GITHUB Report

1. Starting question

The importance of a national conversation is a cruicial aspect for nation building. However, there is a the lack of refined and summarised data to support this theory is a problem. Based on the news topics of the last decade, which aspects of Australian culture are in need of a conversation?

Which additional questions might give us insight to the topic development of the last decade?

How do we categorize the news topics?

How does the result actually contribute to the possibility of national conversation?

1.2 Relevant data

In [6]:

```
pip install textblob
```

```
Requirement already satisfied: textblob in /srv/conda/envs/notebook/
lib/python3.7/site-packages (0.15.3)
Requirement already satisfied: nltk>=3.1 in /srv/conda/envs/noteboo
k/lib/python3.7/site-packages (from textblob) (3.5)
Requirement already satisfied: joblib in /srv/conda/envs/notebook/li
b/python3.7/site-packages (from nltk>=3.1->textblob) (1.0.0)
Requirement already satisfied: click in /srv/conda/envs/notebook/li
b/python3.7/site-packages (from nltk>=3.1->textblob) (7.1.2)
Requirement already satisfied: tqdm in /srv/conda/envs/notebook/lib/
python3.7/site-packages (from nltk>=3.1->textblob) (4.56.0)
Requirement already satisfied: regex in /srv/conda/envs/notebook/li
b/python3.7/site-packages (from nltk>=3.1->textblob) (2020.11.13)
Note: you may need to restart the kernel to use updated packages.
```

In [7]:

```
# import Python libraries
import pandas as pd              # used for tabular datasets
import matplotlib.pyplot
import numpy as np # linear algebra
import pandas as pd # data processing)
from textblob import TextBlob
import nltk
nltk.download('punkt')
nltk.download('stopwords')

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename)) # used for visualisation purposes
```

```
[nltk_data] Downloading package punkt to /home/jovyan/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /home/jovyan/nltk_dat
a...
[nltk_data]   Package stopwords is already up-to-date!
```

In [8]:

```
data3 = pd.read_csv('abcnews-date-text.csv') #read into pd
```

In [9]:

```
data2 = pd.read_csv('abcnews-date-text.csv',parse_dates=[0], infer_datetime_form
at=True) #to be used for insights later
data2.columns = ['date','text']
```

In [10]:

```
data3['publish_year'] = data3['publish_date'].apply(lambda x:int(x/9992))
```

1.3 Analysing the data

In [11]:

```
# How many news headlines are in this dataset?
# We can answer this questions by determining the total number of
# instances (rows) in our dataset

# The dimensional shape of the dataframe
data3.shape
```

Out[11]:

```
(1186018, 3)
```

In [12]:

```
#We only want the number of rows
data3.shape[0]
```

Out[12]:

```
1186018
```

In [13]:

```
print("There are {} news headlines represented in the data".format(data3.shape[0
]))
```

```
There are 1186018 news headlines represented in the data
```

How can we address our original question: Which words are common among the headline texts?

Maybe it would help if we could view the number of topics for each day?

In [14]:

```
daily_topics = data2.groupby('date')['text'].count()
daily_topics
```

Out[14]:

```
date
2003-02-19    198
2003-02-20    250
2003-02-21    250
2003-02-22    126
2003-02-23    136
2003-02-24    250
2003-02-25    250
2003-02-26    250
2003-02-27    221
2003-02-28    249
2003-03-01    176
2003-03-02    168
2003-03-03    232
2003-03-04    215
2003-03-05    239
2003-03-06    214
2003-03-07    209
2003-03-08    124
2003-03-09    164
2003-03-10    217
2003-03-11    220
2003-03-12    226
2003-03-13    224
2003-03-14    229
2003-03-15    134
2003-03-16    119
2003-03-17    226
2003-03-18    226
2003-03-19    225
2003-03-20    219
             ...
2019-12-02     92
2019-12-03    115
2019-12-04    123
2019-12-05    121
2019-12-06    115
2019-12-07     62
2019-12-08     61
2019-12-09    108
2019-12-10     98
2019-12-11    100
2019-12-12    103
2019-12-13    103
2019-12-14     64
2019-12-15     48
2019-12-16     93
2019-12-17     91
2019-12-18    100
2019-12-19    109
2019-12-20    106
2019-12-21     67
2019-12-22     48
2019-12-23     66
2019-12-24     69
2019-12-25     27
2019-12-26     46
2019-12-27     52
2019-12-28     60
```

```
2019-12-29     43
2019-12-30     46
2019-12-31     71
Name: text, Length: 6152, dtype: int64
```

In [15]:

```
#Break it down further for listing

reindexed_data = data2['text']
reindexed_data.index = data2['date']
reindexed_data.head()
```

Out[15]:

```
date
2003-02-19    aba decides against community broadcasting lic...
2003-02-19       act fire witnesses must be aware of defamation
2003-02-19       a g calls for infrastructure protection summit
2003-02-19             air nz staff in aust strike for pay rise
2003-02-19        air nz strike to affect australian travellers
Name: text, dtype: object
```

Or better yet, let's find out the total amount of common words among the headlines

In [16]:

```
corp = str()
for i in range(len(data3['headline_text'])):
    corp += (' ')+data3['headline_text'][i]
```

In [17]:

```
import nltk
words = nltk.word_tokenize(corp)
#data['headline_text'][1] + (' ') + data['headline_text'][2] + data['headline_te
xt'][3]
```

In [18]:

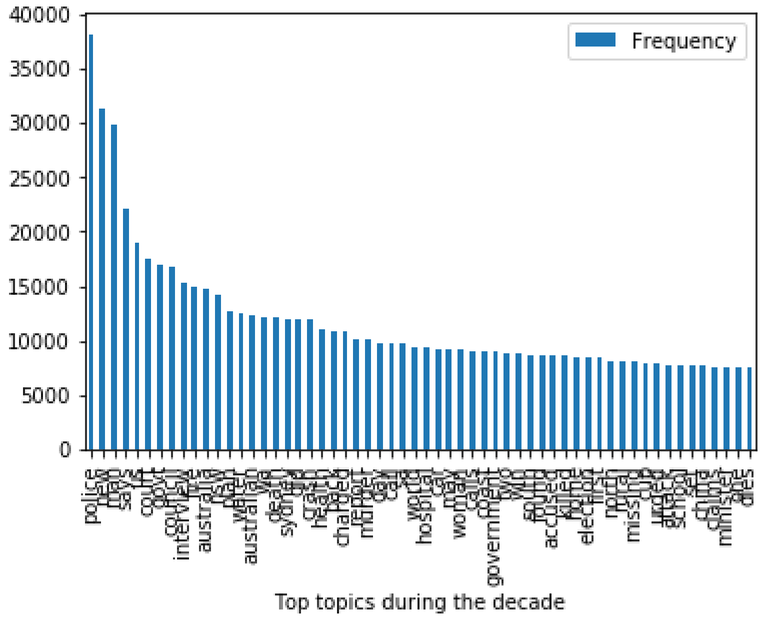
```
from nltk.corpus import stopwords # eliminate words which have no meaning
stop_words = set(stopwords.words('english'))
f_words = [w for w in words if not w in stop_words]

punctuations = '''!()-[]{};:'"\,<>./?@#$%^&*_~'''
fp_words = [w for w in f_words if not w in punctuations]
```

In [19]:

```
fd = nltk.FreqDist(fp_words) # create for loop

df_fdist = pd.DataFrame.from_dict(fd, orient='index')
df_fdist.columns = ['Frequency']
df_fdist.index.name = 'Top topics during the decade'

freq_df = df_fdist[df_fdist['Frequency']>500]
d = freq_df.to_dict()['Frequency']

#plt.figure(figsize=(20, 8))
freq_df1 = df_fdist[df_fdist['Frequency']>7500]
freq_df1.sort_values('Frequency',ascending=False).plot(kind='bar')
#freq_df1.columns
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f62715e1890>
```



