exploration

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1 Exploration and Analysis of Mental Health Data from Shamiri

1.0.1 by F Njakai

1.0.2 Table of contents

1.1 Introduction

1.2 Preliminary Wrangling

[4]:
```
#install and/or upgrade packages

!pip install pandas seaborn pandas-profiling
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pandas in /home/DsF/.local/lib/python3.10/site-
packages (1.5.2)
Requirement already satisfied: seaborn in /home/DsF/.local/lib/python3.10/site-
packages (0.12.2)
Requirement already satisfied: pandas-profiling in
/home/DsF/.local/lib/python3.10/site-packages (3.6.2)
Requirement already satisfied: numpy>=1.21.0 in /usr/lib/python3/dist-packages
(from pandas) (1.23.5)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/lib/python3/dist-
packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/lib/python3/dist-packages
(from pandas) (2022.7)
Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in /usr/lib/python3/dist-
packages (from seaborn) (3.5.2)
Requirement already satisfied: visions[type_image_path]==0.7.5 in
/home/DsF/.local/lib/python3.10/site-packages (from pandas-profiling) (0.7.5)
Requirement already satisfied: multimethod<1.10,>=1.4 in
/home/DsF/.local/lib/python3.10/site-packages (from pandas-profiling) (1.9.1)
```

```
Requirement already satisfied: scipy<1.10,>=1.4.1 in /usr/lib/python3/dist-
packages (from pandas-profiling) (1.8.1)
Requirement already satisfied: jinja2<3.2,>=2.11.1 in /usr/lib/python3/dist-
packages (from pandas-profiling) (3.0.3)
Requirement already satisfied: phik<0.13,>=0.11.1 in
/home/DsF/.local/lib/python3.10/site-packages (from pandas-profiling) (0.12.3)
Requirement already satisfied: pydantic<1.11,>=1.8.1 in /usr/lib/python3/dist-
packages (from pandas-profiling) (1.10.2)
Requirement already satisfied: htmlmin==0.1.12 in
/home/DsF/.local/lib/python3.10/site-packages (from pandas-profiling) (0.1.12)
Requirement already satisfied: tqdm<4.65,>=4.48.2 in /usr/lib/python3/dist-
packages (from pandas-profiling) (4.64.0)
Requirement already satisfied: typeguard<2.14,>=2.13.2 in
/home/DsF/.local/lib/python3.10/site-packages (from pandas-profiling) (2.13.3)
Requirement already satisfied: PyYAML<6.1,>=5.0.0 in /usr/lib/python3/dist-
packages (from pandas-profiling) (6.0)
Requirement already satisfied: requests<2.29,>=2.24.0 in /usr/lib/python3/dist-
packages (from pandas-profiling) (2.28.1)
Requirement already satisfied: statsmodels<0.14,>=0.13.2 in
/home/DsF/.local/lib/python3.10/site-packages (from pandas-profiling) (0.13.5)
Requirement already satisfied: attrs>=19.3.0 in /usr/lib/python3/dist-packages
(from visions[type_image_path]==0.7.5->pandas-profiling) (22.1.0)
Requirement already satisfied: tangled-up-in-unicode>=0.0.4 in
/home/DsF/.local/lib/python3.10/site-packages (from
visions[type_image_path]==0.7.5->pandas-profiling) (0.2.0)
Requirement already satisfied: networkx>=2.4 in
/home/DsF/.local/lib/python3.10/site-packages (from
visions[type_image_path]==0.7.5->pandas-profiling) (3.0)
Requirement already satisfied: Pillow in /usr/lib/python3/dist-packages (from
visions[type_image_path]==0.7.5->pandas-profiling) (9.3.0)
Requirement already satisfied: imagehash in
/home/DsF/.local/lib/python3.10/site-packages (from
visions[type_image_path]==0.7.5->pandas-profiling) (4.3.1)
Requirement already satisfied: joblib>=0.14.1 in
/home/DsF/.local/lib/python3.10/site-packages (from phik<0.13,>=0.11.1->pandas-
profiling) (1.2.0)
Requirement already satisfied: packaging>=21.3 in /usr/lib/python3/dist-packages
(from statsmodels<0.14,>=0.13.2->pandas-profiling) (21.3)
Requirement already satisfied: patsy>=0.5.2 in
/home/DsF/.local/lib/python3.10/site-packages (from
statsmodels<0.14,>=0.13.2->pandas-profiling) (0.5.3)
Requirement already satisfied: six in /usr/lib/python3/dist-packages (from
patsy>=0.5.2->statsmodels<0.14,>=0.13.2->pandas-profiling) (1.16.0)
Requirement already satisfied: PyWavelets in
/home/DsF/.local/lib/python3.10/site-packages (from
imagehash->visions[type_image_path]==0.7.5->pandas-profiling) (1.4.1)
```

[3]:
```
#imports

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.filterwarnings(action='ignore')
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import pandas_profiling
from random import randint
from os import path
from contextlib import suppress

%load_ext autoreload
%autoreload 2
%reload_ext autoreload


%matplotlib inline
```

1.2.1 Default settings for plots

automate, as much as possible, the process of creating visualisations

why?

- it is efficient
- visualisations are consistent

how?

