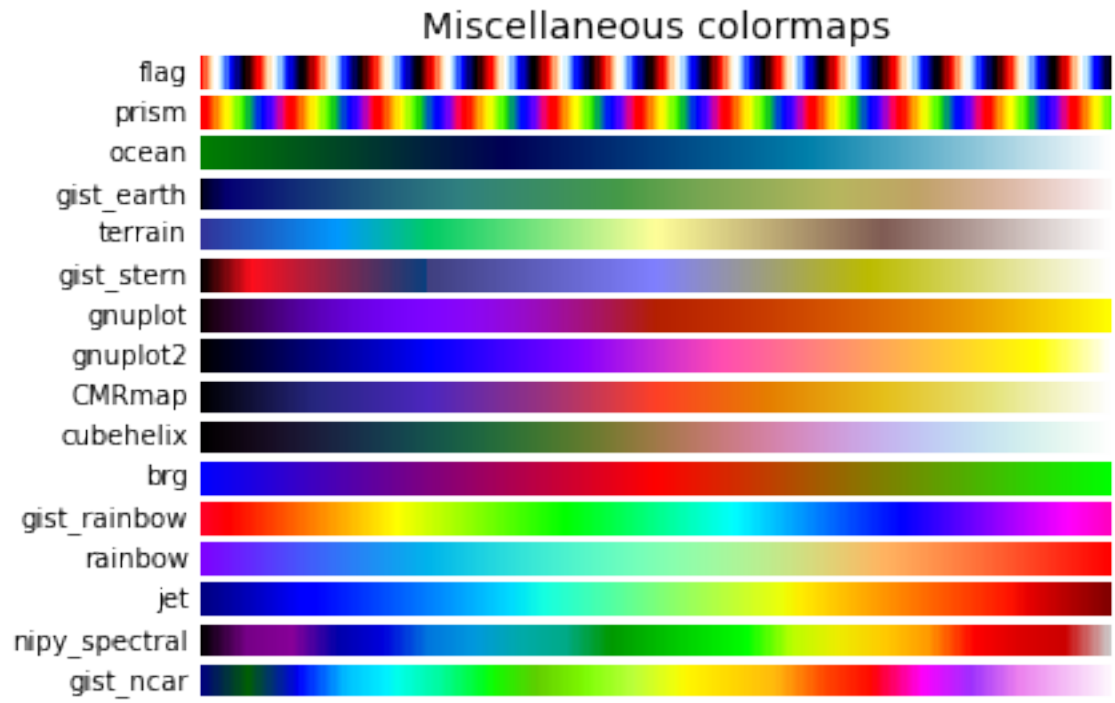

Sequential colormaps
Greys
Purples
Blues
Greens
Oranges
Reds
YlOrBr
YlOrRd
OrRd
PuRd
RdPu
BuPu
GnBu
PuBu
YlGnBu
PuBuGn
BuGn
YlGn


Sequential (2) colormaps
binary
gist_yarg
gist_gray
gray
bone
pink
spring
summer
autumn
winter
cool
Wistia
hot
afmhot
gist_heat
copper


Diverging colormaps
PiYG
PRGn
BrBG
PuOr
RdGy
RdBu
RdYlBu
RdYlGn
Spectral
coolwarm
bwr
seismic


Cyclic colormaps
twilight
twilight_shifted
hsv






```
%matplotlib inline
```

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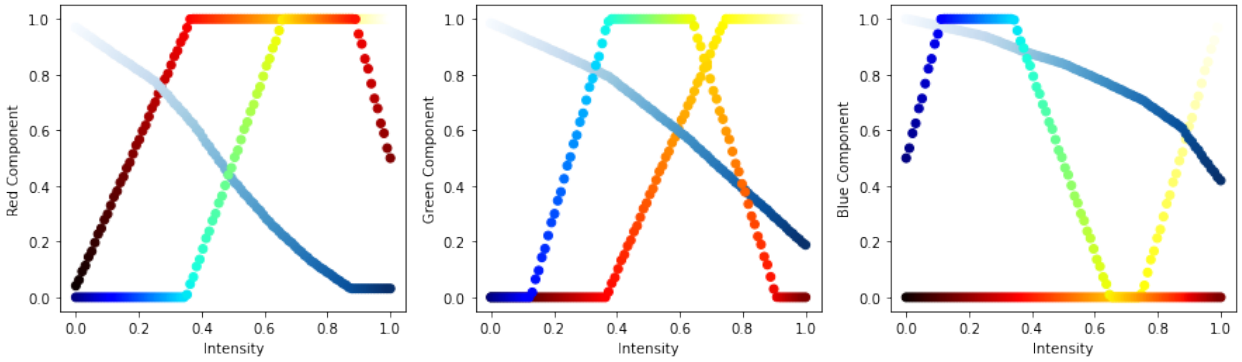
```
import matplotlib.pyplot as plt
import numpy as np
xlin = np.linspace(0, 1, 100)
colors = ['Red','Green','Blue']
plt.figure(figsize=[15,4])
for i in np.arange(0,3) :
    plt.subplot(1,3,i+1)

    plt.scatter(xlin,
            plt.cm.hot(xlin)[:,i],
            c = plt.cm.hot(xlin),label="hot")
    plt.scatter(xlin,
            plt.cm.Blues(xlin)[:,i],
            c = plt.cm.Blues(xlin),label="blues")

    plt.scatter(xlin,
            plt.cm.jet(xlin)[:,i],
            c = plt.cm.jet(xlin),label='jet')

    plt.xlabel('Intensity');
    plt.ylabel('{0} Component'.format(colors[i]));
```



7.3 Applied LUTs

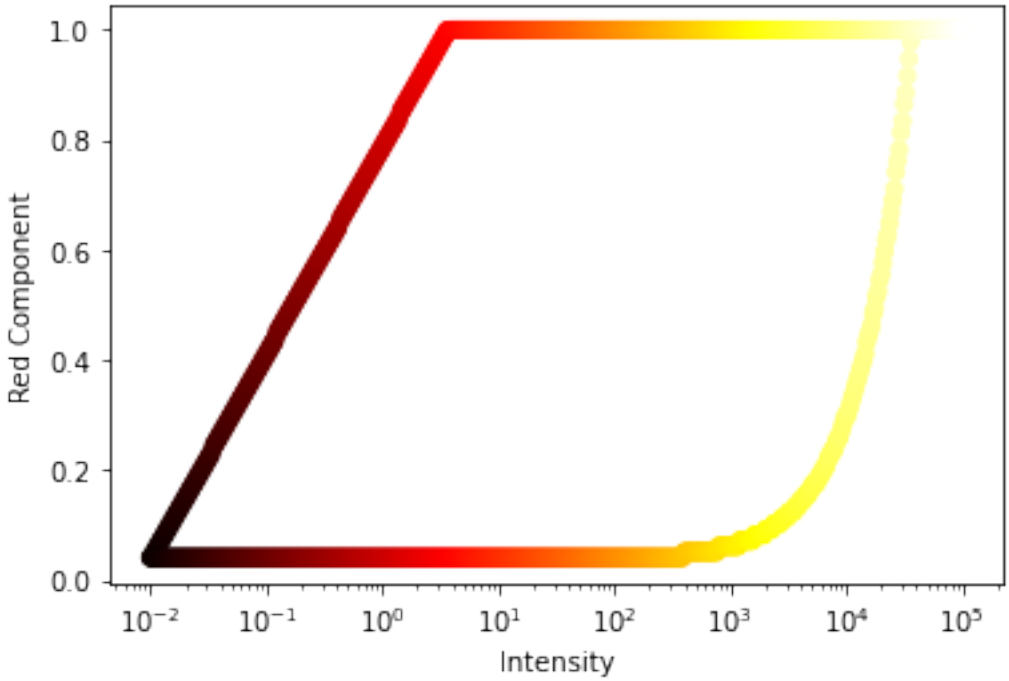
These transformations can also be non-linear as is the case of the graph below where the mapping between the intensity and the color is a log relationship meaning the the difference between the lower values is much clearer than the higher ones

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
xlin = np.logspace(-2, 5, 500)
log_xlin = np.log10(xlin)
norm_xlin = (log_xlin-log_xlin.min())/(log_xlin.max()-log_xlin.min())
fig, ax1 = plt.subplots(1,1)

ax1.scatter(xlin, plt.cm.hot(norm_xlin)[:,0],
            c = plt.cm.hot(norm_xlin))

ax1.scatter(xlin, plt.cm.hot(xlin/xlin.max())[:,0],
```

(continues on next page)

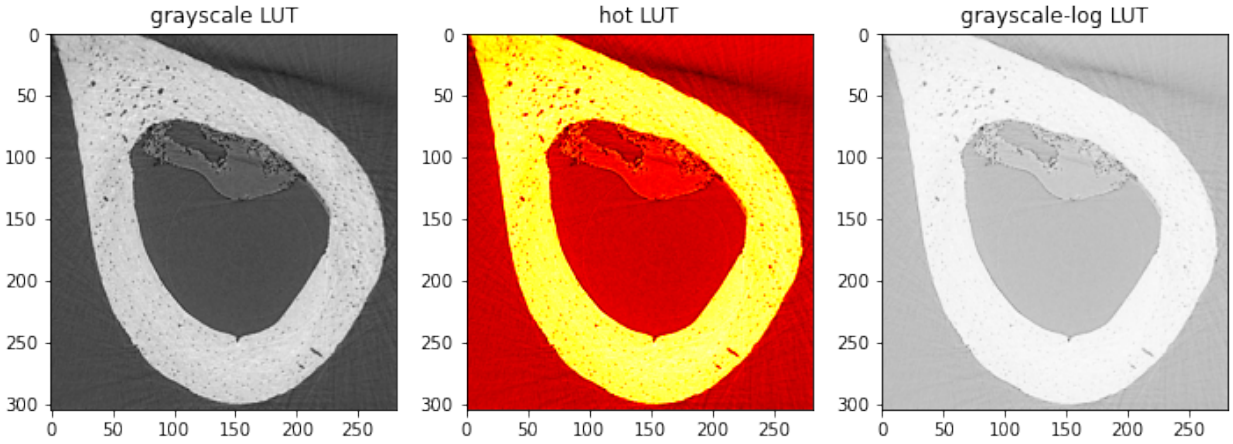
(continued from previous page)

```
            c = plt.cm.hot(norm_xlin))
ax1.set_xscale('log');ax1.set_xlabel('Intensity');ax1.set_ylabel('Red Component');
```



On a real image the difference is even clearer

