Predicting Gender from OkCupid Profiles

By Sergio Avalos S.

1. Introduction

In online dating platforms, user demographics play a crucial role in improving matchmaking algorithms and personalizing user experiences. One key demographic attribute is gender, which influences profile visibility, recommendations, and overall platform engagement. This project aims to build a machine learning model that predicts a user's gender based on various personal attributes from their OkCupid profile. By leveraging structured data such as age, body type, and lifestyle habits, this project seeks to determine how accurately gender can be inferred from available profile information.

1.1. Scoping

Project Goals

The primary research question that will be answered is whether an OkCupid user's gender can be predicted using other variables from their profiles. This project is important since understanding user demographics can help improve recommendations and personalize user experiences.

Data

The project has one dataset provided by Codecademy called `profiles.csv`. In the data, each row represents an OkCupid user, and the columns contain responses to their user profiles, including multiple-choice and short-answer questions. The target variable for prediction is `sex`, which can take values "m" or "f".

The features selected for this analysis include:

- **Age**
- **Body Type**
- **Diet, Drinks, Smokes, Drugs**
- **Education & Job**
- **Height**
- **Religion**
- **Orientation**

Some columns have missing values, and appropriate preprocessing techniques will be used to handle them.

Analysis

This solution will use descriptive statistics and data visualization to explore the distribution, count, and relationships between variables. Since the goal of the project is to make predictions on the user's gender, classification algorithms from the supervised learning family of machine learning models will be implemented. Potential models to explore include:

- Logistic Regression
- Decision Trees
- Random Forest
- Support Vector Machines

Feature engineering, encoding categorical variables, and handling missing data will also be key steps in preparing the dataset for modeling.

Evaluation

The project will conclude with the evaluation of the machine learning model selected using a validation dataset. The output of the predictions can be assessed using a confusion matrix, and metrics such as accuracy, precision, recall, and F1 scores. The final model performance will determine how well gender can be predicted based on the chosen features.

2. Data Preparation and Exploration

2.1. Importing the Modules

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

df = pd.read_csv('profiles.csv', encoding='utf-8')
print(df.head())
```

```
   age       body_type               diet    drinks      drugs  \
0   22  a little extra  strictly anything  socially      never   
1   35         average       mostly other     often  sometimes   
2   38            thin           anything  socially        NaN   
3   23            thin         vegetarian  socially        NaN   
4   29        athletic                NaN  socially      never   

                           education  \
0      working on college/university   
1              working on space camp   
2     graduated from masters program   
3      working on college/university   
4  graduated from college/university   

                                              essay0  \
0  about me:<br />\n<br />\ni would love to think...   
1  i am a chef: this is what that means.<br />\n1...   
2  i'm not ashamed of much, but writing public te...   
3          i work in a library and go to school. . .   
4  hey how's it going? currently vague on the pro...   

                                              essay1  \
0  currently working as an international agent fo...   
1  dedicating everyday to being an unbelievable b...   
2  i make nerdy software for musicians, artists, ...   
3          reading things written by old dead people   
4                         work work work work + play   

                                              essay2  \
0  making people laugh.<br />\nranting about a go...   
1  being silly. having ridiculous amonts of fun w...   
2  improvising in different contexts. alternating...   
3  playing synthesizers and organizing books acco...   
4  creating imagery to look at:<br />\nhttp://bag...   

                                              essay3  ...  \
0  the way i look. i am a six foot half asian, ha...  ...   
1                                                NaN  ...   
2  my large jaw and large glasses are the physica...  ...   
3                  socially awkward but i do my best  ...   
4            i smile a lot and my inquisitive nature  ...   

                          location  \
0  south san francisco, california   
1              oakland, california   
2        san francisco, california   
3             berkeley, california   
4        san francisco, california   

                                      offspring orientation  \
0  doesn&rsquo;t have kids, but might want them    straight   
1  doesn&rsquo;t have kids, but might want them    straight   
2                                           NaN    straight   
3                       doesn&rsquo;t want kids    straight   
4                                           NaN    straight   
```

```
                        pets                                  religion sex  \
0  likes dogs and likes cats     agnosticism and very serious about it   m
1  likes dogs and likes cats  agnosticism but not too serious about it   m
2                   has cats                                       NaN   m
3                 likes cats                                       NaN   m
4  likes dogs and likes cats                                       NaN   m

                                 sign     smokes  \
0                              gemini  sometimes
1                              cancer         no
2  pisces but it doesn&rsquo;t matter         no
3                              pisces         no
4                            aquarius         no

                                              speaks     status
0                                            english     single
1  english (fluently), spanish (poorly), french (...     single
2                               english, french, c++  available
3                           english, german (poorly)     single
4                                            english     single

[5 rows x 31 columns]
```

Data characteristics

The columns in the dataset include:

- **age:** continuous variable of age of user
- **body_type:** categorical variable of body type of user
- **diet:** categorical variable of dietary information
- **drinks:** categorical variable of alcohol consumption
- **drugs:** categorical variable of drug usage
- **education:** categorical variable of educational attainment
- **ethnicity:** categorical variable of ethnic backgrounds
- **height:** continuous variable of height of user
- **income:** continuous variable of income of user
- **job:** categorical variable of employment description
- **offspring:** categorical variable of children status
- **orientation:** categorical variable of sexual orientation
- **pets:** categorical variable of pet preferences
- **religion:** categorical variable of religious background
- **sex:** categorical variable of gender
- **sign:** categorical variable of astrological symbol
- **smokes:** categorical variable of smoking consumption
- **speaks:** categorical variable of language spoken
- **status:** categorical variable of relationship status
- **last_online:** date variable of last login
- **location:** categorical variable of user locations

And a set of open short-answer responses to:

- **essay0:** My self summary
- **essay1:** What I’m doing with my life
- **essay2:** I’m really good at
- **essay3:** The first thing people usually notice about me
- **essay4:** Favorite books, movies, show, music, and food
- **essay5:** The six things I could never do without
- **essay6:** I spend a lot of time thinking about
- **essay7:** On a typical Friday night I am
- **essay8:** The most private thing I am willing to admit
- **essay9:** You should message me if...

For this project's purposes, we will be dropping the essay columns.

In [2]:

```
df = df.drop(columns=['essay0', 'essay1', 'essay2', 'essay3', 'essay4', 'essay5', '
print(df.head())
```

```
   age       body_type               diet    drinks      drugs  \
0   22  a little extra  strictly anything  socially      never   
1   35         average       mostly other     often  sometimes   
2   38            thin           anything  socially        NaN   
3   23            thin         vegetarian  socially        NaN   
4   29        athletic                NaN  socially      never   

                          education            ethnicity  height  income  \
0      working on college/university         asian, white    75.0      -1   
1              working on space camp                white    70.0   80000   
2     graduated from masters program                  NaN    68.0      -1   
3      working on college/university                white    71.0   20000   
4  graduated from college/university  asian, black, other    66.0      -1   

                           job  ...                     location  \
0               transportation  ...  south san francisco, california   
1         hospitality / travel  ...            oakland, california   
2                          NaN  ...        san francisco, california   
3                      student  ...           berkeley, california   
4  artistic / musical / writer  ...        san francisco, california   

                                     offspring orientation  \
0  doesn&rsquo;t have kids, but might want them    straight   
1  doesn&rsquo;t have kids, but might want them    straight   
2                                          NaN    straight   
3                        doesn&rsquo;t want kids    straight   
4                                          NaN    straight   

                        pets                                  religion sex  \
0  likes dogs and likes cats     agnosticism and very serious about it   m   
1  likes dogs and likes cats  agnosticism but not too serious about it   m   
2                   has cats                                       NaN   m   
3                 likes cats                                       NaN   m   
4  likes dogs and likes cats                                       NaN   m   

                                    sign     smokes  \
0                                 gemini  sometimes   
1                                 cancer         no   
2  pisces but it doesn&rsquo;t matter         no   
3                                 pisces         no   
4                               aquarius         no   

                                               speaks     status  
0                                             english     single  
1  english (fluently), spanish (poorly), french (...     single  
2                                english, french, c++  available  
3                            english, german (poorly)     single  
4                                             english     single  

[5 rows x 21 columns]
```

2.2. Data Cleaning and Wrangling

We notice that the features `sign`, `religion`, `ethnicity` and `speaks` could be simplified by getting just the first word of the sentence:

```
In [3]: df.sign = df.sign.str.split().str.get(0)
df.religion = df.religion.str.split().str.get(0)
df.ethnicity = df.ethnicity.str.split().str.get(0)
df.ethnicity = df.ethnicity.str.replace('[,]', '', regex=True)
df.speaks = df.speaks.str.split().str.get(0)
df.speaks = df.speaks.str.replace('[,]', '', regex=True)
print(df.head())
```

```
   age       body_type               diet    drinks      drugs  \
0   22  a little extra  strictly anything  socially      never
1   35         average       mostly other     often  sometimes
2   38            thin           anything  socially        NaN
3   23            thin         vegetarian  socially        NaN
4   29        athletic                NaN  socially      never

                        education ethnicity  height  income  \
0      working on college/university     asian    75.0      -1
1              working on space camp     white    70.0   80000
2     graduated from masters program       NaN    68.0      -1
3      working on college/university     white    71.0   20000
4  graduated from college/university     asian    66.0      -1

                            job  ...                         location  \
0                transportation  ...  south san francisco, california
1          hospitality / travel  ...              oakland, california
2                           NaN  ...        san francisco, california
3                       student  ...             berkeley, california
4  artistic / musical / writer  ...        san francisco, california

                                     offspring orientation  \
0  doesn&rsquo;t have kids, but might want them    straight
1  doesn&rsquo;t have kids, but might want them    straight
2                                          NaN    straight
3                        doesn&rsquo;t want kids    straight
4                                          NaN    straight

                        pets     religion sex      sign     smokes   speaks  \
0  likes dogs and likes cats  agnosticism   m    gemini  sometimes  english
1  likes dogs and likes cats  agnosticism   m    cancer         no  english
2                   has cats          NaN   m    pisces         no  english
3                 likes cats          NaN   m    pisces         no  english
4  likes dogs and likes cats          NaN   m  aquarius         no  english

      status
0     single
1     single
2  available
3     single
4     single

[5 rows x 21 columns]
```

Our location feature mentions both city and state, for this project we will only use the state:

In [4]:
```
df["location"] = df["location"].apply(lambda x: x.split(", ")[-1] if pd.notnull(x)
print(df.head())
```

```
   age        body_type               diet    drinks      drugs  \
0   22  a little extra  strictly anything  socially      never
1   35         average       mostly other     often  sometimes
2   38            thin           anything  socially        NaN
3   23            thin         vegetarian  socially        NaN
4   29        athletic                NaN  socially      never

                           education ethnicity  height  income  \
0      working on college/university     asian    75.0      -1
1              working on space camp     white    70.0   80000
2     graduated from masters program       NaN    68.0      -1
3      working on college/university     white    71.0   20000
4  graduated from college/university     asian    66.0      -1

                              job  ...    location  \
0                  transportation  ...  california
1            hospitality / travel  ...  california
2                             NaN  ...  california
3                         student  ...  california
4  artistic / musical / writer  ...  california

                                  offspring orientation  \
0  doesn&rsquo;t have kids, but might want them    straight
1  doesn&rsquo;t have kids, but might want them    straight
2                                        NaN    straight
3                          doesn&rsquo;t want kids    straight
4                                        NaN    straight

                      pets     religion sex      sign     smokes   speaks  \
0  likes dogs and likes cats  agnosticism   m    gemini  sometimes  english
1  likes dogs and likes cats  agnosticism   m    cancer         no  english
2                   has cats          NaN   m    pisces         no  english
3                 likes cats          NaN   m    pisces         no  english
4  likes dogs and likes cats          NaN   m  aquarius         no  english

      status
0     single
1     single
2  available
3     single
4     single

[5 rows x 21 columns]
```

For this project, the features `last_online`, `offspring` and `pets` won't be considerated neither.

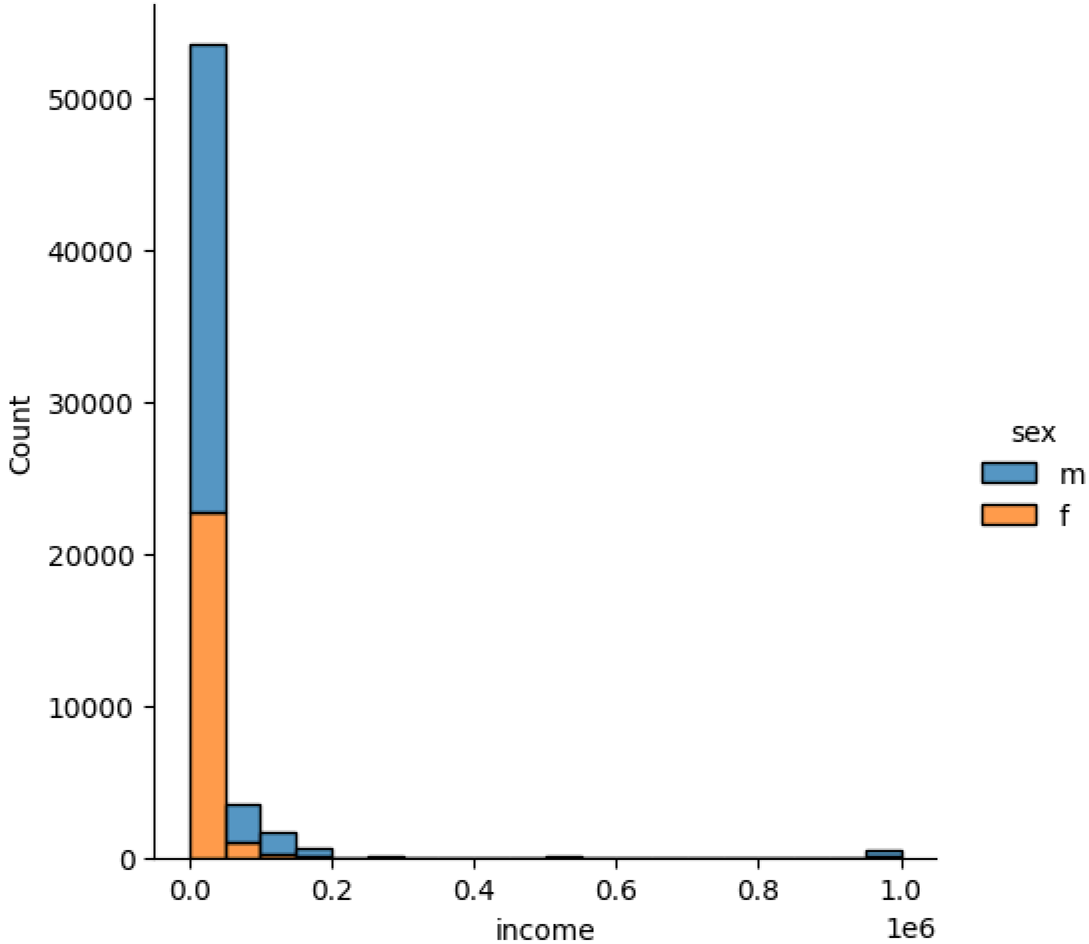
In [5]:
```
df = df.drop(columns=['last_online', 'offspring', 'pets'])
print(df.head())
```