- create templates

[54]:
```
#template no. 1

#default blue
default_blue = sns.color_palette('tab10')[0]

#default orange
default_orange = sns.color_palette('tab10')[1]

#default pink
default_pink = sns.color_palette('tab10')[6]

#default palette
default_palette = sns.color_palette('tab10')
```

[59]:
```
#template no. 2

'''
Simple function to create `Figure` object
using matplotlib. Has an x-lab, y-lab and
title.

"Father Figure", if you like :)

3 params, all type `str`:
@x_lab: x label
@y_lab: y label
@title: title

return: None
'''

def create_fig(x_lab: str, y_lab: str, title: str):
    """Father Figure"""
    try:
        plt.figure(figsize=(10, 6.18), dpi=216, frameon=False, clear=False)
        plt.xlabel(x_lab)
        plt.ylabel(y_lab)
        plt.title(title)
    except ModuleNotFoundError:
        print(f'Please `import matplotlib.pyplot as plt` and try again')
    except:
        print(f'Failed to create template')
        raise
```

[6]:
```
#template no. 3

'''
Simple function to create `Figure` object
using matplotlib for sub-plots.

"Father Figure", for sub-plots :)

2 params, type `int`; number of sub-plots:
@n_row: #rows
@n_col: #cols

return: fig and ax objects
'''

def create_sub(n_row: int=1, n_col: int=1):
    """Father Figure for  sub-plots"""
```

```
    try:
        fig, ax = plt.subplots(n_row, n_col, figsize=(10, 6.18), dpi=216)
        fig.tight_layout(pad=10.0)
        return fig, ax
    except ModuleNotFoundError:
        print(f'Please `import matplotlib.pyplot as plt` and try again')
    except:
        print(f'Failed to create template')
        raise
```

[7]:
```
#confirm that a df exists

'''
Simple function to see if a df exists

1 param: name of variable holding the df

Do not pass the arg as a string.
Repeat: DO NOT pass the arg as a string.

return: None
'''

def confirm_df_exists(df):
    """confirm that a df exists"""
    if not df.empty:
        print(f'This dataframe exists')
        return
    print(f'This dataframe does not exist')
```

[8]:
```
#confirm that a file exists and/or has been
# created in current dir

'''
simple function to confirm that a file exists
and/or has been created in current dir

1 param, type `str`: name of file
@file_name: name of file

return None
'''

def confirm_file_exists(file_name: str):
    """confirm that file exists"""
    if path.exists(file_name):
        print(f'File exists')
```

```
    else:
        print(f'Something went wrong. Investigate')
```

[9]:
```
#group data and find mean

'''
Function to calculate mean of
grouped data

Takes in 2 args:
@var_1 -> variable to average by
@var_2 -> variable to access data by

Both args must be columns of a pandas DF

return: average  of grouped data
'''

def group_avg(var_1, var_2):
    """ function group_avg"""
    if var_1 and var_2:
        avg_gp_data = df.groupby(var_1)[var_2].mean()
        return avg_gp_data
    else:
        print(f'Check that both arguments are columns of a pandas DF and try␣
 ↪again')
```

[10]:
```
#group data and find sum

'''
Function to calculate sum of
grouped data

Takes in 2 args
@var_1 -> variable to sum by
@var_2 -> variable to access data by

Both args must be columns of a pandas DF

return: sum  of grouped data
'''

def group_sum(var_1, var_2):
    """ function group_sum"""
    if var_1 and var_2:
        sum_gp_data = df.groupby(var_1)[var_2].sum()
        return sum_gp_data
```

```
    else:
        print(f'Check that both arguments are columns of a pandas DF and try␣
 ↪again')
```

[11]:
```
#sorting ops

'''
function to create and sort a DF

3 params:
@x: pandas series #1
@y: pandas series #2
@ascending: bool, default T

return: pandas DF
'''
def custom_sort_df(x, y, ascending:bool=True):
    """function custom_sort_df"""
    try:
        dd = pd.DataFrame({k:v for (k, v) in zip(x, y)}, index=['Count']).
 ↪transpose()
        dd.sort_values('Count', inplace=True, ascending=True)
        dd.reset_index(inplace=True)
        return dd
    except:
        print(f'Check that x and y are pandas series and try again')
```

[12]:
```
'''
simple function to create a sum super set

1 param, type `str`:
@search_term: the term to search

return: pandas df
'''

def create_sum_super_set(search_term: str):
    """ create_sum_super_set"""
    li = [i for i in df.columns if i.startswith(search_term)]
    sum_dict = {}

    for i in range(len(li)):
        sum_grp = group_sum(li[i], li[i])
        li_di = dict(sum_grp)
        sum_dict[li[i]] = li_di
    df_sum_dict = pd.DataFrame(sum_dict)
```

```
    return df_sum_dict
```

[13]:
```
'''
simple function to create an average super set

1 param, type `str`:
@search_term: the term to search

return: pandas df
'''

def create_average_super_set(search_term: str):
    """ create_average_super_set"""
    li = [i for i in df.columns if i.startswith(search_term)]
    avg_dict = {}

    for i in range(len(li)):
        avg_grp = group_avg(li[i], li[i])
        li_di = dict(avg_grp)
        avg_dict[li[i]] = li_di
    df_avg_dict = pd.DataFrame(avg_dict)

    return df_avg_dict
```

