TAIWAN TECH
NATIONAL TAIWAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

MRI
HW2-FLASH

Presenter：

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OUTLINE

- EX2.1 Simulate The Timing of M_{xy} and M_z
  - Introduction
  - Method
  - Experimental Results
- EX2.2 The Maximum MRI Image Brightness
  - Introduction
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  - Experimental Results
- EX2.3 Subcortical Structures
  - Introduction
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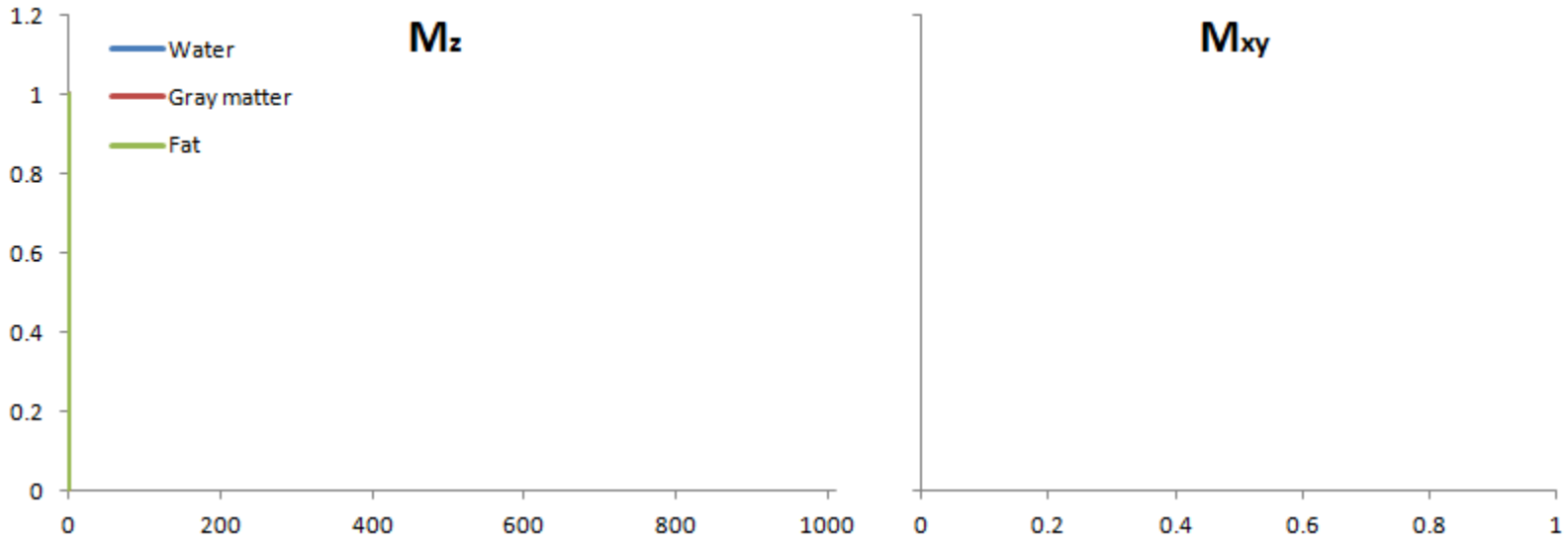
Introduction