```
%matplotlib inline
import matplotlib.pyplot as plt
from skimage.io import imread
fig, (ax1, ax2, ax3) = plt.subplots(1,3, figsize = (12, 4))
in_img = imread('figures/bone-section.png')[:,:,0].astype(np.float32)
ax1.imshow(in_img, cmap = 'gray');
ax1.set_title('grayscale LUT');

ax2.imshow(in_img, cmap = 'hot');
ax2.set_title('hot LUT');

ax3.imshow(np.log2(in_img+1), cmap = 'gray');
ax3.set_title('grayscale-log LUT');
```



7.4 3D Images

For a 3D image, the position or spatial component has a 3rd dimension (z if it is a spatial, or t if it is a movie)

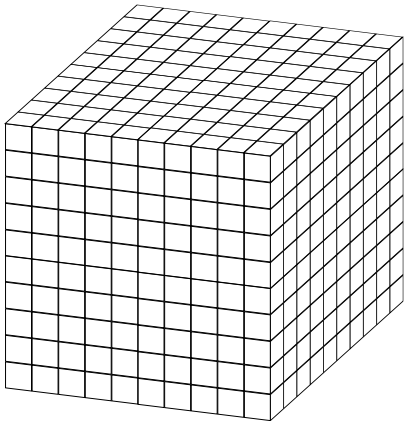


Fig. 7.1: Three-dimensional data can be a volume in space.

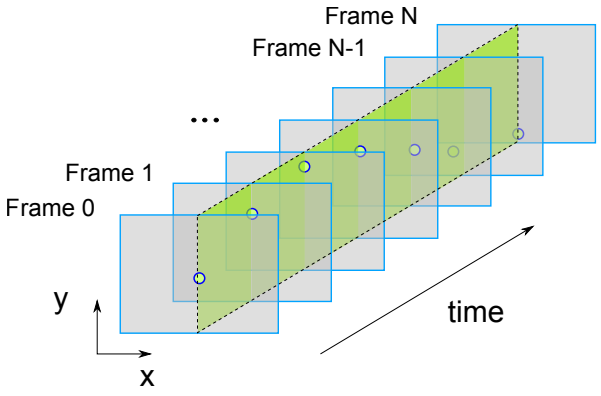


Fig. 7.2: A movie can also be seen as a three-dimensional image.

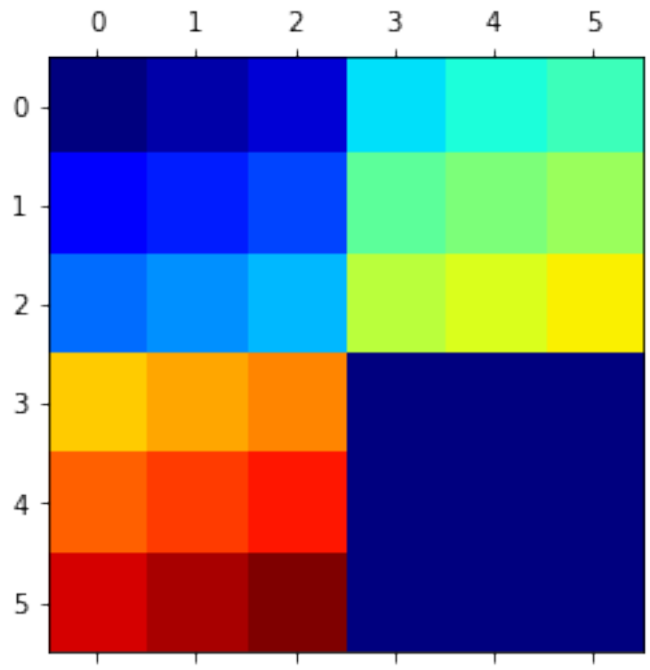
```
import numpy as np
vol_image = np.arange(27).reshape((3,3,3))
print(vol_image)
```

```
[[[ 0  1  2]
  [ 3  4  5]
  [ 6  7  8]]

 [[ 9 10 11]
  [12 13 14]
  [15 16 17]]

 [[18 19 20]
  [21 22 23]
  [24 25 26]]]
```

This can then be rearranged from a table form into an array form and displayed as a series of slices

```
%matplotlib inline
import matplotlib.pyplot as plt
from skimage.util import montage as montage2d
print(montage2d(vol_image, fill = 0))
plt.matshow(montage2d(vol_image, fill = 0), cmap = 'jet');
```

```
[[ 0  1  2  9 10 11]
 [ 3  4  5 12 13 14]
 [ 6  7  8 15 16 17]
 [18 19 20  0  0  0]
 [21 22 23  0  0  0]
 [24 25 26  0  0  0]]
```



7.5 Multiple Values

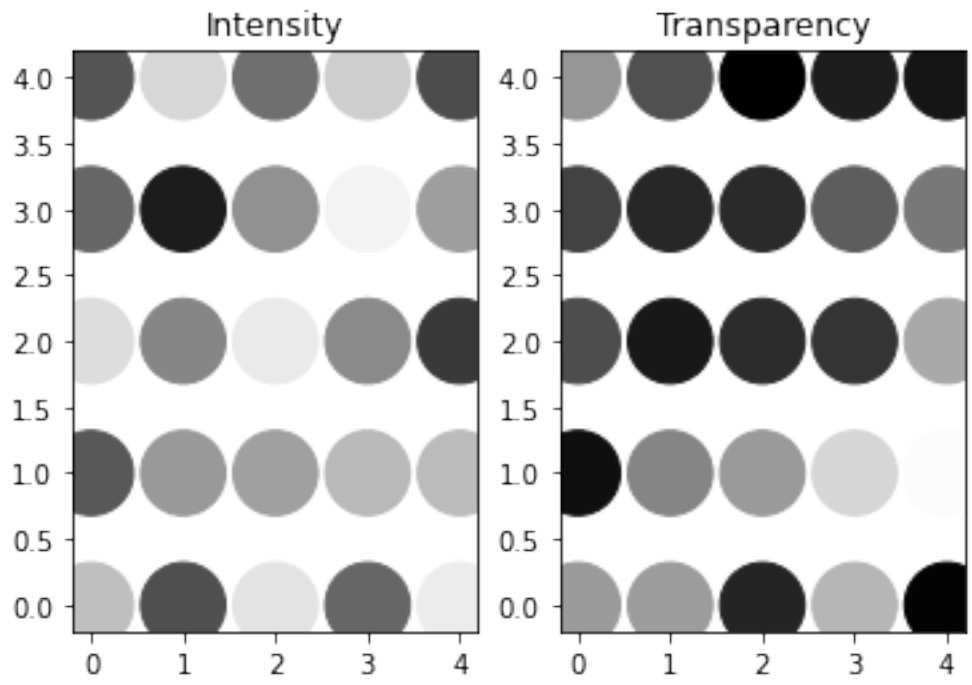
In the images thus far, we have had one value per position, but there is no reason there cannot be multiple values. In fact this is what color images are (red, green, and blue) values and even 4 channels with transparency (alpha) as a different. For clarity we call the **dimensionality** of the image the number of dimensions in the spatial position, and the **depth** the number in the value.

```
import pandas as pd
from itertools import product
import numpy as np
base_df = pd.DataFrame([dict(x = x, y = y) for x,y in product(range(5), range(5))])
base_df['Intensity'] = np.random.uniform(0, 1, 25)
base_df['Transparency'] = np.random.uniform(0, 1, 25)
base_df.head(5)
```

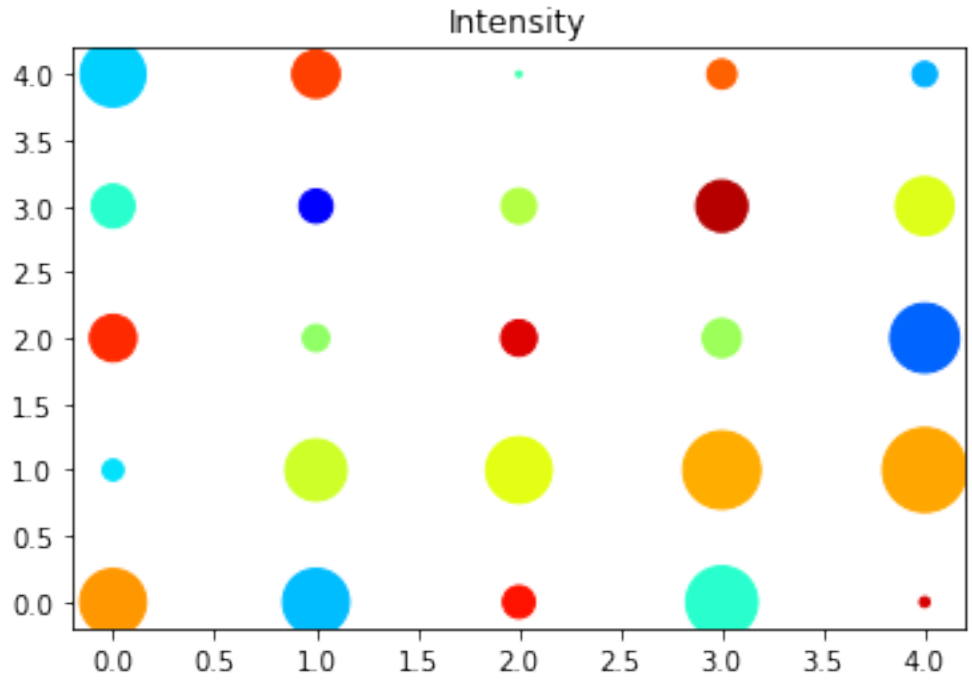
```
   x  y  Intensity  Transparency
0  0  0   0.746783      0.607095
1  0  1   0.347202      0.059656
2  0  2   0.866183      0.301186
3  0  3   0.402008      0.258386
4  0  4   0.328629      0.589196
```

This can then be rearranged from a table form into an array form and displayed as a series of slices