Now we could see which words are common among the headline texts

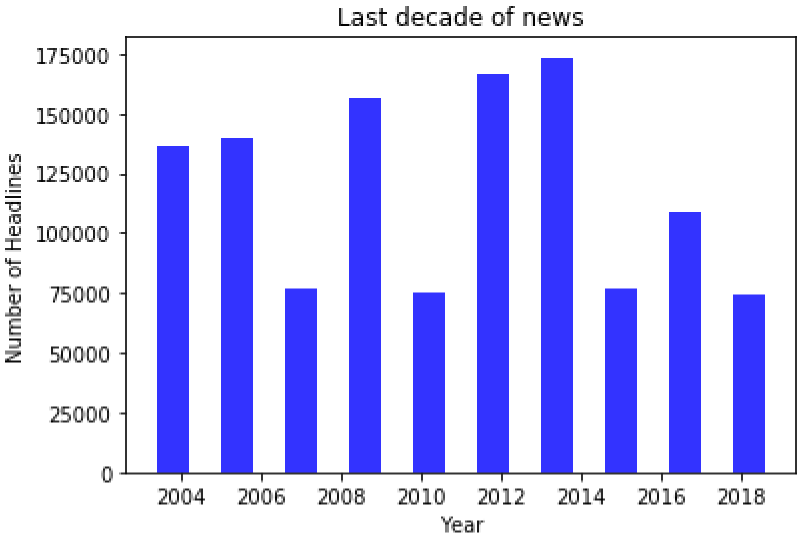
1.4 Visualising the results

In [20]:

```
data3['publish_year'] = data3['publish_date'].apply(lambda x:int(x/10000)) #sepa
rate frequency of news topics into years
```

In [21]:

```
import matplotlib.pyplot as plt
plt.hist(data3['publish_year'], facecolor='blue', alpha=0.8, rwidth = 0.5)
plt.xlabel('Year')
plt.ylabel('Number of Headlines')
plt.title('Last decade of news')
plt.show()
```



Above is the amount of news topics generated during 2004 to 2019

In [22]:

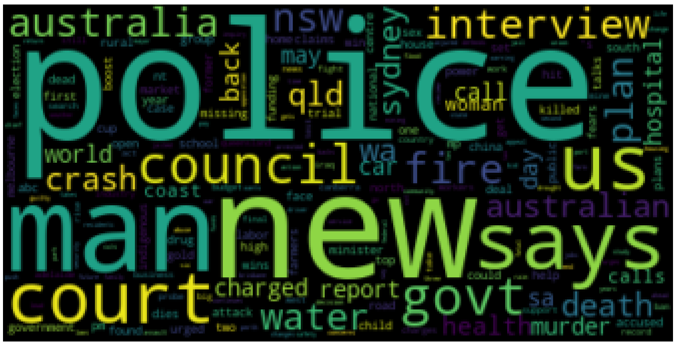
```
pip install wordcloud
```

```
Requirement already satisfied: wordcloud in /srv/conda/envs/noteboo
k/lib/python3.7/site-packages (1.8.1)
Requirement already satisfied: numpy>=1.6.1 in /srv/conda/envs/noteb
ook/lib/python3.7/site-packages (from wordcloud) (1.19.5)
Requirement already satisfied: matplotlib in /srv/conda/envs/noteboo
k/lib/python3.7/site-packages (from wordcloud) (3.1.3)
Requirement already satisfied: pillow in /srv/conda/envs/notebook/li
b/python3.7/site-packages (from wordcloud) (8.1.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /srv/conda/envs/
notebook/lib/python3.7/site-packages (from matplotlib->wordcloud)
(1.3.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.
0.1 in /srv/conda/envs/notebook/lib/python3.7/site-packages (from ma
tplotlib->wordcloud) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /srv/conda/envs/noteb
ook/lib/python3.7/site-packages (from matplotlib->wordcloud) (0.10.
0)
Requirement already satisfied: python-dateutil>=2.1 in /srv/conda/en
vs/notebook/lib/python3.7/site-packages (from matplotlib->wordcloud)
(2.8.1)
Requirement already satisfied: six in /srv/conda/envs/notebook/lib/p
ython3.7/site-packages (from cycler>=0.10->matplotlib->wordcloud)
(1.15.0)
Note: you may need to restart the kernel to use updated packages.
```

In [23]:

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
plt.figure(figsize=(40,40))
wordcloud = WordCloud()
wordcloud.generate_from_frequencies(frequencies=d)
plt.figure()
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

```
<Figure size 2880x2880 with 0 Axes>
```



The wordcloud shows the most popular "words" used during the last decade and beyond

How do we use categorize this data into groups? Particularly into news topics?

1.5 Insight

Let's find a way to group them into news topics

In [24]:

```
# Grouping of words into news topics
import nltk

Politics = [0]*reindexed_data.shape[0]
World = [0]*reindexed_data.shape[0]
Business = [0]*reindexed_data.shape[0]
Sport = [0]*reindexed_data.shape[0]
Law = [0]*reindexed_data.shape[0]
Emergency = [0]*reindexed_data.shape[0]
Health = [0]*reindexed_data.shape[0]

for i in range(reindexed_data.shape[0]):
    words = TextBlob(reindexed_data[i]).words
    for word in words:
        if word == "politics" or word == "government" or word == "govt" or word
== "court": Politics[i]=1
        if word == "world" or word == "finance" or word == "real estate" or word
== "international": World[i]=1
        if word == "business" or word == "finance": Business[i]=1
        if word == "sport" or word == "rugby": Sport[i]=1
        if word == "law" or word == "police" or word == "council" or word == "ch
arged" or word == "accused": Law[i]=1
        if word == "emergency" or word == "fire" or word == "crash" or word ==
"murder": Emergency[i]=1
        if word == "health" or word == "death": Health[i]=1  # as all headlines
 are in lowercase
keywords = pd.DataFrame({'text':reindexed_data,
                        'Politics':Politics,
                        'World':World,
                        'Business':Business,
                        'Sport':Sport,
                        'Law':Law,
                        'Emergency':Emergency,
                        'Health':Health},
                        index=reindexed_data.index)
```

In [25]:

```
# show summary
monthly = keywords.resample('M').sum()
print(monthly)
```

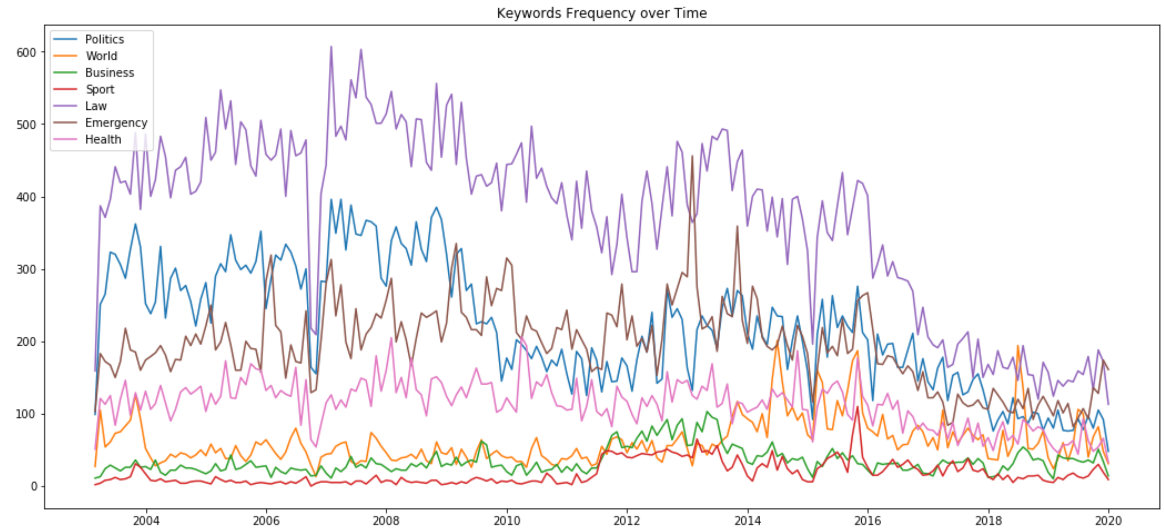
	Politics	World	Business	Sport	Law	Emergency	Health
date							
2003-02-28	99	27	11	2	159	103	51
2003-03-31	251	105	13	4	387	183	121
2003-04-30	265	54	24	8	371	172	113
2003-05-31	323	61	29	9	396	167	125
2003-06-30	320	73	25	12	441	150	84
2003-07-31	306	75	21	9	419	172	120
2003-08-31	287	83	26	10	421	218	146
2003-09-30	327	91	26	13	403	188	98
2003-10-31	362	126	36	31	488	185	129
2003-11-30	330	93	26	26	382	160	105
2003-12-31	252	52	27	17	486	174	131
2004-01-31	238	39	23	8	400	179	106
2004-02-29	254	28	36	7	423	184	114
2004-03-31	331	32	19	10	483	194	139
2004-04-30	232	35	15	6	455	181	115
2004-05-31	287	44	22	7	398	158	90
2004-06-30	301	40	22	8	436	175	106
2004-07-31	270	46	29	4	441	174	130
2004-08-31	277	44	25	4	454	207	136
2004-09-30	255	39	25	6	403	194	127
2004-10-31	221	43	23	7	407	210	132
2004-11-30	258	50	20	7	420	196	138
2004-12-31	281	42	17	5	509	221	103
2005-01-31	225	58	21	3	450	250	128
2005-02-28	290	46	31	13	461	188	113
2005-03-31	307	52	21	9	547	199	124
2005-04-30	296	38	23	6	493	226	173
2005-05-31	347	38	43	8	532	195	122
2005-06-30	312	56	23	5	444	160	121
2005-07-31	299	42	25	5	503	160	150
...	...	...	...	...	...	...	...
2017-07-31	126	70	33	25	204	115	72
2017-08-31	130	80	39	38	213	110	94
2017-09-30	147	70	30	22	150	112	61
2017-10-31	155	64	38	20	203	119	87
2017-11-30	133	71	32	24	150	108	55
2017-12-31	105	38	12	13	168	106	67
2018-01-31	76	37	13	9	154	135	49
2018-02-28	91	36	15	17	187	126	73
2018-03-31	103	77	28	9	164	116	89
2018-04-30	86	41	22	15	162	104	63
2018-05-31	122	57	31	5	178	101	70
2018-06-30	93	194	46	12	146	120	58
2018-07-31	96	136	54	10	194	107	92
2018-08-31	87	52	48	14	154	135	85
2018-09-30	102	51	36	14	153	92	76
2018-10-31	100	59	38	15	120	112	82
2018-11-30	77	76	35	8	171	124	78
2018-12-31	94	39	19	6	157	111	62
2019-01-31	80	24	10	5	124	97	52
2019-02-28	105	38	43	12	146	118	46
2019-03-31	77	60	39	9	138	101	57
2019-04-30	76	35	38	15	146	114	57
2019-05-31	77	57	38	18	144	82	63
2019-06-30	93	106	35	13	159	94	44
2019-07-31	78	100	33	11	154	107	93
2019-08-31	97	40	36	14	179	93	63
2019-09-30	80	68	32	23	133	136	48
2019-10-31	105	82	51	30	188	128	54

```
2019-11-30          92       48          34       19   172          174       66
2019-12-31          48       31          14        9   113          161       33

[203 rows x 7 columns]
```