$$M_z = M * (1 - e^{-t/T1})$$

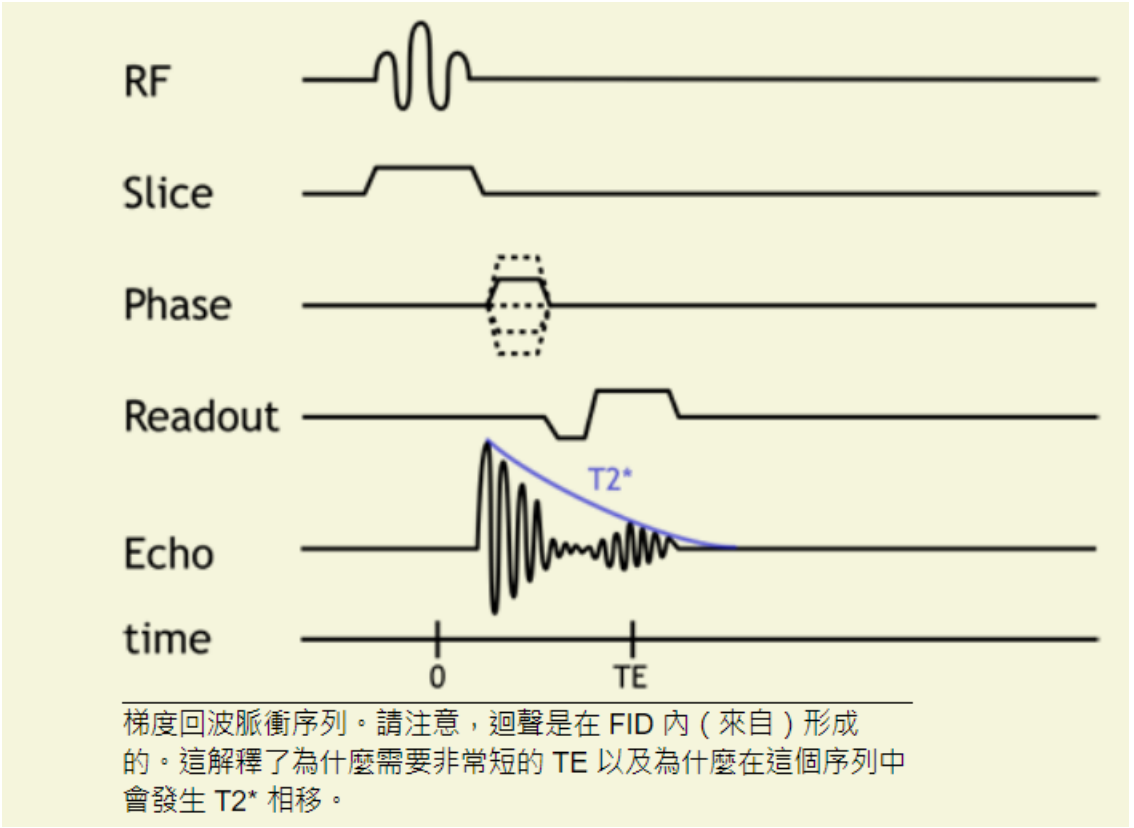
$$M_{xy} = M_0 * e^{-t/T2}$$



http://xrayphysics.com/sequences.html

Gradient Echo

- 由於 T2 效應未被抵消，GRE 序列的信號損失更快，因此通常使用更短的 TE。
- 更短的 TE 允許使用更短的 TR，這增加 了T1 權重



梯度回波脈衝序列。請注意，迴聲是在 FID 內（來自）形成的。這解釋了為什麼需要非常短的 TE 以及為什麼在這個序列中會發生 T2* 相移。

http://xrayphysics.com/sequences.html

Introduction

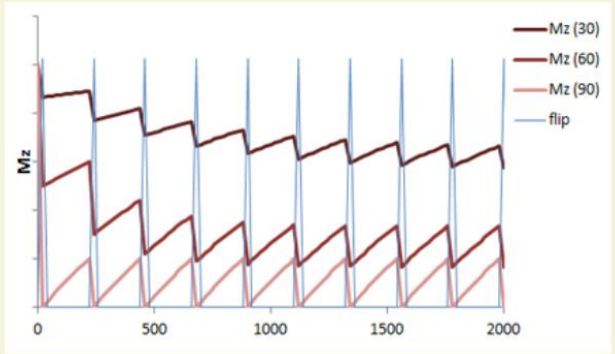


Illustration of the recovery of longitudinal magnetization in a GRE sequence with short TR and varying flip angles over successive applications of the pulse sequence. Given the short TR, there is not much time for the longitudinal magnetization (M_z, **red**) to recover. Using small flip angles (e.g. 30 degrees, 60 degrees) allows a larger fraction of the longitudinal magnetization to remain, so recovery is shorter. The 90 degree flip angle gives the lowest amount of signal (**light red**).

$$M_z = 終 + (初 - 終)e^{-t/T1}$$

$$初 = \left(\frac{\left(1-e^{-\frac{TR}{T1}}\right)\sin\alpha}{1-e^{-\frac{TR}{T1}}\cos\alpha}\right) * e^{-TE/T2^*}$$

事實上信號強度的公式是

- 信號正比於

$$\frac{(1 - e^{-TR/T1})\sin\alpha}{1 - e^{-TR/T1}\cos\alpha}\, e^{-TE/T2^*}$$

- α：偏折角

Initialize

```
% Initialize values
clear;clc;
TR = 50;
T1 = 1000;
T2_dephasing = 50;
n=6;
Alpha =
linspace(pi/12,pi/2,n);
```

```
% Iteration: N times of RF
N = 10;
% Mz
M_decade = ones(N,n);
M_recovery=[];
Mz=ones(1,n);
% Mxy
Mxy_decade = [];
Mxy_recovery=zeros(N,n);
Mxy=zeros(1,n);
```

Iteration

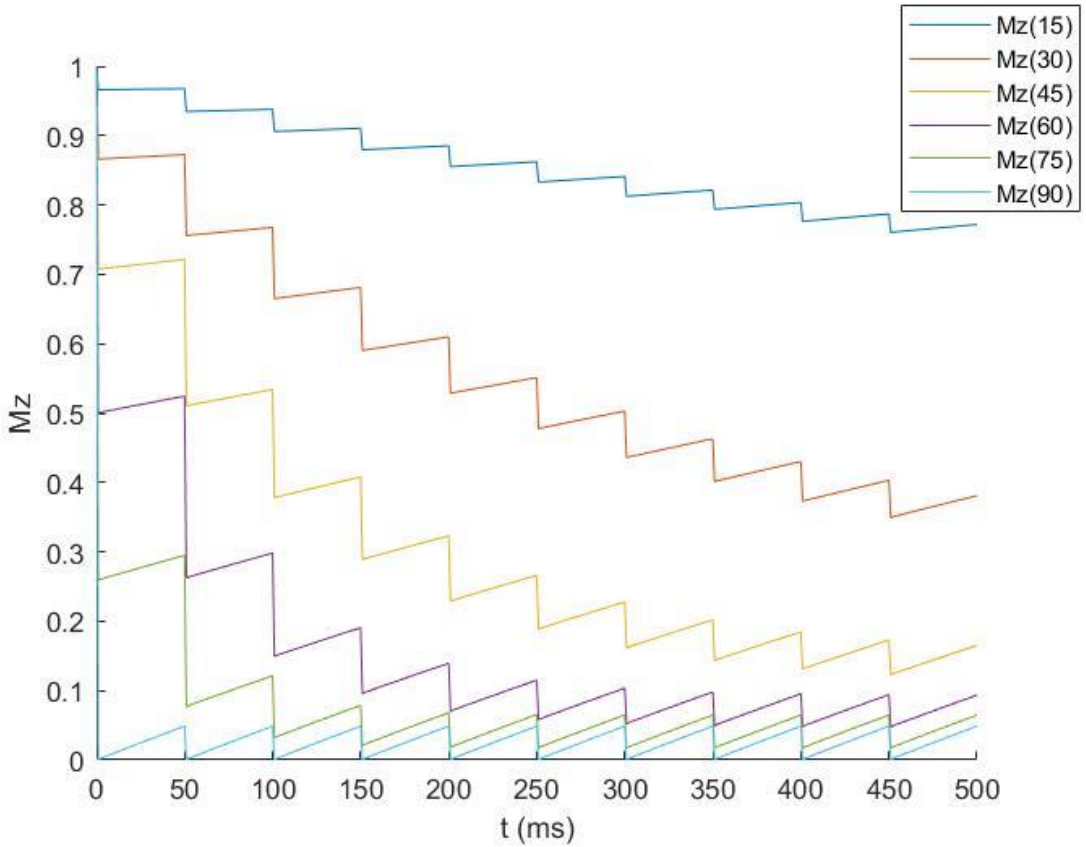
```
for i=1:N
    % Excitation
    if i>1
        M_decade(i,:) =
        Mz(end,:).*cos(Alpha);
        Mxy_recovery(i,:) =
        Mz(end,:).*sin(Alpha);
    else
        M_decade(i,:) =
        ones(1,n).*cos(Alpha);
        Mxy_recovery(i,:) =
        ones(1,n).*sin(Alpha);
    end
    Mz = [Mz; M_decade(i,:)];
    Mxy = [Mxy; Mxy_recovery(i,:)];
        % Relaxation
        for j=2:TR
            M_recovery =
            [M_recovery;1+(M_decade(i,:)-
            1).*exp(-(j)/T1)];
            Mz = [Mz; M_recovery(end,:)];
            Mxy_decade = [Mxy_decade;
            Mxy_recovery(i,:).*exp(-
            (j)/T2_dephasing)];
            Mxy = [Mxy; Mxy_decade(end,:)];
        end
end
```

