

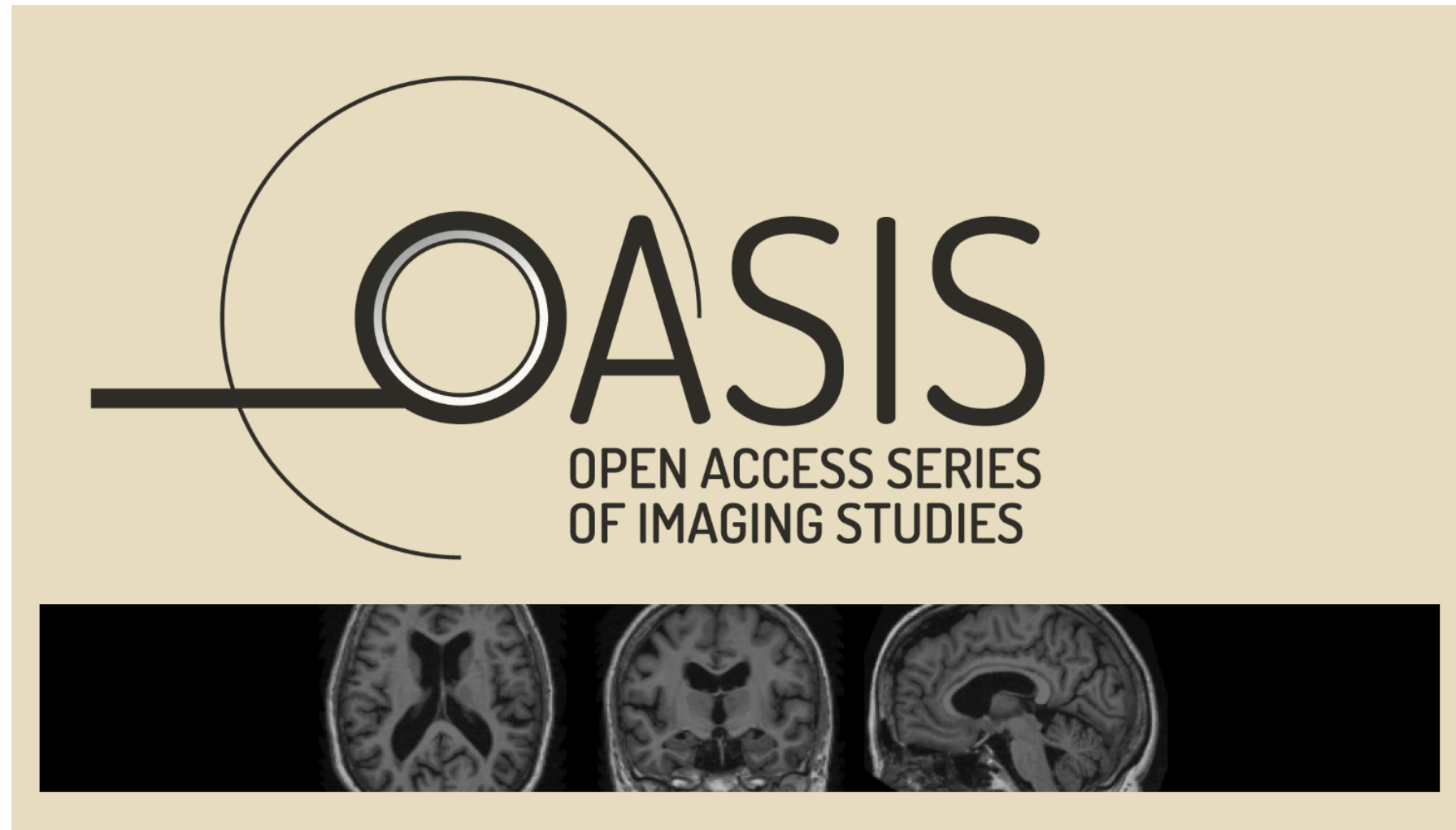


BIOMEDICAL IMAGE ANALYSIS IN PYTHON

# Spatial Transformation

Stephen Bailey  
Instructor

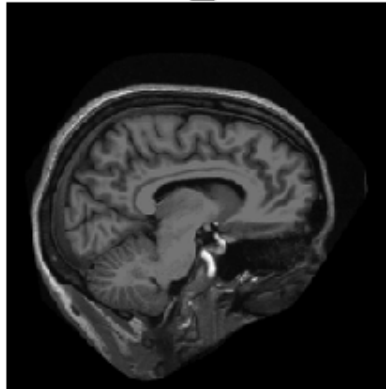
# OASIS Database



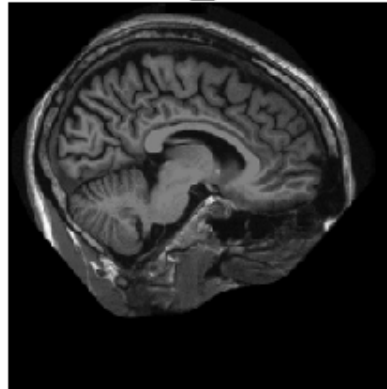


# Significant variability

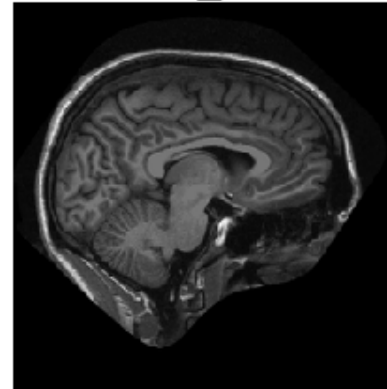
OAS1\_0058



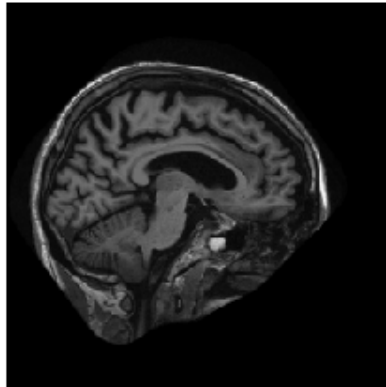
OAS1\_0069



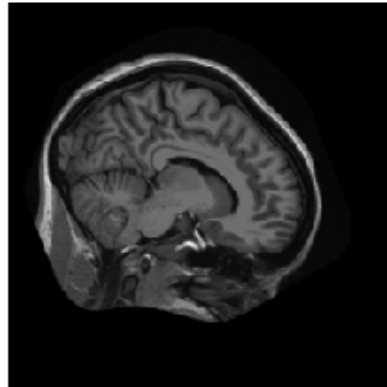
OAS1\_0144



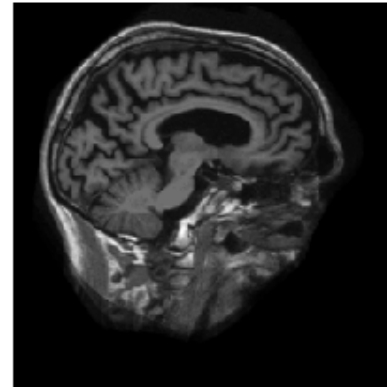
OAS1\_0226



OAS1\_0249

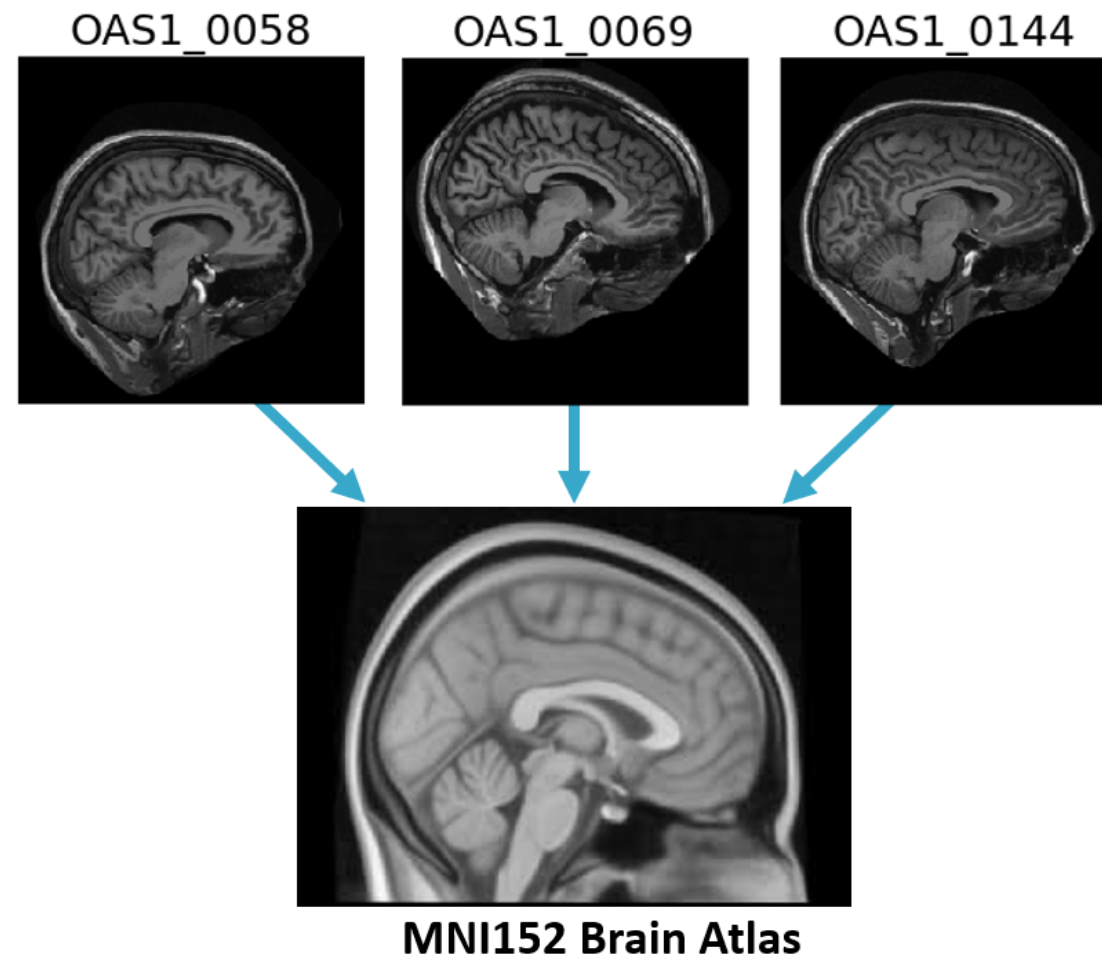


OAS1\_0351



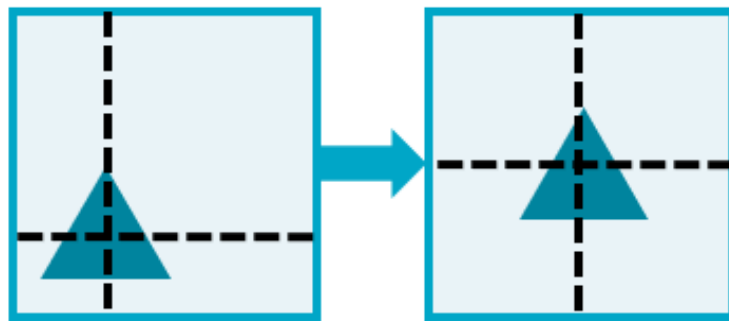
# Registration

- Align images to template
- Minimize spatial variability