```
   age       body_type               diet    drinks      drugs  \
0   22  a little extra  strictly anything  socially      never
1   35         average       mostly other     often  sometimes
2   38            thin           anything  socially        NaN
3   23            thin         vegetarian  socially        NaN
4   29        athletic                NaN  socially      never

                         education ethnicity  height  income  \
0     working on college/university     asian    75.0      -1
1             working on space camp     white    70.0   80000
2    graduated from masters program       NaN    68.0      -1
3     working on college/university     white    71.0   20000
4  graduated from college/university     asian    66.0      -1

                         job    location orientation     religion sex  \
0             transportation  california    straight  agnosticism   m
1        hospitality / travel  california    straight  agnosticism   m
2                        NaN  california    straight          NaN   m
3                    student  california    straight          NaN   m
4  artistic / musical / writer  california    straight          NaN   m

       sign     smokes   speaks     status
0    gemini  sometimes  english     single
1    cancer         no  english     single
2    pisces         no  english  available
3    pisces         no  english     single
4  aquarius         no  english     single
```

From the method .head() we can observe that the `income` has values equal to -1, which doesn't make sense for what the feature represents, meaning that these indicate missing values. To get an idea of the distribution of these values, we can plot a histogram of the feature:

In [6]:
```python
print('Missing income values: ', len(df[df.income == -1]))
print('Total values: ', len(df))
print('Percentage of missing income values: ', len(df[df.income == -1]) * 100 / len

sns.displot(data=df, x="income",hue="sex", kind="hist", binwidth = 50000, multiple
plt.show()
plt.clf()
```

```
Missing income values:  48442
Total values:  59946
Percentage of missing income values:  80.80939512227671 %
```




```
<Figure size 640x480 with 0 Axes>
```

Since more than 80% of the income values are missing, we will have to drop this feature as well.

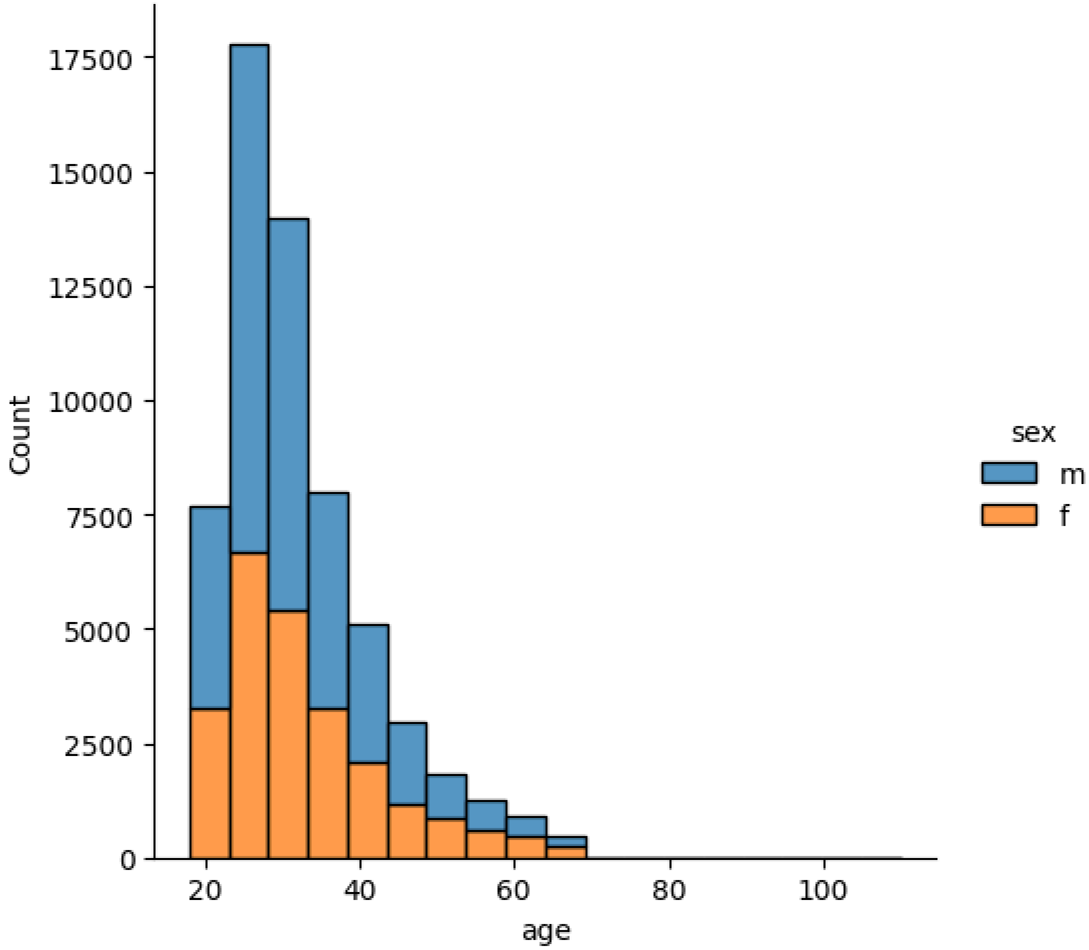
In [7]:
```
df = df.drop(columns=['income'])
print(df.head())
```

```
   age        body_type               diet    drinks      drugs  \
0   22  a little extra  strictly anything  socially      never
1   35         average       mostly other     often  sometimes
2   38            thin           anything  socially        NaN
3   23            thin         vegetarian  socially        NaN
4   29        athletic                NaN  socially      never

                          education ethnicity  height  \
0      working on college/university     asian    75.0
1              working on space camp     white    70.0
2     graduated from masters program       NaN    68.0
3      working on college/university     white    71.0
4  graduated from college/university     asian    66.0

                            job    location orientation     religion sex  \
0                transportation  california    straight  agnosticism   m
1          hospitality / travel  california    straight  agnosticism   m
2                           NaN  california    straight          NaN   m
3                       student  california    straight          NaN   m
4  artistic / musical / writer  california    straight          NaN   m

       sign     smokes   speaks     status
0    gemini  sometimes  english     single
1    cancer         no  english     single
2    pisces         no  english  available
3    pisces         no  english     single
4  aquarius         no  english     single
```

We will now inspect our other numerical variables in order to make sure we don't have any more missing values or outliers.

In [8]:

```
sns.displot(data=df, x="age",hue="sex", kind="hist", binwidth = 5, multiple = "stac
plt.show()
plt.clf()

print('People that claim to be over 100: ', len(df[df.age > 100]))
print('People that claim to be over 68: ', len(df[df.age > 68]))
```

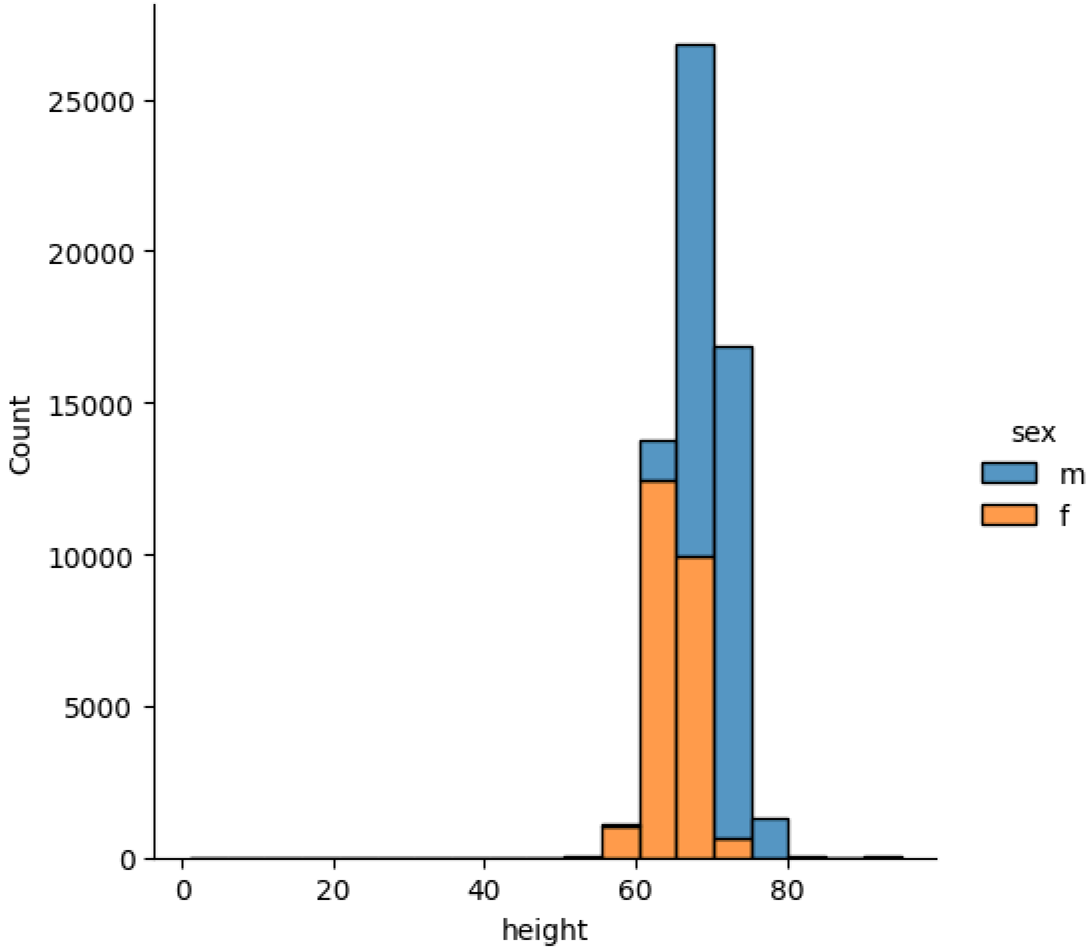