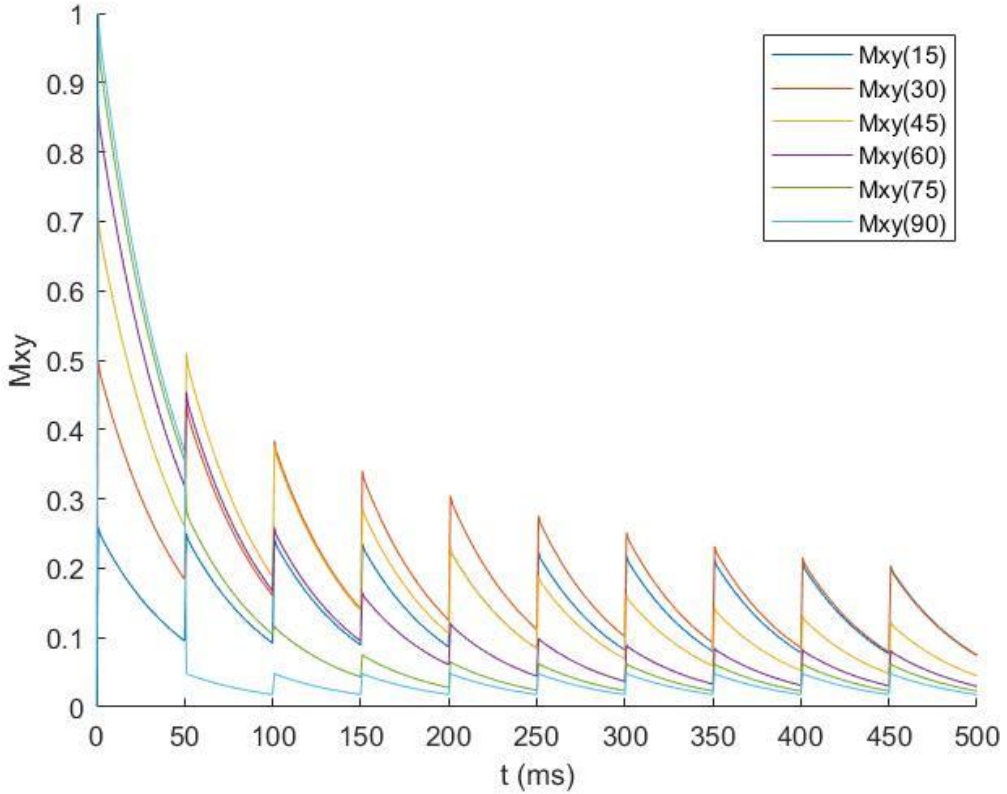
Plot

```
% Plot Mz
T = 0:TR*N;
figure();
hold on;
for i=1:n
    plot(T,Mz(:,i));
end
LineName =
    ['Mz(15)';'Mz(30)';'Mz(45)';
     'Mz(60)’;'Mz(75)';'Mz(90)'] ;
legend(LineName);
axis([min(T(:)) max(T(:)) 0 1]);
ylabel('Mz'); xlabel('t (ms)')
```

```
% Plot Mxy
T = 0:TR*N;
figure();
hold on;
for i=1:n
    plot(T,Mxy(:,i));
end
LineName =
    ['Mxy(15)';'Mxy(30)';'Mxy(45)';
     'Mxy(60)';'Mxy(75)';'Mxy(90)'] ;
legend(LineName);
axis([min(T(:)) max(T(:)) 0 1]);
ylabel('Mxy'); xlabel('t (ms)')
```

Experimental Results





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事實上信號強度的公式是

- 信號正比於

$$\frac{(1 - e^{-TR/T1}) \sin \alpha}{1 - e^{-TR/T1} \cos \alpha} e^{-TE/T2^*}$$

- α：偏折角

Initialize & Calculate

```
% Initialize values
clear;clc;
TR = 100;
T2_dephasing = 50;
n=901;
Alpha = linspace(0,pi/2,n);
```