```
%matplotlib inline
import matplotlib.pyplot as plt
fig, (ax1, ax2) = plt.subplots(1, 2)
ax1.scatter(base_df['x'], base_df['y'], c = plt.cm.gray(base_df['Intensity']), s =␣
↪1000)
ax1.set_title('Intensity')
ax2.scatter(base_df['x'], base_df['y'], c = plt.cm.gray(base_df['Transparency']), s =␣
↪1000)
ax2.set_title('Transparency');
```



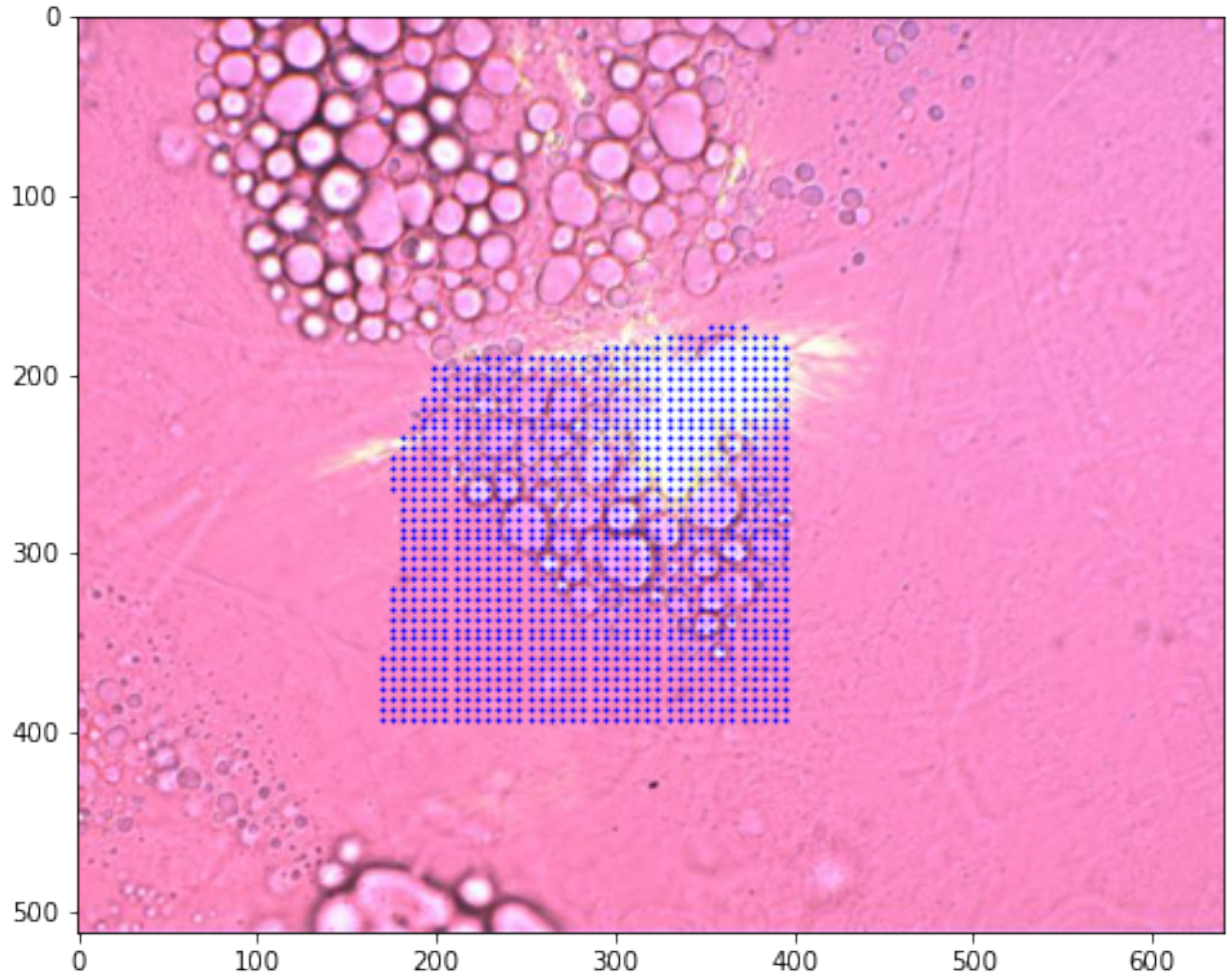

```
fig, (ax1) = plt.subplots(1, 1)
ax1.scatter(base_df['x'], base_df['y'], c = plt.cm.jet(base_df['Intensity']), s =␣
↪1000*base_df['Transparency'])
ax1.set_title('Intensity');
```



7.6 Hyperspectral Imaging

At each point in the image (black dot), instead of having just a single value, there is an entire spectrum. A selected group of these (red dots) are shown to illustrate the variations inside the sample. While certainly much more complicated, this still constitutes and image and requires the same sort of techniques to process correctly.

```
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
from skimage.io import imread
import os
raw_img = imread('../../common/data/raw.jpg')
im_pos = pd.read_csv('../../common/data/impos.csv', header = None)
im_pos.columns = ['x', 'y']
fig, ax1 = plt.subplots(1,1, figsize = (8, 8));
ax1.imshow(raw_img);
ax1.scatter(im_pos['x'], im_pos['y'], s = 1, c = 'blue');
```

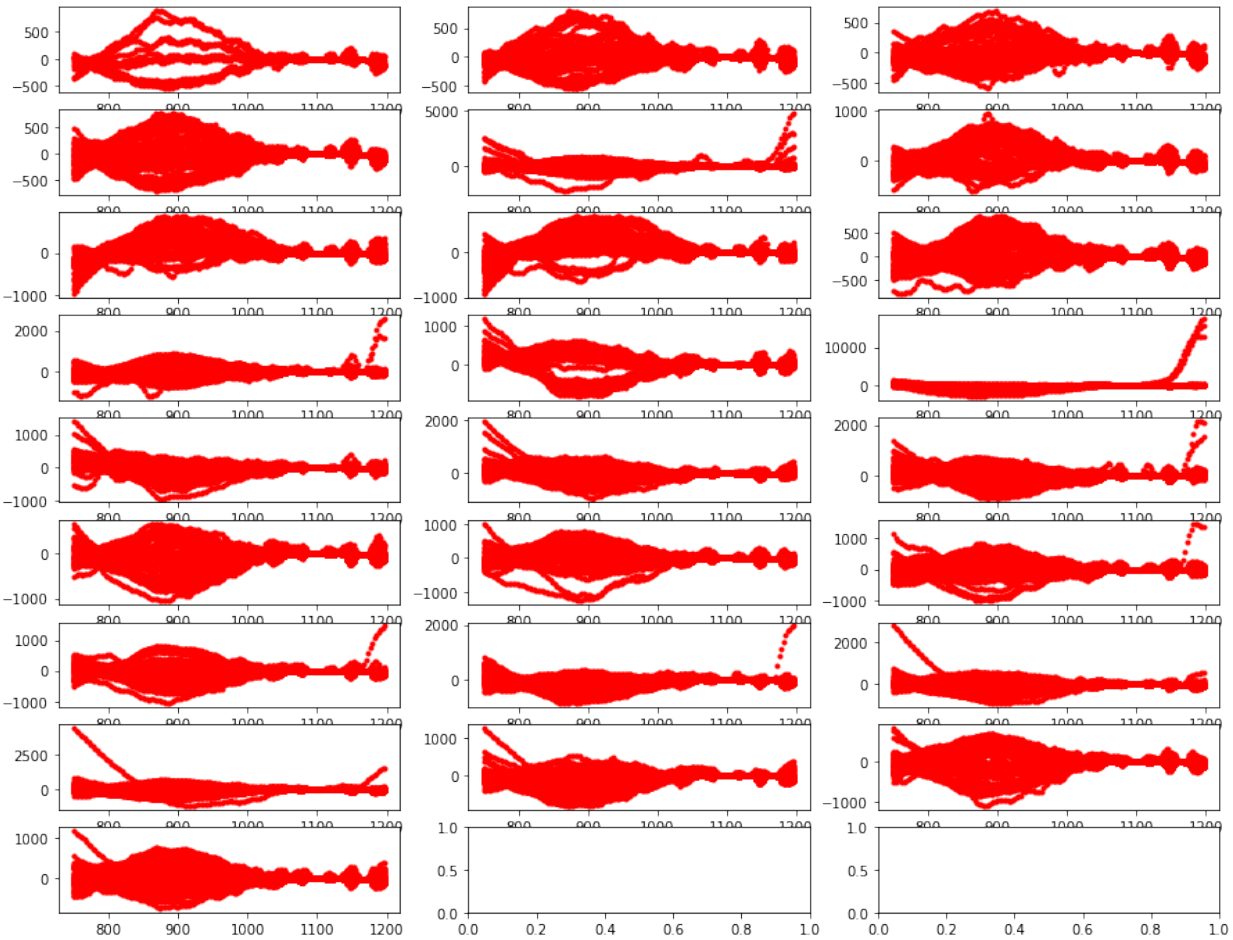



```
full_df = pd.read_csv('../../common/data/full_img.csv').query('wavenum<1200')
print(full_df.shape[0], 'rows')
full_df.head(5)
```