```
People that claim to be over 100:  2
People that claim to be over 68:  33
<Figure size 640x480 with 0 Axes>
```

Since in the feature `age` we have to people that claim to be over 100 years old, we can attribute this to be a mistake, therefore we will drop these values. In total, there are 33 people that claim to be over the age of 68, while this could be true, in order to avoid skewness in our data, all of these values will be dropped.

In [9]:
```
df = df[df.age <= 68]
```

In [10]:
```
sns.displot(data=df, x="height",hue="sex", kind="hist", binwidth = 5, multiple = "s
plt.show()
plt.clf()

print('People tha claim to be over 80 in: ', len(df[df.height > 80]))
print('People tha claim to be under 55 in: ', len(df[df.height < 55]))
```



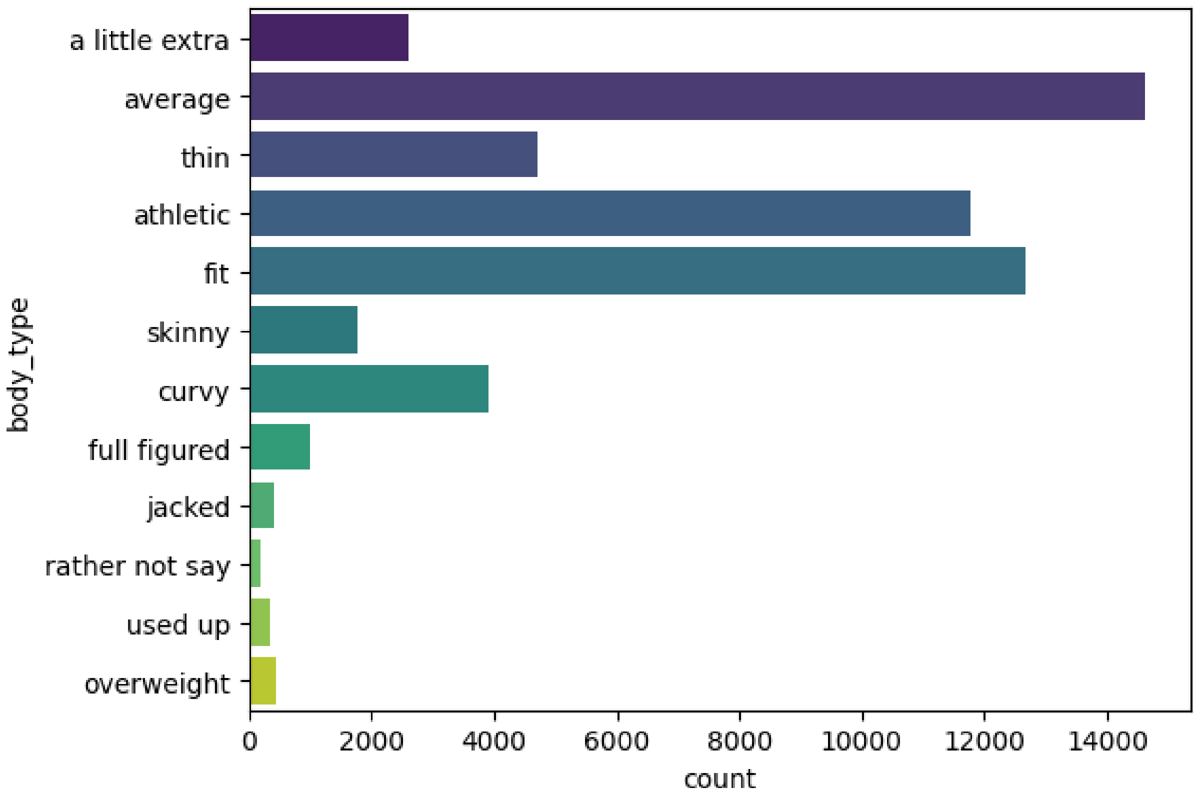