[29]:
```
'''
Simple function to sum the scores of
a particular metric

2 params, type `str`:
@var_1 -> ...
@var_2 -> ...

return: pandas df
'''

def create_sum_metric(var_1: str, var_2: str):
    """ create_sum_metric"""
    li = [i for i in df.columns if i.startswith(var_2)]
    avg_dict = {}

    for i in range(len(li)):
        avg_grp = group_sum(var_1, li[i])
        li_di = dict(avg_grp)
        avg_dict[li[i]] = li_di
    df_avg_dict = pd.DataFrame(avg_dict).style.format('{:2f}')

    return df_avg_dict
```

1.2.2 Load the data

[14]:
```
df = pd.read_csv('shamiri_imputed_dataset.csv', sep=',')
confirm_df_exists(df)
```

```
This dataframe exists
```

[28]:
```
df.shape
```

[28]:
```
(658, 33)
```

[25]:
```
df.duplicated().value_counts()
```

[25]:
```
False    658
dtype: int64
```

[26]:
```
df.drop_duplicates()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 658 entries, 0 to 657
Data columns (total 33 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   ParticipantID     658 non-null    object
 1   PHQ1              658 non-null    int64
 2   PHQ2              658 non-null    int64
 3   PHQ3              658 non-null    int64
 4   PHQ4              658 non-null    int64
 5   PHQ5              658 non-null    int64
 6   PHQ6              658 non-null    int64
 7   PHQ7              658 non-null    int64
 8   PHQ8              658 non-null    int64
 9   GAD1              658 non-null    int64
 10  GAD2              658 non-null    int64
 11  GAD3              658 non-null    int64
 12  GAD4              658 non-null    int64
 13  GAD5              658 non-null    int64
 14  GAD6              658 non-null    int64
 15  GAD7              658 non-null    int64
 16  MSSS1             658 non-null    int64
 17  MSSS2             658 non-null    int64
 18  MSSS3             658 non-null    int64
 19  MSSS4             658 non-null    int64
 20  MSSS5             658 non-null    int64
 21  MSSS6             658 non-null    int64
 22  MSSS7             658 non-null    int64
 23  MSSS8             658 non-null    int64
```

```
 24  MSSS9             658 non-null    int64
 25  MSSS10            658 non-null    int64
 26  MSSS11            658 non-null    int64
 27  MSSS12            658 non-null    int64
 28  Tribe             658 non-null    object
 29  Gender            658 non-null    object
 30  School            658 non-null    object
 31  Age               658 non-null    float64
 32  School_Resources  658 non-null    object
dtypes: float64(1), int64(27), object(5)
memory usage: 169.8+ KB
```

[31]:
```
df.ParticipantID.nunique()
```

[31]:
```
626
```

[27]:
```
df.sample(randint(5, 15))
```

[27]:

	ParticipantID	PHQ1	PHQ2	PHQ3	PHQ4	PHQ5	PHQ6	PHQ7	PHQ8	GAD1	…	\
137	EH_058	0	1	0	0	0	2	0	2	0	…	
572	OLY_127	1	0	0	1	2	0	2	0	2	…	
470	OLY_025	1	1	2	1	0	1	0	0	0	…	
430	AGHS_142	2	1	1	2	0	1	1	3	1	…	
520	OLY_075	1	0	0	3	0	0	2	0	0	…	
620	OLY_175	2	3	1	0	1	1	1	1	0	…	
271	AHS_115	3	0	0	3	1	1	3	3	2	…	
120	EH_041	2	2	2	2	2	3	2	2	2	…	

	MSSS8	MSSS9	MSSS10	MSSS11	MSSS12	Tribe	Gender	School	Age	\
137	7	4	6	7	4	Minority	F	Elite	17.0	
572	2	3	2	3	3	Minority	F	Olympic	14.0	
470	2	1	5	6	5	Minority	M	Olympic	14.0	
430	4	6	6	4	5	Majority	F	AGHS	15.0	
520	7	7	7	7	7	Minority	F	Olympic	16.0	
620	6	6	6	6	6	Minority	M	Olympic	17.0	
271	1	5	3	1	4	Majority	M	AHS	17.0	
120	6	3	7	4	2	Minority	M	Elite	16.0	

	School_Resources
137	Poor
572	Medium
470	Medium
430	Rich
520	Medium
620	Medium
271	Rich
120	Poor

```
[8 rows x 33 columns]
```

1.2.3 Structure

General

- 658 observations
- 33 variables
  - 27 of type `int`
  - 1 of type `float`
  - 5 of type `str`

Missing and null values

- `df` has no missing or null values

Duplicated observations

- `df` has no duplicated observations

Multiple values for a variable

- observations in twtr_archive have a single value per variable

1.2.4 Quality

- no missing values
- values follow the definition of variables

1.2.5 Tidiness

- variables are properly defined
- each variable represents one piece of information
- observations in twtr_archive have a single value per variable

Cleaning operation is not needed

1.3 Exploration

Research Question 1

- What are the `PHQ-8` scores?
  - what is the score between tribes?
  - what is the score among males?
  - what is the score among females?