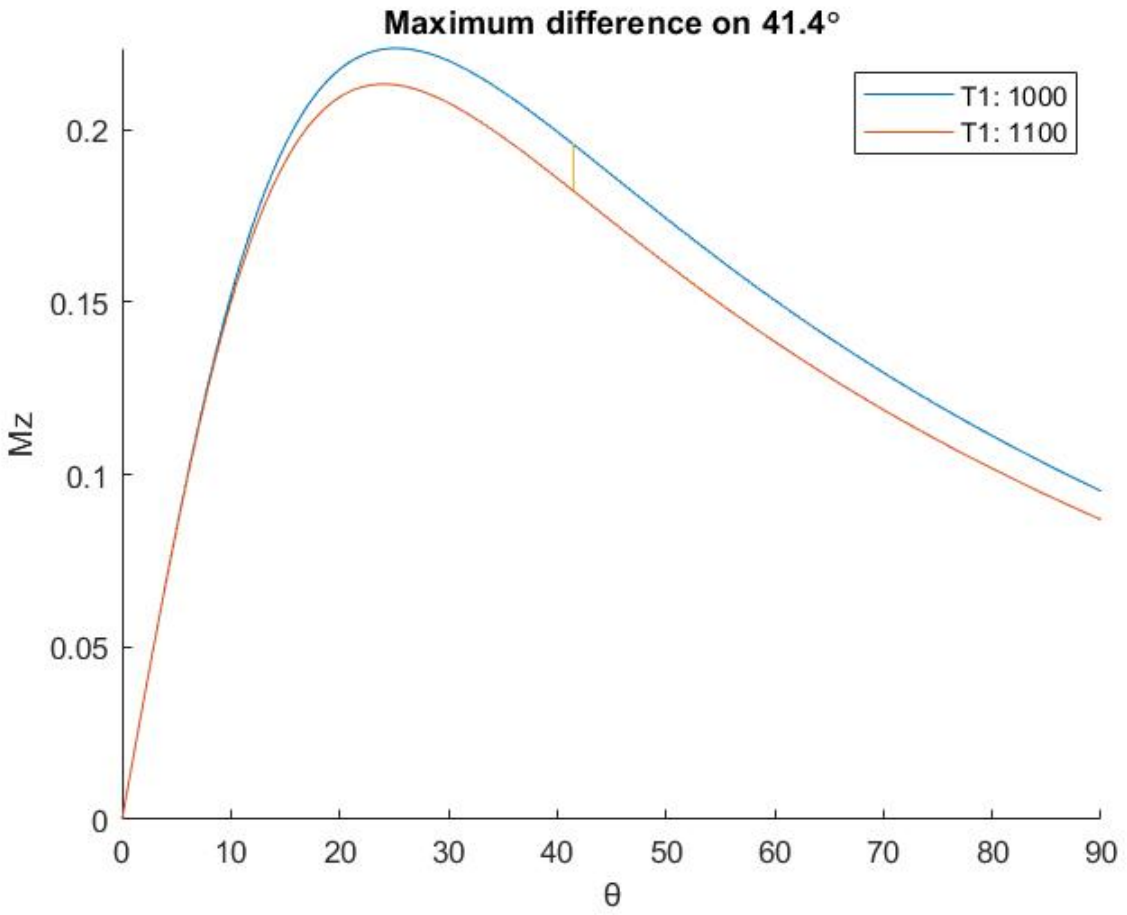
```
% Calculate Mz
T1 = [1000 1100]
% for T1_1
Mz(1,:) = ((1-exp(-TR/T1(1))).*sin(Alpha))./(1-exp(-
TR/T1(1)).*cos(Alpha));

% for T1_2
Mz(2,:) = ((1-exp(-TR/T1(2))).*sin(Alpha))./(1-exp(-
TR/T1(2)).*cos(Alpha));
```

Find the Different between two number

```
% Find maximum MRI image brightness
difference between the two tissues(T1s)
different = abs(Mz(2,:)-Mz(1,:));
index = find(different ==
max(different));
maxAngle = Alpha(index)*180/pi
```

```
% Show the result
figure();
hold on
plot(Alpha*180/pi,Mz(1,:))
plot(Alpha*180/pi,Mz(2,:))
plot([index/10 index/10],Mz(:,index))
txt = ['Maximum difference on ‘,
       num2str(maxAngle),'\circ'];
xlabel("θ")
ylabel("Mz")
title(txt)
legend([strcat("T1: ",num2str(T1(1)));
        strcat("T1: ",num2str(T1(2)))])
axis([0 90 min(Mz(:)) max(Mz(:))])
```