```
People tha claim to be over 80 in:  77
People tha claim to be under 55 in:  39
<Figure size 640x480 with 0 Axes>
```

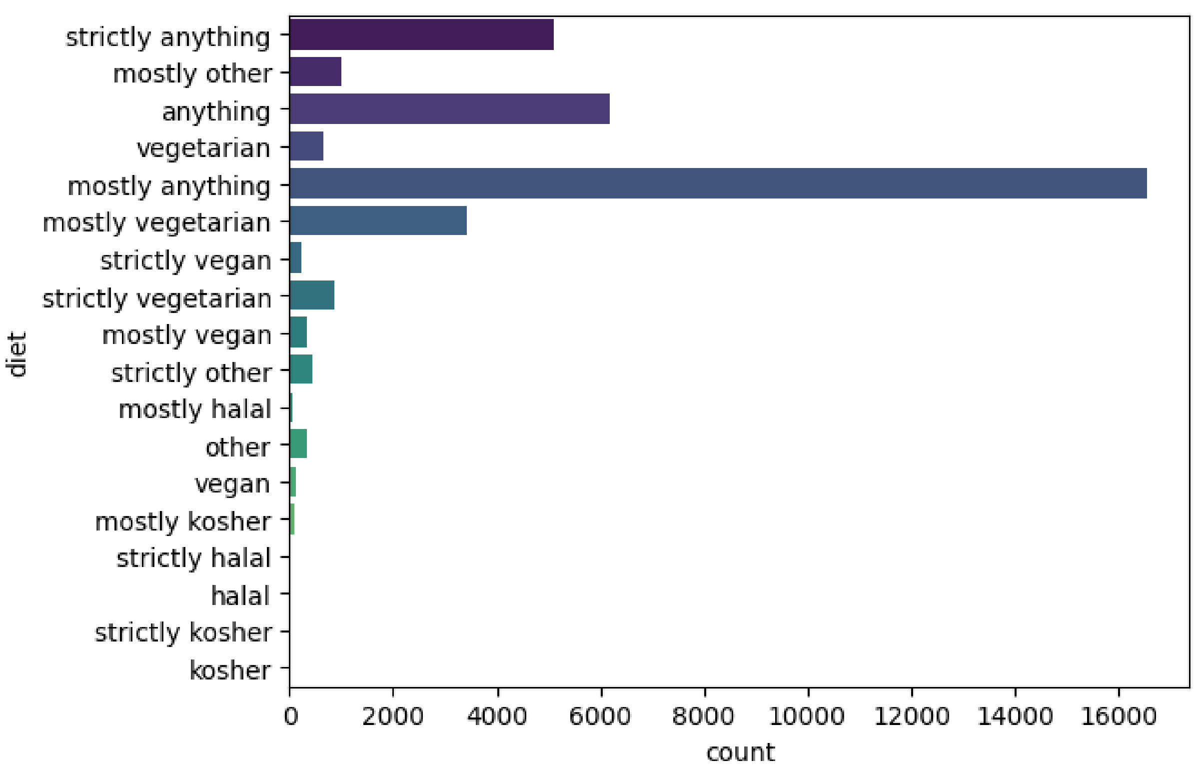
In the feature `height` we have 77 people that claim to be over 80 in (203.2 cm) and 39 people that claim to be under 55 in (139.7 cm), while this could be true, omce again, we will eliminate these values to avoid skewness.

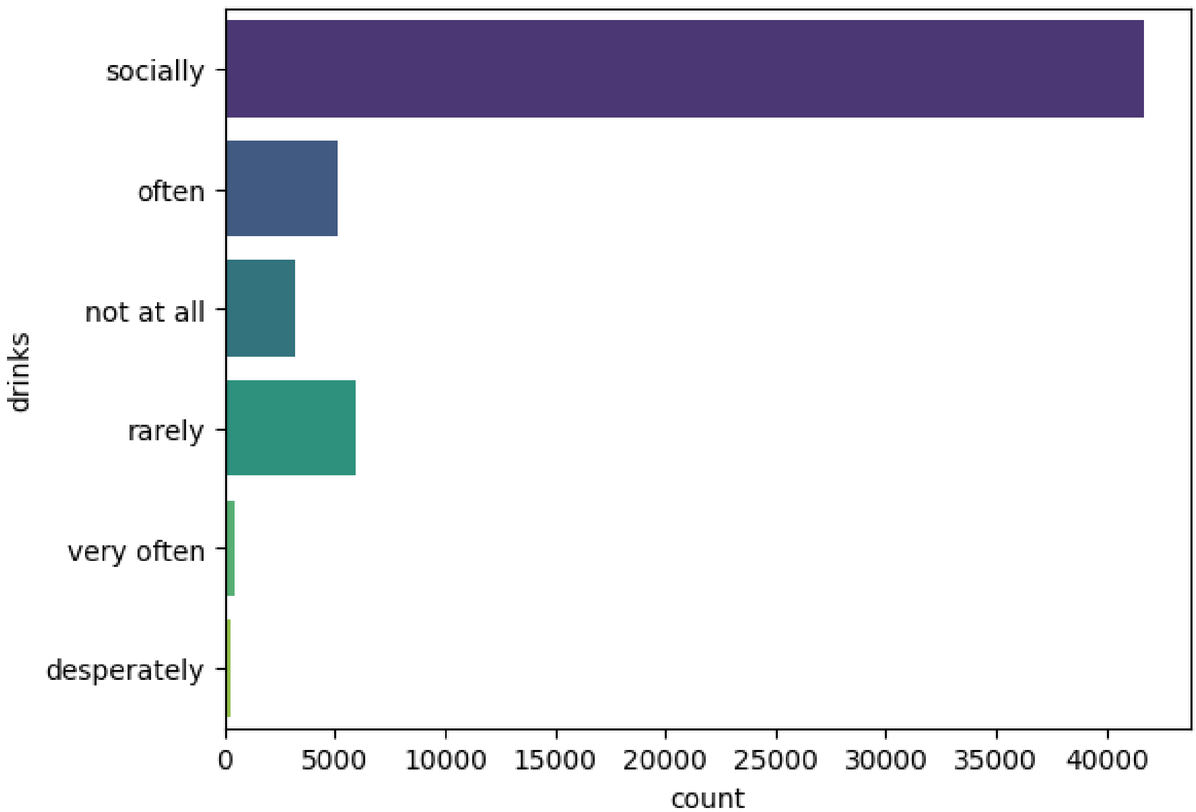
In [11]:
```
df = df[(df.height >= 55) & (df.height <= 80)]
```

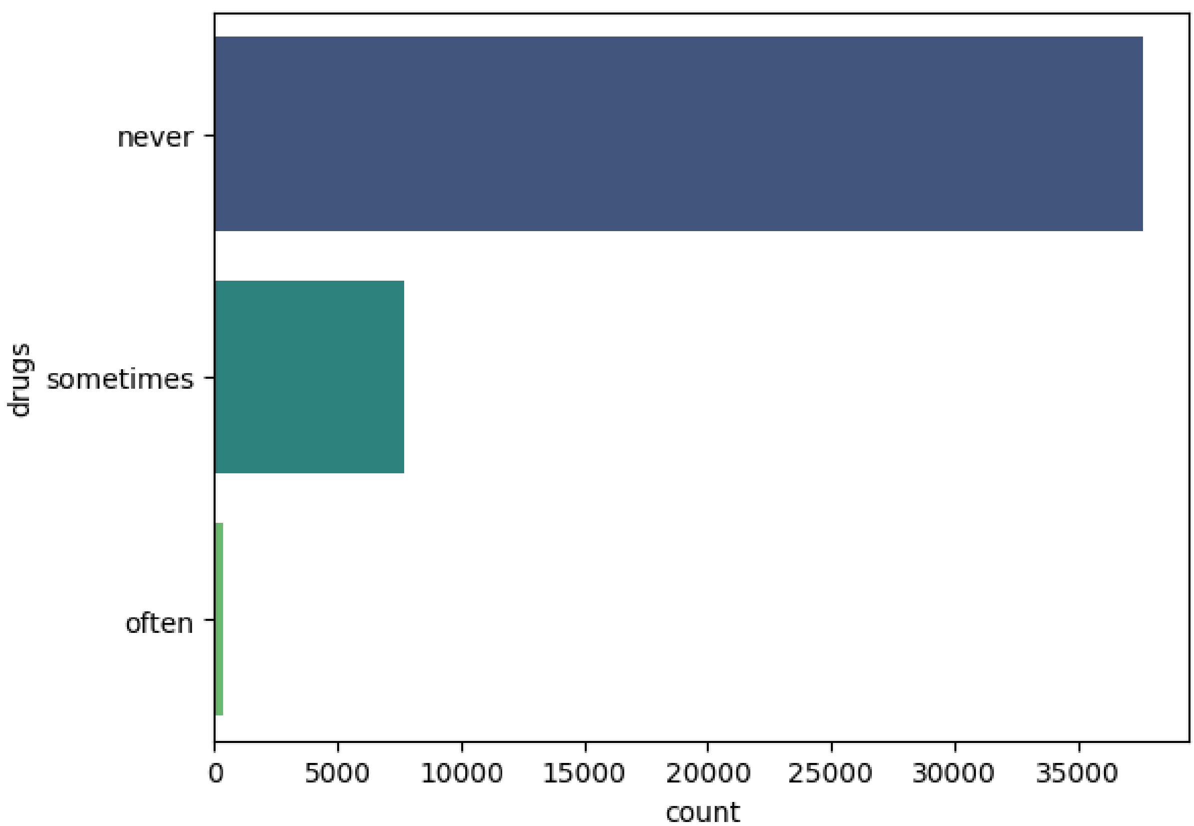
Now, we will plot the rest of our variables using a for loop.

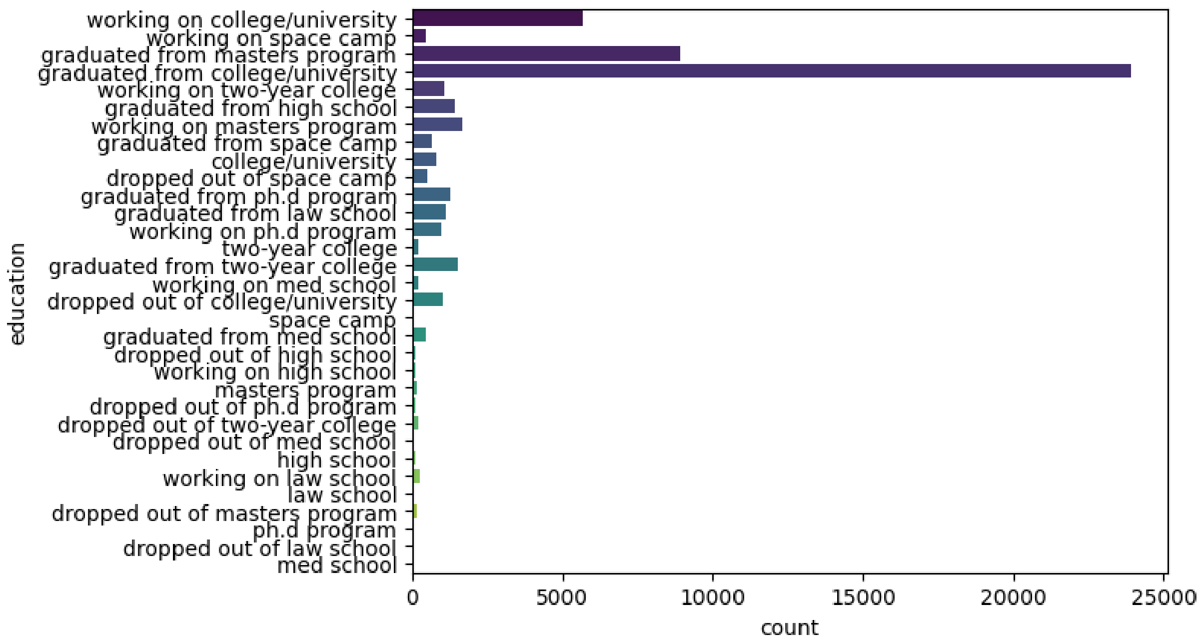
In [12]:
```
for column in df.columns:
    if column not in ['age', 'height']:
        sns.countplot(data=df, y=column, hue=column, legend=False, palette=sns.colo
        plt.show()
        plt.clf()
```

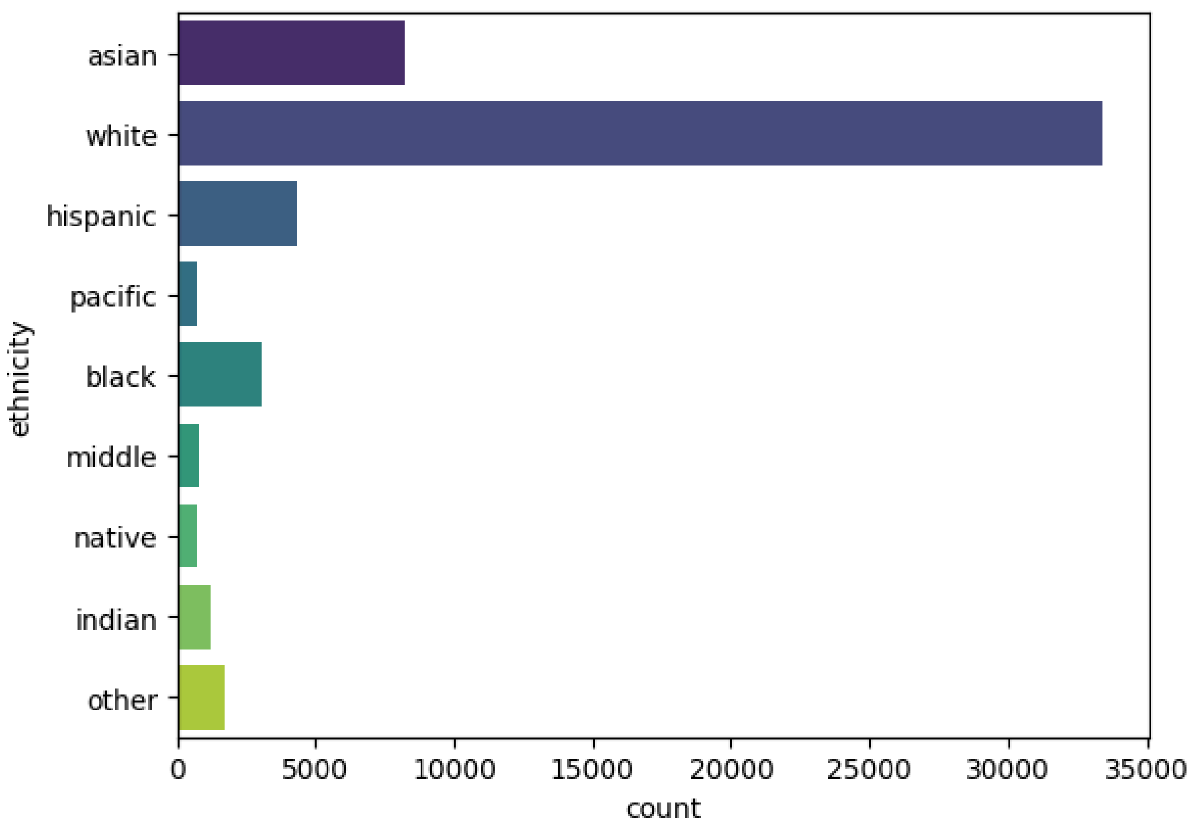

body_type
a little extra
average
thin
athletic
fit
skinny
curvy
full figured
jacked
rather not say
used up
overweight
0
2000
4000
6000
8000
10000
12000
14000
count

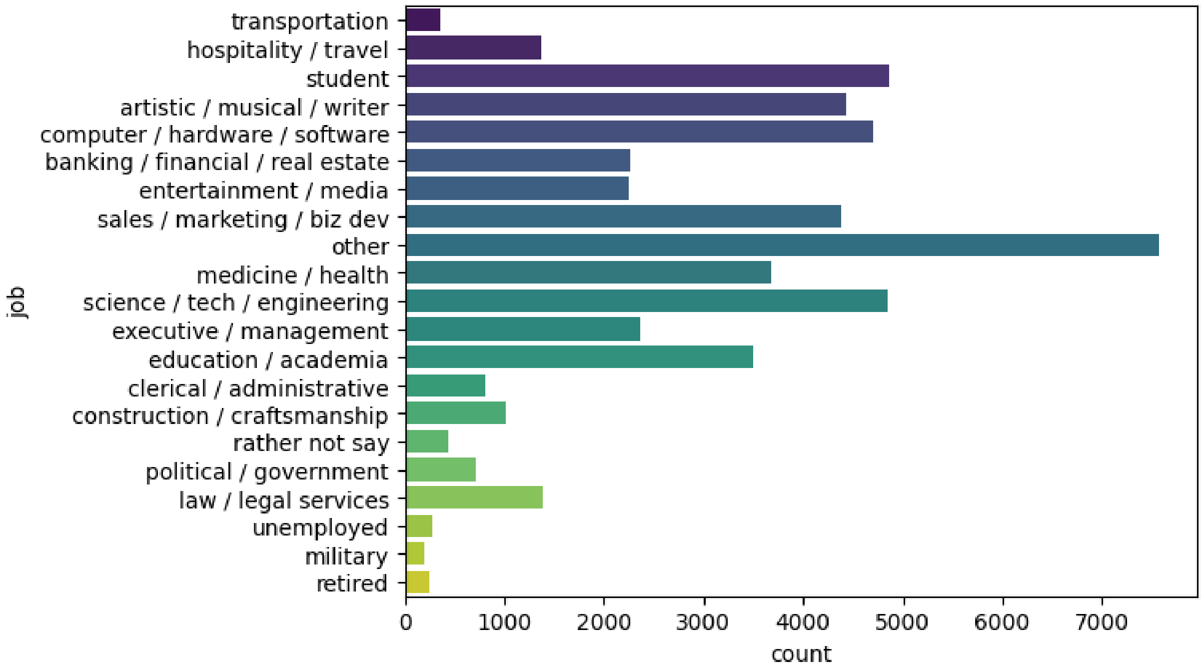

diet
strictly anything
mostly other
anything
vegetarian
mostly anything
mostly vegetarian
strictly vegan
strictly vegetarian
mostly vegan
strictly other
mostly halal
other
vegan
mostly kosher
strictly halal
halal
strictly kosher
kosher
0
2000
4000
6000
8000
10000
12000
14000
16000
count


socially
often
not at all
rarely
very often
desperately
drinks
0
5000
10000
15000
20000
25000
30000
35000
40000
count

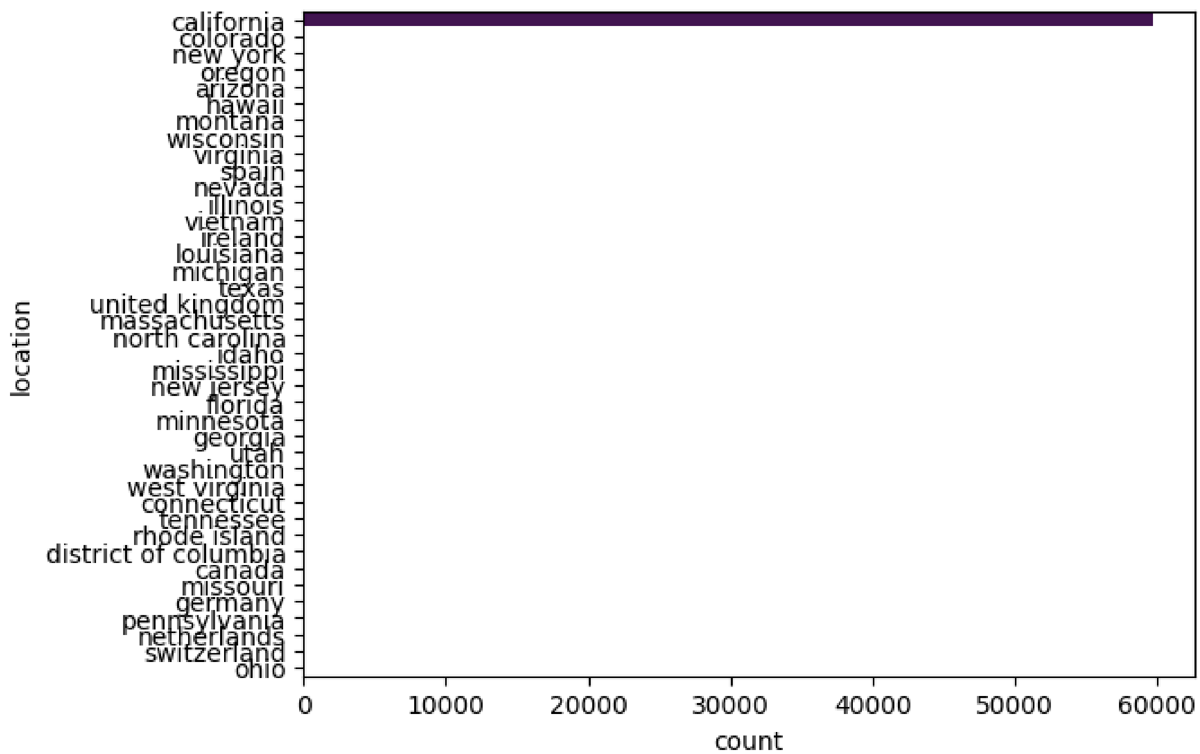

never
sometimes
often
drugs
0
5000
10000
15000
20000
25000
30000
35000
count


working on college/university
working on space camp
graduated from masters program
graduated from college/university
working on two-year college
graduated from high school
working on masters program
graduated from space camp
college/university
dropped out of space camp
graduated from ph.d program
graduated from law school
working on ph.d program
two-year college
graduated from two-year college
working on med school
dropped out of college/university
space camp
graduated from med school
dropped out of high school
working on high school
masters program
dropped out of ph.d program
dropped out of two-year college
dropped out of med school
high school
working on law school
law school
dropped out of masters program
ph.d program
dropped out of law school
med school
education
0
5000
10000
15000
20000
25000
count

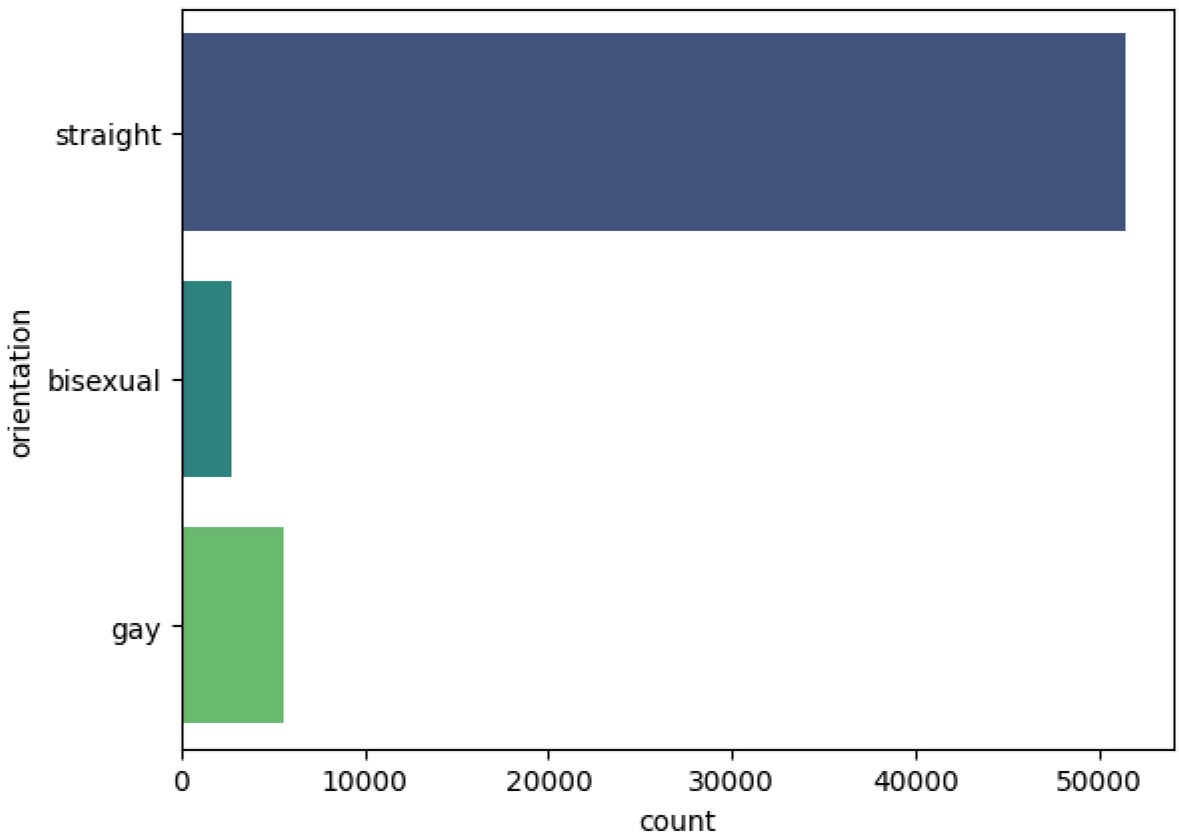

asian
white
hispanic
pacific
black
middle
native
indian
other
ethnicity
0
5000
10000
15000
20000
25000
30000
35000
count

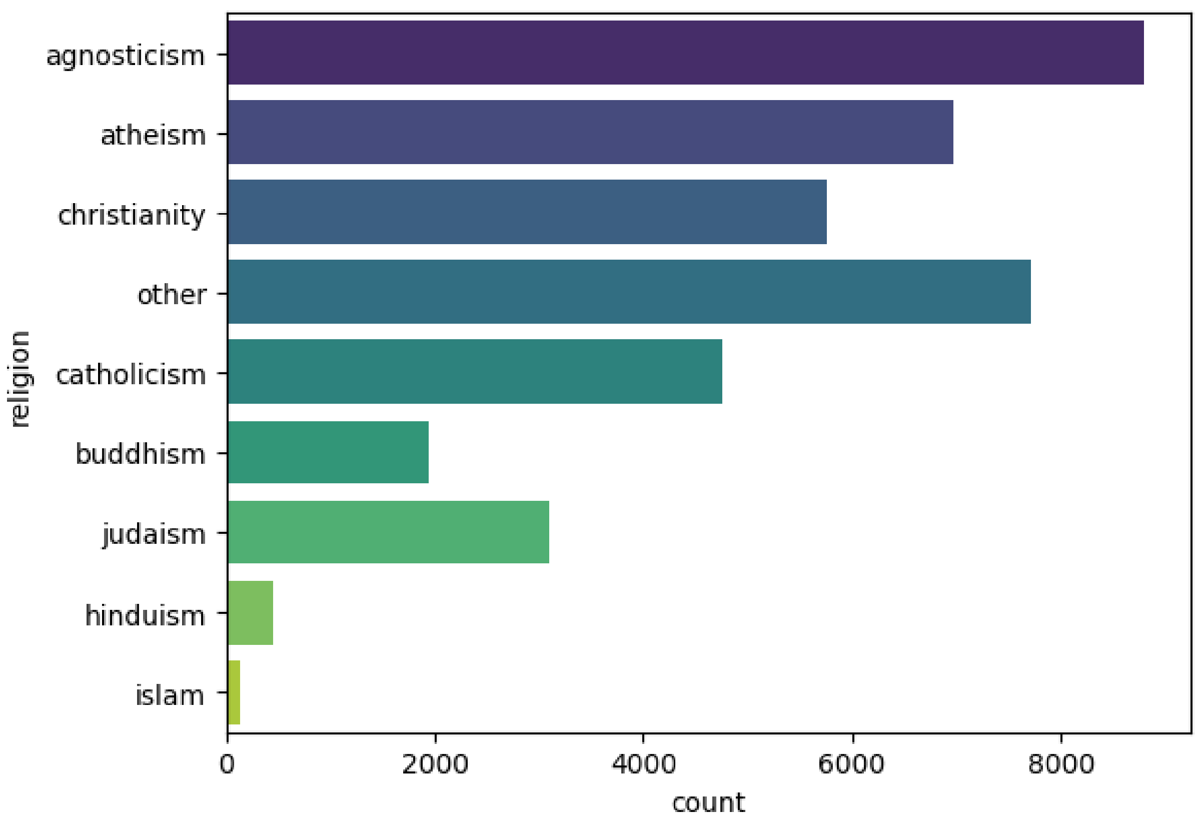


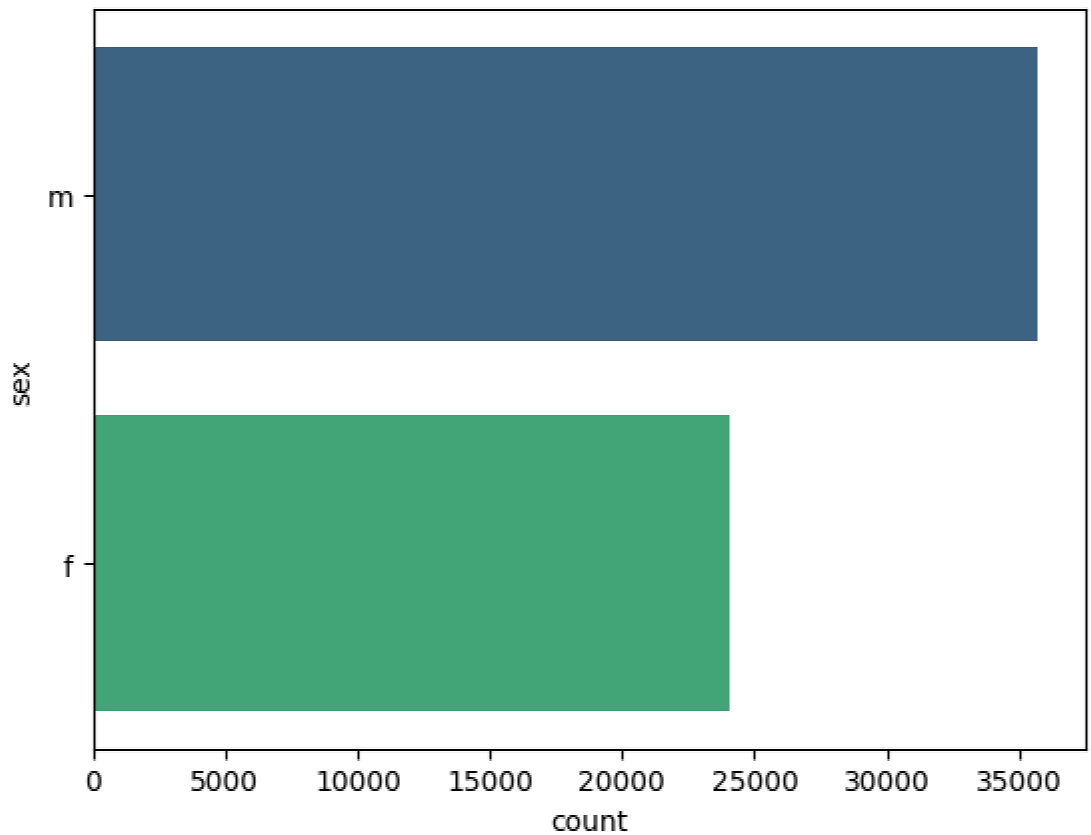
transportation
hospitality / travel
student
artistic / musical / writer
computer / hardware / software
banking / financial / real estate
entertainment / media
sales / marketing / biz dev
other
medicine / health
science / tech / engineering
executive / management
education / academia
clerical / administrative
construction / craftsmanship
rather not say
political / government
law / legal services
unemployed
military
retired
job
0
1000
2000
3000
4000
5000
6000
7000
count

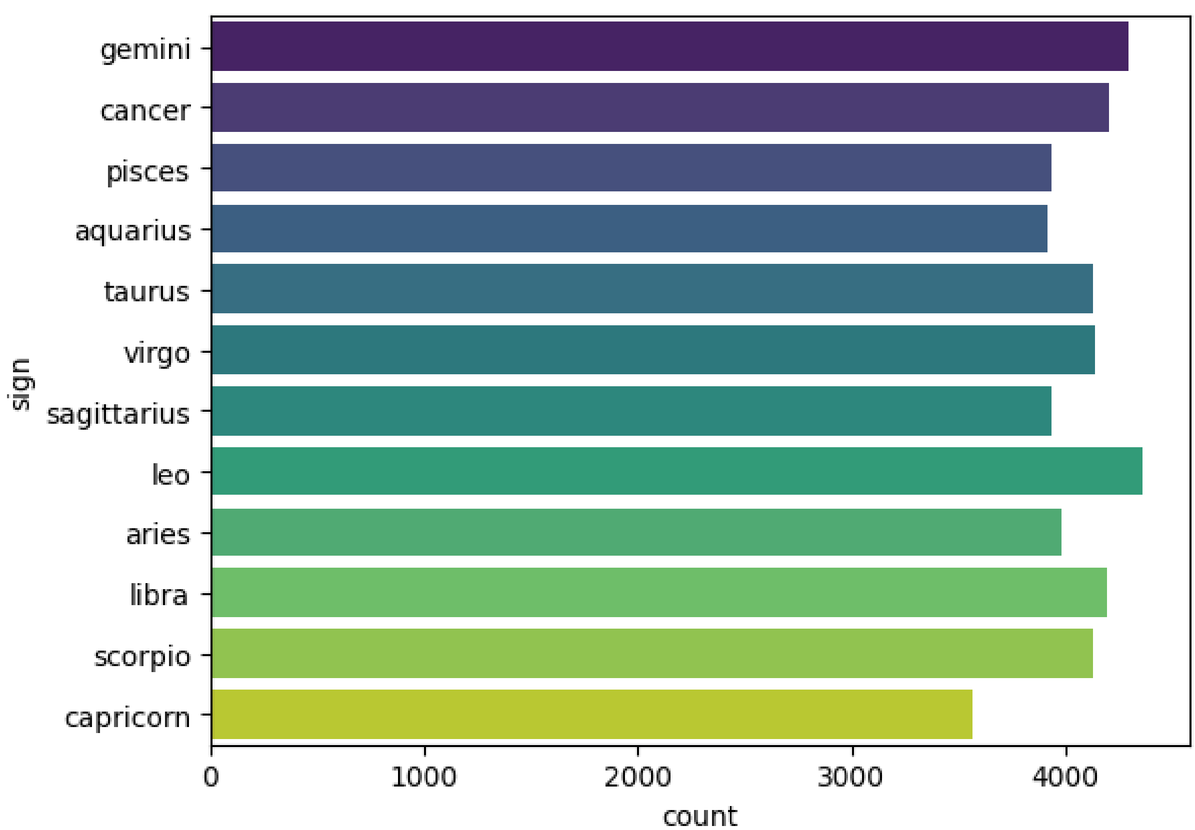


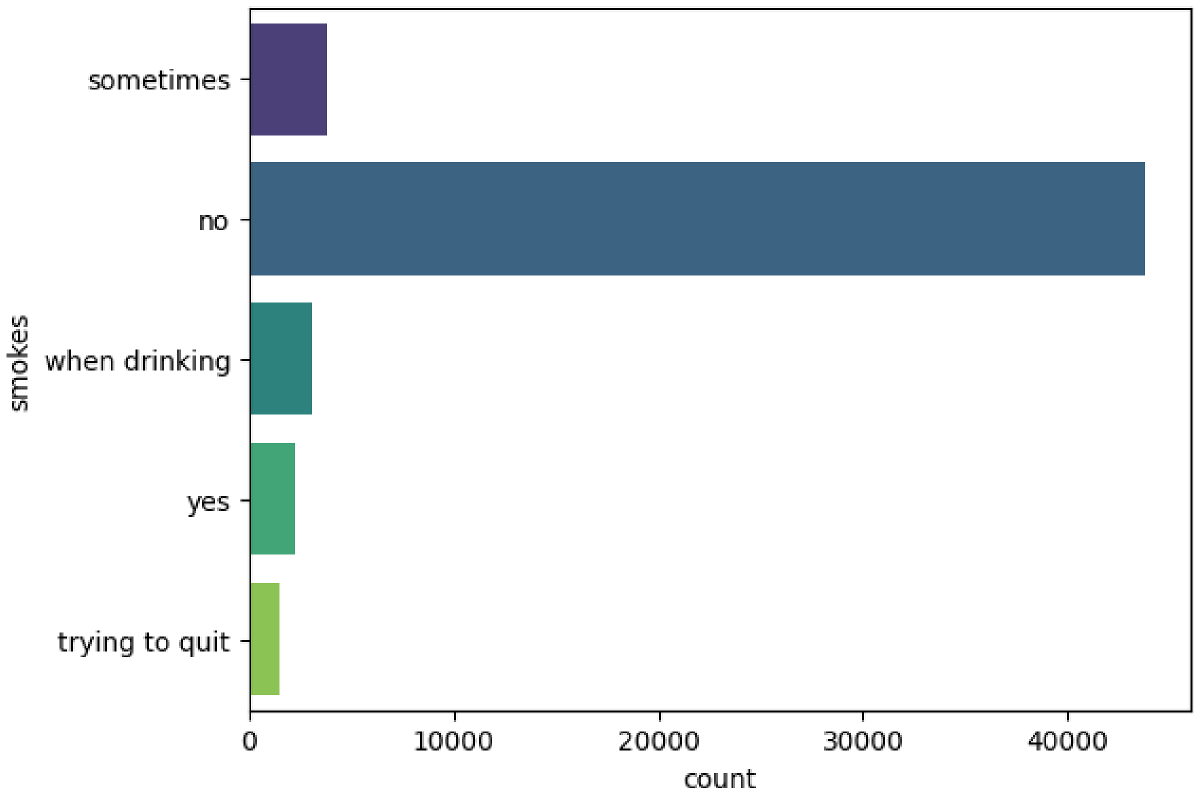
california
colorado
new york
oregon
arizona
hawaii
montana
wisconsin
virginia
spain
nevada
illinois
vietnam
ireland
louisiana
michigan
texas
united kingdom
massachusetts
north carolina
idaho
mississippi
new jersey
florida
minnesota
georgia
utah
washington
west virginia
connecticut
tennessee
rhode island
district of columbia
canada
missouri
germany
pennsylvania
netherlands
switzerland
ohio
location
0
10000
20000
30000
40000
50000
60000
count

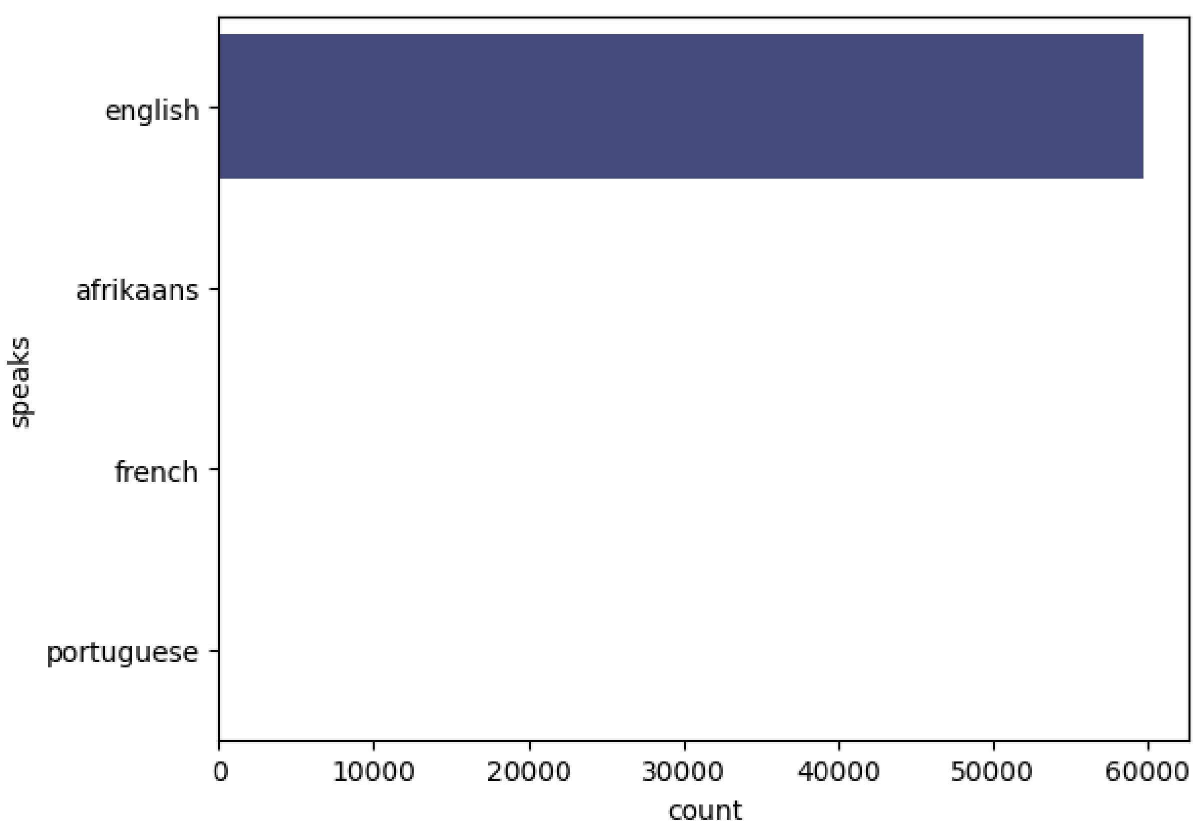

straight
bisexual
gay
orientation
0
10000
20000
30000
40000
50000
count

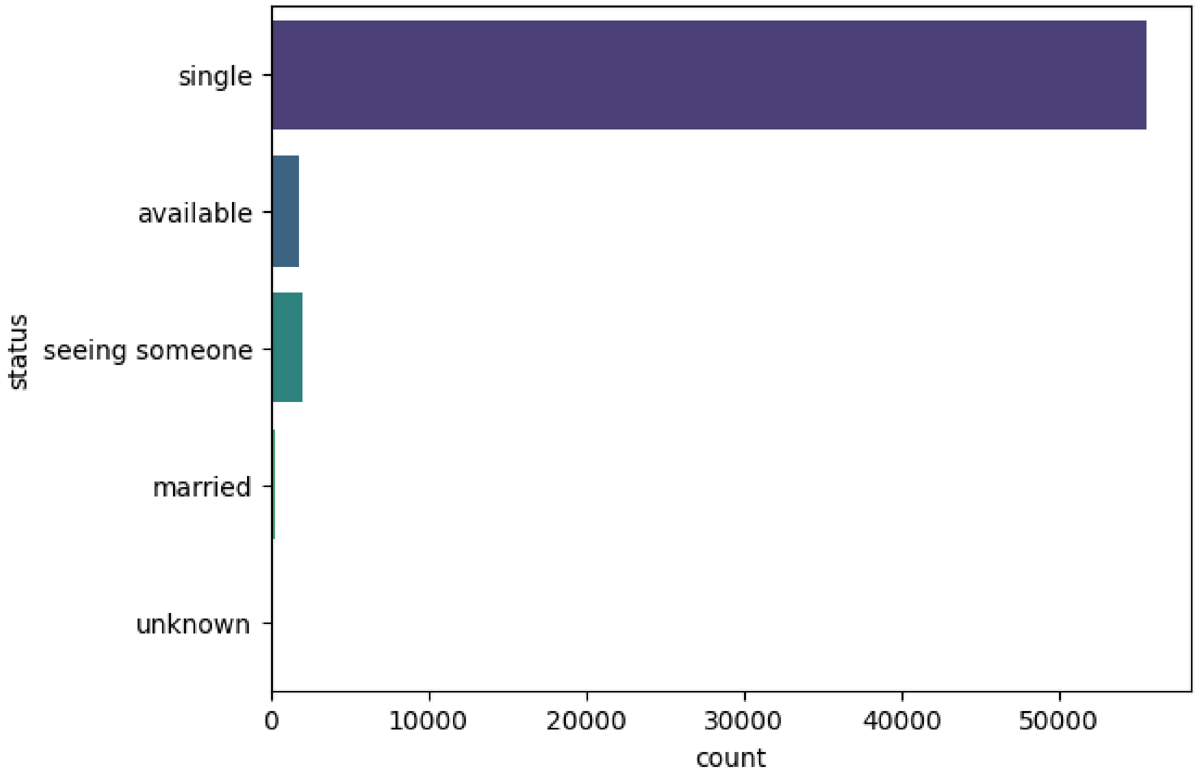

agnosticism
atheism
christianity
other
catholicism
buddhism
judaism
hinduism
islam
religion
0
2000
4000
6000
8000
count


m
f
sex
0
5000
10000
15000
20000
25000
30000
35000
count


gemini
cancer
pisces
aquarius
taurus
virgo
sagittarius
leo
aries
libra
scorpio
capricorn
sign
0
1000
2000
3000
4000
count


sometimes
no
when drinking
yes
trying to quit
smokes
0
10000
20000
30000
40000
count


english
afrikaans
french
portuguese
speaks
0
10000
20000
30000
40000
50000
60000
count