[29]:
```
sum_phq = create_sum_super_set('PHQ')
sum_phq
```

[29]:

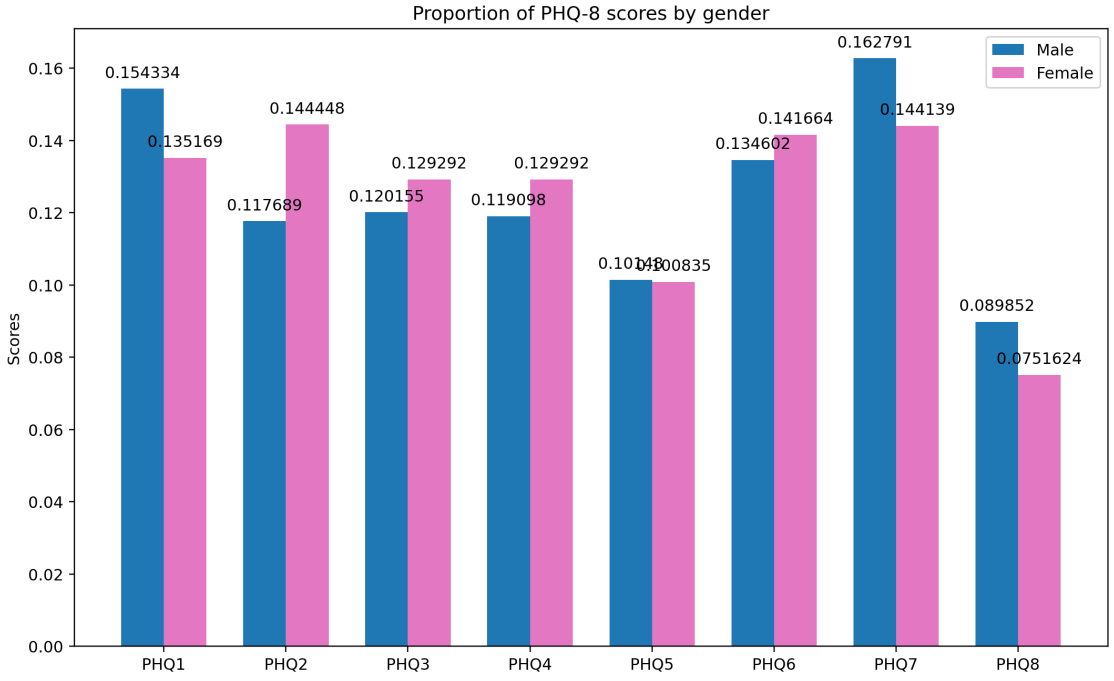
	PHQ1	PHQ2	PHQ3	PHQ4	PHQ5	PHQ6	PHQ7	PHQ8
0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0
1	251.0	207.0	163	234.0	157.0	194.0	231.0	153.0
2	198.0	204.0	192	252.0	136.0	154.0	190.0	150.0
3	426.0	390.0	396	270.0	321.0	492.0	507.0	195.0
4	NaN	NaN	8	NaN	NaN	NaN	NaN	NaN

[64]:
```
avg_phq = create_average_super_set('PHQ')
avg_phq
```

[64]:

	PHQ1	PHQ2	PHQ3	PHQ4	PHQ5	PHQ6	PHQ7	PHQ8
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
2	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
3	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
4	NaN	NaN	4.0	NaN	NaN	NaN	NaN	NaN

[202]:
```
aa = create_sum_metric('Gender', 'PHQ')
# a = create_percentage_df(aa)
# a = a.transpose()
aa = aa.transpose()
ab = [i/ aa['F'].sum() for i in aa['F']]
ac = [i/ aa['M'].sum() for i in aa['M']]
ad = pd.DataFrame([ab, ac], index=['Female', 'Male'], columns=aa.transpose().
 ↪columns).transpose()
ad
x = ad.index.values[:]
y1 = ad.values[0:8,0]
y2 = ad.values[0:8,1]
lab1 = [f'{i*100:.2f}%' for i in y1]
lab2 = [f'{i*100:.2f}%' for i in y2]
# create_fig('', '', 'PHQ Score')
# plt.bar(x, y1, color=default_pink)
# plt.bar(x, y2, color=default_blue)
labels = x
i = np.arange(len(labels))
width = 0.35
fig, ax = create_sub()
rects1 = ax.bar(i - width/2, y2, width, label='Male', color=default_blue)
rects2 = ax.bar(i + width/2, y1, width, label='Female', color=default_pink)
ax.set_ylabel('Scores')
ax.set_title('Proportion of PHQ-8 scores by gender')
ax.set_xticks(i, labels)
ax.bar_label(rects1, padding=5)
ax.bar_label(rects2, padding=5)
ax.legend()
fig.tight_layout();
```