- Templates:
  - may represent multiple subjects
  - may be an "average" image
- Entails many spatial transformations

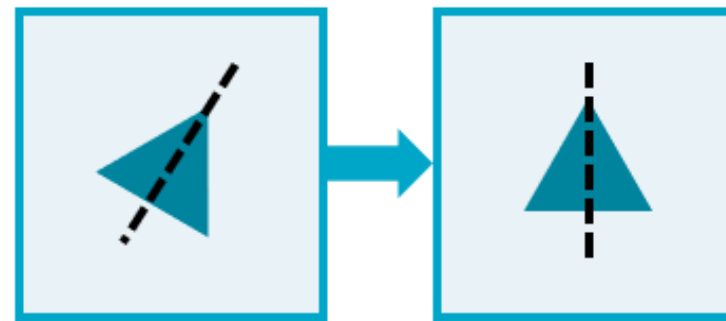


# Affine transformations preserve points, lines, and planes

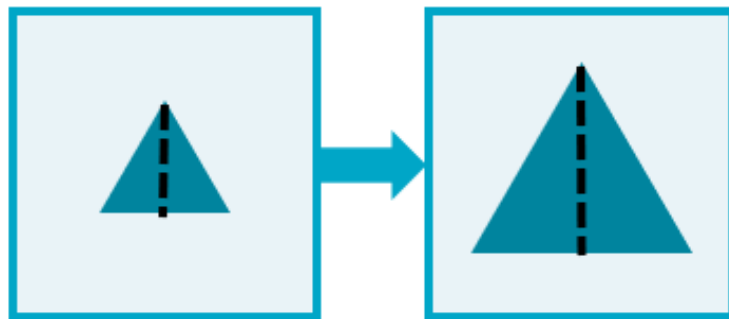
Translate



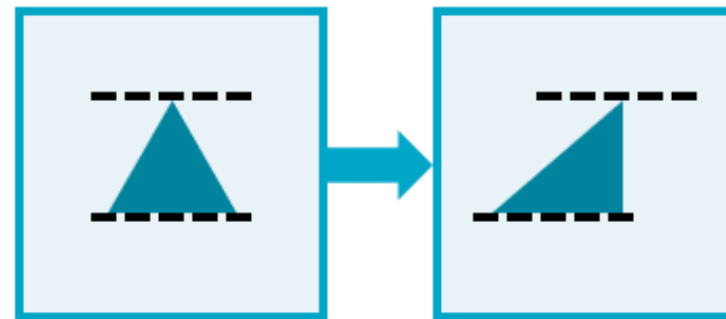
Rotate



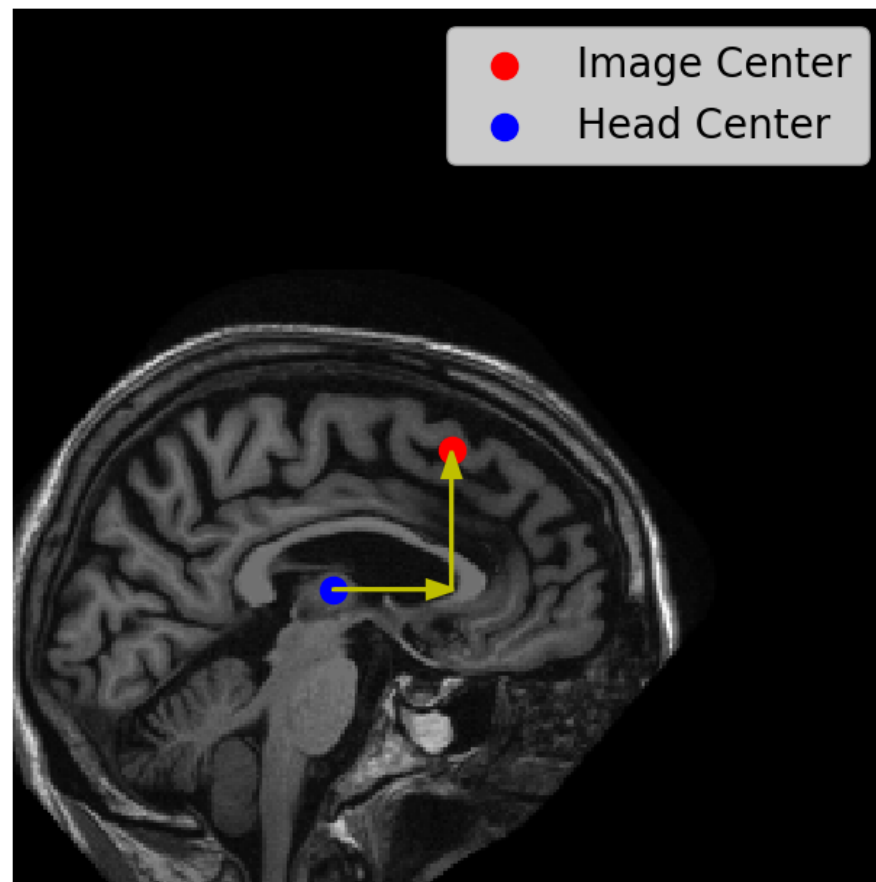
Scale



Shear



# Translation



```
import imageio
import scipy.ndimage as ndi

im=imageio.imread('0AS1036-2d.dcm')
im.shape
(256, 256)

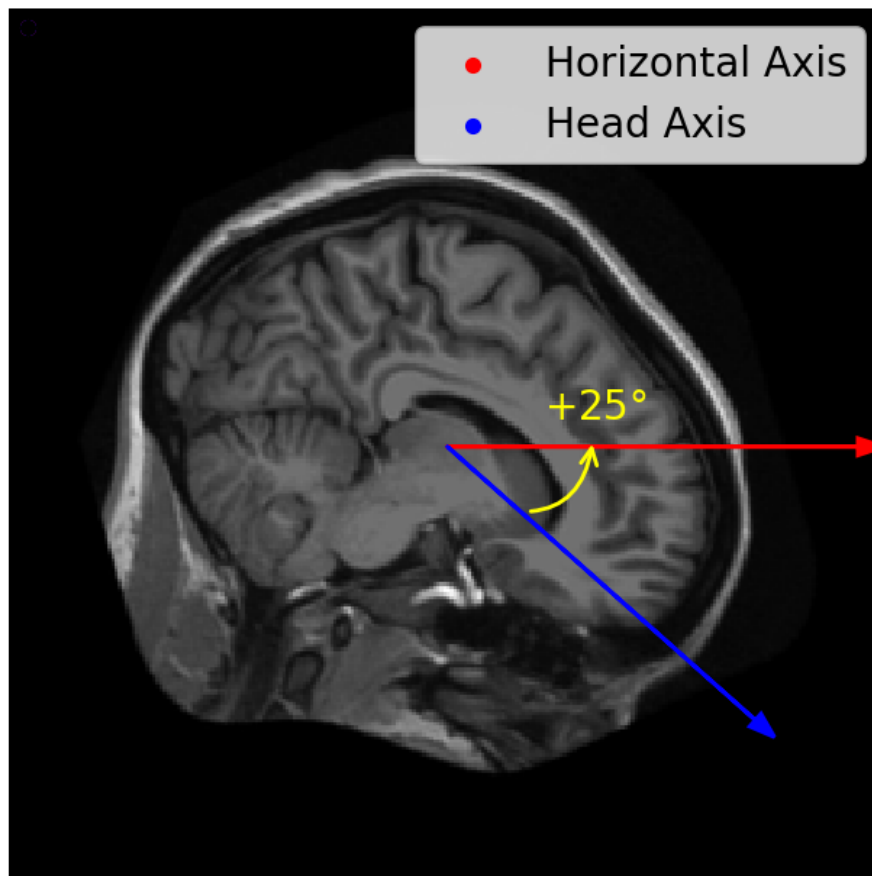
com = ndi.center_of_mass(im)

d0 = 128 - com[0]
d1 = 128 - com[1]

xfm = ndi.shift(im, shift=[d0, d1])
```