```
210750 rows
```

```
        x      y  wavenum         val
0  168.95  358.8      750  527.571102
1  168.95  358.8      753  459.778584
2  168.95  358.8      756  406.337255
3  168.95  358.8      759  341.858123
4  168.95  358.8      762  246.645673
```

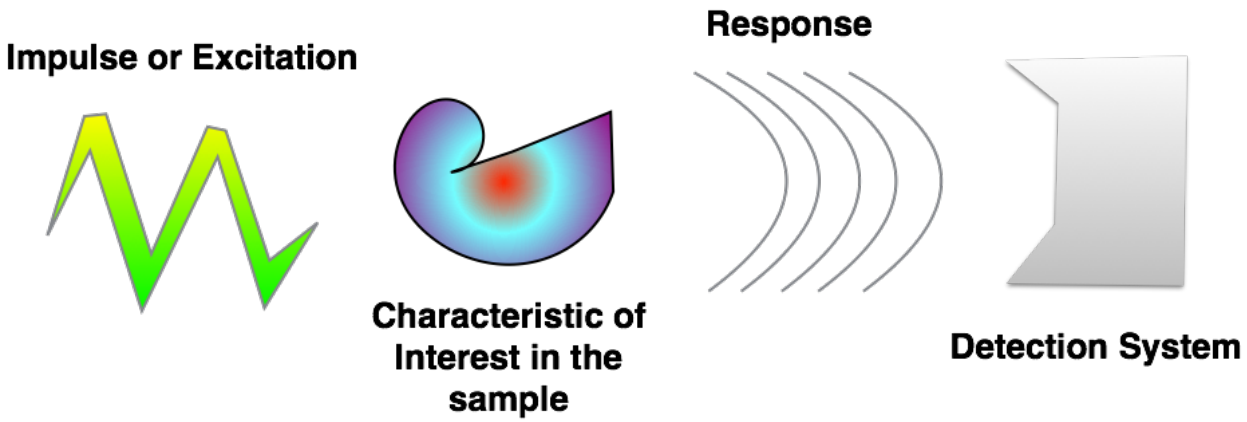
```
full_df['g_x'] = pd.cut(full_df['x'], 5)
full_df['g_y'] = pd.cut(full_df['y'], 5)
fig, m_axs = plt.subplots(9, 3, figsize = (15, 12)); m_axs=m_axs.ravel()
for ((g_x, g_y), c_rows), c_ax in zip(full_df.sort_values(['x','y']).groupby(['g_x',
↪'g_y']),m_axs):
    c_ax.plot(c_rows['wavenum'], c_rows['val'], 'r.')
```



CHAPTER

EIGHT

IMAGE FORMATION



- **Impulses** Light, X-Rays, Electrons, A sharp point, Magnetic field, Sound wave
- **Characteristics** Electron Shell Levels, Electron Density, Phonons energy levels, Electronic, Spins, Molecular mobility
- **Response** Absorption, Reflection, Phase Shift, Scattering, Emission
- **Detection** Your eye, Light sensitive film, CCD / CMOS, Scintillator, Transducer

8.1 Where do images come from?

Modality	Impulse	Characteristic	Response	Detection
Light Microscopy	White Light	Electronic interactions	Absorption	Film, Camera
Phase Contrast	Coherent light	Electron Density (Index of Refraction)	Phase Shift	Phase stepping, holography, Zernike
Confocal Microscopy	Laser Light	Electronic Transition in Fluorescence Molecule	Absorption and reemission	Pinhole in focal plane, scanning detection
X-Ray Radiography	X-Ray light	Photo effect and Compton scattering	Absorption and scattering	Scintillator, microscope, camera
Neutron Radiography	Neutrons	Interaction with nucleus	Scattering and absorption	Scintillator, optics, camera
Ultrasound	High frequency sound waves	Molecular mobility	Reflection and Scattering	Transducer
MRI	Radio-frequency EM	Unmatched Hydrogen spins	Absorption and reemission	RF coils to detect
Atomic Force Microscopy	Sharp Point	Surface Contact	Contact, Repulsion	Deflection of a tiny mirror

CHAPTER

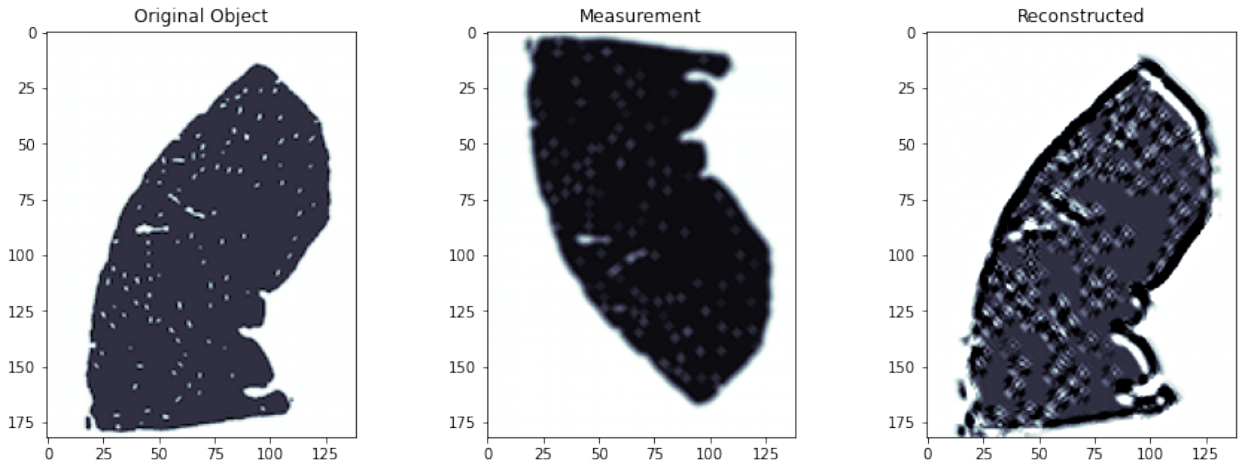
NINE

ACQUIRING IMAGES

9.1 Traditional / Direct imaging

- Visible images produced or can be easily made visible
- Optical imaging, microscopy

```
bone_img  = imread('figures/tiny-bone.png').astype(np.float32)
# simulate measured image
conv_kern = np.pad(disk(2), 1, 'constant', constant_values = 0)
meas_img  = convolve(bone_img[::-1], conv_kern)
# run deconvolution
dekern    = np.fft.ifft2(1/np.fft.fft2(conv_kern))
rec_img   = convolve(meas_img, dekern)[::-1]
# show result
fig, (ax_orig, ax1, ax2) = plt.subplots(1,3, figsize = (15, 5))
ax_orig.imshow(bone_img, cmap = 'bone'); ax_orig.set_title('Original Object')

ax1.imshow(np.real(meas_img), cmap = 'bone'); ax1.set_title('Measurement')

ax2.imshow(np.real(rec_img), cmap = 'bone', vmin = 0, vmax = 255); ax2.set_title(
↪'Reconstructed');
```

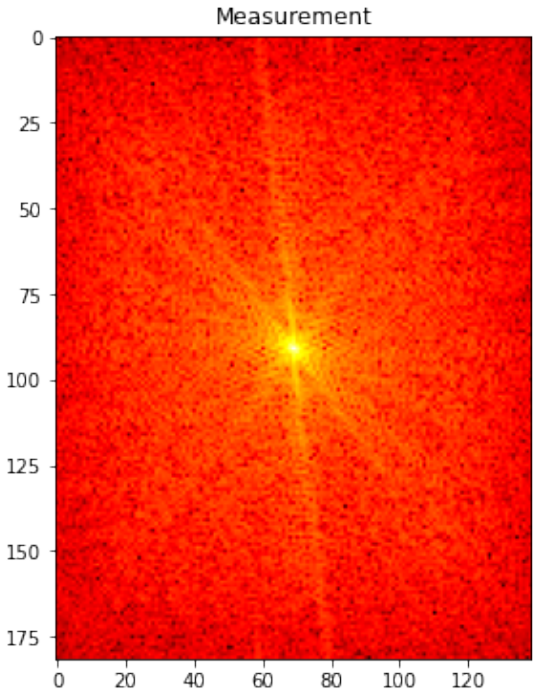


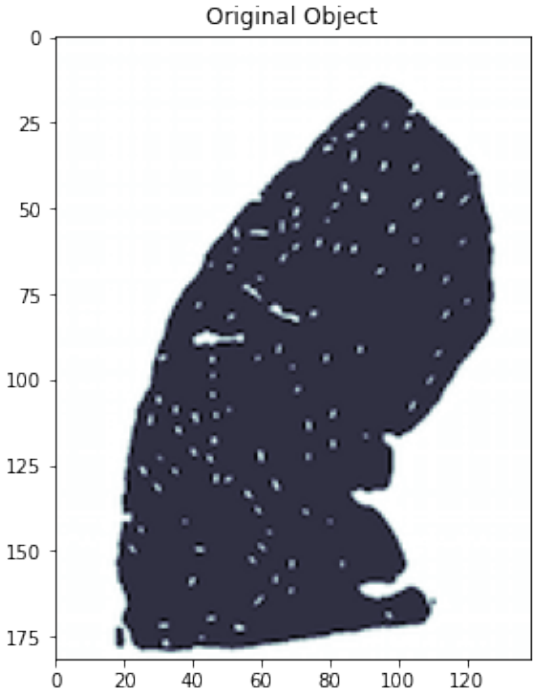
9.2 Indirect / Computational imaging

- Recorded information does not resemble object
- Response must be transformed (usually computationally) to produce an image

```
bone_img = imread('figures/tiny-bone.png').astype(np.float32)
# simulate measured image
meas_img = np.log10(np.abs(np.fft.fftshift(np.fft.fft2(bone_img))))
print(meas_img.min(), meas_img.max(), meas_img.mean())
fig, (ax1, ax_orig) = plt.subplots(1,2,
                                   figsize = (12, 6))
ax_orig.imshow(bone_img, cmap = 'bone')
ax_orig.set_title('Original Object')