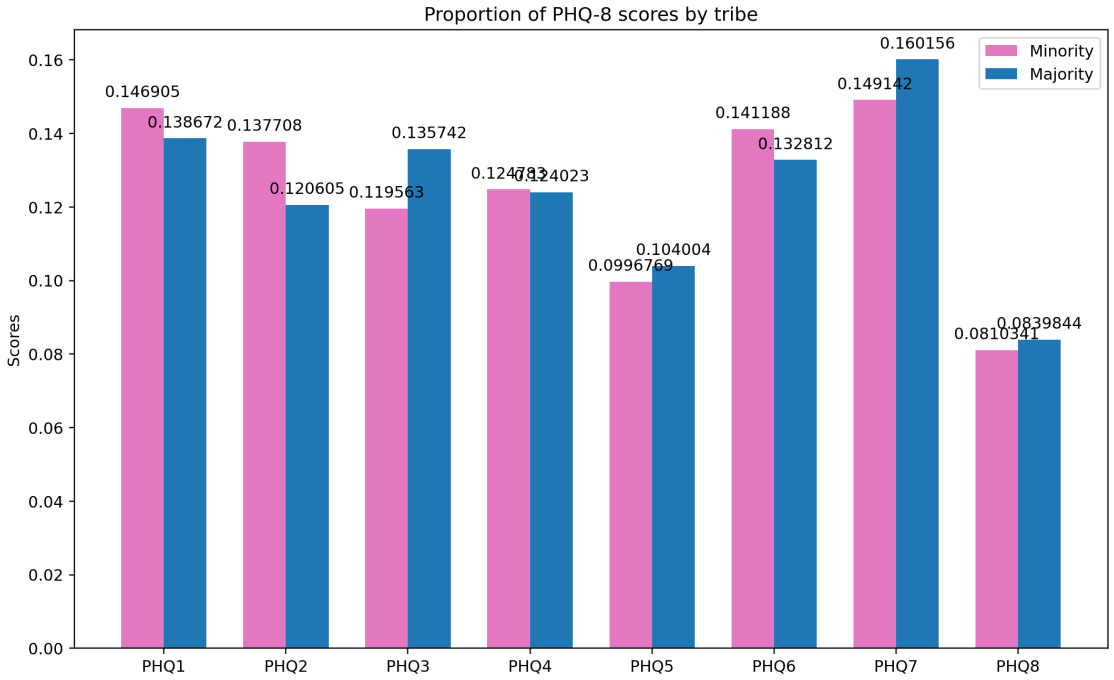


Findings

- Proportion of males that scored higher in each question of PHQ test is higher in 5 out of 8 questions
- Proportion of females that scored higher in each question of PHQ test is higher in 3 out of 8 questions
- Males scored higher in questions `PHQ1`, `PHQ5`, `PHQ6`, `PHQ7`and `PHQ8`
- Females scored higher in questions `PHQ2`, `PHQ3` and `PHQ4`

[201]:
```
aa = create_sum_metric('Tribe', 'PHQ')
# a = create_percentage_df(aa)
# a = a.transpose()
aa = aa.transpose()
ab = [i/ aa['Majority'].sum() for i in aa['Majority']]
ac = [i/ aa['Minority'].sum() for i in aa['Minority']]
ad = pd.DataFrame([ab, ac], index=['Majority', 'Minority'], columns=aa.
 ↪transpose().columns).transpose()
ad
x = ad.index.values[:]
y1 = ad.values[0:8,0]
y2 = ad.values[0:8,1]
lab1 = [f'{i*100:.2f}%' for i in y1]
lab2 = [f'{i*100:.2f}%' for i in y2]
# create_fig('', '', 'PHQ Score')
# plt.bar(x, y1, color=default_pink)
```

```
# plt.bar(x, y2, color=default_blue)
labels = x
i = np.arange(len(labels))
width = 0.35
fig, ax = create_sub()
rects1 = ax.bar(i - width/2, y2, width, label='Minority', color=default_pink)
rects2 = ax.bar(i + width/2, y1, width, label='Majority', color=default_blue)
ax.set_ylabel('Scores')
ax.set_title('Proportion of PHQ-8 scores by tribe')
ax.set_xticks(i, labels)
ax.bar_label(rects1, padding=5)
ax.bar_label(rects2, padding=5)
ax.legend()
fig.tight_layout();
```



Findings

- Proportion of participants belonging to minority tribes that scored higher in each question of PHQ test is higher in 4 out of 8 questions
- Proportion of participants belonging to majority tribes that scored higher in each question of PHQ test is higher in 4 out of 8 questions
- Participants belonging to minority tribes scored higher in questions `PHQ1`, `PHQ2`, `PHQ4`, and `PHQ6`
- Participants belonging to majority tribes scored higher in questions `PHQ3`, `PHQ5` `PHQ7`and `PHQ8`

[42]:
```
li = [i for i in df.columns if i.startswith('PHQ')]
su = df[li]
su = su.sum(axis=1)
bins = [0, 5, 10, 15, 20, 24]
su_cu = su.value_counts(bins=bins, normalize=True).to_frame().style.format('{:.
↪2%}')
# su_cu = pd.DataFrame(su_cu)

su_cu
```

[42]:
```
<pandas.io.formats.style.Styler at 0x7fdf335f89a0>
```

Findings

- 27.36% of participants scored below 5
- 34.5% between 5 and 10
- 25.5% between 10 and 15
- 10.33% between 15 and 20
- and 2.43% above 20

Research Question 2

- What are the GAD-7 scores?
  - what is the score between tribes?
  - what is the score among males?
  - what is the score among females?

[32]:
```
sum_gad = create_sum_super_set('GAD')
sum_gad
```

[32]:

	GAD1	GAD2	GAD3	GAD4	GAD5	GAD6	GAD7
0	0	0	0	0	0	0	0
1	239	198	213	176	141	237	186
2	196	202	208	148	190	150	206
3	255	468	576	333	180	405	435