# Rotation

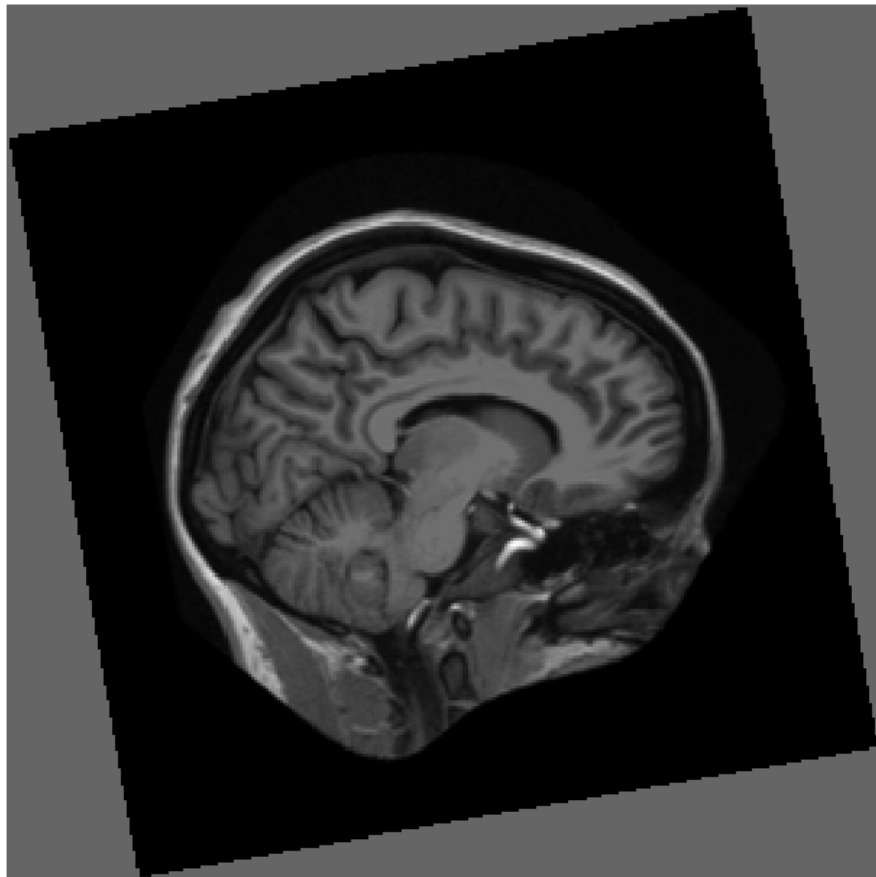
```
ndi.rotate(im,  
           angle=25,  
           axes=(0,1))
```



# Image rotation

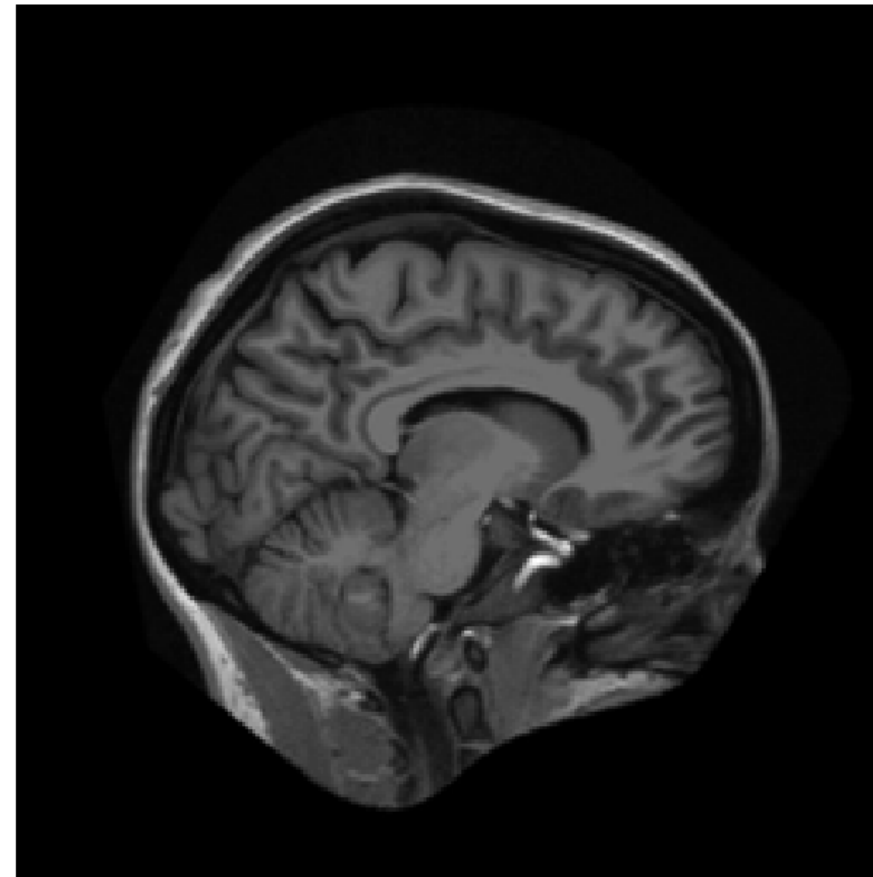
```
xfm = ndi.rotate(im, angle=25)
```

```
xfm.shape  
(297, 297)
```



```
xfm = ndi.rotate(im, angle=25,  
                  reshape=False)
```

```
xfm.shape  
(256, 256)
```







# Transformation matrix

**Transformation matrix:** applied to one image for registration.

Elements of the matrix encode "instructions" for different affine transformations.

Translation

$$\begin{bmatrix} 1 & 0 & T_x \\ 0 & 1 & T_y \\ 0 & 0 & 1 \end{bmatrix}$$

Rotation

$$\begin{bmatrix} \cos(\Theta) & -\sin(\Theta) & 0 \\ \sin(\Theta) & \cos(\Theta) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Scale

$$\begin{bmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Shear

$$\begin{bmatrix} 1 & Sh_x & 0 \\ Sh_y & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

# Applying a transformation matrix

```
# Identity matrix
mat = [[1, 0, 0],
       [0, 1, 0],
       [0, 0, 1]]

xfm = ndi.affine_transform(im, mat)
```

```
# Translate and rescale
mat = [[0.8, 0, -20],
       [0, 0.8, -10],
       [0, 0, 1]]

xfm = ndi.affine_transform(im, mat)
```

Translate

$$\begin{bmatrix} 1 & 0 & T_x \\ 0 & 1 & T_y \\ 0 & 0 & 1 \end{bmatrix}$$

Rotate

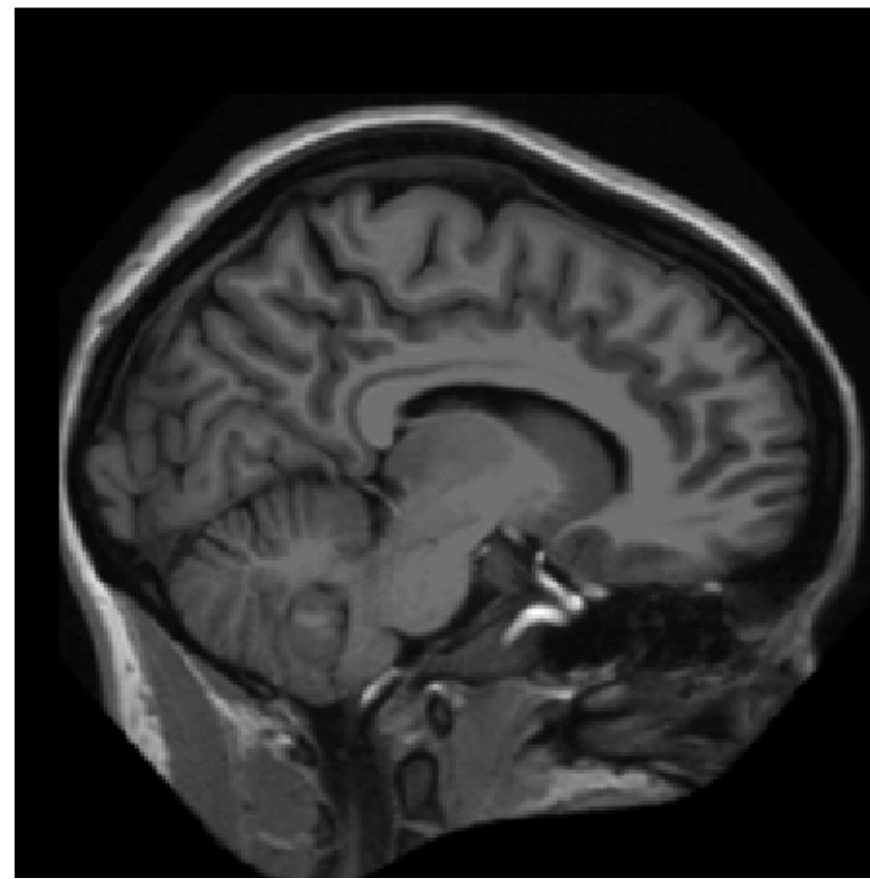
$$\begin{bmatrix} \cos(\Theta) & -\sin(\Theta) & 0 \\ \sin(\Theta) & \cos(\Theta) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Scale

$$\begin{bmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Shear

$$\begin{bmatrix} 1 & Sh_x & 0 \\ Sh_y & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$