ax1.imshow(meas_img, cmap = 'hot')
ax1.set_title('Measurement');
```

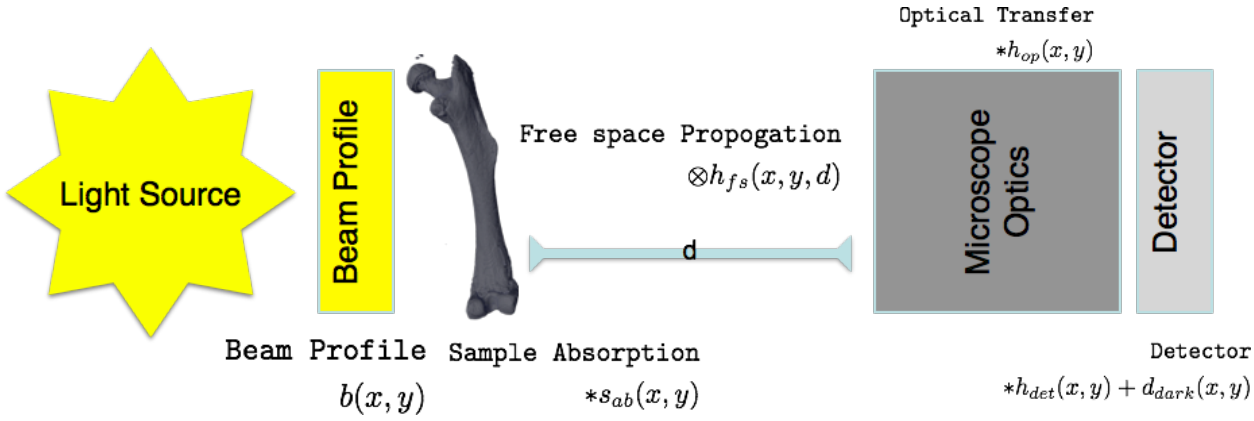
```
1.146423838816545 6.61125552595089 3.3563935033662253
```





9.3 Traditional Imaging

9.4 Traditional Imaging: Model



$$[([b(x,y) * s_{ab}(x,y)] \otimes h_{fs}(x,y)) * h_{op}(x,y)] * h_{det}(x,y) + d_{dark}(x,y)$$

s_{ab} is the only information you are really interested in, so it is important to remove or correct for the other components

For color (non-monochromatic) images the problem becomes even more complicated $\$\int_0^\infty [([b(x,y,\lambda) * s_{ab}(x,y,\lambda)] \otimes h_{fs}(x,y,\lambda)) * h_{op}(x,y,\lambda)] * h_{det}(x,y,\lambda)\mathrm{d}\lambda + d_{dark}(x,y)\$$

9.5 Indirect Imaging (Computational Imaging)

- Tomography through projections
- Microlenses Light-field photography
- Diffraction patterns
- Hyperspectral imaging with Raman, IR, CARS
- Surface Topography with cantilevers (AFM)

9.6 Image Analysis

- An image is a bucket of pixels.
- How you choose to turn it into useful information is strongly dependent on your background

9.7 Image Analysis: Experimentalist

9.7.1 Characteristics

- Problem-driven
- Top-down
- *Reality* Model-based

9.7.2 Examples

- cell counting
- porosity

9.8 Image Analysis: Computer Vision Approaches

9.8.1 Characteristics

- Method-driven
- Feature-based
- *Image* Model-based
- Engineer features for solving problems

9.8.2 Examples

- Edge detection
- Face detection

9.9 Image Analysis: Deep Learning Approach

9.9.1 Characteristics

- Results-driven
- Biology 'inspired'
- Build both image processing and analysis from scratch

9.9.2 Examples

- Captioning images
- Identifying unusual events

CHAPTER

TEN

ON SCIENCE

10.1 What is the purpose?

- Discover and validate new knowledge

10.1.1 How?

- Use the scientific method as an approach to convince other people
- Build on the results of others so we don't start from the beginning

10.1.2 Important Points

- While **qualitative** assessment is important, it is difficult to reliably produce and scale
- **Quantitative** analysis is far from perfect, but provides metrics which can be compared and regenerated by anyone

Inspired by: imagej-pres

10.2 Science and Imaging

Images are great for qualitative analyses since our brains can quickly interpret them without large *programming* investements.

10.2.1 Proper processing and quantitative analysis is however much more difficult with images.

- If you measure a temperature, quantitative analysis is easy, $50K$.
- If you measure an image it is much more difficult and much more prone to mistakes, subtle setup variations, and confusing analyses

10.2.2 Furthermore in image processing there is a plethora of tools available

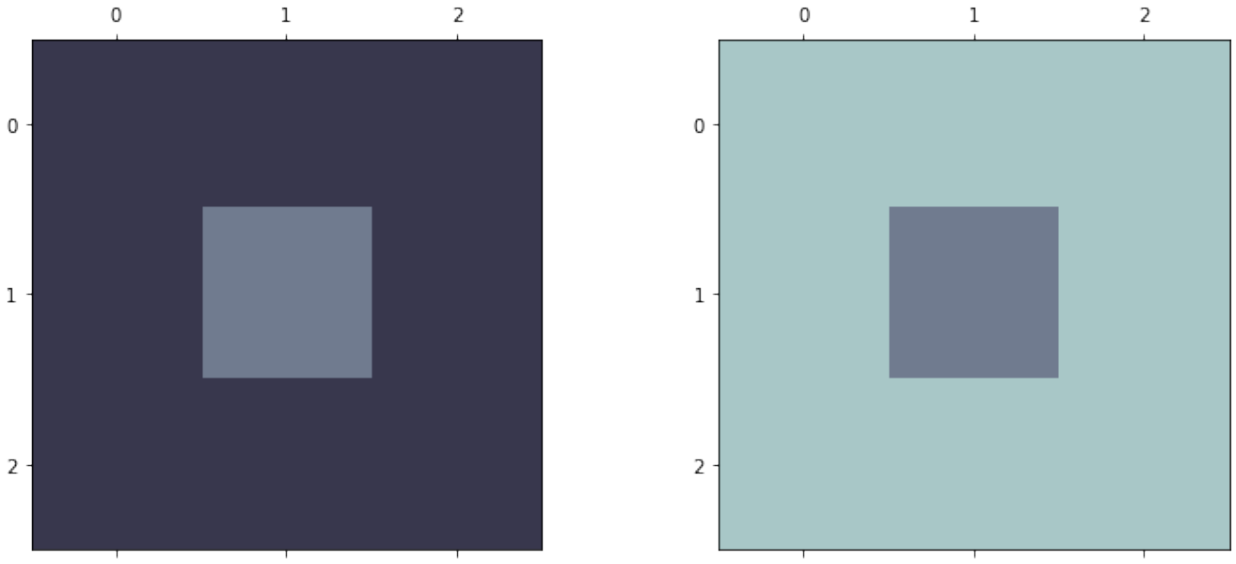
- Thousands of algorithms available
- Thousands of tools
- Many images require multi-step processing
- Experimenting is time-consuming

10.3 Why quantitative?

10.3.1 Human eyes have issues

Which center square seems brighter?

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
xlin = np.linspace(-1,1, 3)
xx, yy = np.meshgrid(xlin, xlin)
img_a = 25*np.ones((3,3))
img_b = np.ones((3,3))*75
img_a[1,1] = 50
img_b[1,1] = 50
fig, (ax1, ax2) = plt.subplots(1,2, figsize = (12, 5));
ax1.matshow(img_a, vmin = 0, vmax = 100, cmap = 'bone');
ax2.matshow(img_b, vmin = 0, vmax = 100, cmap = 'bone');
```

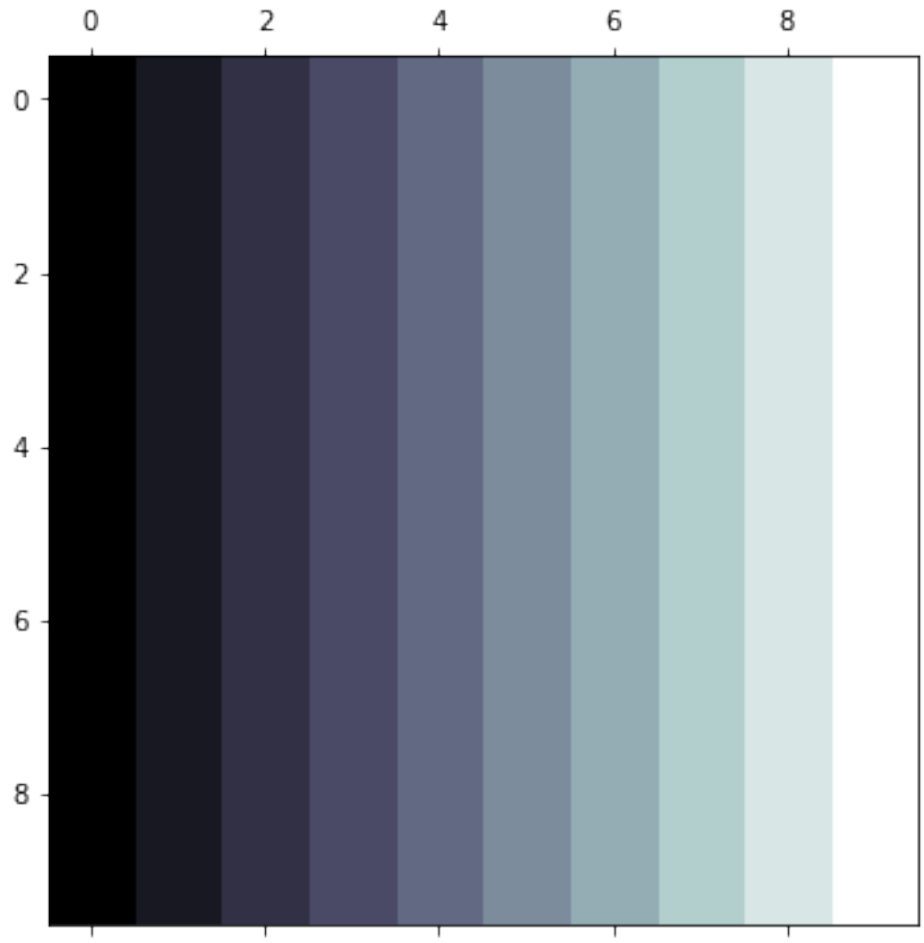


10.4 Intensity gradients

Are the intensities constant in the image?

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
xlin = np.linspace(-1,1, 10)
xx, yy = np.meshgrid(xlin, xlin)

fig, ax1 = plt.subplots(1,1, figsize = (6, 6))
ax1.matshow(xx, vmin = -1, vmax = 1, cmap = 'bone')
```