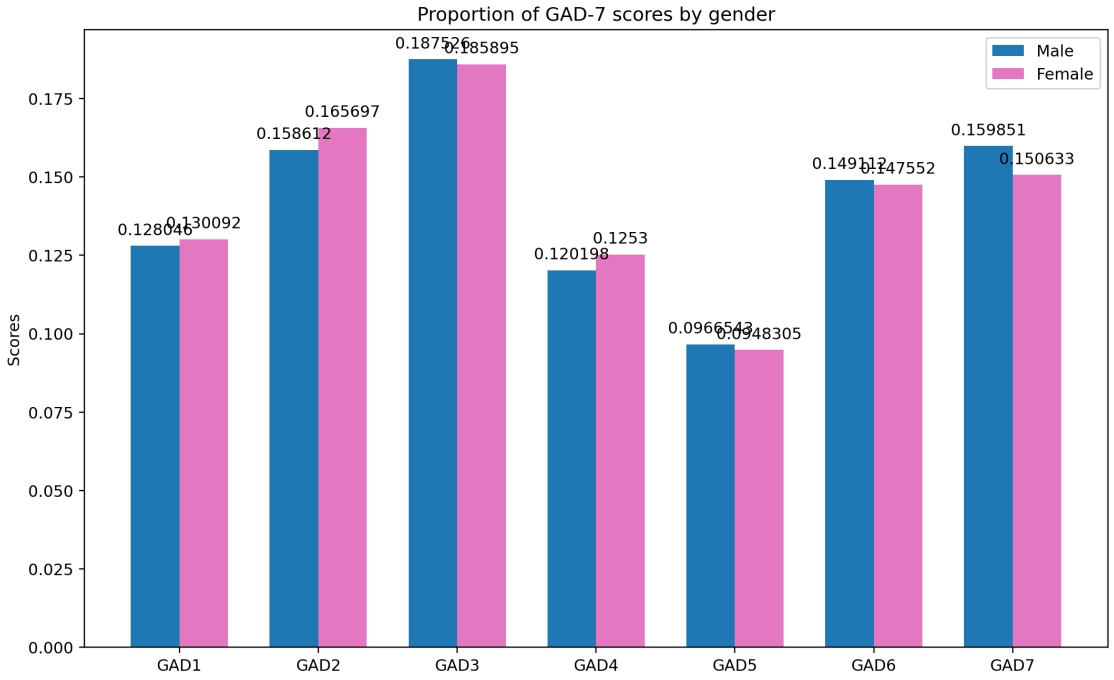
[37]:
```
avg_gad = create_average_super_set('GAD')
avg_gad
```

[37]:

	GAD1	GAD2	GAD3	GAD4	GAD5	GAD6	GAD7
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	1.0	1.0	1.0	1.0	1.0	1.0	1.0
2	2.0	2.0	2.0	2.0	2.0	2.0	2.0
3	3.0	3.0	3.0	3.0	3.0	3.0	3.0

[200]:
```
aa = create_sum_metric('Gender', 'GAD')
# a = create_percentage_df(aa)
# a = a.transpose()
```

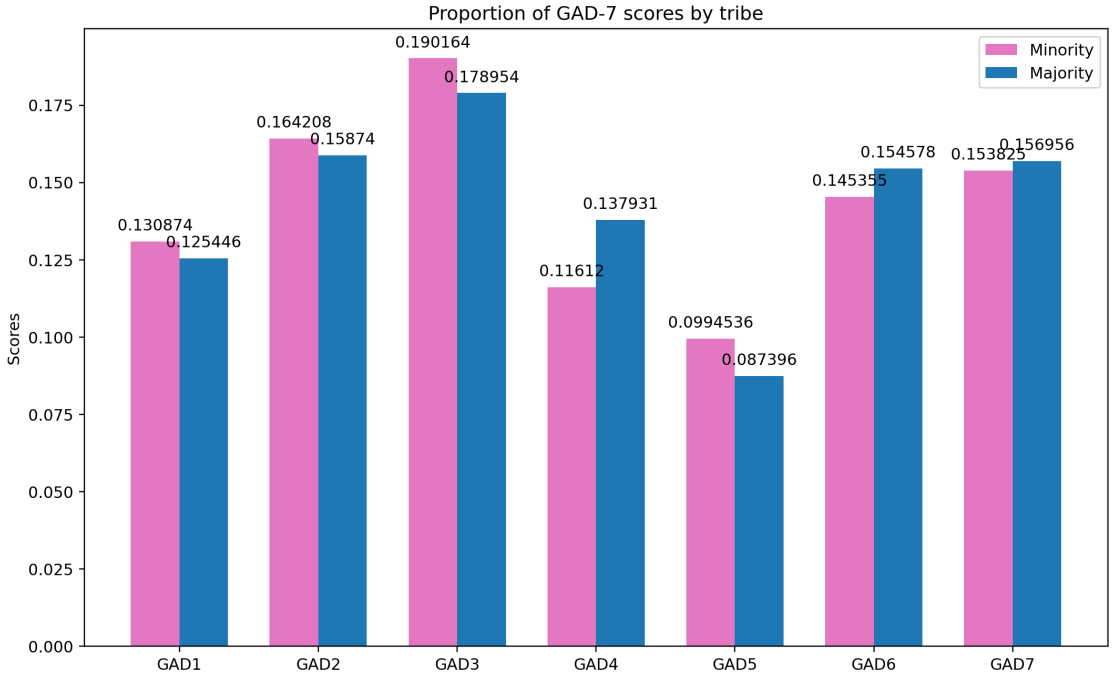
```
aa = aa.transpose()
ab = [i/ aa['F'].sum() for i in aa['F']]
ac = [i/ aa['M'].sum() for i in aa['M']]
ad = pd.DataFrame([ab, ac], index=['Female', 'Male'], columns=aa.transpose().
 ↪columns).transpose()
ad
x = ad.index.values[:]
y1 = ad.values[0:8,0]
y2 = ad.values[0:8,1]
lab1 = [f'{i*100:.2f}%' for i in y1]
lab2 = [f'{i*100:.2f}%' for i in y2]
# create_fig('', '', 'PHQ Score')
# plt.bar(x, y1, color=default_pink)
# plt.bar(x, y2, color=default_blue)
labels = x
i = np.arange(len(labels))
width = 0.35
fig, ax = create_sub()
rects1 = ax.bar(i - width/2, y2, width, label='Male', color=default_blue)
rects2 = ax.bar(i + width/2, y1, width, label='Female', color=default_pink)
ax.set_ylabel('Scores')
ax.set_title('Proportion of GAD-7 scores by gender')
ax.set_xticks(i, labels)
ax.bar_label(rects1, padding=5)
ax.bar_label(rects2, padding=5)
ax.legend()
fig.tight_layout();
```