Now we see the words grouped into news topics

In [26]:

```
fig, ax = plt.subplots(figsize=(18,8))

ax.plot(monthly['Politics'], label='Politics');
ax.plot(monthly['World'], label='World');
ax.plot(monthly['Business'], label='Business');
ax.plot(monthly['Sport'], label='Sport');
ax.plot(monthly['Law'], label='Law');
ax.plot(monthly['Emergency'], label='Emergency');
ax.plot(monthly['Health'], label='Health');
ax.set_title('Keywords Frequency over Time');
ax.legend(loc='upper left');
```



Key points from 2010 to 2019 :

- News topics on "Law" were the most popular out of all the groups (Keep in mind that keywords for Law include "police", "council", etc.)
- These were primarily keywords that focused on legislation or the process of it (et. al "police")

- During early 2013, "Emergency" was trending so much that it was almost able to take the top spot for that time period
- It could be noted that news on the Victoria bushfires were sought after at this point

- Topics on "Politics" were surprisingly trending down from 2009 to 2019
- It was overtaken numerous times more urgent topics from the "Emergency" section

- World news had a spike during early 2016 and 2019, which can be attributed to the US elections (Donald Trump) & China-USA tensions
- Topics on "Sports" were the least popular in the last decade

Based on the presented data above, it is safe to assume that Australia's national conversation were predominantly dominated by topics on legislative matters ("Laws"). It comes to no surprise that matters of the "council" or "police" directly affects the economic status and well-being of the average Aussie family. When push comes to shove, more urgent topics such as "bushfires" will come into the limelight as news agencies feel that this is more important. It is worth noting that "Emergency" topics also focus on attention grabbing headlines such as "murder". We may question the media's intention for this: Was the topic made for viewership's sake or from a geniune source of concern? The data also represents the citizen's concern for global topics as they are well aware of international news.

2.1 Second question

According to the WHO, mental health is about the state of a peron's wellnes rather than an illness. There is a difference between "mental health" and a mental condition. However, there is no official international guideline on how to effectively tackle mental health issues. Thus, each country uniquely addresses the problems faced by its citizen thru their own wellness programs. Which leads us to the question:

How does the frequency of mental health illness and attitudes towards mental health vary by geographic location?

What are the health effects of its frequency?

2.2 Relevant data

In [27]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
%matplotlib inline
# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list
 the files in the input directory

from subprocess import check_output
print(check_output(["ls", "mentalhealthsurvey.csv"]).decode("utf8"))
```

```
mentalhealthsurvey.csv
```

In [28]:

```
df = pd.read_csv('mentalhealthsurvey.csv')
df2 = pd.read_csv('master.csv')
```

2.3 Analysing the data

Let's check the data first

In [29]:

```
df.head() #show info
```

Out[29]:

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	work_i
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes	
1	2014-08-27 11:29:37	44	M	United States	IN	NaN	No	No	
2	2014-08-27 11:29:44	32	Male	Canada	NaN	NaN	No	No	
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	NaN	Yes	Yes	
4	2014-08-27 11:30:22	31	Male	United States	TX	NaN	No	No	

5 rows × 27 columns

In [30]:

```
df.info() #how many responses were there?
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
Timestamp                    1259 non-null object
Age                          1259 non-null int64
Gender                       1259 non-null object
Country                      1259 non-null object
state                        744 non-null object
self_employed                1241 non-null object
family_history               1259 non-null object
treatment                    1259 non-null object
work_interfere               995 non-null object
no_employees                 1259 non-null object
remote_work                  1259 non-null object
tech_company                 1259 non-null object
benefits                     1259 non-null object
care_options                 1259 non-null object
wellness_program             1259 non-null object
seek_help                    1259 non-null object
anonymity                    1259 non-null object
leave                        1259 non-null object
mental_health_consequence    1259 non-null object
phys_health_consequence      1259 non-null object
coworkers                    1259 non-null object
supervisor                   1259 non-null object
mental_health_interview      1259 non-null object
phys_health_interview        1259 non-null object
mental_vs_physical           1259 non-null object
obs_consequence              1259 non-null object
comments                     164 non-null object
dtypes: int64(1), object(26)
memory usage: 265.6+ KB
```

In [31]:

```
#### We can see that some survey questions were lacking answers
```

In [32]:

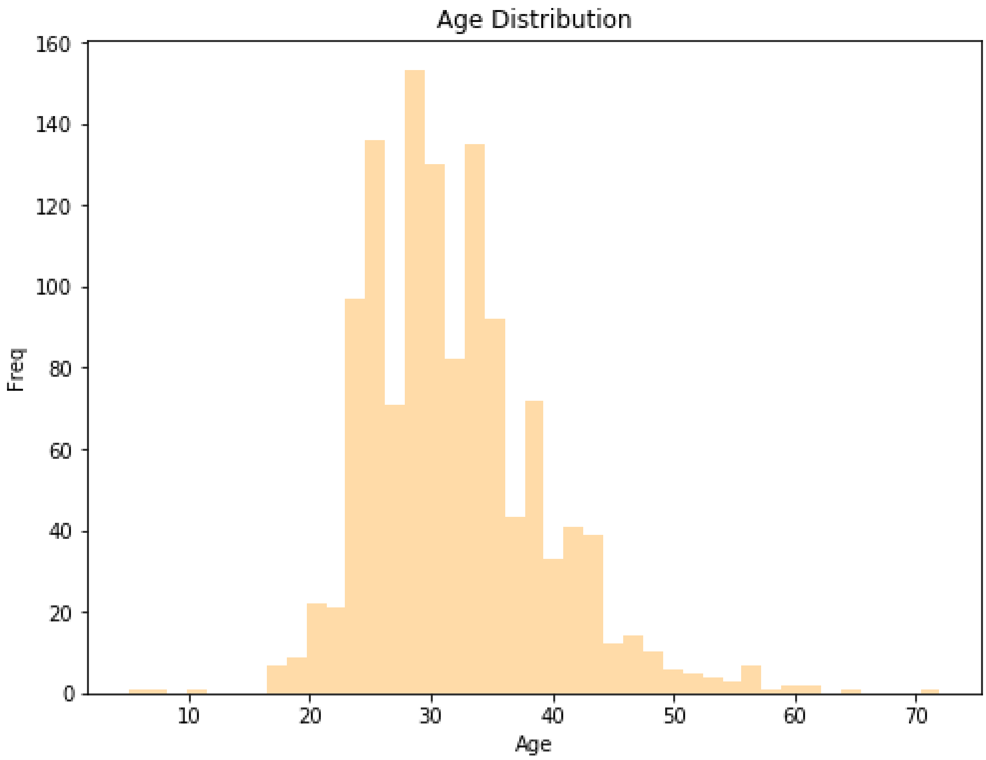
```
df['Age'] = pd.to_numeric(df['Age'],errors='coerce') #make an age group
def age_process(age):
    if age>=0 and age<=100:
        return age
    else:
        return np.nan
df['Age'] = df['Age'].apply(age_process)
```

In [33]:

```
fig,ax = plt.subplots(figsize=(8,6))
sns.distplot(df['Age'].dropna(),ax=ax,kde=False,color='#ffa726')
plt.title('Age Distribution')
plt.ylabel('Freq')
```

Out[33]:

```
Text(0, 0.5, 'Freq')
```



df['Timestamp'] = pd.to_datetime(df['Timestamp'],format='%Y-%m-%d') #convert into format df['Year'] = df['Timestamp'].apply(lambda x:x.year)#### Above is the age distribution of mental health responses

- Most responses were from workers aged around their early 20's to mid 30's
- With the most responses from people aged around 26 - 29
- Worth noticing that there were responses from people below 10 years old, this could be a discrepency

In [34]:

```
df['Timestamp'] = pd.to_datetime(df['Timestamp'],format='%Y-%m-%d') #convert int
o format
df['Year'] = df['Timestamp'].apply(lambda x:x.year)
```

In [35]:

```
df['Age_Group'] = pd.cut(df['Age'].dropna(), #categorize into age groups
                         [0,18,25,35,45,99],
                         labels=['<18','18-24','25-34','35-44','45+'])
```

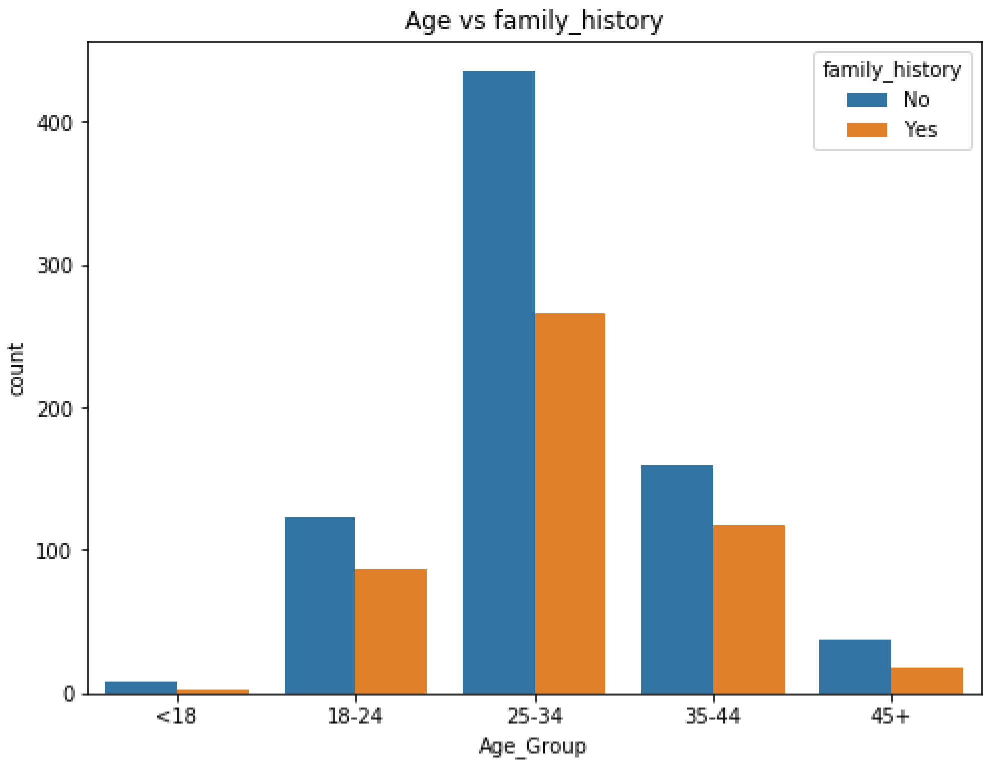
Do workers have a family history of mental illness?

In [36]:

```
fig,ax = plt.subplots(figsize=(8,6)) #create comparison plot
sns.countplot(data=df,x = 'Age_Group',hue= 'family_history',ax=ax)
plt.title('Age vs family_history')
```

Out[36]:

```
Text(0.5, 1.0, 'Age vs family_history')
```

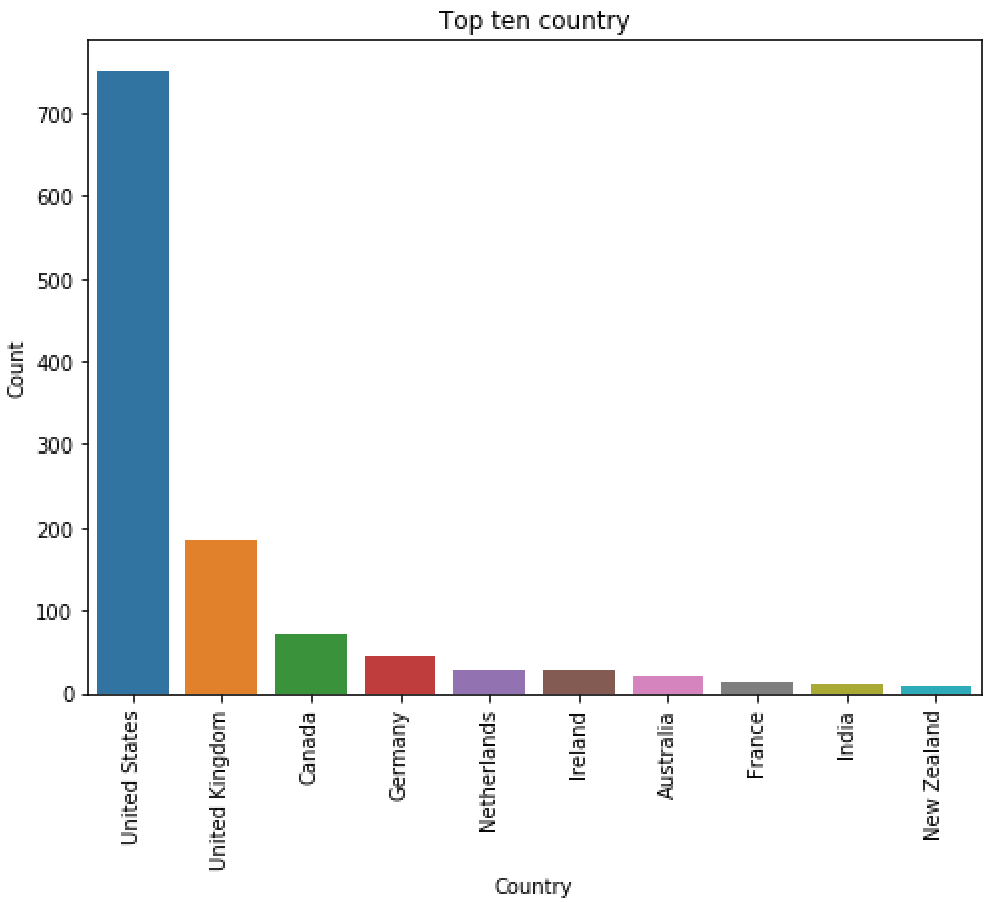


It can be seen that there is a relationship between a person's family history with their mental ilness.

1.4 Visualising the results

In [37]:

```
# plot top 10 countries with mental health cases

country_count = Counter(df['Country'].dropna().tolist()).most_common(10)
country_idx = [country[0] for country in country_count]
country_val = [country[1] for country in country_count]
fig,ax = plt.subplots(figsize=(8,6))
sns.barplot(x = country_idx,y=country_val ,ax =ax)
plt.title('Top ten country')
plt.xlabel('Country')
plt.ylabel('Count')
ticks = plt.setp(ax.get_xticklabels(),rotation=90)
```



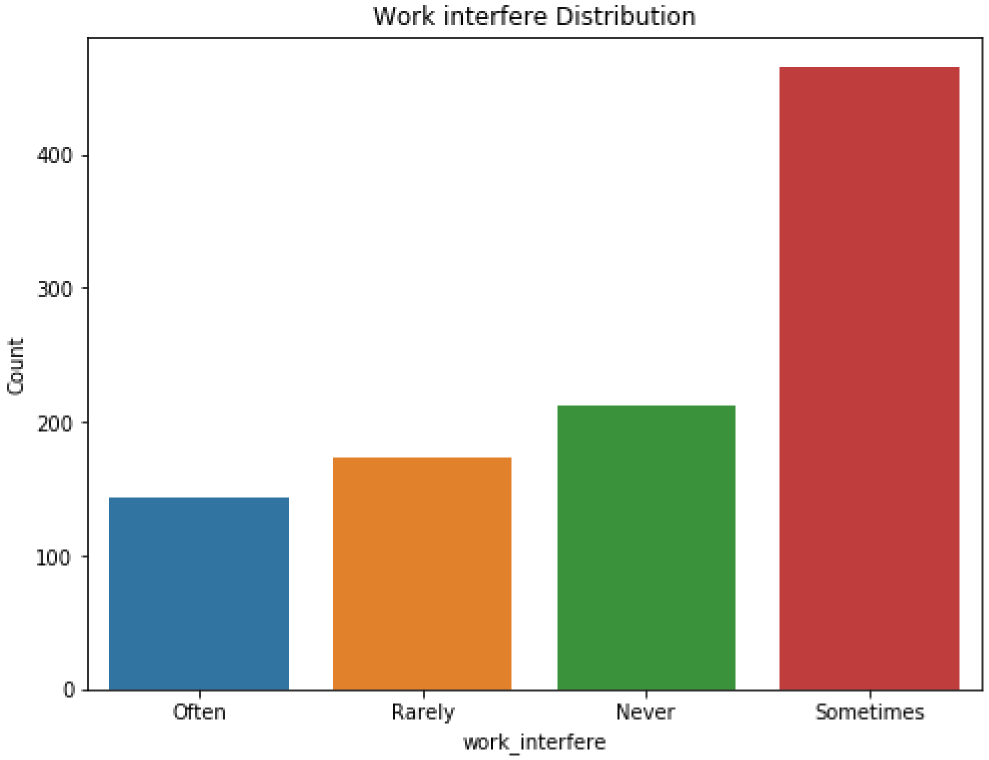
The graph above shows the top 10 countries with the most recorded number of mental illnesses. USA comes into a distant lead over the next country (UK).

In [38]:

```
# plot work disturbance responses

fig,ax  =plt.subplots(figsize=(8,6))
sns.countplot(df['work_interfere'].dropna(),ax=ax)
plt.title('Work interfere Distribution')
plt.ylabel('Count')
```

Out[38]:

```
Text(0, 0.5, 'Count')
```



Above is the frequency of mental health issue interferences for workers

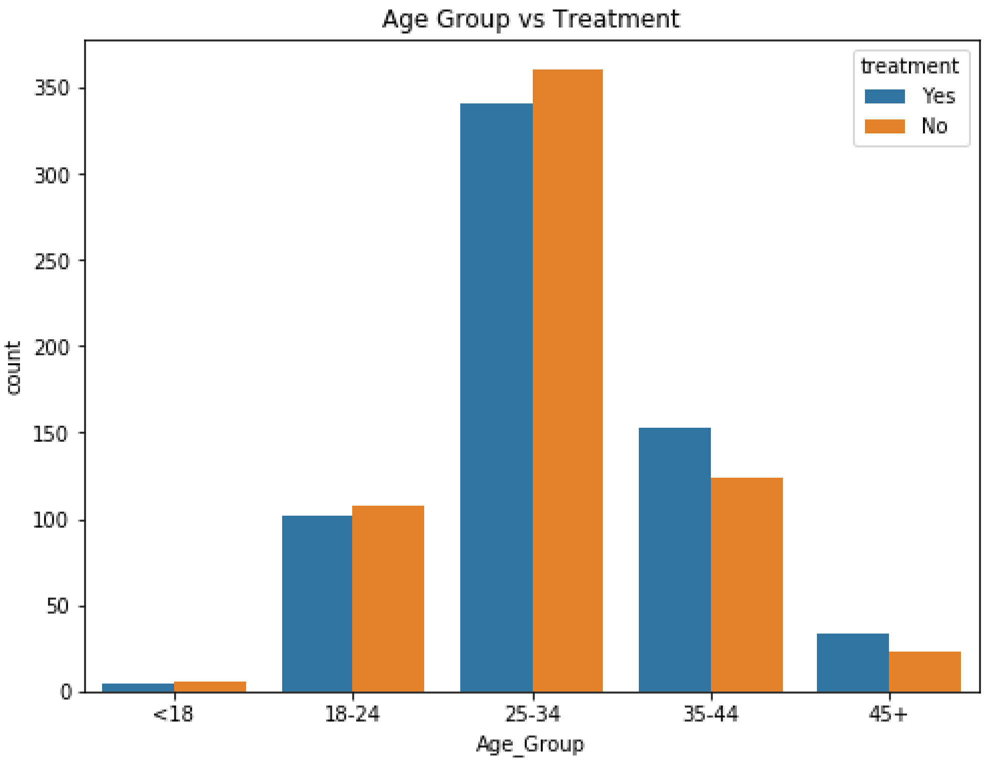
2.5 Insight

In [39]:

```
#Create treatment chart

fig,ax =plt.subplots(figsize=(8,6))
sns.countplot(data = df,x = 'Age_Group', hue='treatment')
plt.title('Age Group vs Treatment')
```

Out[39]:

```
Text(0.5, 1.0, 'Age Group vs Treatment')
```



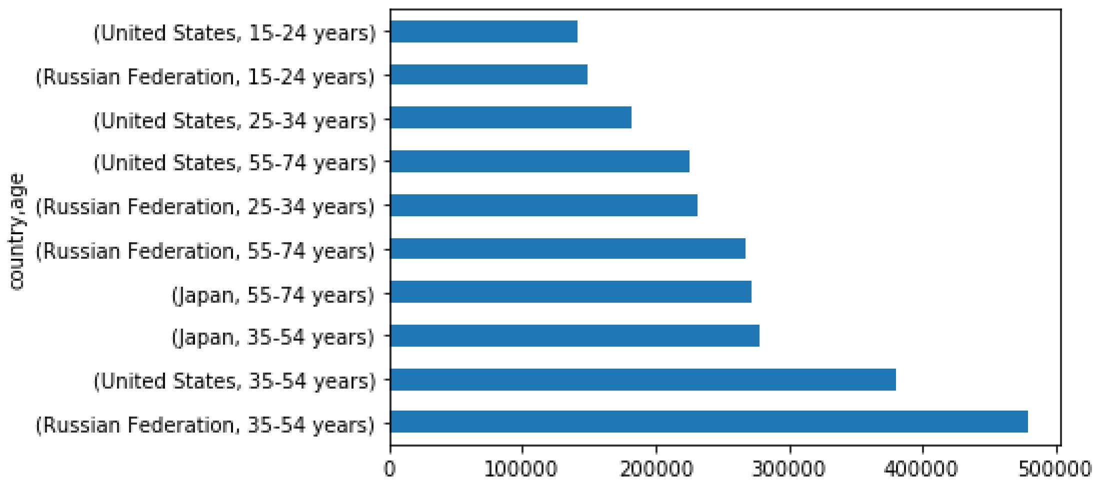
Less people diagnosed with mental health problems are seeking treatment. This could possibly be either attributed to the fact that there is either a lack of support or society's stigma as a whole.

In [40]:

```
df2.groupby(['country','age']).suicides_no.sum().nlargest(10).plot(kind='barh')
```

Out[40]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f626d189150>
```



Above is a chart derived from WHO data. It explains the frequency of diagnosed mental illnesses from developed countries and its suicide rate per million persons.

Key points from the WHO survey analysis:

```
* People with a history of family mental health issues are more likely to
 suffer the same diagnosis than those who don't have a record.
* Workers from the early 20's to early 30's seem to be the most vulnerable
to developing a mental illness
* USA and UK had the most reported cases while other countries were laggin
g
* The number of people seeking treatment was less than those who did not
* Majority of mental health related issues only "sometimes" interfered wit
h work
* Based on suicide rates, the countries of Japan, Russia and USA were prom
inent on the list at different age groups
```

2.6 Third question

The topic of mental health has lately been trending as an area of interest among the scientific community, particularly its causes and effects within the workspace. Although novel, we a researchers within the tech world would like to know what are the common atittudes towards mental illnesses and what could be the possible predictors for it?