## BIOMEDICAL IMAGE ANALYSIS IN PYTHON

**Let's practice!**

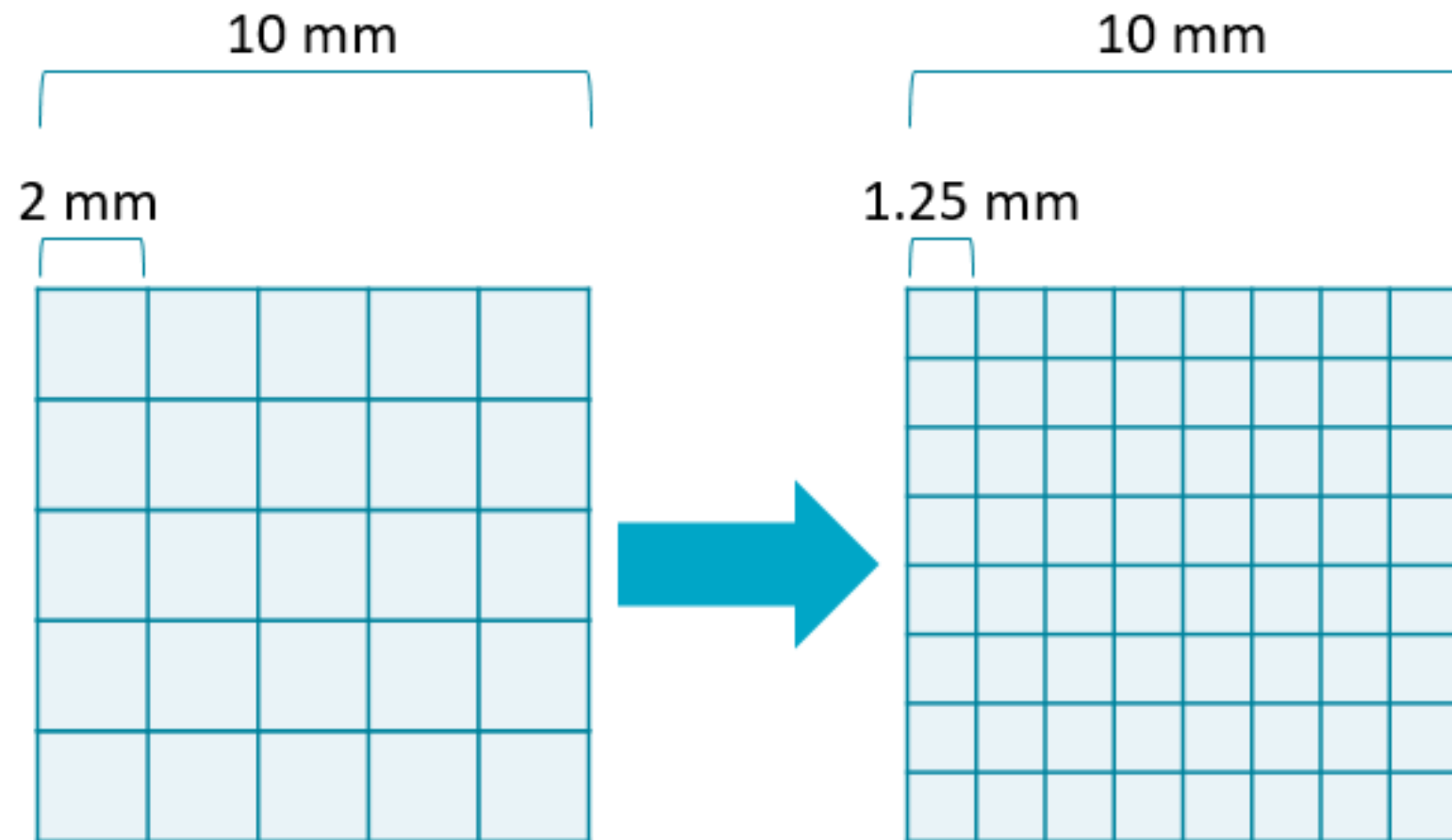


BIOMEDICAL IMAGE ANALYSIS IN PYTHON

# Resampling and Interpolation

Stephen Bailey  
Instructor

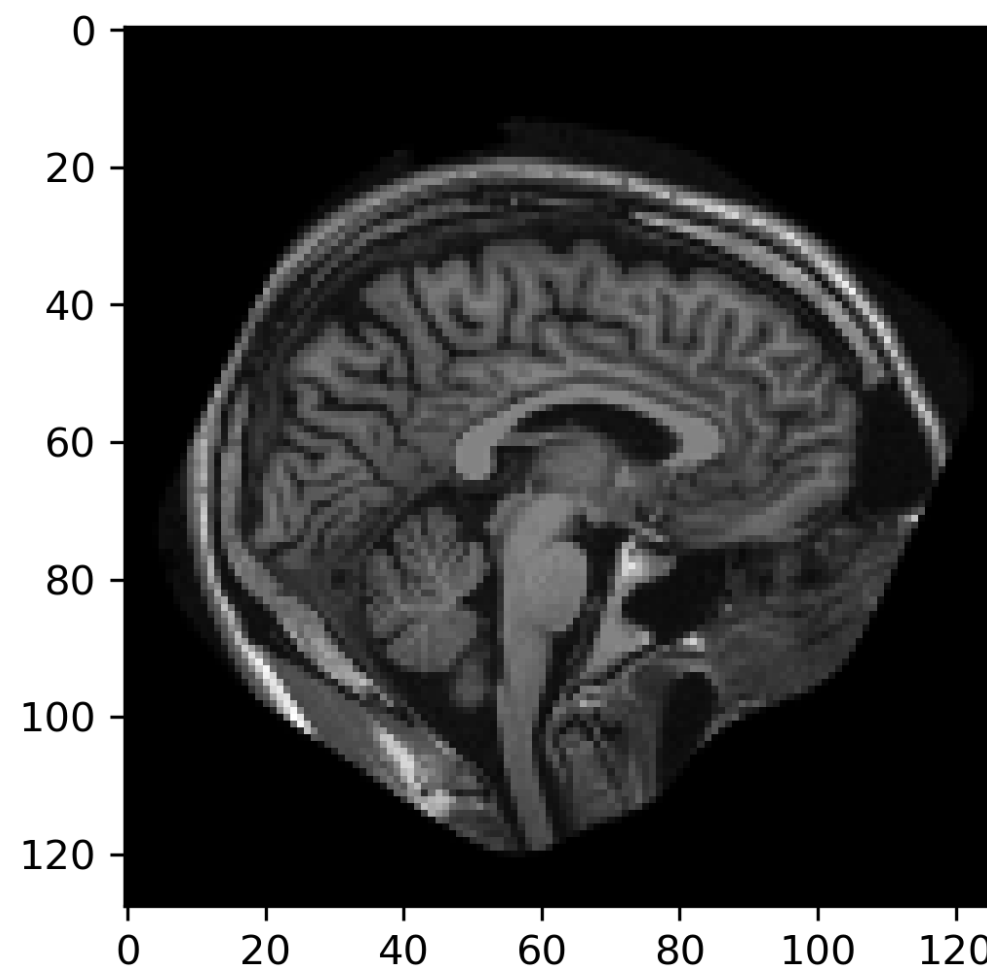
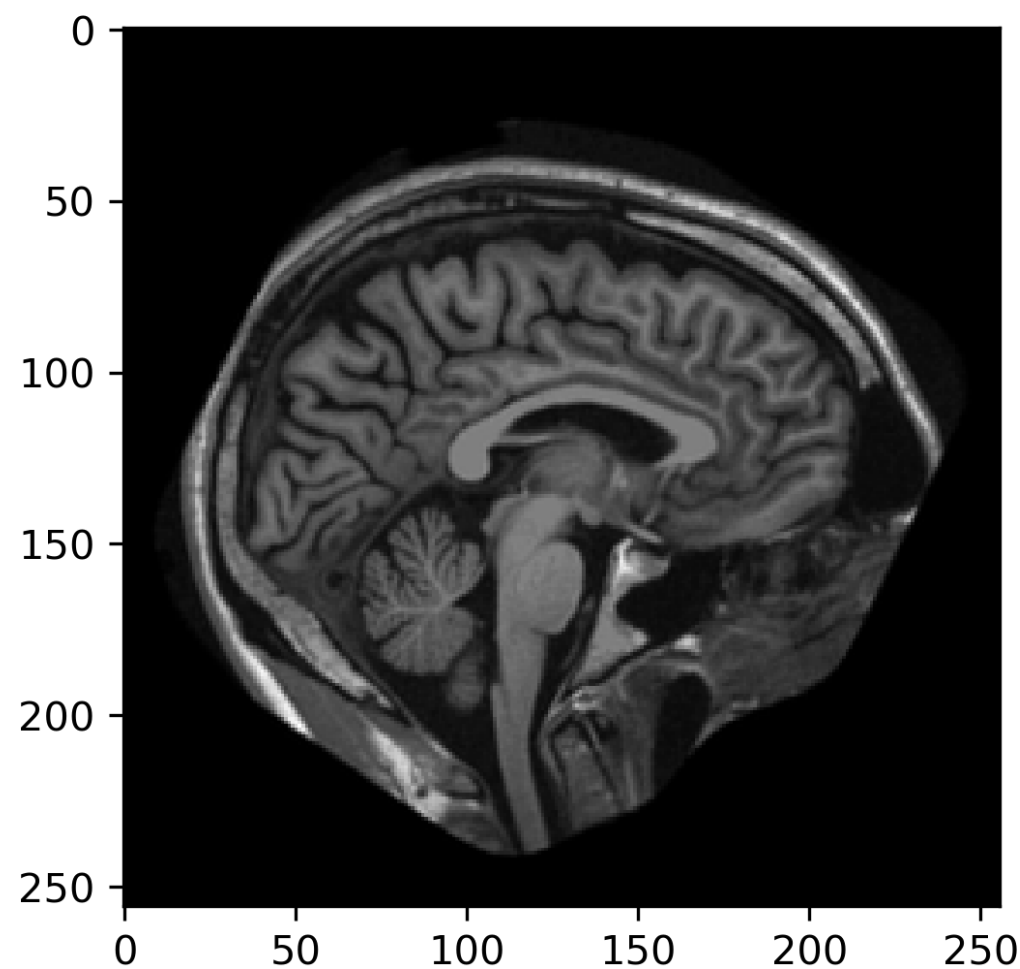
# Resampling changes the array shape