Findings

- Proportion of males that scored higher in each question of GAD test is higher in 4 out of 7 questions
- Proportion of females that scored higher in each question of PHQ test is higher in 3 out of 7 questions
- Males scored higher in questions `GAD3`, `GAD5`, `GAD6` and `GAD7`
- Females scored higher in questions `GAD1`, `GAD2` and `GAD4`

[203]:
```
aa = create_sum_metric('Tribe', 'GAD')
# a = create_percentage_df(aa)
# a = a.transpose()
aa = aa.transpose()
ab = [i/ aa['Majority'].sum() for i in aa['Majority']]
ac = [i/ aa['Minority'].sum() for i in aa['Minority']]
ad = pd.DataFrame([ab, ac], index=['Majority', 'Minority'], columns=aa.
 ↪transpose().columns).transpose()
ad
x = ad.index.values[:]
y1 = ad.values[0:8,0]
y2 = ad.values[0:8,1]
lab1 = [f'{i*100:.2f}%' for i in y1]
lab2 = [f'{i*100:.2f}%' for i in y2]
# create_fig('', '', 'PHQ Score')
# plt.bar(x, y1, color=default_pink)
# plt.bar(x, y2, color=default_blue)
labels = x
i = np.arange(len(labels))
width = 0.35
fig, ax = create_sub()
rects1 = ax.bar(i - width/2, y2, width, label='Minority', color=default_pink)
rects2 = ax.bar(i + width/2, y1, width, label='Majority', color=default_blue)
ax.set_ylabel('Scores')
ax.set_title('Proportion of GAD-7 scores by tribe')
ax.set_xticks(i, labels)
ax.bar_label(rects1, padding=5)
ax.bar_label(rects2, padding=5)
ax.legend()
fig.tight_layout();
```



Findings

- Proportion of participants belonging to minority tribes that scored higher in each question of GAD test is higher in 4 out of 7 questions
- Proportion of participants belonging to majority tribes that scored higher in each question of GAD test is higher in 3 out of 7 questions
- Participants belonging to minority tribes scored higher in questions `GAD1`, `GAD2`, `GAD3`, and `GAD5`
- Participants belonging to majority tribes scored higher in questions `GAD4`, `GAD6` and `GAD7`

[73]:
```
li = [i for i in df.columns if i.startswith('GAD')]
su_gad = df[li]
su_gad = su_gad.sum(axis=1)
bins = [0, 5, 10, 15, 21]
su_cu_gad = su_gad.value_counts(bins=bins, normalize=True).to_frame().style.
 ↪format('{:.2%}')
su_cu_gad
```

[73]:
```
<pandas.io.formats.style.Styler at 0x7fa24ea3ee30>
```

Findings

- 35.11% of participants scored below 5
- 33.59% between 5 and 10
- 22.04% between 10 and 15

- and 9.27% above 15

Research Question 3

- What are the MPSS-12 scores?
  - what is the score of the various groups?

[33]:
```
sum_mpss = create_sum_super_set('MSSS')
sum_mpss
```

[33]:

	MSSS1	MSSS2	MSSS3	MSSS4	MSSS5	MSSS6	MSSS7	MSSS8	MSSS9	\
1	40.0	48.0	23.0	39.0	41.0	54.0	71.0	63.0	49.0	
2	110.0	106.0	50.0	88.0	90.0	104.0	190.0	122.0	106.0	
3	123.0	93.0	72.0	102.0	90.0	174.0	153.0	102.0	141.0	
4	204.0	176.0	132.0	184.0	260.0	400.0	348.0	260.0	260.0	
5	535.0	470.0	250.0	530.0	410.0	795.0	710.0	550.0	690.0	
6	1146.0	1254.0	1218.0	1050.0	1056.0	1044.0	876.0	966.0	1164.0	
7	1211.0	1253.0	2100.0	1498.0	1533.0	427.0	462.0	1148.0	784.0	
8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

	MSSS10	MSSS11	MSSS12
1	48	31.0	79.0
2	118	68.0	164.0
3	117	105.0	192.0
4	224	224.0	336.0
5	405	410.0	775.0
6	882	1152.0	816.0
7	1589	1596.0	406.0
8	8	NaN	NaN

[38]:
```
avg_mpss = create_average_super_set('MSSS')
avg_mpss
```

[38]:

	MSSS1	MSSS2	MSSS3	MSSS4	MSSS5	MSSS6	MSSS7	MSSS8	MSSS9	MSSS10	\
1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	
2	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	
3	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	
4	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	
5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	
6	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	
7	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	
8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8.0	

	MSSS11	MSSS12
1	1.0	1.0
2	2.0	2.0
3	3.0	3.0
4	4.0	4.0

```
5     5.0     5.0
6     6.0     6.0
7     7.0     7.0
8     NaN     NaN
```