```
<Figure size 640x480 with 0 Axes>
```

From these plots we can observe that:

1. Most people are from California, given that most of there's so little data about other locations, this feature will be removed.
2. Most people speak English as their primary language, so this feature will be removed for not having enough data about the rest as well.
3. Some people have their status as unknown, this is a clear mistake. While the most probable option is that they are also single, given that is such a short amount of data, these will be removed.
4. The status married is so rare that could affect the performance of our models later on, so these values will be ignored.
5. The values of the feature smokes could be grouped so we only have yes and no.
6. There are several other features that can be further simplified.

In [13]:
```
df = df.drop(columns=['location', 'speaks'])
df = df[(df.status != 'unknown') & (df.status != 'married')]
df['smokes'] = df['smokes'].map(lambda x: 'yes' if x != 'no' else 'no')
```

In [14]:
```
diet_mapping = {
    'mostly anything': 'anything', 'anything': 'anything', 'strictly anything': 'an
    'mostly vegetarian': 'vegetarian', 'vegetarian': 'vegetarian', 'strictly vegeta
    'mostly vegan': 'vegan', 'vegan': 'vegan', 'strictly vegan': 'vegan',
    'mostly other': 'other', 'other': 'other', 'strictly other': 'other',
    'mostly kosher': 'kosher', 'kosher': 'kosher', 'strictly kosher': 'kosher',
    'mostly halal': 'halal', 'halal': 'halal', 'strictly halal': 'halal'
}
```