```
<matplotlib.image.AxesImage at 0x1c5b4853d0>
```



10.5 Reproducibility vs. Repeatability

10.5.1 Reproducibility

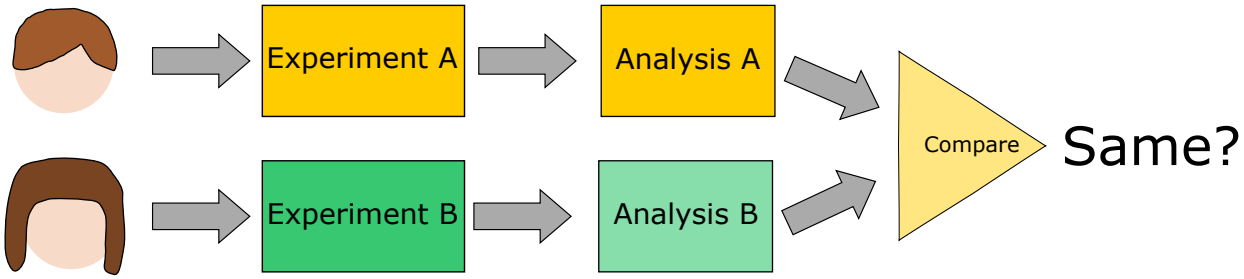


Fig. 10.1: A workflow describing the concept of reproducibility.

10.5.2 Repeatability

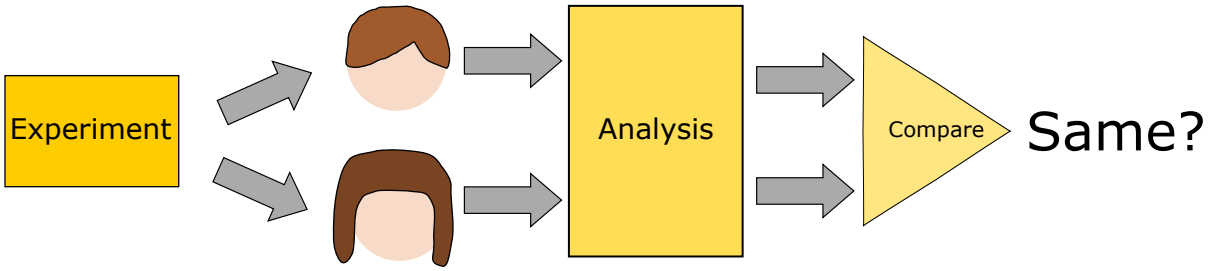


Fig. 10.2: A workflow describing the concept of reproducibility.

10.6 Reproducibility vs. Repeatability

Science demands **repeatability**! and really wants **reproducability**

- Experimental conditions can change rapidly and are difficult to make consistent
- Animal and human studies are prohibitively time consuming and expensive to reproduce
- Terabyte datasets cannot be easily passed around many different groups
- Privacy concerns can also limit sharing and access to data

- *Science* is already difficult enough
- Image processing makes it even more complicated
- Many image processing tasks are multistep, have many parameters, use a variety of tools, and consume a very long time

10.7 How can we keep track of everything for ourselves and others?

- We can make the data analysis easy to repeat by an independent 3rd party
- Document the analysis steps
- Write clear and understandable code

CHAPTER

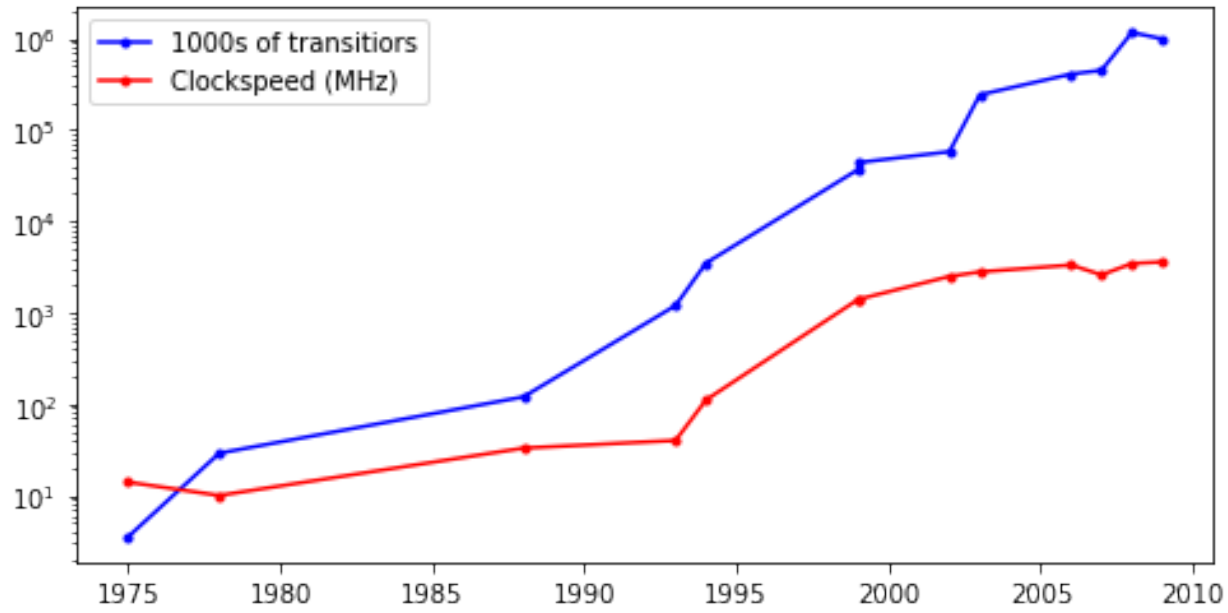
ELEVEN

COMPUTING HAS CHANGED: PARALLEL

11.1 Moores Law

$$\text{Transistors} \propto 2^{T/(18\text{ months})}$$

```
%matplotlib inline
# stolen from https://gist.github.com/humberto-ortiz/de4b3a621602b78bf90d
import pandas as pd
import matplotlib.pyplot as plt
from io import StringIO
moores_txt=["Id Name  Year  Count(1000s)  Clock(MHz)\n",
        "0            MOS65XX  1975          3.51          14\n",
        "1          Intel8086  1978         29.00          10\n",
        "2          MIPSR3000  1988        120.00          33\n",
        "3           AMDAm486  1993       1200.00          40\n",
        "4        NexGenNx586  1994       3500.00         111\n",
        "5          AMDAthlon  1999      37000.00        1400\n",
        "6   IntelPentiumIII  1999      44000.00        1400\n",
        "7         PowerPC970  2002      58000.00        2500\n",
        "8       AMDAthlon64  2003     243000.00        2800\n",
        "9    IntelCore2Duo  2006     410000.00        3330\n",
        "10         AMDPhenom  2007     450000.00        2600\n",
        "11      IntelCorei7  2008    1170000.00        3460\n",
        "12      IntelCorei5  2009     995000.00        3600"]

sio_table = StringIO(''.join(moores_txt)); moore_df = pd.read_table(sio_table, sep =
↪'\s+', index_col = 0);
fig, ax1 = plt.subplots(1,1, figsize = (8, 4)); ax1.semilogy(moore_df['Year'], moore_
↪df['Count(1000s)'], 'b.-', label = '1000s of transitiors'); ax1.semilogy(moore_df[
↪'Year'], moore_df['Clock(MHz)'], 'r.-', label = 'Clockspeed (MHz)') ;ax1.legend(loc␣
↪= 2);
```



Based on data from https://gist.github.com/humberto-ortiz/de4b3a621602b78bf90d

---

There are now many more transistors inside a single computer but the processing speed hasn't increased. How can this be?

- Multiple Core
- Many machines have multiple cores for each processor which can perform tasks independently
- Multiple CPUs
- More than one chip is commonly present
- New modalities
  - GPUs provide many cores which operate at slow speed

11.1.1 → Parallel Code is important

11.2 Computing has changed: Cloud

- Computer, servers, workstations are *wildly underused* (majority are <50%)
- Buying a big computer that sits *idle most of the time* is a waste of money
  - http://www-inst.eecs.berkeley.edu/~cs61c/sp14/
  - "The Case for Energy-Proportional Computing," Luiz André Barroso, Urs Hölzle, IEEE Computer, December 2007
- Traditionally the most important performance criteria was time, how fast can it be done
- With Platform as a service servers can be *rented instead of bought*
- Speed is still important but using cloud computing $ / Sample is the real metric
- In Switzerland a PhD student is 400x as expensive per hour as an Amazon EC2 Machine

- Many competitors keep prices low and offer flexibility

11.3 Cloud Computing Costs

The figure shows the range of cloud costs (determined by peak usage) compared to a local workstation with utilization shown as the average number of hours the computer is used each week.

11.4 Cloud: Equal Cost Point

Here the equal cost point is shown where the cloud and local workstations have the same cost. The x-axis is the percentage of resources used at peak-time and the y shows the expected usable lifetime of the computer. The color indicates the utilization percentage and the text on the squares shows this as the numbers of hours used in a week.

CHAPTER

TWELVE

SOUP/RECIPE EXAMPLE

12.1 Simple Soup

Easy to follow the list, anyone with the right steps can execute and repeat (if not reproduce) the soup

1. Buy {carrots, peas, tomatoes} at market
2. *then* Buy meat at butcher
3. *then* Chop carrots into pieces
4. *then* Chop potatos into pieces
5. *then* Heat water
6. *then* Wait until boiling then add chopped vegetables
7. *then* Wait 5 minutes and add meat

12.2 More complicated soup

Here it is harder to follow and you need to carefully keep track of what is being performed

12.2.1 Steps 1-4

1. *then* Mix carrots with potatos $\rightarrow mix_1$
2. *then* add egg to mix_1 and fry for 20 minutes
3. *then* Tenderize meat for 20 minutes
4. *then* add tomatoes to meat and cook for 10 minutes $\rightarrow mix_2$
5. *then* Wait until boiling then add mix_1
6. *then* Wait 5 minutes and add mix_2

CHAPTER

THIRTEEN

USING FLOW CHARTS / WORKFLOWS

13.1 Simple Soup

```
from IPython.display import SVG
import pydot
graph = pydot.Dot(graph_type='digraph', rankdir="LR")
node_names = ["Buy\nvegetables","Buy meat","Chop\nvegetables","Heat water", "Add␣
↪Vegetables",
              "Wait for\nboiling","Wait 5\nadd meat"]
nodes = [pydot.Node(name = '%04d' % i, label = c_n)
         for i, c_n in enumerate(node_names)]
for c_n in nodes:
    graph.add_node(c_n)

for (c_n, d_n) in zip(nodes, nodes[1:]):
    graph.add_edge(pydot.Edge(c_n, d_n))

SVG(graph.create_svg())
```

```
<IPython.core.display.SVG object>
```

13.2 Workflows

Clearly a linear set of instructions is ill-suited for even a fairly easy soup, it is then even more difficult when there are dozens of steps and different pathsways

---

Furthermore a clean workflow allows you to better parallelize the task since it is clear which tasks can be performed independently

```
from IPython.display import SVG
import pydot
graph = pydot.Dot(graph_type='digraph', rankdir="LR")
node_names = ["Buy\nvegetables","Buy meat","Chop\nvegetables","Heat water", "Add␣
↪Vegetables",
              "Wait for\nboiling","Wait 5\nadd meat"]
nodes = [pydot.Node(name = '%04d' % i, label = c_n, style = 'filled')
         for i, c_n in enumerate(node_names)]
for c_n in nodes:
    graph.add_node(c_n)
```

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```
def e(i,j, col = None):
    if col is not None:
        for c in [i,j]:
            if nodes[c].get_fillcolor() is None:
                nodes[c].set_fillcolor(col)
    graph.add_edge(pydot.Edge(nodes[i], nodes[j]))

e(0, 2, 'gold'); e(2, 4); e(3, -2, 'springgreen'); e(-2, 4, 'orange'); e(4, -1) ; e(1,
↪ -1, 'dodgerblue')

SVG(graph.create_svg())
```

```
<IPython.core.display.SVG object>
```

CHAPTER

FOURTEEN

DIRECTED ACYCLICAL GRAPHS (DAG)

We can represent almost any computation without loops as DAG. What this allows us to do is now break down a computation into pieces which can be carried out independently. There are a number of tools which let us handle this issue.

- PyData Dask - https://dask.pydata.org/en/latest/
- Apache Spark - https://spark.apache.org/
- Spotify Luigi - https://github.com/spotify/luigi
- Airflow - https://airflow.apache.org/
- KNIME - https://www.knime.com/
- Google Tensorflow - https://www.tensorflow.org/
- Pytorch / Torch - http://pytorch.org/

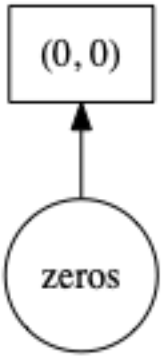
CHAPTER

FIFTEEN

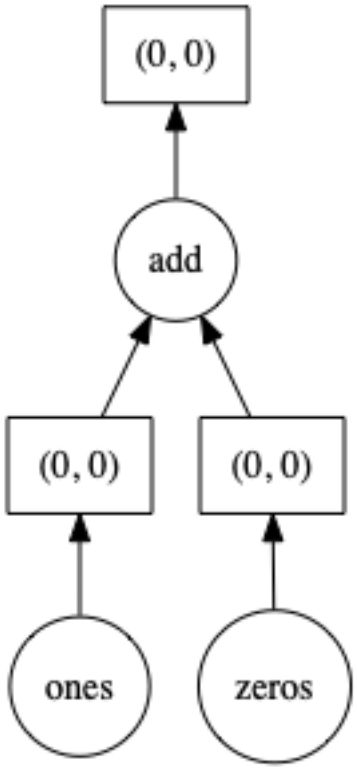
CONCRETE EXAMPLE

What is a DAG good for?