[85]:
```
li = [i for i in df.columns if i.startswith('MSS') and i.endswith(('S1', 'S2',␣
 ↪'5', '10'))]
su_mpss = df[li]
su_mpss = su_mpss.sum(axis=1).apply(lambda x : x/4)
su_cu_mpss = su_mpss.value_counts(bins=4, normalize=True).to_frame().style.
 ↪format('{:.2%}')
su_cu_mpss
```

[85]:
```
<pandas.io.formats.style.Styler at 0x7fa24ea3dd80>
```

Findings for MPSS1, 2, 5 and 10

- 7.6% of participants scored below 2.5
- 16.41% between 2.55 and 4
- 27.81% between 4 and 5.5
- and 48.18% above 5.5

[87]:
```
li = [i for i in df.columns if i.startswith('MSS') and i.endswith(('3', '4',␣
 ↪'8', '11'))]
su_mpss = df[li]
su_mpss = su_mpss.sum(axis=1).apply(lambda x : x/4)
su_cu_mpss = su_mpss.value_counts(bins=4, normalize=True).to_frame().style.
 ↪format('{:.2%}')
su_cu_mpss
```

[87]:
```
<pandas.io.formats.style.Styler at 0x7fa24f952530>
```

Findings for MPSS3, 4, 8 and 11

- 6.84% of participants scored below 2.5
- 12.77% between 2.55 and 4
- 25.38% between 4 and 5.5
- and 55.02% above 5.5

[89]:
```
li = [i for i in df.columns if i.startswith('MSS') and i.endswith(('6', '7',␣
 ↪'9', '12'))]
su_mpss = df[li]
su_mpss = su_mpss.sum(axis=1).apply(lambda x : x/4)
su_cu_mpss = su_mpss.value_counts(bins=4, normalize=True).to_frame().style.
 ↪format('{:.2%}')
su_cu_mpss
```

[89]: <pandas.io.formats.style.Styler at 0x7fa24ea3cf40>

Findings for MPSS6, 7, 9 and 12

- 12.16% of participants scored below 2.5
- 24.47% between 2.55 and 4
- 40.58% between 4 and 5.5
- and 22.8% above 5.5

1.4 Summary of Findings

1.4.1 PHQ-8

Overall score

- 27.36% of participants scored below 5
- 34.5% between 5 and 10
- 25.5% between 10 and 15
- 10.33% between 15 and 20
- and 2.43% above 20 #### Gender
- Proportion of males that scored higher in each question of PHQ test is higher in 5 out of 8 questions
- Proportion of females that scored higher in each question of PHQ test is higher in 3 out of 8 questions
- Males scored higher in questions `PHQ1`, `PHQ5`, `PHQ6`, `PHQ7`and `PHQ8`
- Females scored higher in questions `PHQ2`, `PHQ3` and `PHQ4` #### Tribe
- Proportion of participants belonging to minority tribes that scored higher in each question of PHQ test is higher in 4 out of 8 questions
- Proportion of participants belonging to majority tribes that scored higher in each question of PHQ test is higher in 4 out of 8 questions
- Participants belonging to minority tribes scored higher in questions `PHQ1`, `PHQ2`, `PHQ4`, and `PHQ6`
- Participants belonging to majority tribes scored higher in questions `PHQ3`, `PHQ5` `PHQ7`and `PHQ8` ### GAD-7 #### Overall score
- 35.11% of participants scored below 5
- 33.59% between 5 and 10
- 22.04% between 10 and 15
- and 9.27% above 15 #### Gender
- Proportion of males that scored higher in each question of GAD test is higher in 4 out of 7 questions
- Proportion of females that scored higher in each question of PHQ test is higher in 3 out of 7 questions
- Males scored higher in questions `GAD3`, `GAD5`, `GAD6` and `GAD7`
- Females scored higher in questions `GAD1`, `GAD2` and `GAD4` #### Tribe
- Proportion of participants belonging to minority tribes that scored higher in each question of GAD test is higher in 4 out of 7 questions
- Proportion of participants belonging to majority tribes that scored higher in each question of GAD test is higher in 3 out of 7 questions

- Participants belonging to minority tribes scored higher in questions `GAD1`, `GAD2`, `GAD3`, and `GAD5`
- Participants belonging to majority tribes scored higher in questions `GAD4`, `GAD6` and `GAD7` ### MPSS-12 #### MPSS1, 2, 5 and 10
- 7.6% of participants scored below 2.5
- 16.41% between 2.55 and 4
- 27.81% between 4 and 5.5
- and 48.18% above 5.5 #### MPSS3, 4, 8 and 11
- 6.84% of participants scored below 2.5
- 12.77% between 2.55 and 4
- 25.38% between 4 and 5.5
- and 55.02% above 5.5 #### MPSS6, 7, 9 and 12
- 12.16% of participants scored below 2.5
- 24.47% between 2.55 and 4
- 40.58% between 4 and 5.5
- and 22.8% above 5.5

1.5 Conclusions

- Males proportionally score higher than females on 2 out of 3 tests
- Members of minority tribes proportionally score higher than those of majority tribes on 2 out of 3 tests
- The scores of a majority of participants lie close to the middle of the respective scales
  - the groups `MPSS1, 2, 5 and 10` and `MPSS3, 4, 8 and 11` are the only exceptions

[ ]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'exploration.html'])
```