Based on the survey, what are the atittudes and predictors for mental illness within the tech space?

In [41]:

```
### 2.2 Relevant data
```

In [42]:

```
import numpy as np
import pandas as pd
import random as rnd

import seaborn as sns
sns.set_palette('Set2')
import matplotlib.pyplot as plt
%matplotlib inline
```

In [43]:

```
data = pd.read_csv('mental-heath-in-tech-2016_20161114.csv')
```

2.3 Analyze data

In [44]:

```
# Let's get a feel for the data

data.describe()
```

Out[44]:

	Are you self-employed?	Is your employer primarily a tech company/organization?	Is your primary role within your company related to tech/IT?	Do you have medical coverage (private insurance or state-provided) which includes treatment of mental health issues?	Do you have previous employers?	Have yo ever sougl treatment fc a ment: health issu from mental healt professional
count	1433.000000	1146.000000	263.000000	287.000000	1433.000000	1433.00000
mean	0.200279	0.770506	0.942966	0.644599	0.882066	0.58548
std	0.400349	0.420691	0.232350	0.479471	0.322643	0.49281
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	0.000000	1.000000	1.000000	0.000000	1.000000	0.00000
50%	0.000000	1.000000	1.000000	1.000000	1.000000	1.00000
75%	0.000000	1.000000	1.000000	1.000000	1.000000	1.00000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.00000

In [45]:

```
# Another view of the data

data.head()
```

Out[45]:

	Are you self-employed?	How many employees does your company or organization have?	Is your employer primarily a tech company/organization?	Is your primary role within your company related to tech/IT?	Does your employer provide mental health benefits as part of healthcare coverage?	Do you know the options for mental health care available under your employer-provided coverage?	empl ... c men (for ex ... car oth commu
0	0	26-100	1.0	NaN	Not eligible for coverage / N/A	NaN	
1	0	6-25	1.0	NaN	No	Yes	
2	0	6-25	1.0	NaN	No	NaN	
3	1	NaN	NaN	NaN	NaN	NaN	
4	0	6-25	0.0	1.0	Yes	Yes	

5 rows × 63 columns

In [46]:

```
data.loc[(data['What is your age?'] > 90), 'What is your age?'] = 34
data.loc[(data['What is your age?'] < 10), 'What is your age?'] = 34
```

In [47]:

```
#### We now have to group the data into Gender roles: Male, Female, etc.
```

In [48]:

```
# clean the genders by grouping the genders into 3 categories: Female, Male, Genderqueer/Other
data['What is your gender?'] = data['What is your gender?'].replace([
    'male', 'Male ', 'M', 'm', 'man', 'Cis male',
    'Male.', 'Male (cis)', 'Man', 'Sex is male',
    'cis male', 'Malr', 'Dude', "I'm a man why didn't you make this a drop down question. You should of asked sex? And I would of answered yes please. Seriously how much text can this take? ",
    'mail', 'M|', 'male ', 'Cis Male', 'Male (trans, FtM)',
    'cisdude', 'cis man', 'MALE'], 'Male')
data['What is your gender?'] = data['What is your gender?'].replace([
    'female', 'I identify as female.', 'female ',
    'Female assigned at birth ', 'F', 'Woman', 'fm', 'f',
    'Cis female', 'Transitioned, M2F', 'Female or Multi-Gender Femme',
    'Female ', 'woman', 'female/woman', 'Cisgender Female',
    'mtf', 'fem', 'Female (props for making this a freeform field, though)',
    ' Female', 'Cis-woman', 'AFAB', 'Transgender woman',
    'Cis female '], 'Female')
data['What is your gender?'] = data['What is your gender?'].replace([
    'Bigender', 'non-binary,', 'Genderfluid (born female)',
    'Other/Transfeminine', 'Androgynous', 'male 9:1 female, roughly',
    'nb masculine', 'genderqueer', 'Human', 'Genderfluid',
    'Enby', 'genderqueer woman', 'Queer', 'Agender', 'Fluid',
    'Genderflux demi-girl', 'female-bodied; no feelings about gender',
    'non-binary', 'Male/genderqueer', 'Nonbinary', 'Other', 'none of your business',
    'Unicorn', 'human', 'Genderqueer'], 'Genderqueer/Other')

# replace the one null with Male, the mode gender, so we don't have to drop the row
data['What is your gender?'] = data['What is your gender?'].replace(np.NaN, 'Male')
data['What is your gender?'].unique()
```

Out[48]:

```
array(['Male', 'Female', 'Genderqueer/Other'], dtype=object)
```

In [49]:

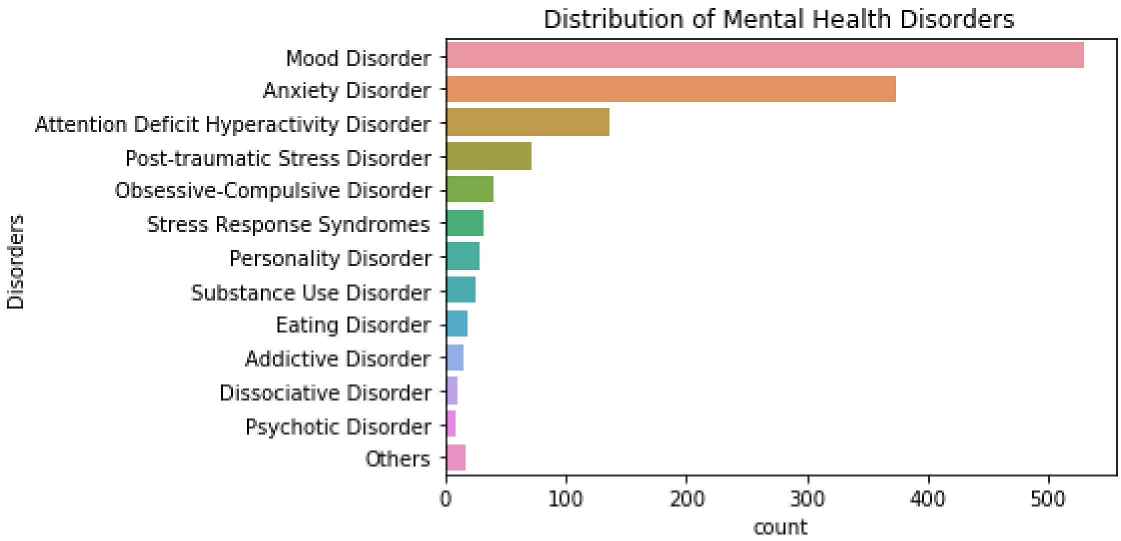
```
data.drop(['Why or why not?', 'Why or why not?.1'], axis=1, inplace=True)
```

2.9 Visualization

Show common mental disorders

In [50]:

```
disorders = {}

disorderCounts = dict(data['If so, what condition(s) were you diagnosed with?'].
value_counts())
for i in disorderCounts:
    # get the disorders separately in case someone answered with more than one d
isorder
    disorderList = i.split('|')
    for j in disorderList:
        j = j.split(' (')[0]
        disorders[j] = disorders.get(j, 0) + disorderCounts[i]

tmp = pd.DataFrame()
for i in disorders:
    tmp = tmp.append([i] * disorders[i])

tmp[0] = tmp[0].replace([
    'Autism Spectrum Disorder', 'Autism - while not a "mental illness", still gr
eatly affects how I handle anxiety',
    'autism spectrum disorder', 'PDD-NOS'], 'Autism')
tmp[0] = tmp[0].replace(['Aspergers', 'Asperger Syndrome'], "Asperger's Syndrom
e")
tmp[0] = tmp[0].replace(['posttraumatic stress disourder'], 'Post-traumatic Stre
ss Disorder')
tmp[0] = tmp[0].replace(['ADD', 'Attention Deficit Disorder', 'attention deficit
disorder'],
                         'Attention Deficit Hyperactivity Disorder')
tmp[0] = tmp[0].replace(['Schizotypal Personality Disorder'], 'Personality Disor
der')
tmp[0] = tmp[0].replace(['Depression'], 'Mood Disorder')
tmp[0] = tmp[0].replace([
    'Autism', "Asperger's Syndrome", 'Intimate Disorder',
    'Seasonal Affective Disorder', 'Burn out', 'Gender Identity Disorder',
    'Suicidal Ideation', 'Gender Dysphoria', 'MCD'], 'Others')

# print(tmp[0].value_counts())
g = sns.countplot(y=tmp[0], order=[
    'Mood Disorder', 'Anxiety Disorder', 'Attention Deficit Hyperactivity Disord
er',
    'Post-traumatic Stress Disorder', 'Obsessive-Compulsive Disorder',
    'Stress Response Syndromes', 'Personality Disorder', 'Substance Use Disorde
r',
    'Eating Disorder', 'Addictive Disorder', 'Dissociative Disorder',
    'Psychotic Disorder', 'Others'])
g.set_ylabel('Disorders')
g.set_title('Distribution of Mental Health Disorders')
plt.show()
```