Experimental Results



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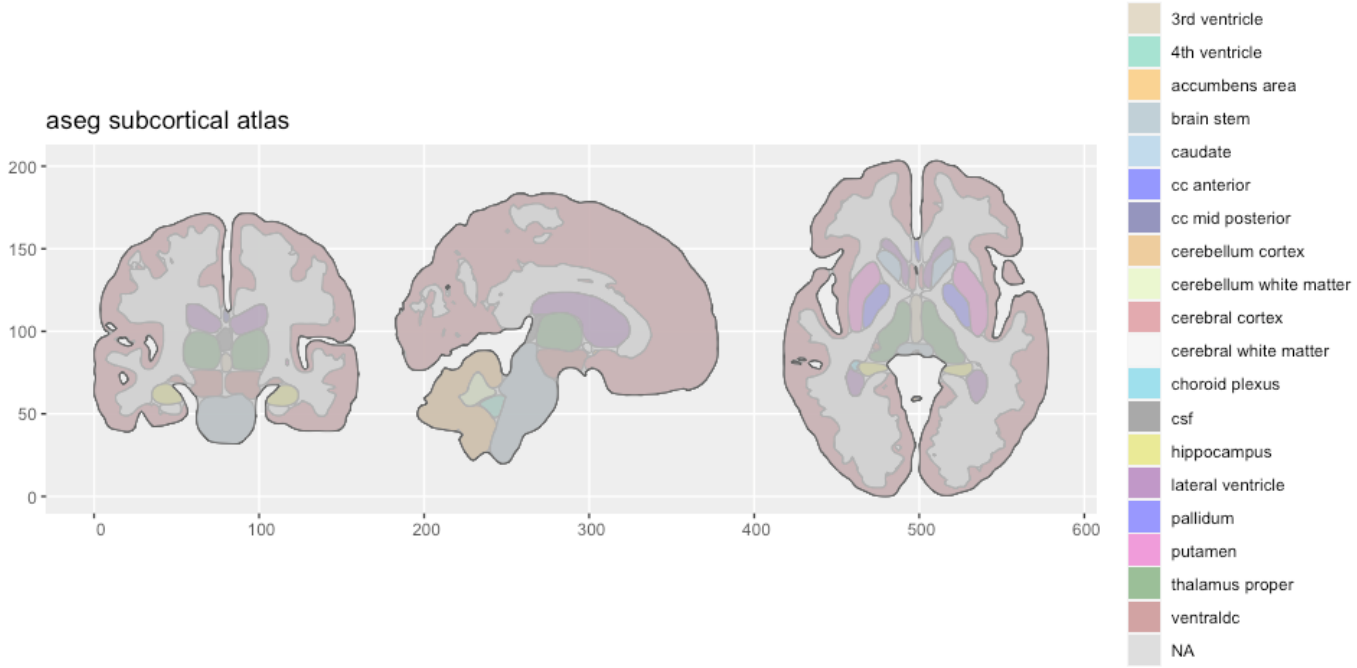
The subcortical

1. Read the nii.gz of MRI files.
2. Calculate volumes of each subcortical area.
3. Read the IXI.xls by pandas dataform.
4. Correlation analysis between volume and personal informations.



https://ggseg.github.io/ggsegExtra/articles/createaseg.html

Import

```
import nibabel as nib
import pandas as pd
import numpy as np
import os
import glob
import seaborn as sns
import matplotlib.pyplot as plt
```

- nibabel: to read nii file
- pandas: to data analysis
- numpy: for calculate
- os: write and read the file
- glob: read the path of file
- matplotlib and seaborn: plot the result

Method

Initialize

```
# setting the path of files
files = glob.glob('IXI_aseg/*.nii.gz’)

# create list to save labels of each area
labels=[4,5,7,8,10,11,12,13,14,15,16,17,18,
        24,26,28,30,31,43,44,46,47,49,50,51,
        52,53,54,58,60,62,63,72,77,78,79,80,
        81,82,85,251,252,253,254,255]
```

Label No.	Structure Name	Label No.	Structure Name
4	Left-Lateral-Ventricle	50	Right-Caudate
5	Left-Inf-Lat-Vent	51	Right-Putamen
7	Left-Cerebellum-White-Matter	52	Right-Pallidum
8	Left-Cerebellum-Cortex	53	Right-Hippocampus
10	Left-Thalamus-Proper	54	Right-Amygdala
11	Left-Caudate	58	Right-Accumbens-area
12	Left-Putamen	60	Right-VentralDC
13	Left-Pallidum	62	Right-vessel
14	3rd-Ventricle	63	Right-choroid-plexus
15	4th-Ventricle	72	5th-Ventricle
16	Brain-Stem	77	WM-hypointensities
17	Left-Hippocampus	78	Left-WM-hypointensities
18	Left-Amygdala	79	Right-WM-hypointensities
24	CSF	80	non-WM-hypointensities
26	Left-Accumbens-area	81	Left-non-WM-hypointensities
28	Left-VentralDC	82	Right-non-WM-hypointensities
30	Left-vessel	85	Optic-Chiasm
31	Left-choroid-plexus	251	CC_Posterior
43	Right-Lateral-Ventricle	252	CC_Mid_Posterior
44	Right-Inf-Lat-Vent	253	CC_Central
46	Right-Cerebellum-White-Matter	254	CC_Mid_Anterior
47	Right-Cerebellum-Cortex	255	CC_Anterior
49	Right-Thalamus-Proper		

Calculate

```
# calculate volumes of each area
if not os.path.exists('vol_all.npy'):
    vol_all = []
    for file in files:
        vol = []
        img = nib.load(file)
        img_array = img.get_fdata()
        factor = np.prod(img.header.get_zooms())
        for label in labels:
            vol.append(np.sum(img_array==label)*factor)
        vol_all.append(vol)
    # save result to `*.npy`
    np.save('vol_all',vol_all)
# if done, load the `*.npy`
else:
    vol_all = np.load('vol_all.npy')
```

Method

Dataform

```
# create list to save the ID of each nii file.
id = [int(os.path.basename(file).split('-')[0][3:6]) for file in files]
# read xls file by pandas
df = pd.read_excel('IXI.xls')
# change index
df.index = df['IXI_ID']


# match ID between nii file and xls
id_new = [i for i in id if i in df['IXI_ID']]
# create new df
df_new = df.loc[id_new]
df_new.drop_duplicates(subset='IXI_ID', keep='first', inplace=True)
# save new df
df_new.to_excel('df_new.xlsx')
```