# Downsampling

```
vol = imageio.volread('0AS1_0255')
vol.shape
(256, 256, 256)
```

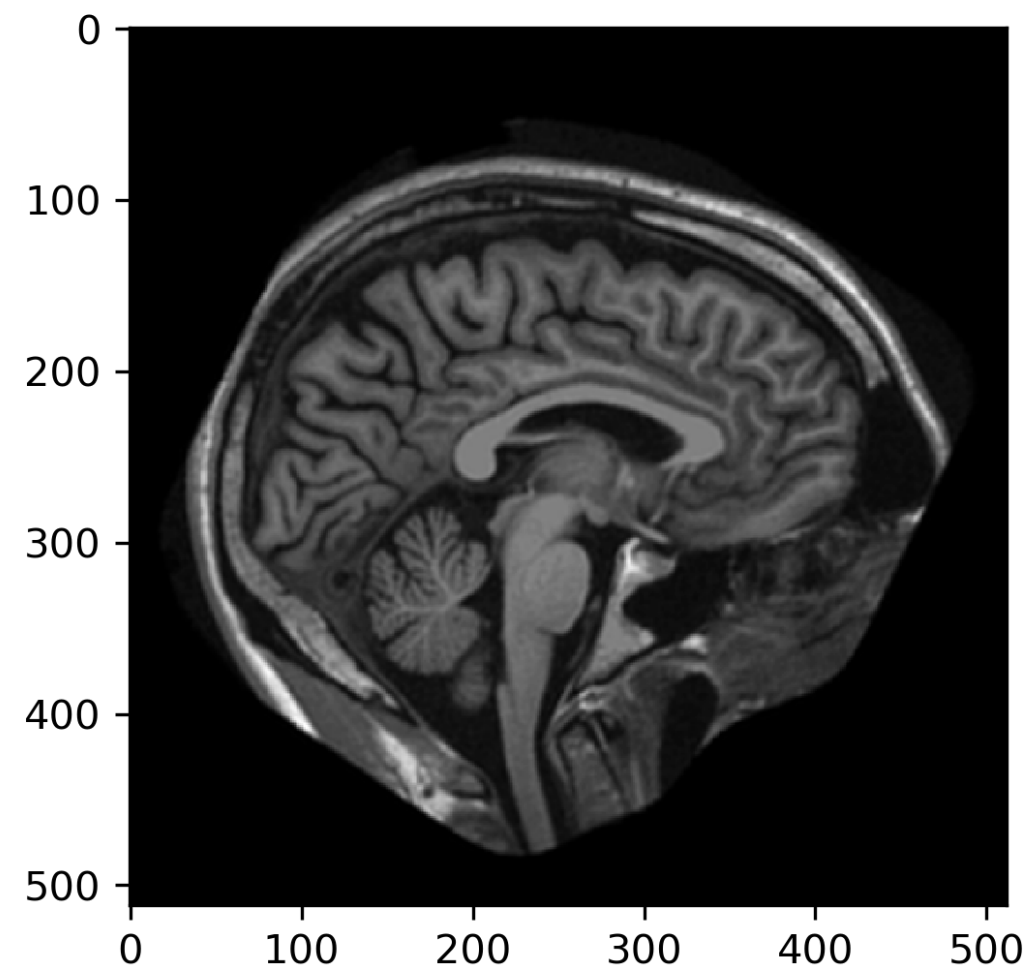
```
vol_dn = ndi.zoom(vol, zoom=0.5)
vol_dn.shape
(128, 128, 128)
```



# Upsampling

- Resampling to a larger grid
- Not the same as collecting higher-resolution data
- Useful for standardizing sampling rates that are unequal

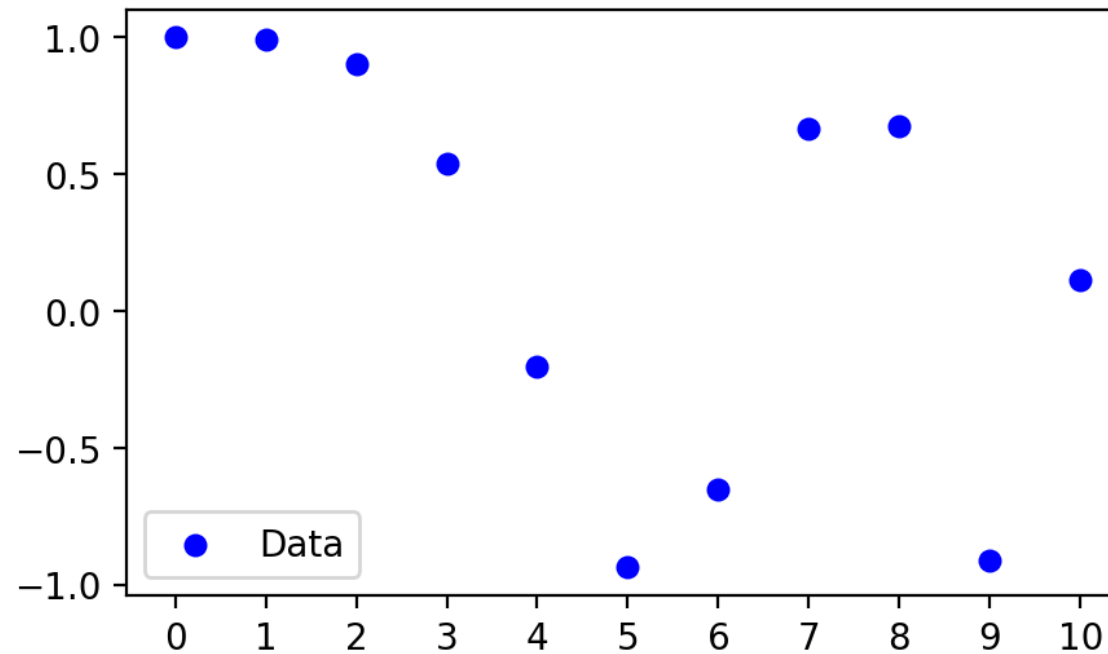
```
vol_up = ndi.zoom(vol, zoom=2)
vol_up.shape
(512, 512, 512)
```



# Interpolation

- "Stitches together" grid points to model the space between points.

*Interpolation in 1 Dimension*

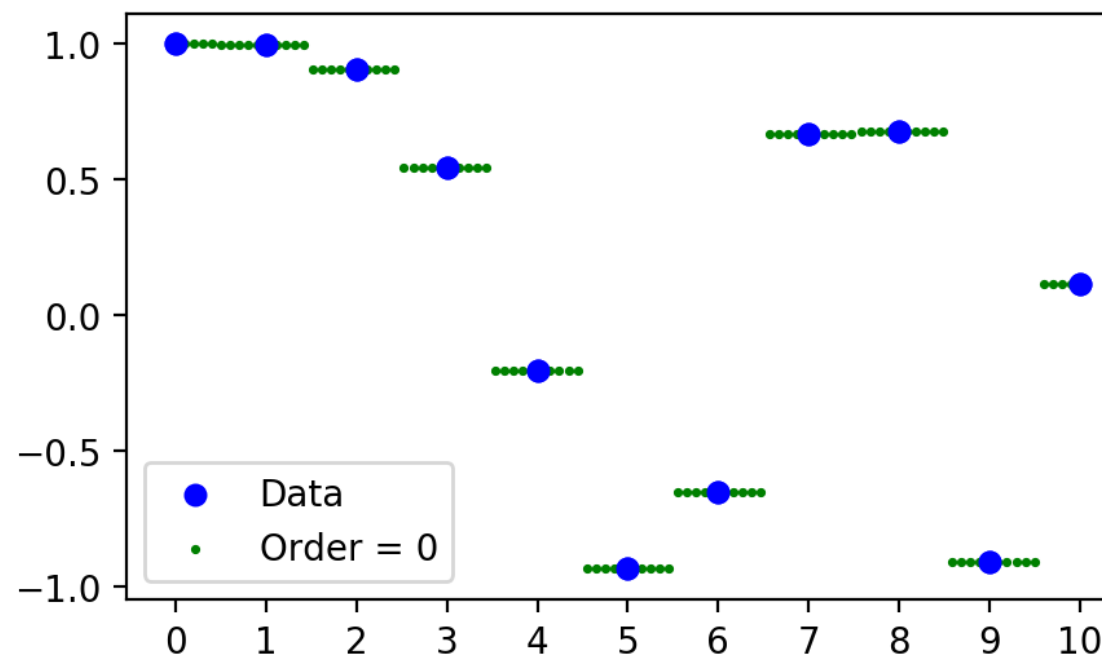




# Interpolation

- "Stitches together" grid points to model the space between points.
- **Nearest-neighbor**: uses the closest measured value.