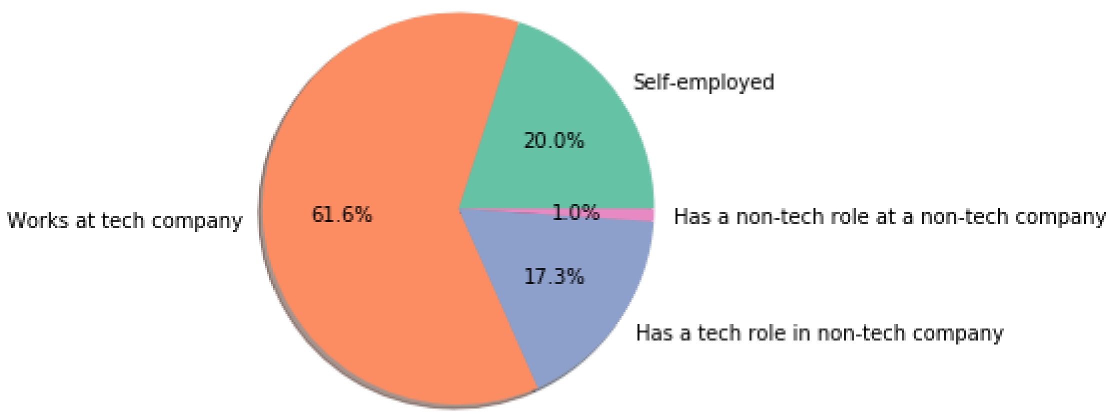


Above we can see that the most common mental health problems in the tech space are mood and anxiety disorders

Employee job roles

In [51]:

```
# pie chart of workers
labels = ['Self-employed', 'Works at tech company', 'Has a tech role in non-tech
company', 'Has a non-tech role at a non-tech company']
sizes = [data['Are you self-employed?'].value_counts()[1],
         data['Is your employer primarily a tech company/organization?'].value_c
ounts()[1],
         data['Is your primary role within your company related to tech/IT?'].va
lue_counts()[1],
         data['Is your primary role within your company related to tech/IT?'].va
lue_counts()[0]
        ]
# print(sizes) # adds up to 1433, which is the total number of participants
fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True)
ax1.axis('equal')
plt.show()
```



A lot of the respodents work for a tech company, while the rest are either self-employed or has a tech role in a non-tech company

Mental health among age and gender groups

In [52]:

```
# shorten column names
data.rename(columns={'What is your age?': 'Age',
                     'What is your gender?': 'Gender',
                     'Do you currently have a mental health disorder?': 'Has MH
D'}, inplace=True)
```

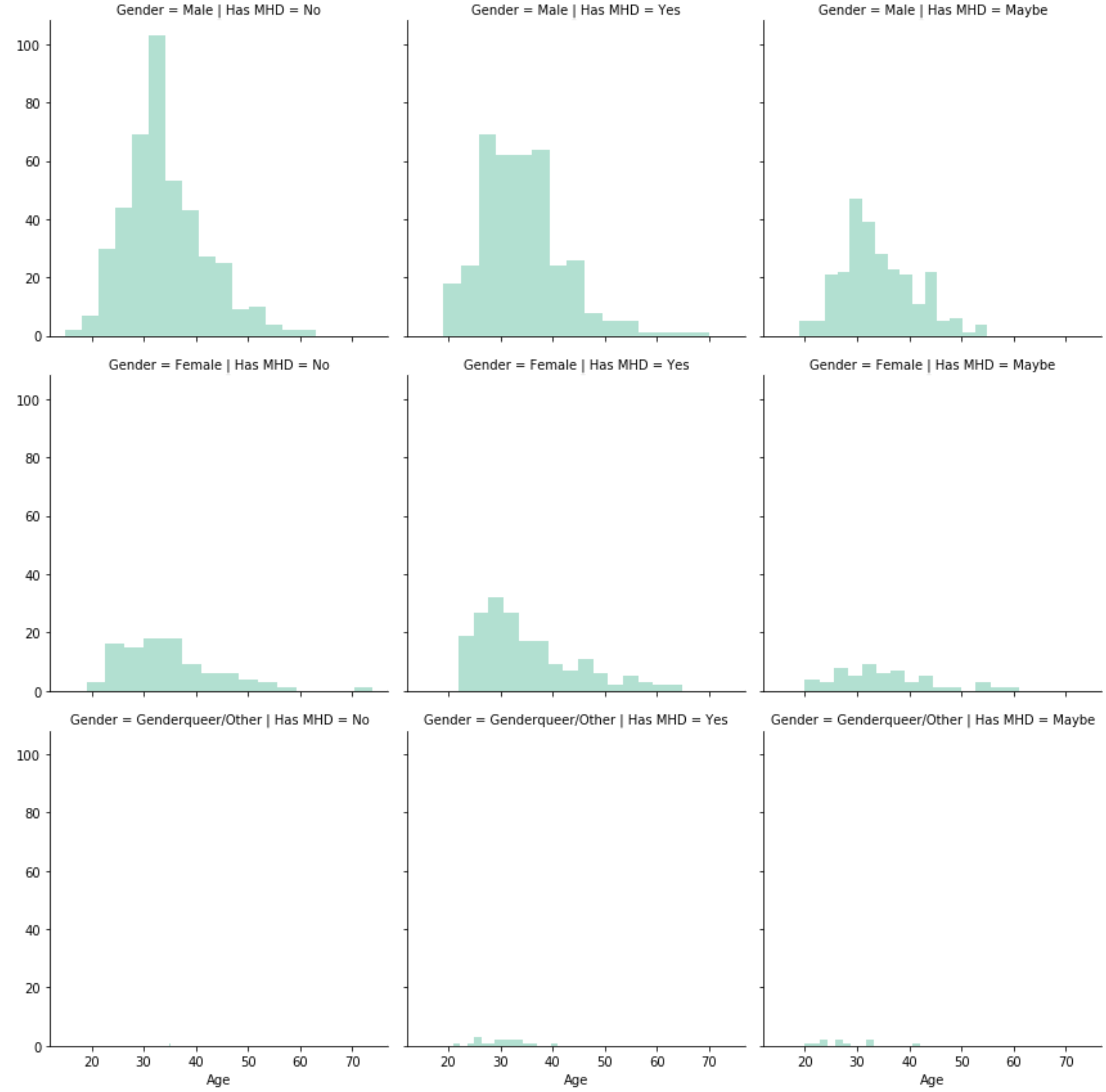
In [53]:

```
g = sns.FacetGrid(data, row='Gender', col='Has MHD', size=4)
g.map(plt.hist, 'Age', alpha=0.5, bins=15)
g.add_legend()
```

```
/srv/conda/envs/notebook/lib/python3.7/site-packages/seaborn/axisgri
d.py:230: UserWarning: The `size` paramter has been renamed to `heig
ht`; please update your code.
  warnings.warn(msg, UserWarning)
```