Dataform

```
# create df of volumes
vol_all = np.array(vol_all)
df_vol = pd.DataFrame(vol_all, columns = labels)
df_vol.insert(loc=0, column="IXI_ID", value=id)
df_vol.index = df_vol['IXI_ID']

# match ID between nii file and xls
df_vol_new = df_vol.loc[id_new]
df_vol_new.drop_duplicates(subset='IXI_ID', keep='first', inplace=True)
df_vol_new.to_excel('df_vol_new.xlsx')
```

Dataform

```
# concat df and df_vol
df_concat = pd.concat([df_new,df_vol_new.drop(['IXI_ID'],axis=1)],axis=1)
df_concat.to_excel('df_concat.xlsx')

# drop some information we don't use: 'IXI_ID','DOB','DATE_AVAILABLE','STUDY_DATE'
df_concat = df_concat.drop(['IXI_ID','DOB','DATE_AVAILABLE','STUDY_DATE'],axis=1)
# Fill 0 to Nan value
df_concat.fillna(0)
# change 0 to mean value
df_concat['HEIGHT'] = df_concat['HEIGHT'].replace(0,df_concat['HEIGHT'].mean())
df_concat['WEIGHT'] = df_concat['WEIGHT'].replace(0,df_concat['WEIGHT'].mean())
df_concat['AGE'] = df_concat['AGE'].replace(0,df_concat['AGE'].mean())
# drop some missing data
df_concat = df_concat[df_concat['ETHNIC_ID'] != 0]
df_concat = df_concat[df_concat['MARITAL_ID'] != 0]
df_concat = df_concat[df_concat['OCCUPATION_ID'] != 0]
df_concat = df_concat[df_concat['QUALIFICATION_ID'] != 0]
```

Dataform

IXI_ID	SEX_ID (1=m, 2=f)	HEIGHT	WEIGHT	ETHNIC_ID	MARITAL_ID	OCCUPATION_ID	QUALIFICATION_ID	AGE	4	5	...	79	80	81	82	85	251	252	
2	2	164.0	58.0	1	4	1	5	35.800137	4520.379385	167.694896	...	0.0	0.0	0.0	0.0	67.499832	1066.286411	762.537166	
12	1	175.0	70.0	1	2	1	5	38.781656	9688.387846	129.726944	...	0.0	0.0	0.0	0.0	205.664667	933.401181	591.681426	1
13	1	182.0	70.0	1	2	1	5	46.710472	7583.197982	91.757750	...	0.0	0.0	0.0	0.0	82.265569	1008.280566	681.327663	
14	2	163.0	65.0	1	4	1	5	34.236824	3846.445747	84.375010	...	0.0	0.0	0.0	0.0	13.710939	1021.992303	651.796949	1
15	1	181.0	90.0	2	1	6	5	24.284736	5560.327583	59.062660	...	0.0	0.0	0.0	0.0	82.265848	1485.004028	861.682025	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
648	1	193.0	120.0	1	1	6	4	47.723477	12749.104289	257.344594	...	0.0	0.0	0.0	0.0	202.500664	1152.777216	781.525999	
651	1	175.0	61.0	3	2	8	2	50.395619	2762.226250	132.890610	...	0.0	0.0	0.0	0.0	143.437484	975.585827	553.710875	
652	1	163.0	80.0	1	1	1	5	42.989733	7538.916475	111.797027	...	0.0	0.0	0.0	0.0	121.289227	1352.111209	786.797942	1
653	1	172.0	100.0	1	3	1	5	46.220397	5079.384760	258.398934	...	0.0	0.0	0.0	0.0	156.094050	1219.221093	634.923095	
662	1	182.0	98.0	1	4	1	3	41.741273	8095.806871	473.556186	...	0.0	0.0	0.0	0.0	209.883477	993.518769	561.095526	

471 rows × 53 columns

Correlation Analysis

```
# correlation analysis
for lebel in labels:
    df_corr = df_concat.iloc[:,0:8]
    corr_label = lebel
    df_corr[lebel]=df_concat[lebel]

    # compute pairwise correlation of columns by df.corr
    corr = df_corr.corr()
    corr_result = corr[lebel]
```