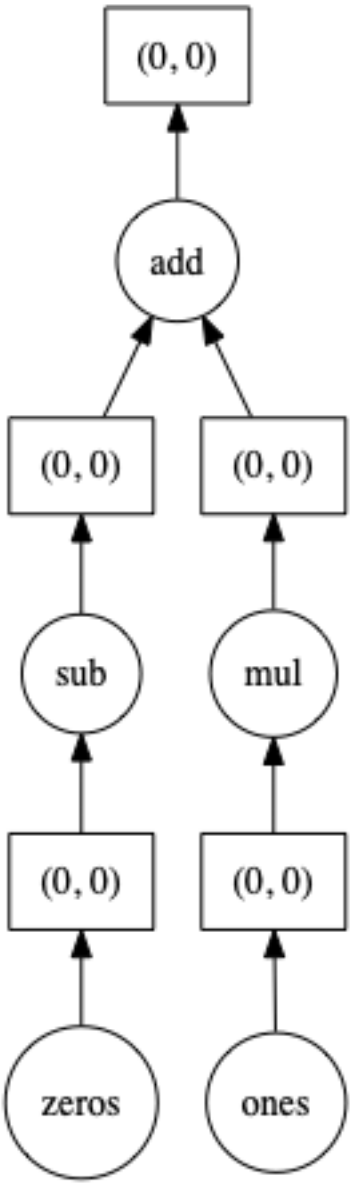
```
import dask.array as da

from dask.dot import dot_graph
image_1 = da.zeros((5,5), chunks = (5,5))
image_2 = da.ones((5,5), chunks = (5,5))
dot_graph(image_1.dask)
```




```
image_3 = image_1 + image_2
dot_graph(image_3.dask)
```




```
image_4 = (image_1-10) + (image_2*50)
dot_graph(image_4.dask)
```


(0, 0)
add
(0, 0)
(0, 0)
sub
mul
(0, 0)
(0, 0)
zeros
ones

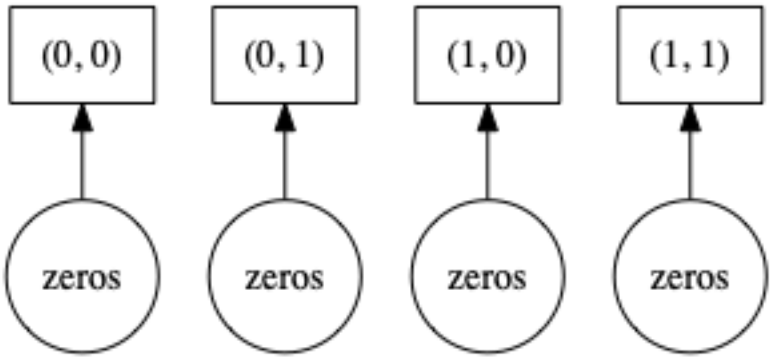
CHAPTER

SIXTEEN

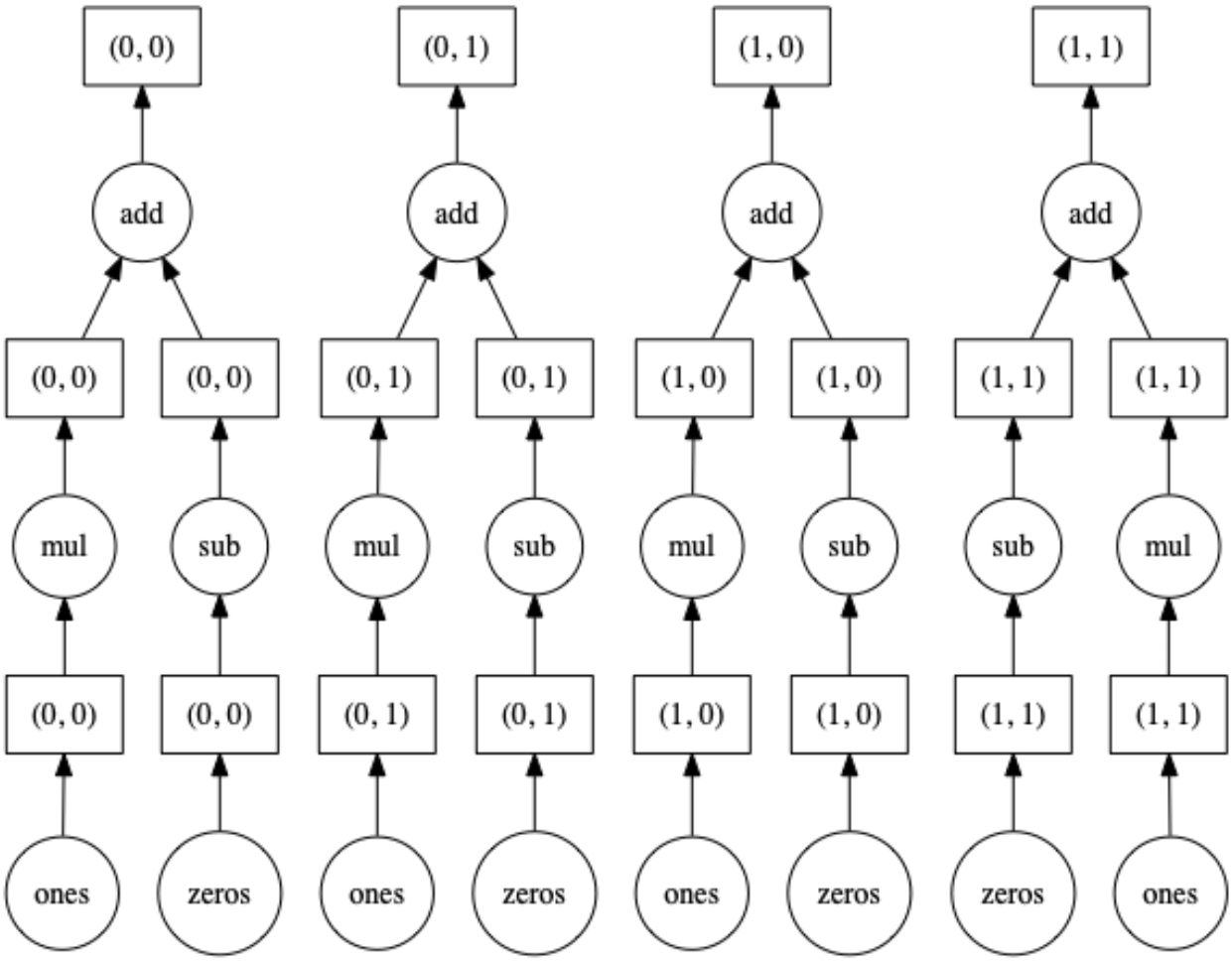
LET'S GO BIG

Now let's see where this can be really useful

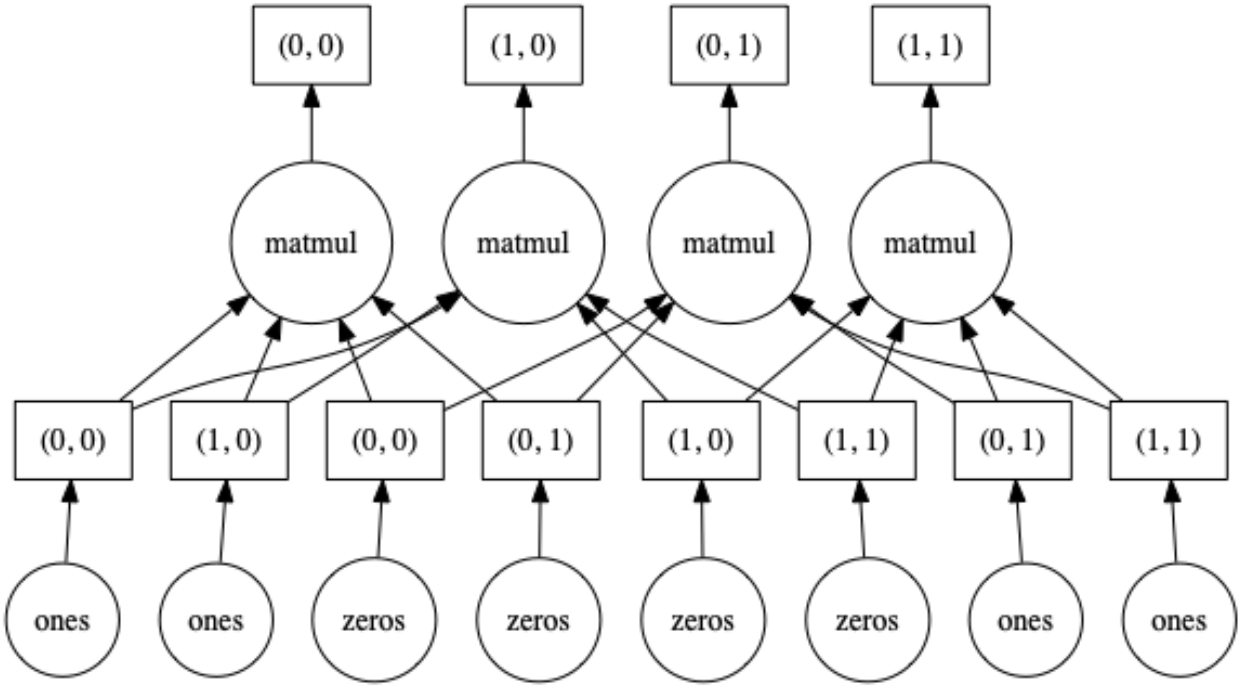
```
import dask.array as da
from dask.dot import dot_graph
image_1 = da.zeros((1024, 1024), chunks = (512, 512))
image_2 = da.ones((1024 ,1024), chunks = (512, 512))
dot_graph(image_1.dask)
```