*Interpolation in 1 Dimension*

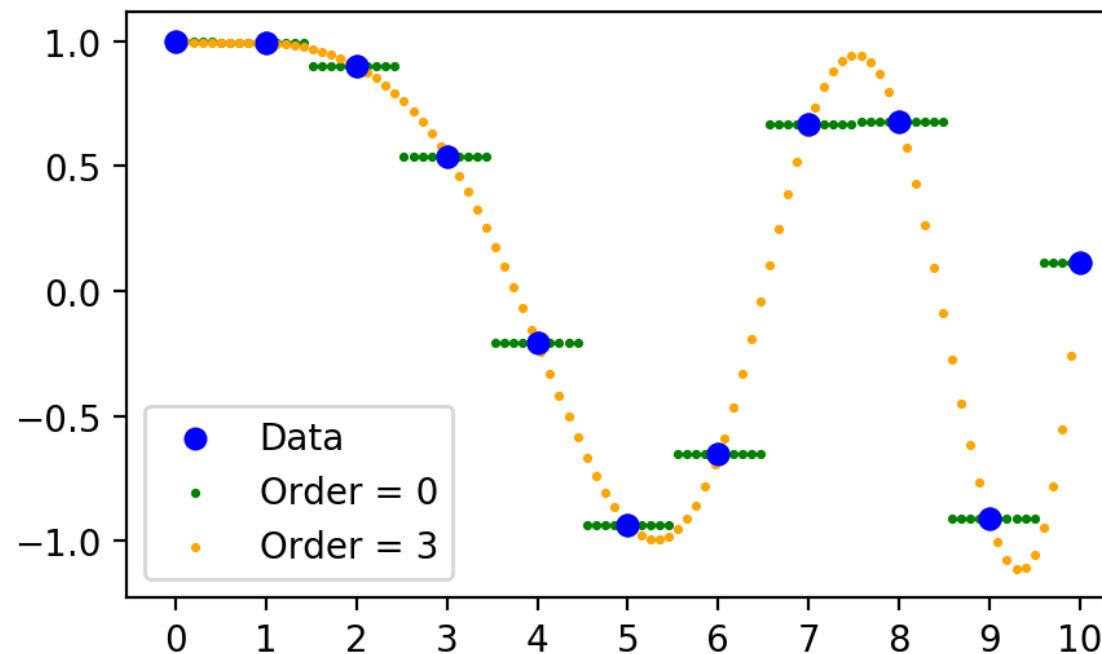




# Interpolation

- "Stitches together" grid points to model the space between points.
- **Nearest-neighbor**: uses the closest measured value.
  - `order = 0`
- **B-spline interpolation**: models space between points with spline functions of a specified order.
  - `order` is between 1 and 5

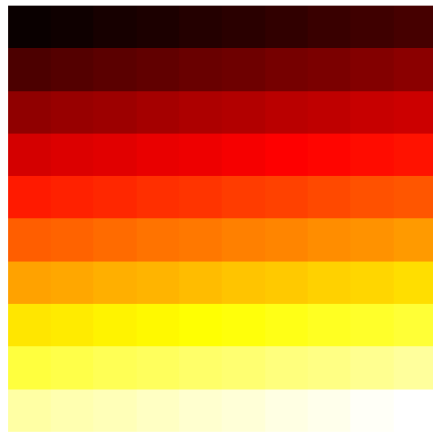
*Interpolation in 1 Dimension*



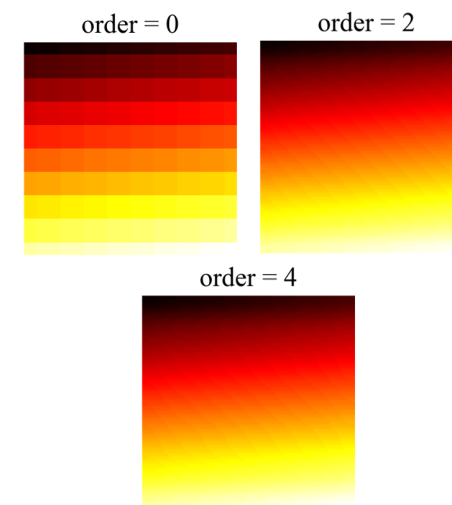


# Interpolation in 2D

```
im=np.arange(100).reshape([10,10])
```



```
zm1=ndi.zoom(im, zoom=10, order=0)  
zm2=ndi.zoom(im, zoom=10, order=2)  
zm3=ndi.zoom(im, zoom=10, order=4)
```





## BIOMEDICAL IMAGE ANALYSIS IN PYTHON

**Let's practice!**



BIOMEDICAL IMAGE ANALYSIS IN PYTHON

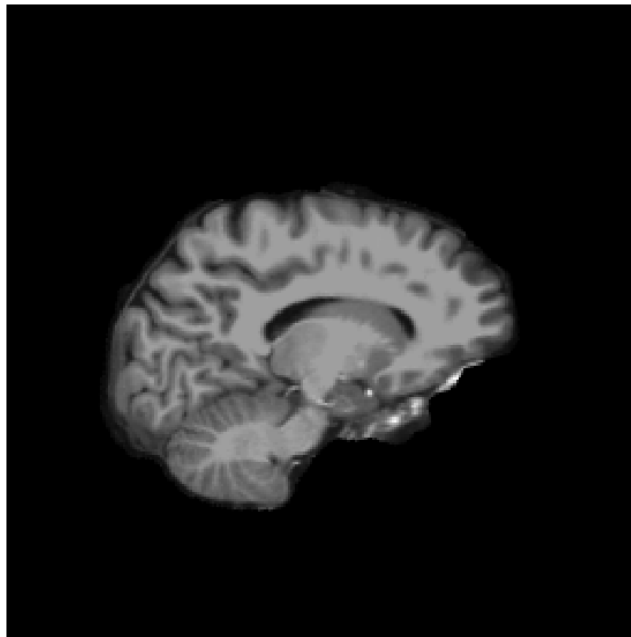
# Comparing Images

Stephen Bailey  
Instructor

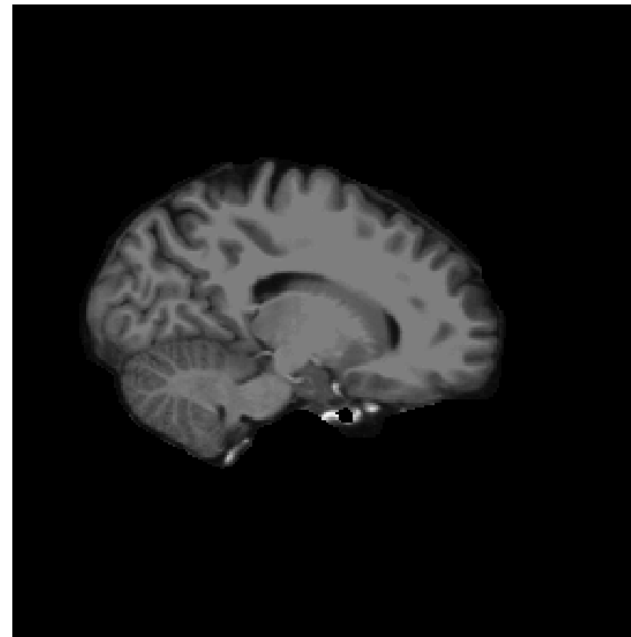


# Comparing images

Visit 1



Visit 2



Mask Overlay





# Summary metrics

Goal: *define* a metric of similarity between two images.

**Cost functions** produce metrics to be minimized.

**Objective functions** produce metrics to be maximized.

# Mean absolute error

```
import imageio
import numpy as np

i1=imageio.imread('OAS1035-v1.dcm')
i2=imageio.imread('OAS1035-v2.dcm')

err = i1 - i2

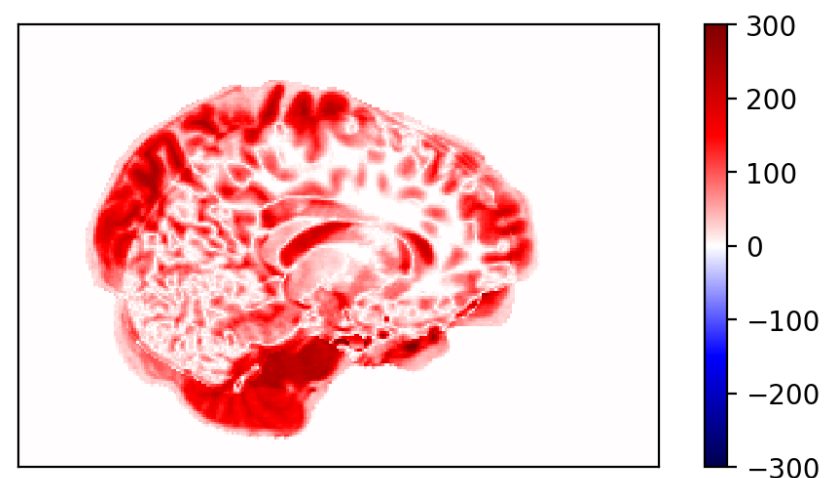
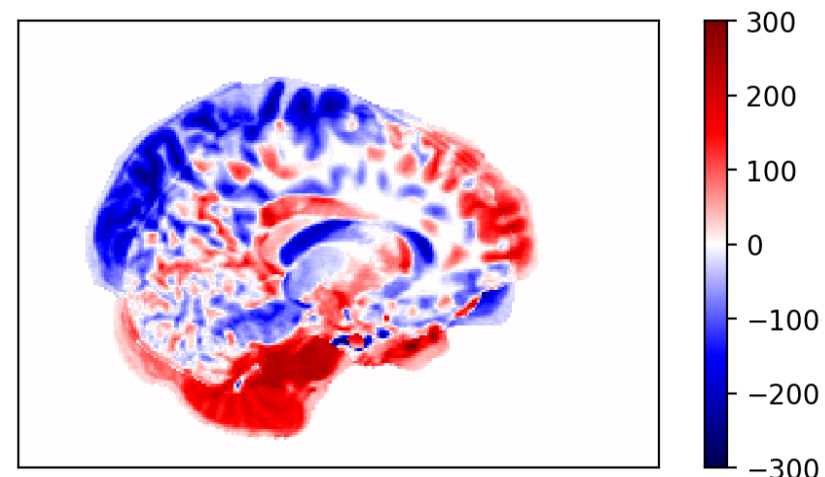
plt.imshow(err)

abs_err = np.abs(err)

plt.imshow(abs_err)

mae = np.mean(abs_err)

mae
29.8570
```