```
df['diet'] = df['diet'].map(diet_mapping)
```

In [15]:
```
body_type_mapping = {
    'thin': 'slim', 'skinny': 'slim',
    'average': 'average',
    'fit': 'athletic', 'athletic': 'athletic', 'jacked': 'athletic',
    'curvy': 'curvy_extra', 'a little extra': 'curvy_extra', 'full figured': 'curvy
    'overweight': 'overweight',
    'used up': 'other', 'rather not say': 'other'
}

df['body_type'] = df['body_type'].map(body_type_mapping)
```

In [16]:
```
education_mapping = {
    'high school': 'high_school', 'working on high school': 'high_school', 'dropped
    'graduated from two-year college': 'two_year_college', 'working on two-year col
    'dropped out of two-year college': 'two_year_college', 'two-year college': 'two
    'graduated from college/university': 'college_university', 'working on college/
    'dropped out of college/university': 'college_university', 'college/university'
    'graduated from masters program': 'masters', 'working on masters program': 'mas
    'dropped out of masters program': 'masters', 'masters program': 'masters',
    'graduated from ph.d program': 'phd_professional', 'working on ph.d program': '
    'dropped out of ph.d program': 'phd_professional', 'ph.d program': 'phd_profess
    'graduated from law school': 'phd_professional', 'working on law school': 'phd_
    'dropped out of law school': 'phd_professional', 'law school': 'phd_professiona
    'graduated from med school': 'phd_professional', 'working on med school': 'phd_
    'dropped out of med school': 'phd_professional', 'med school': 'phd_professiona
    'graduated from space camp': 'space_camp', 'working on space camp': 'space_camp
    'dropped out of space camp': 'space_camp', 'space camp': 'space_camp'
}

df['education'] = df['education'].map(education_mapping)
```

In [17]:
```
job_mapping = {
    'computer / hardware / software': 'stem', 'science / tech / engineering': 'stem
    'artistic / musical / writer': 'creative_media', 'entertainment / media': 'crea
    'sales / marketing / biz dev': 'business_finance', 'banking / financial / real
    'executive / management': 'business_finance',
    'medicine / health': 'healthcare_law', 'law / legal services': 'healthcare_law'
    'education / academia': 'education_government', 'political / government': 'educ
    'hospitality / travel': 'trades_services', 'construction / craftsmanship': 'tra
    'clerical / administrative': 'trades_services', 'transportation': 'trades_servi
    'unemployed': 'unemployed_retired', 'retired': 'unemployed_retired',
    'rather not say': 'other_unknown', 'other': 'other_unknown',
    'military': 'military',
    'student': 'student'
}

df['job'] = df['job'].map(job_mapping)
```

Now we can drop the rest of null values to have a completely clean dataset.

In [18]:
```python
new_df = df.dropna()
print(new_df.head())
```

```
    age    body_type      diet      drinks      drugs            education  \
0    22  curvy_extra  anything    socially      never  college_university
1    35      average     other       often  sometimes          space_camp
7    31      average  anything    socially      never  college_university
9    37     athletic  anything  not at all      never     two_year_college
11   28      average  anything    socially      never  college_university

   ethnicity  height               job orientation      religion sex  \
0      asian    75.0    trades_services    straight   agnosticism   m
1      white    70.0    trades_services    straight   agnosticism   m
7      white    65.0     creative_media    straight  christianity   f
9      white    65.0            student    straight       atheism   m
11     white    72.0   business_finance    straight  christianity   m

           sign smokes          status
0        gemini    yes          single
1        cancer     no          single
7   sagittarius     no          single
9        cancer     no          single
11          leo     no  seeing someone
```

We can also show some summary statistics for our data:

In [19]:
```python
print(new_df.describe())
for column in new_df.columns:
    if column not in ['age', 'height']:
        print(f'\nValue counts for {column}: ')
        print(new_df[column].value_counts())
print(new_df.shape)
```

```
                age        height
count  14478.000000  14478.000000
mean      32.788023     68.248791
std       10.144015      3.846002
min       18.000000     55.000000
25%       26.000000     65.000000
50%       30.000000     68.000000
75%       38.000000     71.000000
max       68.000000     80.000000

Value counts for body_type:
body_type
athletic       6266
average        3907
curvy_extra    2349
slim           1669
other           149
overweight      138
Name: count, dtype: int64

Value counts for diet:
diet
anything      11361
vegetarian     1952
other           798
vegan           276
kosher           60
halal            31
Name: count, dtype: int64

Value counts for drinks:
drinks
socially       10275
rarely          1669
often           1252
not at all      1049
very often       142
desperately       91
Name: count, dtype: int64