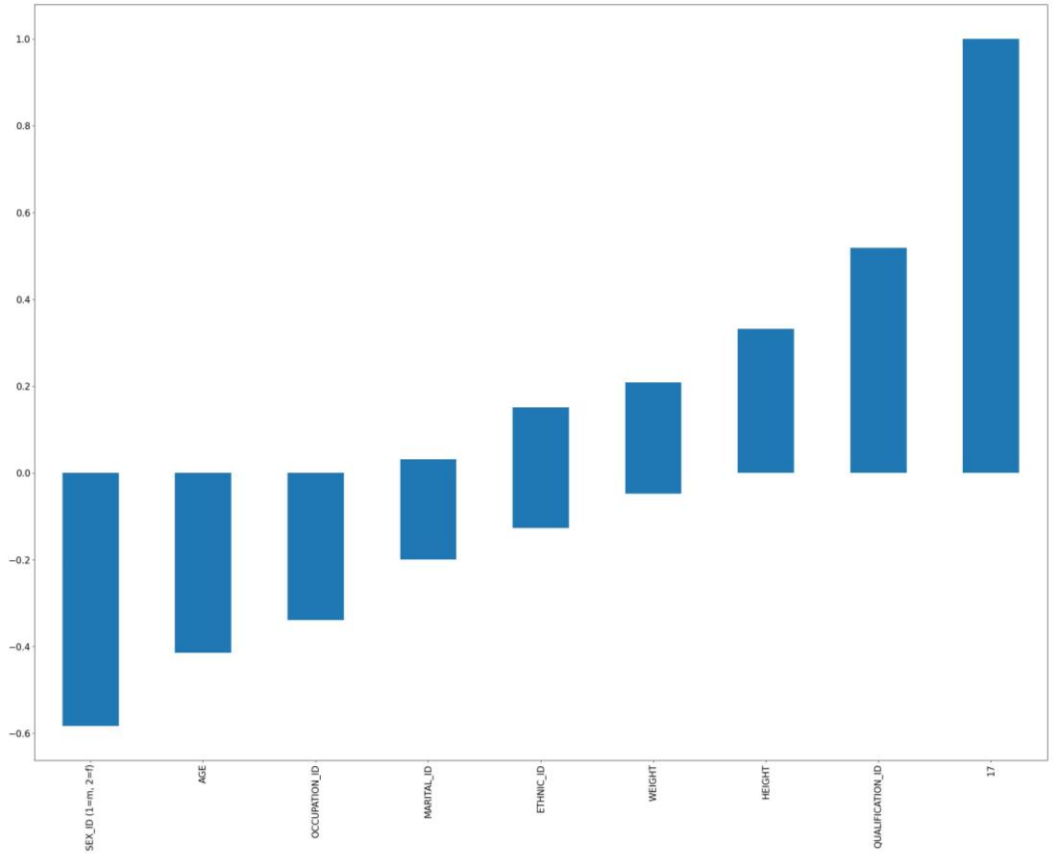
Method

Plot

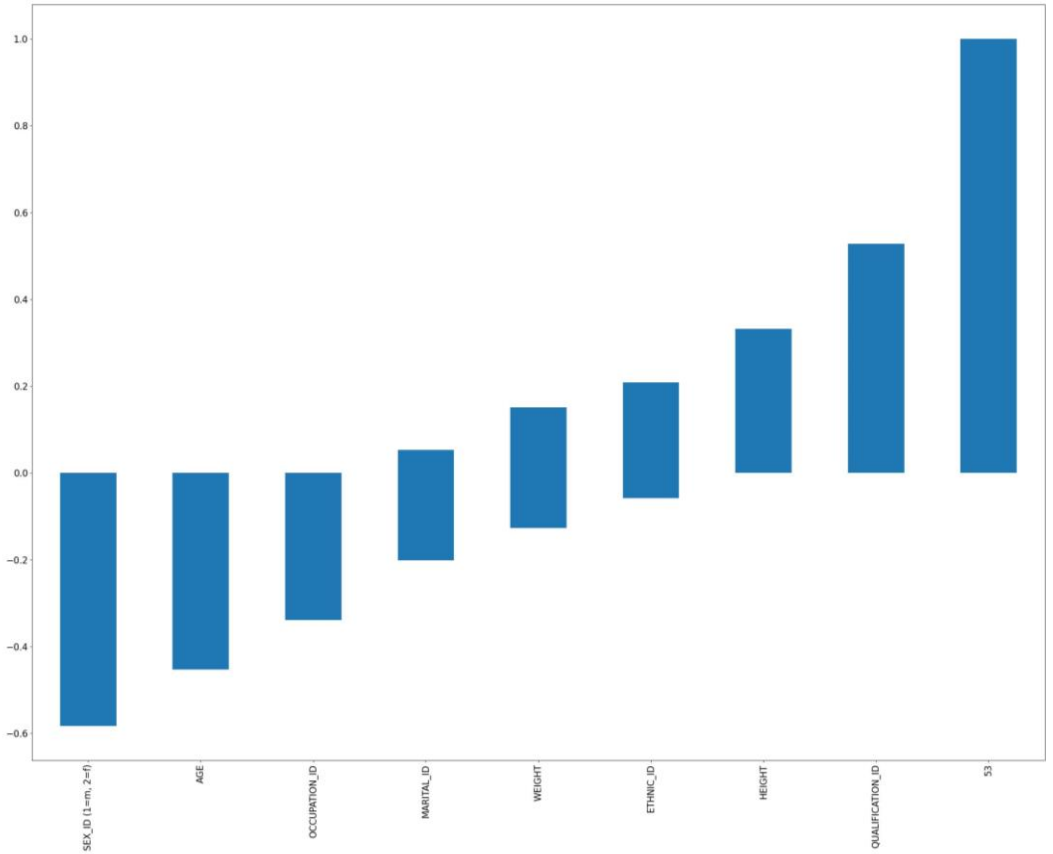
```
# plot the result bar
fig = plt.figure(figsize=(6,4))
corr_result.sort_values().plot(kind='bar',figsize=(32, 24), fontsize=24).get_figure()
# save the result of bar
if not os.path.exists('images/result/'):
    os.mkdir('images/result')
fig.savefig('images/result/IXI_Volume_'+str(lebel)+'.jpg')
# clear fig
plt.cla()
plt.clf()
# plot the result by heatmap
sns.heatmap(corr, vmin=-1, vmax=1, annot=True, linecolor="white")
# save the result of heatmap
fig.savefig('images/result/IXI_Volume_heatmap_'+str(lebel)+'.jpg')
# close fig
plt.close()
```