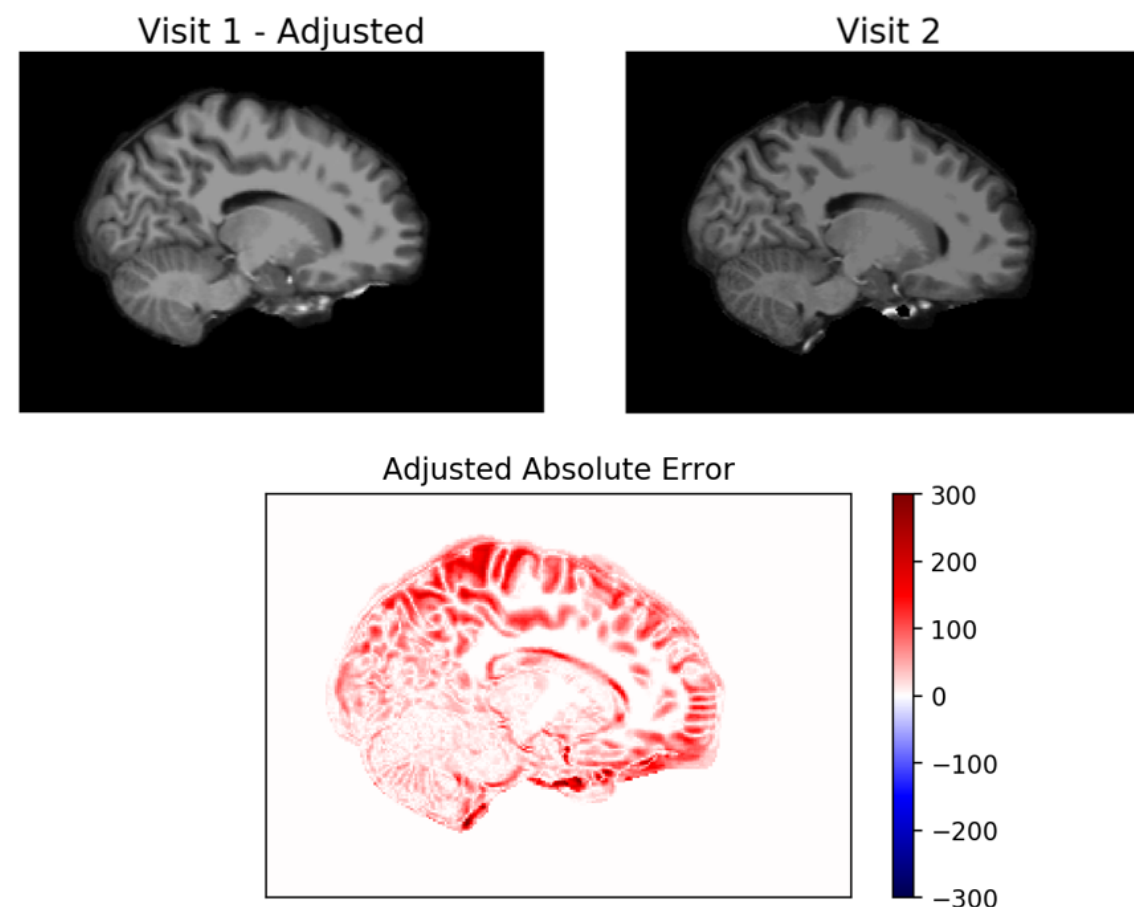
# Mean absolute error

Goal: *minimize* the cost function

```
# Improve im1 alignment to im2
xfm=ndi.shift(im1, shift=(-8, -8))
xfm=ndi.rotate(xfm, -18,
               reshape=False)
```

```
# Calculate cost
abs_err = np.abs(im1 - im2)
mean_abs_err = np.mean(abs_err)
```

```
mean_abs_err
13.0376
```



# Intersection of the Union

$$IOU = \frac{I_1 \cap I_2}{I_1 \cup I_2}$$

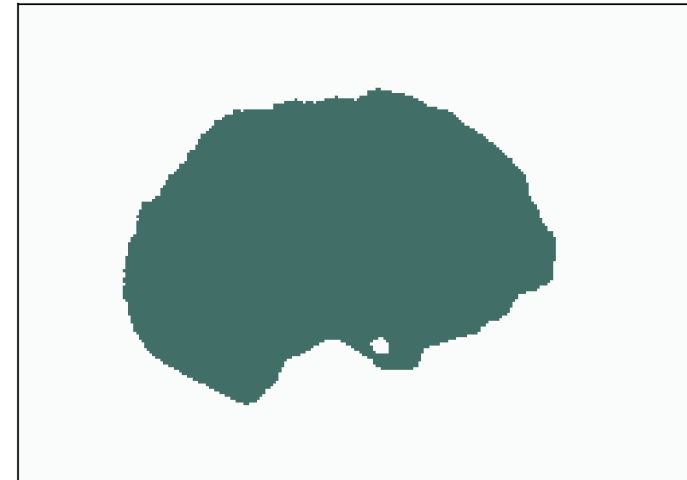
```
mask1 = im1 > 0
mask2 = im2 > 0

intsn = mask1 & mask2
plt.imshow(intsn)

union = mask1 | mask2
plt.imshow(union)

iou = intsn.sum() / union.sum()

iou
0.68392
```