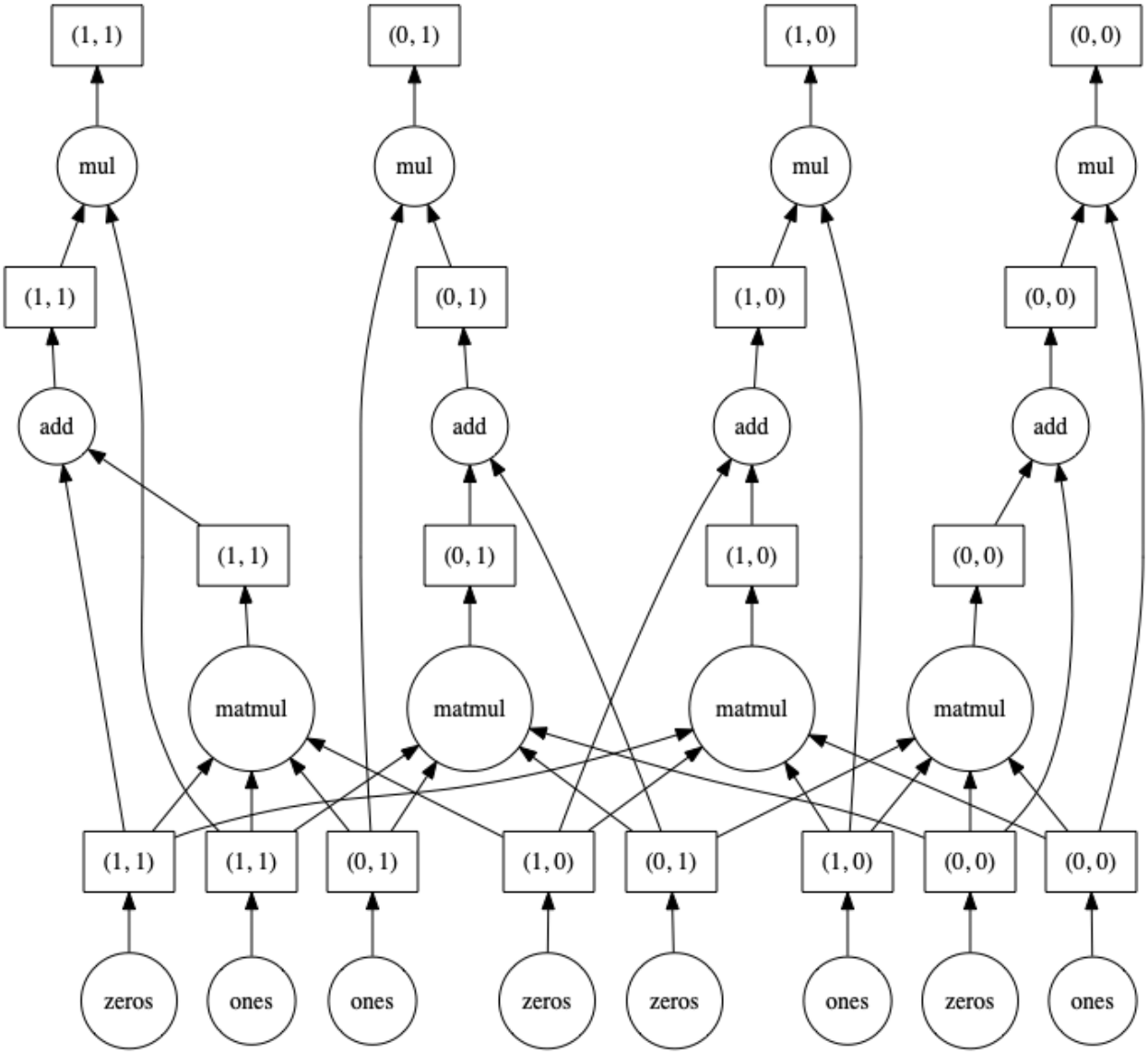

```
image_4 = (image_1-10) + (image_2*50)
dot_graph(image_4.dask)
```



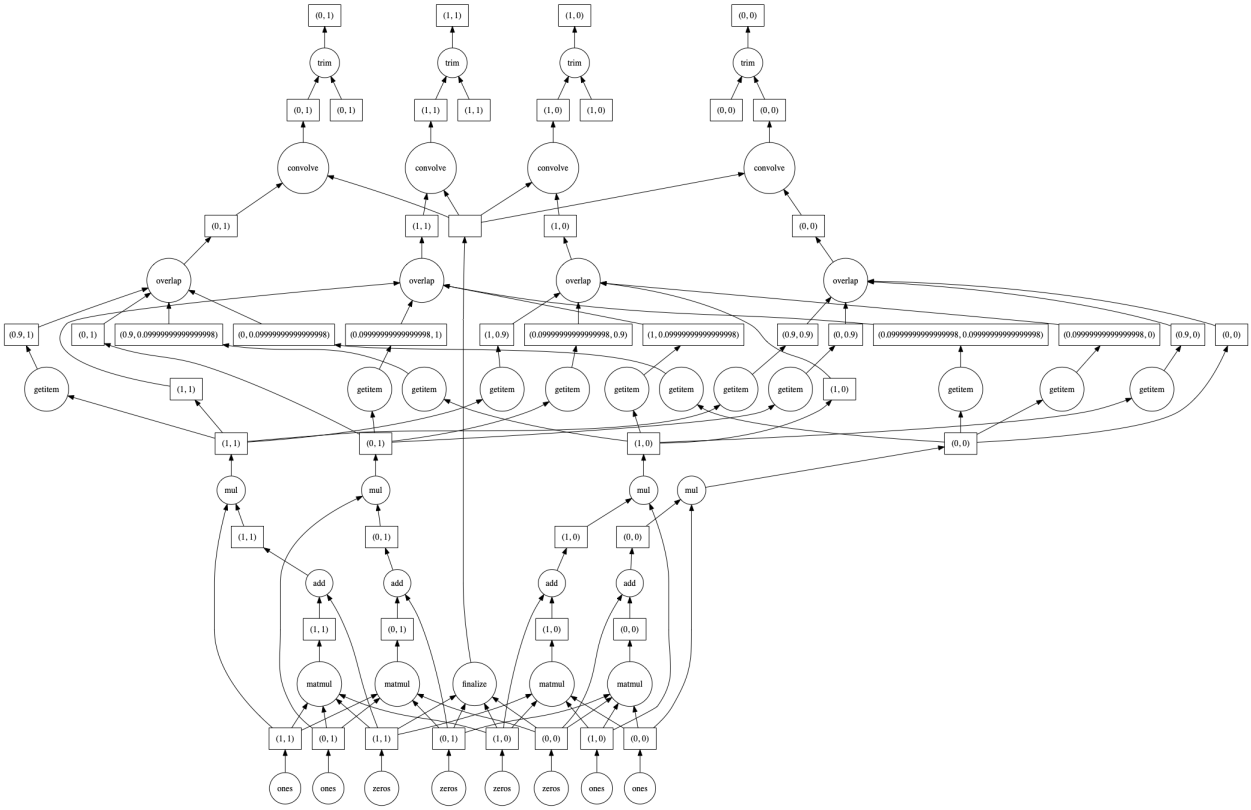

```
image_5 = da.matmul(image_1, image_2)
dot_graph(image_5.dask)
```




```
image_6 = (da.matmul(image_1, image_2)+image_1)*image_2
dot_graph(image_6.dask)
```




```
import dask_ndfilters as da_ndfilt
image_7 = da_ndfilt.convolve(image_6, image_1)
dot_graph(image_7.dask)
```


(0, 1)
(1, 1)
(1, 0)
(0, 0)
trim
convolve
overlap
getitem
mul
add
matmul
finalize
ones
zeros
(0.9, 1)
(0.9, 0.0999999999999998)
(0, 0.0999999999999998)
(0.0999999999999998, 1)
(1, 0.9)
(0.0999999999999998, 0.9)
(1, 0.0999999999999998)
(0.9, 0.9)
(0, 0.9)
(0.0999999999999998, 0.0999999999999998)
(0.0999999999999998, 0)
(0.9, 0)
(0, 0)

CHAPTER

SEVENTEEN

DEEP LEARNING

We won't talk too much about deep learning now, but it certainly shows why DAGs are so important.

The steps above are simple toys compared to what tools are already in use for machine learning

https://keras.io/api/utils/model_plotting_utils/

```
from IPython.display import SVG
from keras.applications.resnet50 import ResNet50
from keras.utils.vis_utils import model_to_dot
resnet = ResNet50(weights = None)
SVG(model_to_dot(resnet,rankdir="LR",).create_svg())
```

```
<IPython.core.display.SVG object>
```

```
from IPython.display import clear_output, Image, display, HTML
#import keras.backend as K
import tensorflow.python.keras.backend as K
import tensorflow as tf
import numpy as np
def strip_consts(graph_def, max_const_size=32):
    """Strip large constant values from graph_def."""
    strip_def = tf.GraphDef()
    for n0 in graph_def.node:
        n = strip_def.node.add()
        n.MergeFrom(n0)
        if n.op == 'Const':
            tensor = n.attr['value'].tensor
            size = len(tensor.tensor_content)
            if size > max_const_size:
                tensor.tensor_content = ("<stripped %d bytes>"%size).encode('ascii')
    return strip_def

def show_graph(graph_def, max_const_size=32):
    """Visualize TensorFlow graph."""
    if hasattr(graph_def, 'as_graph_def'):
        graph_def = graph_def.as_graph_def()
    strip_def = strip_consts(graph_def, max_const_size=max_const_size)
    code = """
        <script>
          function load() {{
            document.getElementById("{id}").pbtxt = {data};
          }}
        </script>
        <link rel="import" href="https://tensorboard.appspot.com/tf-graph-basic.build.
↪html" onload=load()>
```

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```
        <div style="height:600px">
          <tf-graph-basic id="{id}"></tf-graph-basic>
        </div>
    """.format(data=repr(str(strip_def)), id='graph'+str(np.random.rand()))

    iframe = """
        <iframe seamless style="width:1200px;height:620px;border:0" srcdoc="{}"></
↪iframe>
    """.format(code.replace('"', '&quot;'))
    display(HTML(iframe))

sess = K.get_session()
show_graph(sess.graph)
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-75-f9fa486b2250> in <module>
     40
     41 sess = K.get_session()
---> 42 show_graph(sess.graph)

<ipython-input-75-f9fa486b2250> in show_graph(graph_def, max_const_size)
     21     if hasattr(graph_def, 'as_graph_def'):
     22         graph_def = graph_def.as_graph_def()
---> 23     strip_def = strip_consts(graph_def, max_const_size=max_const_size)
     24     code = """
     25         <script>

<ipython-input-75-f9fa486b2250> in strip_consts(graph_def, max_const_size)
      6 def strip_consts(graph_def, max_const_size=32):
      7     """Strip large constant values from graph_def."""
----> 8     strip_def = tf.GraphDef()
      9     for n0 in graph_def.node:
     10         n = strip_def.node.add()

AttributeError: module 'tensorflow' has no attribute 'GraphDef'
```