Value counts for drugs:
drugs
never        11504
sometimes     2825
often          149
Name: count, dtype: int64

Value counts for education:
education
college_university    8661
masters               2924
phd_professional      1150
two_year_college      1107
space_camp             533
high_school            103
Name: count, dtype: int64
```

```
Value counts for ethnicity:
ethnicity
white       8908
asian       2142
hispanic    1173
black        850
other        433
indian       361
middle       218
pacific      198
native       195
Name: count, dtype: int64

Value counts for job:
job
stem                    2607
business_finance        2498
other_unknown           2139
creative_media          1836
student                 1532
healthcare_law          1372
education_government    1226
trades_services         1007
unemployed_retired       198
military                  63
Name: count, dtype: int64

Value counts for orientation:
orientation
straight    12622
gay          1198
bisexual      658
Name: count, dtype: int64

Value counts for religion:
religion
agnosticism     3127
other           2939
atheism         2318
christianity    2233
catholicism     1881
judaism          970
buddhism         748
hinduism         209
islam             53
Name: count, dtype: int64

Value counts for sex:
sex
m    8603
f    5875
Name: count, dtype: int64

Value counts for sign:
sign
```

```
gemini         1314
cancer         1302
virgo          1277
leo            1258
libra          1242
scorpio        1207
taurus         1200
aries          1190
pisces         1165
sagittarius    1155
aquarius       1112
capricorn      1056
Name: count, dtype: int64

Value counts for smokes:
smokes
no     11516
yes     2962
Name: count, dtype: int64

Value counts for status:
status
single            13642
seeing someone      428
available           408
Name: count, dtype: int64
(14478, 15)
```

2.3. Data Preprocessing

Now that we have a clean dataset, we will have to transform it's values into new ones that our models will be able to accept. This will be done through the methods of One-Hot encoding and Standardization.

In [20]:
```
columns = ['age', 'body_type', 'diet', 'drinks', 'smokes', 'drugs', 'education', 'j
data = new_df[columns]
```

In [21]:
```
from sklearn.preprocessing import StandardScaler

num_features = ['age', 'height']
cat_features = ['body_type', 'diet', 'drinks', 'drugs', 'education', 'job', 'religi

data.loc[:, 'sex'] = data['sex'].map({'m': 0, 'f': 1})
data.loc[:, 'smokes'] = data['smokes'].map({'no': 0, 'yes': 1})

scaler = StandardScaler()
for num in num_features:
    data.loc[:, num] = scaler.fit_transform(data[[num]])

cat_data = pd.get_dummies(data[cat_features], drop_first=True).astype(int)
data_preprocessed = pd.concat([data[num_features + ['sex', 'smokes']], cat_data], a

print(data_preprocessed.head())
```

```
        age    height  sex  smokes  body_type_average  body_type_curvy_extra  \
0  -1.063523  1.755444    0       1                  0                      1
1   0.218065  0.455348    0       0                  1                      0
7  -0.176270 -0.844748    1       0                  1                      0
9   0.415232 -0.844748    0       0                  0                      0
11 -0.472021  0.975387    0       0                  1                      0

    body_type_other  body_type_overweight  body_type_slim  diet_halal  ...  \
0                 0                     0               0           0  ...
1                 0                     0               0           0  ...
7                 0                     0               0           0  ...
9                 0                     0               0           0  ...
11                0                     0               0           0  ...

    religion_atheism  religion_buddhism  religion_catholicism  \
0                  0                  0                     0
1                  0                  0                     0
7                  0                  0                     0
9                  1                  0                     0
11                 0                  0                     0

    religion_christianity  religion_hinduism  religion_islam  \
0                       0                  0               0
1                       0                  0               0
7                       1                  0               0
9                       0                  0               0
11                      1                  0               0

    religion_judaism  religion_other  orientation_gay  orientation_straight
0                  0               0                0                     1
1                  0               0                0                     1
7                  0               0                0                     1
9                  0               0                0                     1
11                 0               0                0                     1

[5 rows x 45 columns]
```

```
C:\Users\sergi\AppData\Local\Temp\ipykernel_8204\4048868718.py:11: FutureWarning: Se
tting an item of incompatible dtype is deprecated and will raise in a future error o
f pandas. Value '[-1.06352322  0.21806485 -0.17626994 ... -0.86635582  0.90815074
 -0.57060473]' has dtype incompatible with int64, please explicitly cast to a compat
ible dtype first.
  data.loc[:, num] = scaler.fit_transform(data[[num]])
```

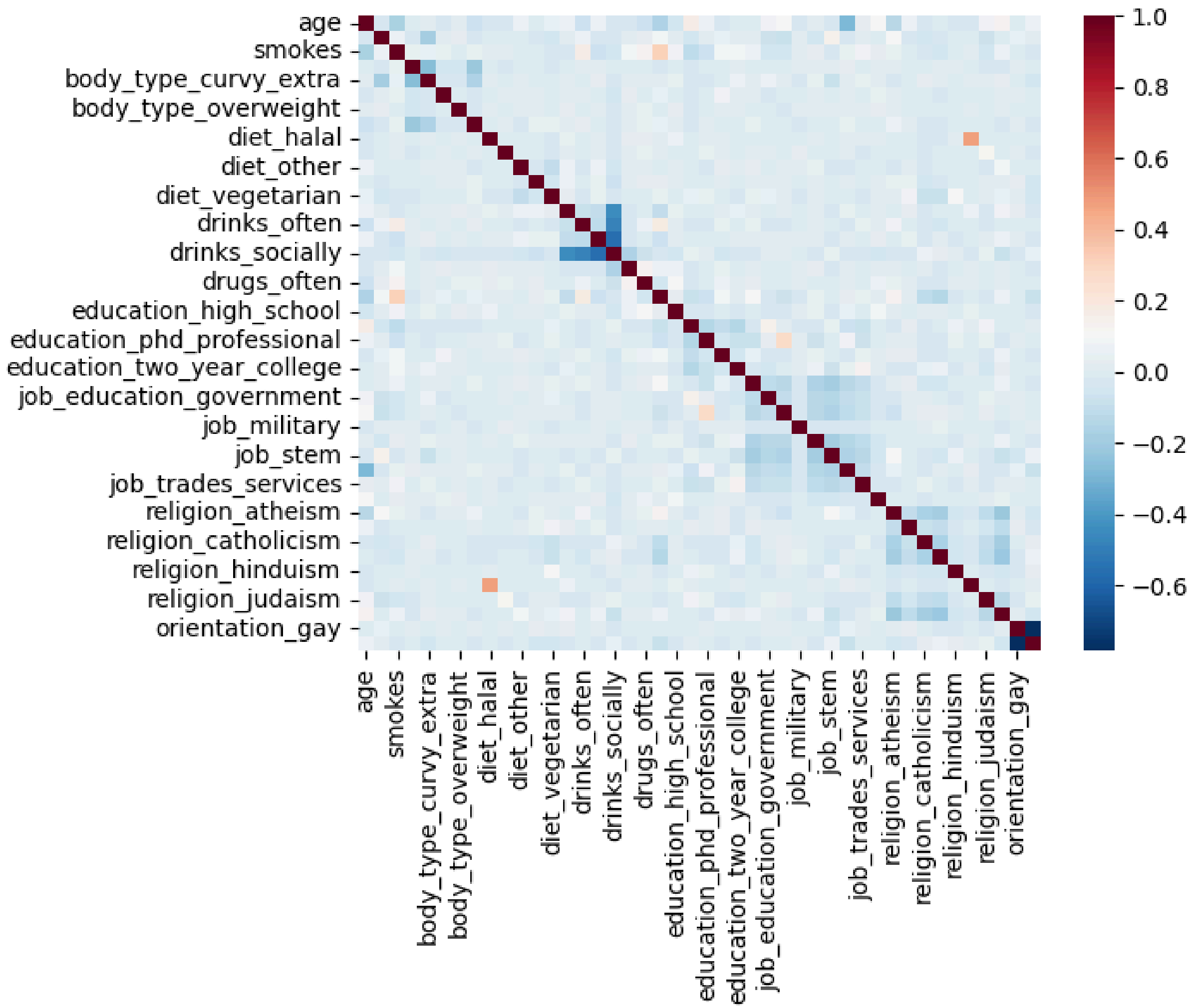
We can now assign values for our independent variable (X) and our target variable (y):

In [22]:
```
X = data_preprocessed.drop(columns= 'sex')
y = data_preprocessed['sex']
y = y.astype(int)
```

It's always a good practice to look for multicolinearity in our data, therefore we plot the correlation matrix using a heatmap:

In [23]:
```
corr_matrix = X.corr(method='pearson')
sns.heatmap(corr_matrix, cmap='RdBu_r')
```

```
plt.show()
plt.clf()
```




```
<Figure size 640x480 with 0 Axes>
```

Now that we've made sure that our data is ready for modelling, we finally can split our data for proper training and testing:

In [24]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.8, test_size
```

3. Modelling

3.1. Logistic Regression

In this section we will implement an optimized version of logistic regression using BayesSearchCV.

In [25]:
```
from skopt import BayesSearchCV
from sklearn.linear_model import LogisticRegression

lr_opt = BayesSearchCV(
```

```
    LogisticRegression(solver='liblinear', random_state=1),
    {
        'C': (1e-6, 1e+6, 'log-uniform'),
        'penalty': ['l1', 'l2'],
    },
    n_iter=32,
    cv=5
)

lr_opt.fit(X_train, y_train)

print("Best parameters:", lr_opt.best_params_)
print("Validation score:", lr_opt.best_score_)
print("Test score:", lr_opt.score(X_test, y_test))
```

```
Best parameters: OrderedDict({'C': 0.7010828232480305, 'penalty': 'l1'})
Validation score: 0.8647896862046167
Test score: 0.8756906077348067
```

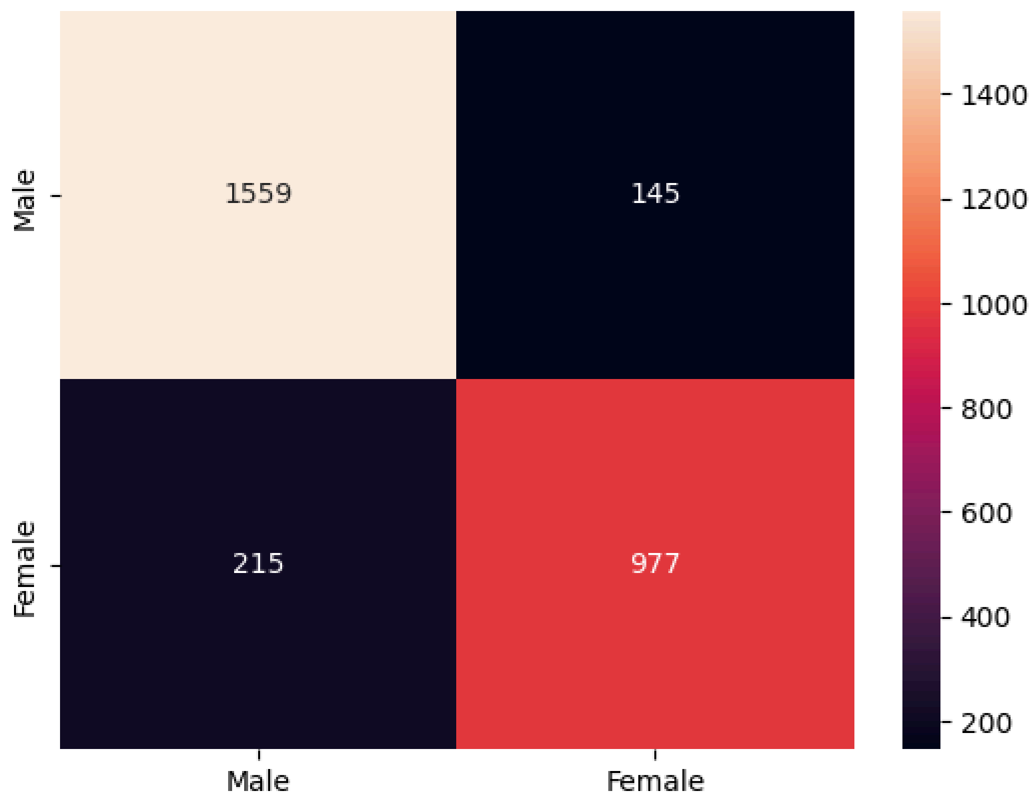
Now we print the classification report to take a look at our model's scores:

In [26]:
```
from sklearn.metrics import classification_report

y_pred = lr_opt.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.91      0.90      1704
           1       0.87      0.82      0.84      1192

    accuracy                           0.88      2896
   macro avg       0.87      0.87      0.87      2896
weighted avg       0.88      0.88      0.88      2896
```

Finally, we plot the confussion matrix using a heatmap:

In [27]:
```
from sklearn.metrics import confusion_matrix

def plot_cm(y_test, y_pred):
    cart_cm = confusion_matrix(y_test, y_pred)
    ax= plt.subplot()
    sns.heatmap(cart_cm, annot=True, ax = ax,fmt="d");
    ax.xaxis.set_ticklabels(['Male', 'Female']);
    ax.yaxis.set_ticklabels(['Male', 'Female']);
    plt.show()
    plt.clf()

plot_cm(y_test, y_pred)
```



<Figure size 640x480 with 0 Axes>

3.2. Decision Tree

For this section, we will use a decision tree instead to see if we can achieve better results. Like in the previous section we will first create and fit the model, then we will print the classification report and lastly we will plot the confussion matrix.