## BIOMEDICAL IMAGE ANALYSIS IN PYTHON

**Let's practice!**



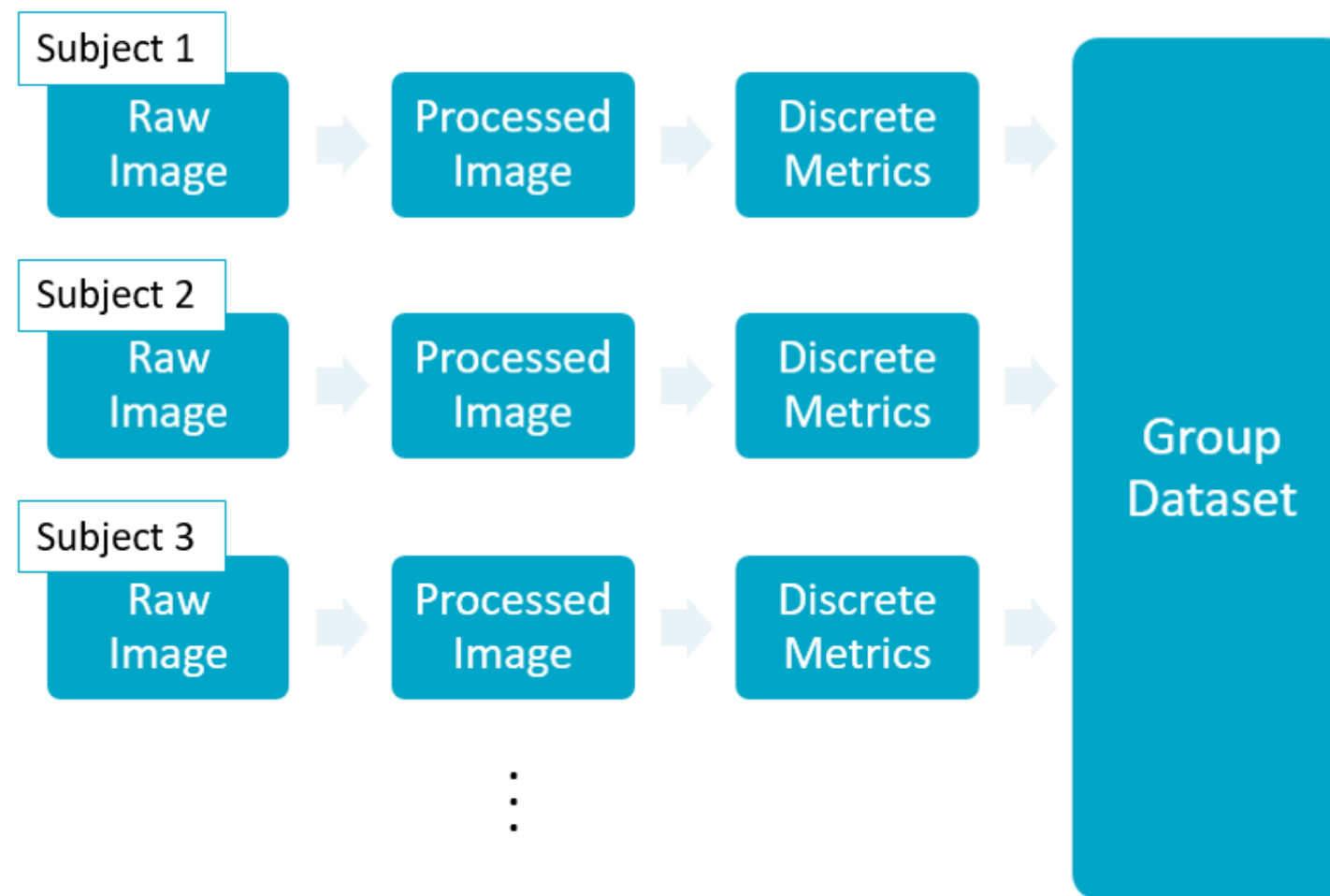
BIOMEDICAL IMAGE ANALYSIS IN PYTHON

# Normalizing Measurements

Stephen Bailey  
Instructor



# Analysis workflow





# OASIS Population

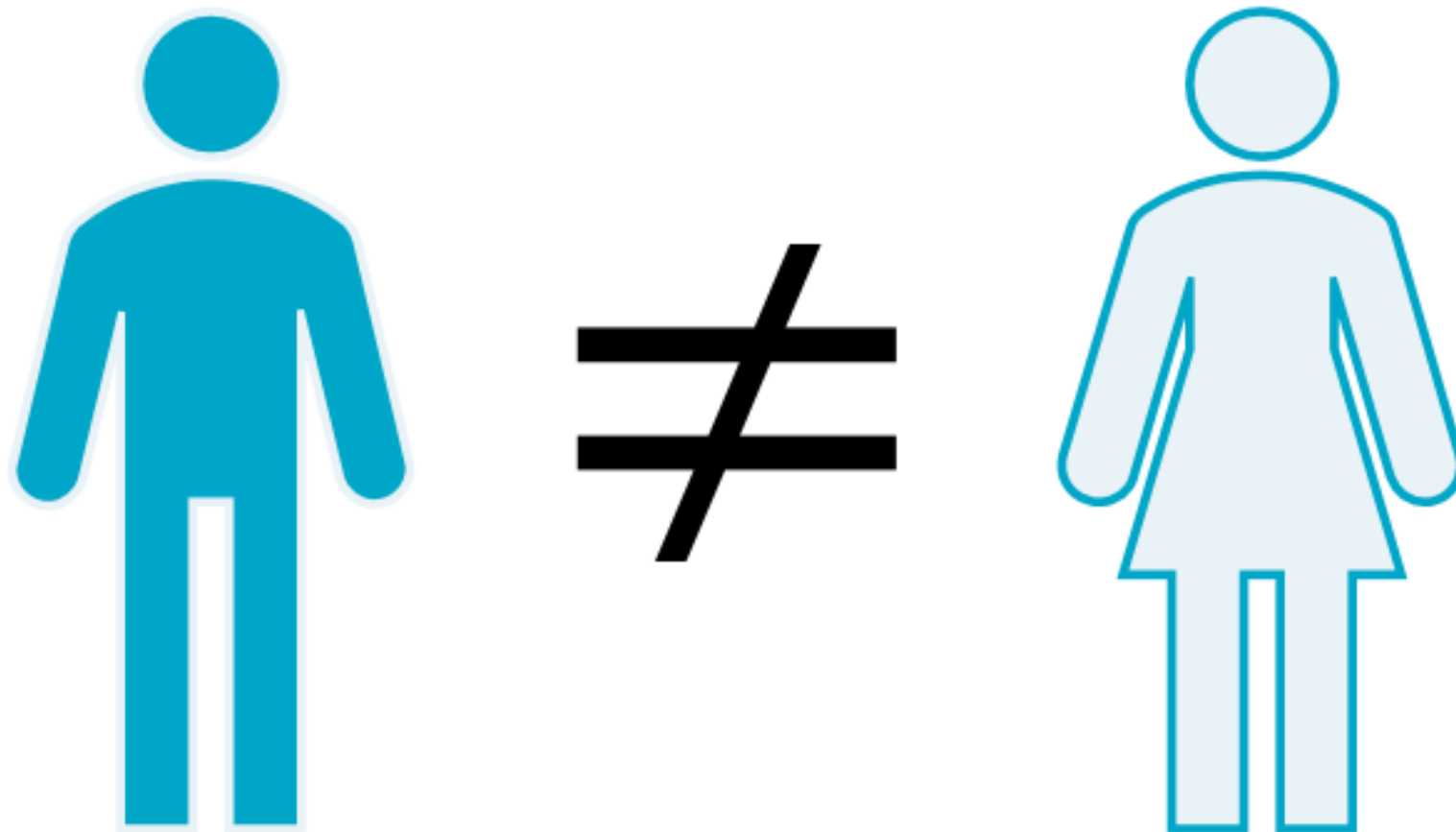
```
df.shape  
(400, 5)
```

```
df.sample(5)
```

ID	age	sex	alzheimers	brain_vol	skull_vol
OAS1_0272	75	F	True	851.451	1411.125695
OAS1_0112	69	F	False	894.801	1434.146892
OAS1_0213	48	F	False	925.859	1412.781004
OAS1_0311	22	F	False	980.163	1363.413762
OAS1_0201	85	F	False	904.104	1420.631447



# Hypothesis testing





# Hypothesis testing

**Null hypothesis:** two populations' mean brain volumes ( $\mu_m, \mu_w$ ) are equal.

$$H_{null} : \mu_w = \mu_m$$

$$H_{alt} : \mu_w \neq \mu_m$$

$$t = \frac{\bar{X} - \mu}{s / \sqrt{n}}$$

Implemented in `scipy.stats.ttest_ind()`





# Hypothesis testing

```
brain_m = df.loc[df.sex == 'M', 'brain_vol']  
brain_f = df.loc[df.sex == 'F', 'brain_vol']  
from scipy.stats import ttest_ind  
results = ttest_ind(brain_m, brain_f)
```

```
results.statistic  
10.20986  
  
results.pvalue  
5.03913e-22
```

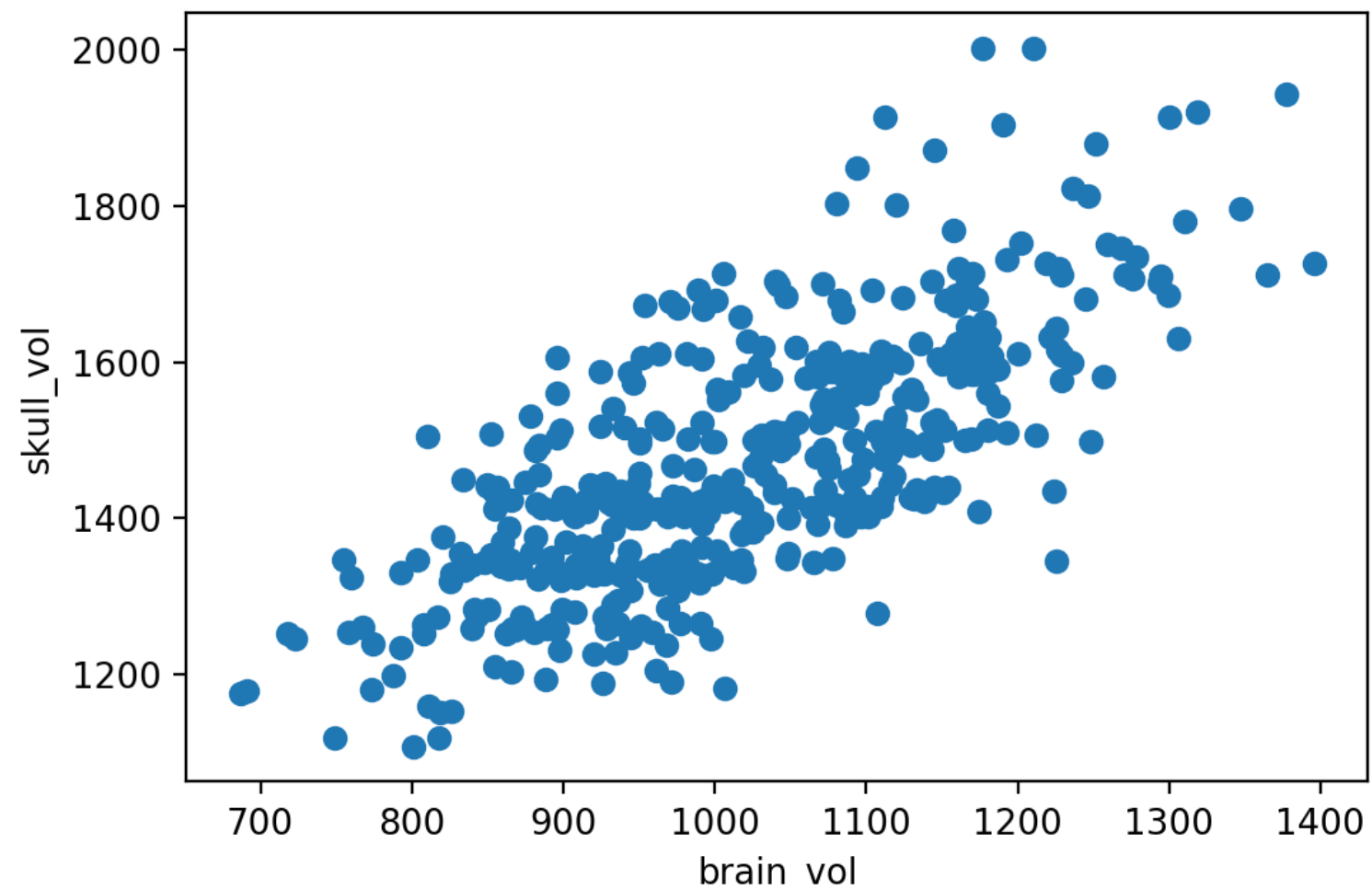
A large  $t$ -statistic and low  $p$ -value suggests that there is a significant difference!



# Correlated measurements

```
df[['brain_vol', 'skull_vol']].corr()
```

	'brain_vol'	'skull_vol'
'brain_vol'	1.000	0.736
'skull_vol'	0.736	1.000





# Normalization

```
df['brain_norm'] = df.brain_vol / df.skull_vol

brain_norm_m = df.loc[df.sex == 'M', 'brain_norm']
brain_norm_f = df.loc[df.sex == 'F', 'brain_norm']

results = ttest_ind(brain_norm_m, brain_norm_f)
```

```
results.statistic
-0.94011

results.pvalue
0.34769
```

Size, not gender likely drove original results.



# Many potential confounds in imaging

## Image acquisition

- Contrast
- Resolution
- Field of view

## Subject / object

- Age
- Gender
- Pathology

## Context

- Hospital
- Radiologist
- Equipment

## Data Quality

- Format
- Artifacts

# Congratulations!

## Exploration

- Loading images
- N-D data
- Subplots

## Masks and Filters

- Intensity distributions
- Convolutions
- Edge detection

## Measurement

- Labelling
- Multi-object measurement
- Morphology

## Image Comparison

- Transformations
- Resampling
- Cost functions
- Normalization



## BIOMEDICAL IMAGE ANALYSIS IN PYTHON

**Good luck!**