Out[53]:

```
<seaborn.axisgrid.FacetGrid at 0x7f625ed73250>
```

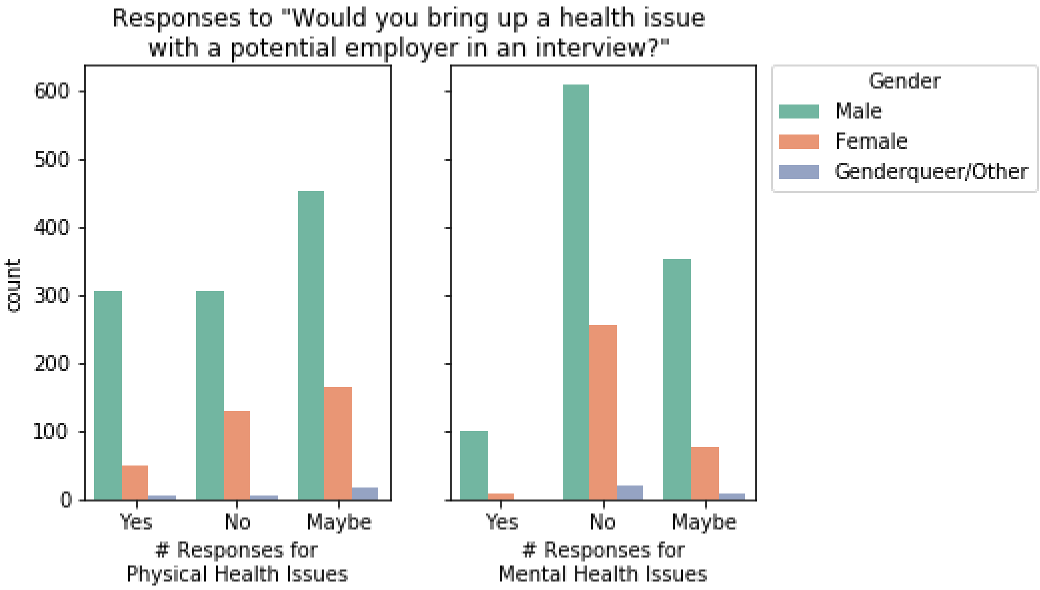

Gender = Male | Has MHD = No
Gender = Male | Has MHD = Yes
Gender = Male | Has MHD = Maybe
Gender = Female | Has MHD = No
Gender = Female | Has MHD = Yes
Gender = Female | Has MHD = Maybe
Gender = Genderqueer/Other | Has MHD = No
Gender = Genderqueer/Other | Has MHD = Yes
Gender = Genderqueer/Other | Has MHD = Maybe
0
20
40
60
80
100
20
30
40
50
60
70
Age

From the charts above, we could see that male respondents aged in their mid 20s to early 30's are more prone to some sort of mental ilness

Attitude: Willingness to Bring Up Health Issues in an Interview: Physical vs. Mental

In [54]:

```
fig, (ax1, ax2) = plt.subplots(ncols=2, sharey=True)
fig.suptitle('Responses to "Would you bring up a health issue\nwith a potential
 employer in an interview?"')
g1 = sns.countplot(x='Would you be willing to bring up a physical health issue w
ith a potential employer in an interview?',
                   hue='Gender', data=data, ax=ax1, order=['Yes', 'No', 'Maybe'])

g2 = sns.countplot(x='Would you bring up a mental health issue with a potential
 employer in an interview?',
                   hue='Gender', data=data, ax=ax2, order=['Yes', 'No', 'Maybe'])

g1.legend_.remove()
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0., title='Gender')
g1.set_xlabel('# Responses for\nPhysical Health Issues')
g2.set_xlabel('# Responses for\nMental Health Issues')
g2.set_ylabel('')
plt.show()
```

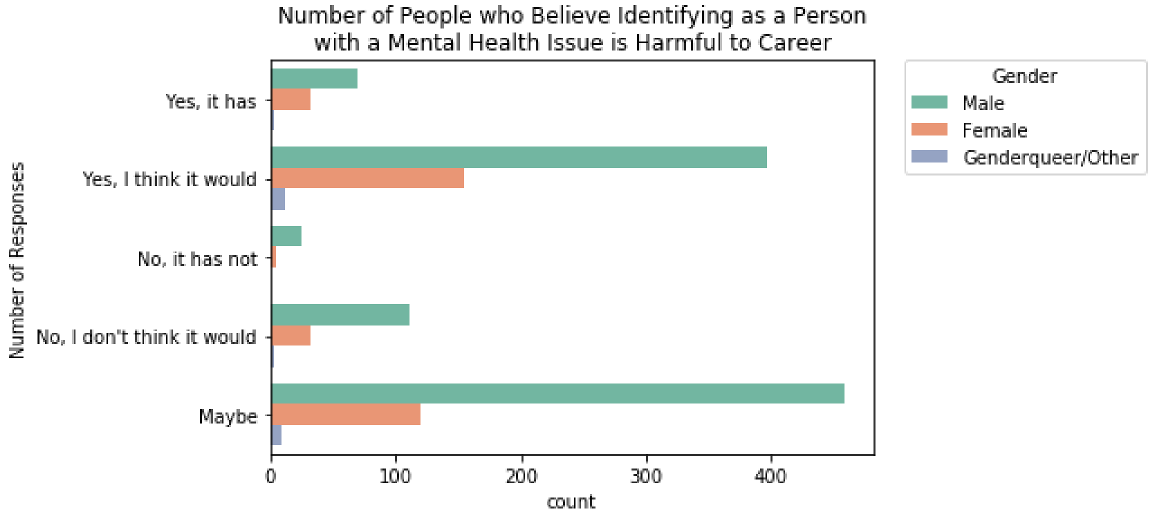


Based on the survey, less males in the tech world are more willing to bring up mental health issues than physical ones.

Attitude: Is Having Mental Health Issues is Harmful to One's Career?

In [55]:

```
g = sns.countplot(y='Do you feel that being identified as a person with a mental 
health issue would hurt your career?',
                  hue='Gender', data=data,
                   order=['Yes, it has', 'Yes, I think it would',
                         'No, it has not', "No, I don't think it would", 'Maybe'
])
plt.title('Number of People who Believe Identifying as a Person\nwith a Mental H
ealth Issue is Harmful to Career')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0., title='Gender')
plt.ylabel('Number of Responses')
plt.show()
```



In [56]:

```
*There is more stigma for the male respondents as a lot of them either think men
tal health issues are harmful to one's career*
```

```
  File "<ipython-input-56-d9dd37497b93>", line 1
    *There is more stigma for the male respondents as a lot of them
 either think mental health issues are harmful to one's career*
           ^
SyntaxError: invalid syntax
```

Attitude: Potential Negative Consequences for Discussing Health Issues with Employer: Physical vs. Mental

In [ ]:

```
fig, (ax1, ax2) = plt.subplots(ncols=2, sharey=True)
fig.suptitle('Responses to "Do you think that discussing a health issue\nwith yo
ur employer would have negative consequences?"')
g1 = sns.countplot(x='Do you think that discussing a physical health issue with
 your employer would have negative consequences?',
                  hue='Gender', data=data, ax=ax1, order=['Yes', 'No', 'Maybe'])

g2 = sns.countplot(x='Do you think that discussing a mental health disorder with
your employer would have negative consequences?',
                  hue='Gender', data=data, ax=ax2, order=['Yes', 'No', 'Maybe'])

g1.legend_.remove()
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0., title='Gender')
g1.set_xlabel('# Responses for\nPhysical Health Issues')
g2.set_xlabel('# Responses for\nMental Health Issues')
g2.set_ylabel('')
plt.show()
```

From the two graphs, we could see that: having disucussions with employers on physical health issues will have less consequences than mental health topics

2.10 Insights

Key points from the Tech survey analysis:

```
* Mood and anxiety disorders were the most common forms of reported illnes
es, followed by ADHD, PTSD, etc.
* Most repondents came from a tech company or at least serving traditional
a tech role in a non-tech company

* Indicators point that adult males (age 27 - 34) were the most vulnerable
out of all the age groups:

    * They had an attitude/belief that mental issues were harmful to one's
career
    * Discussion with employers on physical health topics had less negativ
e consequences than mental health topics
    * They were less willing to bring up mental health issues in an employ
ee interview
```

References:

Szamil. (2018, August 29). WHO Suicide Statistics. Retrieved from https://www.kaggle.com/szamil/who-suicide-statistics/kernels (https://www.kaggle.com/szamil/who-suicide-statistics/kernels)

Modified codes from:

https://www.kaggle.com/andradaolteanu/preprocess-visualise-model-mental-health-in-tech (https://www.kaggle.com/andradaolteanu/preprocess-visualise-model-mental-health-in-tech)

https://www.kaggle.com/jchen2186/data-visualization-with-python-seaborn (https://www.kaggle.com/jchen2186/data-visualization-with-python-seaborn)

https://www.kaggle.com/kairosart/machine-learning-for-mental-health-1 (https://www.kaggle.com/kairosart/machine-learning-for-mental-health-1)

https://www.kaggle.com/lostarious/most-used-words-in-a-million-headlines (https://www.kaggle.com/lostarious/most-used-words-in-a-million-headlines)

https://www.kaggle.com/rcushen/topic-modelling-with-lsa-and-lda (https://www.kaggle.com/rcushen/topic-modelling-with-lsa-and-lda)