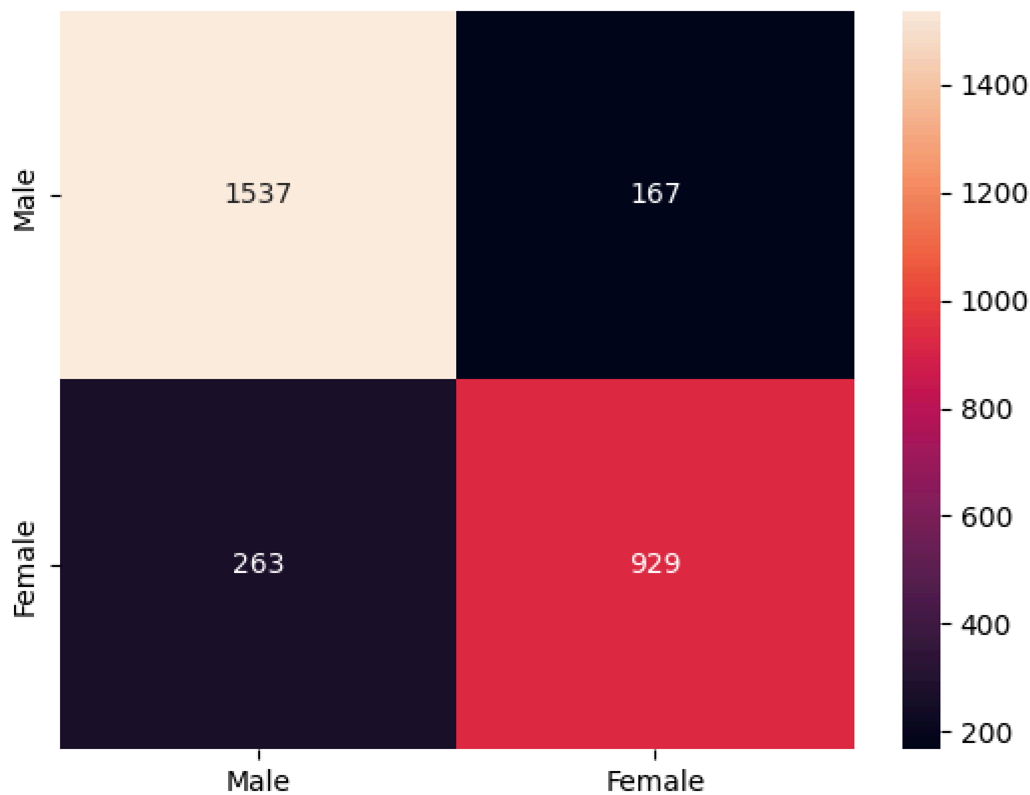
In [28]:
```python
from sklearn.tree import DecisionTreeClassifier

dt_opt = BayesSearchCV(
    DecisionTreeClassifier(random_state=1),
    {
        'max_depth': (1, 50),
        'min_samples_split': (2, 20),
        'min_samples_leaf': (1, 20),
        'max_features': ['sqrt', 'log2', None],
        'criterion': ['gini', 'entropy']
    },
    n_iter=32,
    cv=5
)

dt_opt.fit(X_train, y_train)

print("Best parameters:", dt_opt.best_params_)
print("Validation score:", dt_opt.best_score_)
print("Test score:", dt_opt.score(X_test, y_test))
```

```
Best parameters: OrderedDict({'criterion': 'gini', 'max_depth': 45, 'max_features':
None, 'min_samples_leaf': 20, 'min_samples_split': 20})
Validation score: 0.8484713870520736
Test score: 0.8515193370165746
```

In [29]:
```python
y_pred = dt_opt.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.90      0.88      1704
           1       0.85      0.78      0.81      1192

    accuracy                           0.85      2896
   macro avg       0.85      0.84      0.84      2896
weighted avg       0.85      0.85      0.85      2896
```

In [30]:
```python
plot_cm(y_test, y_pred)
```




```
<Figure size 640x480 with 0 Axes>
```

3.3. Random Forest

For this section, we will use a random forest classifier instead to see if we can achieve better results. Like in the previous section we will first create and fit the model, then we will print the classification report and lastly we will plot the confussion matrix.

In [31]:
```python
from sklearn.ensemble import RandomForestClassifier
```

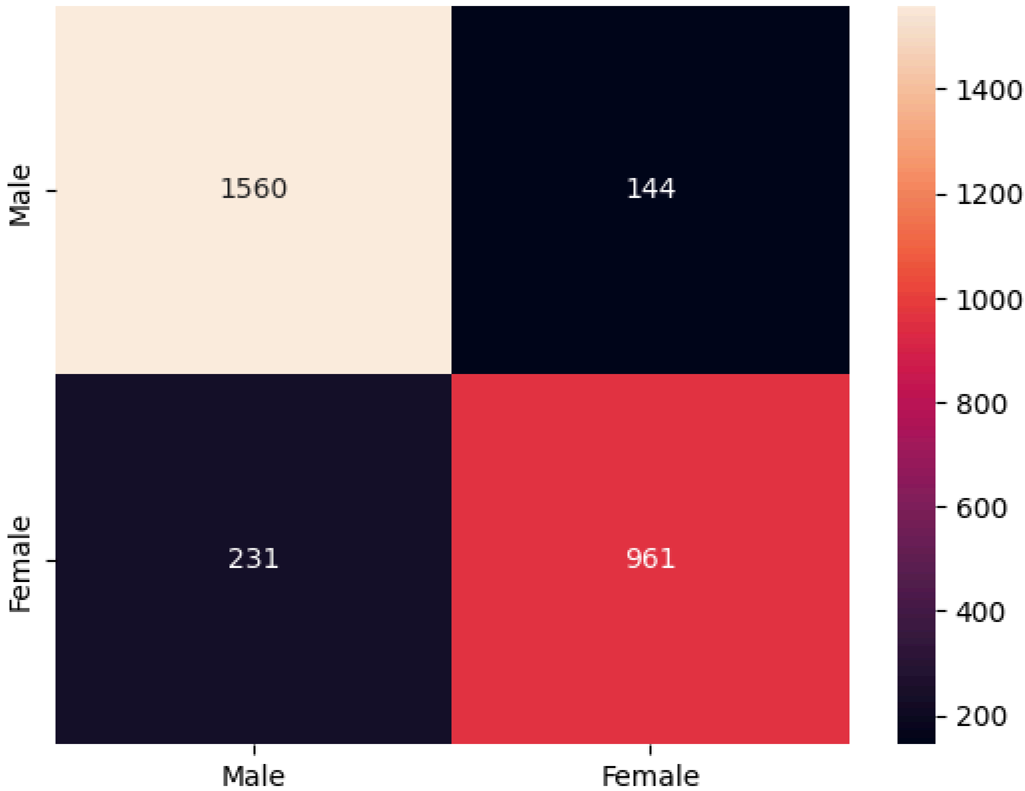
```python
rfc_opt = BayesSearchCV(
    RandomForestClassifier(n_jobs=-1, random_state=1),
    {
        'n_estimators': (50, 500),
        'max_depth': (5, 50),
        'min_samples_split': (2, 20),
        'min_samples_leaf': (1, 20),
        'max_features': ['sqrt', 'log2', None],
        'bootstrap': [True, False],
        'criterion': ['gini', 'entropy']
    },
    n_iter=32,
    cv=5
)

rfc_opt.fit(X_train, y_train)

print("Best parameters:", rfc_opt.best_params_)
print("Validation score:", rfc_opt.best_score_)
print("Test score:", rfc_opt.score(X_test, y_test))
```

```
Best parameters: OrderedDict({'bootstrap': True, 'criterion': 'gini', 'max_depth': 5
0, 'max_features': 'sqrt', 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimat
ors': 376})
Validation score: 0.859955029395256
Test score: 0.8705110497237569
```

In [32]:
```python
y_pred = rfc_opt.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.92      0.89      1704
           1       0.87      0.81      0.84      1192

    accuracy                           0.87      2896
   macro avg       0.87      0.86      0.86      2896
weighted avg       0.87      0.87      0.87      2896
```

In [33]:
```python
plot_cm(y_test, y_pred)
```




```
<Figure size 640x480 with 0 Axes>
```

3.4. Support Verctor Machine

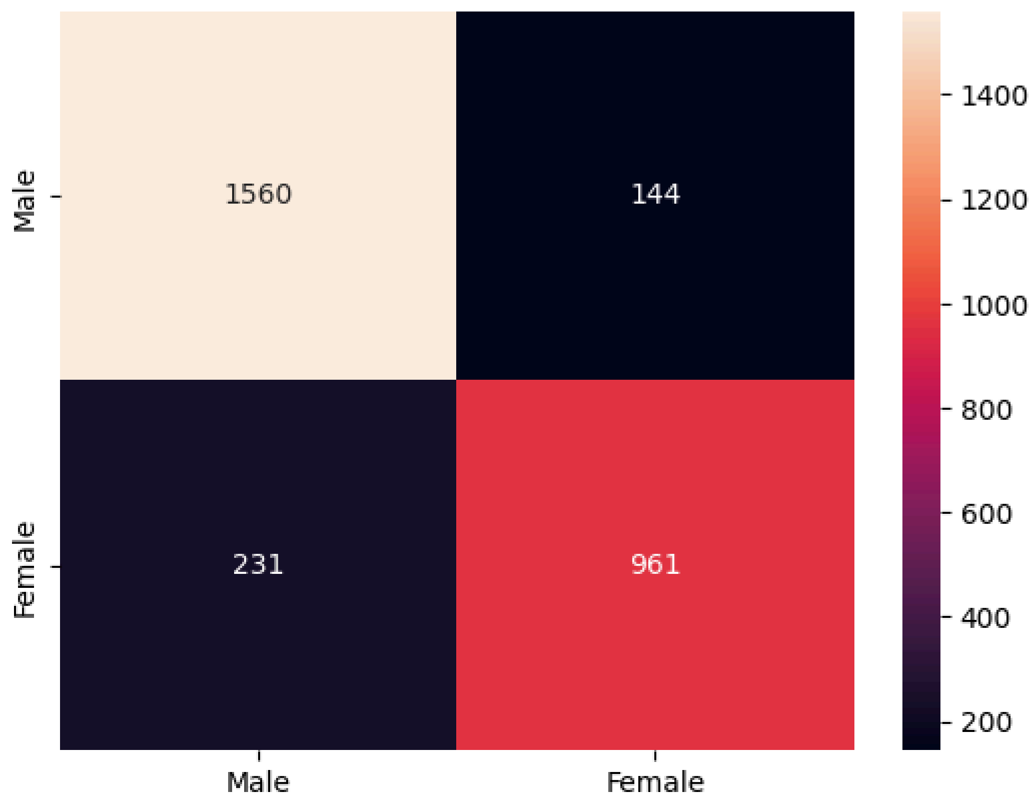
In [34]:
```
from sklearn.svm import SVC

svm_opt = BayesSearchCV(
    SVC(kernel="rbf"),
    {
        'C': (1e-3, 1e+2, 'log-uniform'),
        'gamma': (1e-4, 1, 'log-uniform'),
    },
    n_iter=20,
    cv=3
)

svm_opt.fit(X_train, y_train)

print("Best parameters:", svm_opt.best_params_)
print("Validation score:", svm_opt.best_score_)
print("Test score:", svm_opt.score(X_test, y_test))
```

```
Best parameters: OrderedDict({'C': 0.9662810507409029, 'gamma': 0.1309846024920814})
Validation score: 0.8655669444097769
Test score: 0.8756906077348067
```

In [35]:
```
y_pred = rfc_opt.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.92      0.89      1704
           1       0.87      0.81      0.84      1192

    accuracy                           0.87      2896
   macro avg       0.87      0.86      0.86      2896
weighted avg       0.87      0.87      0.87      2896
```

In [36]:
```
plot_cm(y_test, y_pred)
```




```
<Figure size 640x480 with 0 Axes>
```

4. Conclusion

In this analysis, we aimed to predict users' gender on the OKCupid dataset using four machine learning models: **Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM)**. After preprocessing the data by encoding categorical variables, standardizing numerical features, and performing hyperparameter tuning, we evaluated the models based on their validation and test scores.

- **Best Performing Model**: The **SVM** model achieved the highest test score of **0.8809**, indicating its strong ability to generalize.
- **Efficiency vs. Performance Tradeoff**: While **Random Forest** and **SVM** provided competitive results, they took significantly longer to train compared to **Logistic Regression**, which performed nearly as well in just 21 seconds.

- **Decision Tree Weakness**: The **Decision Tree** had the lowest test score (**0.8567**), likely due to its tendency to overfit.

Overall, **SVM** provided the best results but at the cost of processing time, while **Logistic Regression** was a strong contender with much lower computational demand.

4.1. Next Steps for Further Analysis

1. **Feature Engineering & Selection**
    - Explore new features that could enhance prediction accuracy, such as **profile text analysis (NLP techniques)**.
2. **Ensemble Learning**
    - Combine multiple models (e.g., **Stacking or Boosting**) to leverage their strengths and improve prediction robustness.
3. **Deep Learning Approach**
    - Implement a **Neural Network (MLP)** and compare its performance with traditional models.
4. **Explainability & Bias Analysis**
    - Investigate whether certain features disproportionately affect gender classification, ensuring the model is fair and interpretable.