Experimental Results

Left-Hippocampus

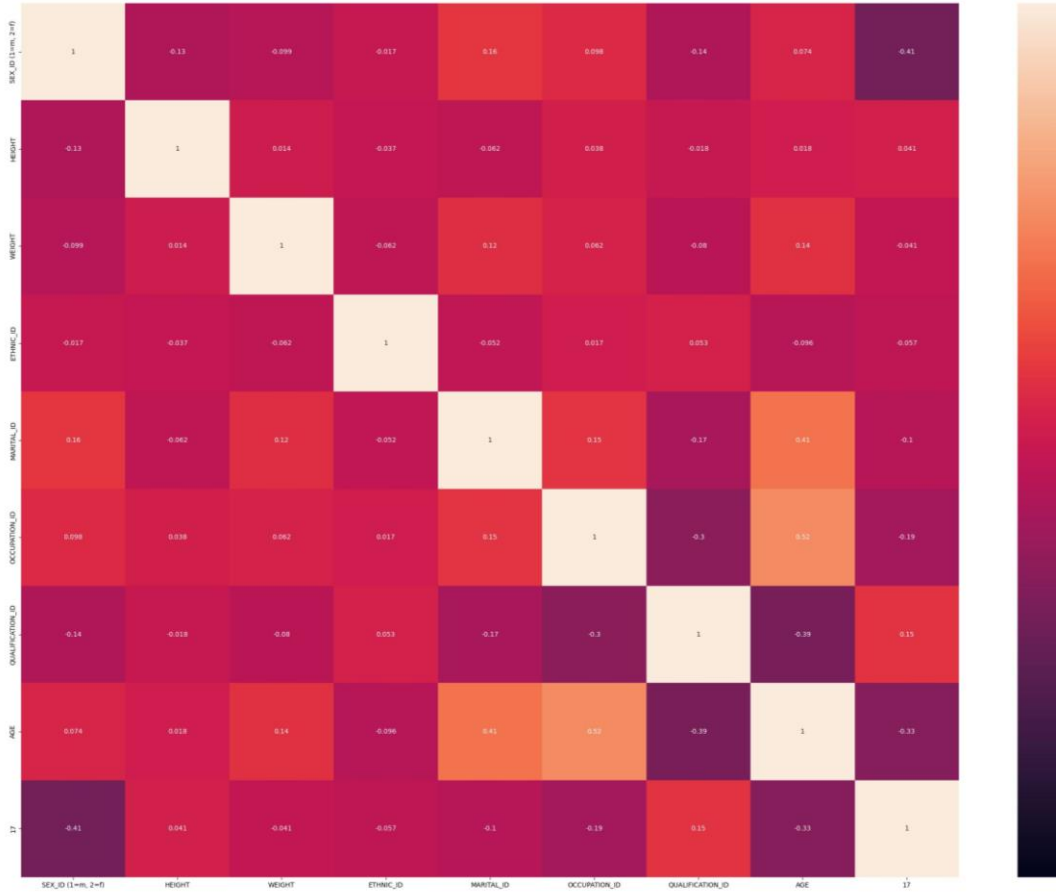


Right-Hippocampus

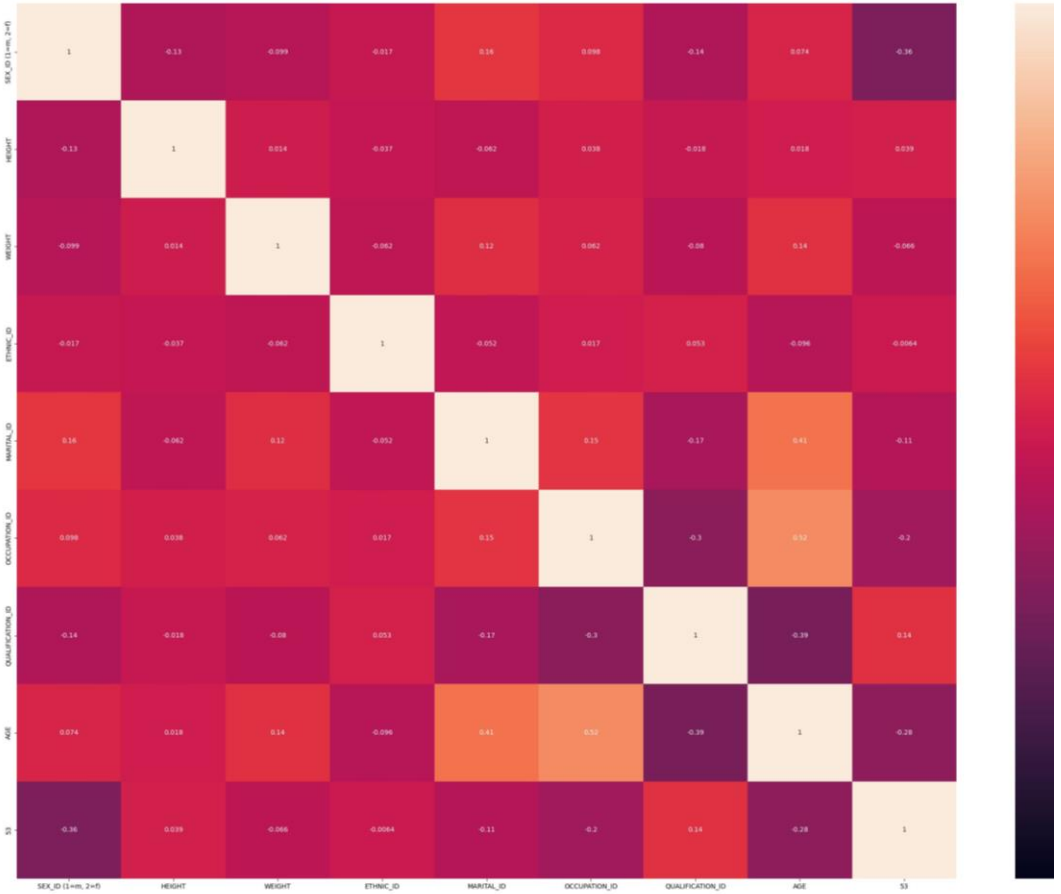


Experimental Results

Left-Hippocampus



Right-Hippocampus



Q&A

Thanks

GitHub