date-a-scientist_Carlos_solution

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1 Portfolio Project: OKCupid Date-A-Scientist

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1.2 Introduction

The objective of this project is to analyze the data from OKCupid, an online dating application, and find patters inside the data provided on the platform by its users similar to the exercise OKCupid does to identify good matches amongst their members. Like OKCupid, many other apps use sophisticated data science techniques to recommend possible matches and to optimize the user experience, and this project will leverage on the vast amount of information that they have access to.

1.3 Scoping

This project will be divided in four sections. First, the overall project goals will be defined as well as the intention of the project. Secondly follows the explanation of the source of the data including a basic description of the information contained within it. Then, the project will describe the analysis, methods and tools used to achieve the project goals. Finally, some conclusions and recommendations will be drawn from the analysis of the obtained results.

1.3.1 Project Goals

This project has 2 main goals. The first goal is to provide some problem solving, data analysis, and coding skills to the aspiring Data Scientist in the context of the respective Career Path in Codecademy. Second, to answer a critical research question: Can OKCupid's use some variables from the users profile to accurately predict their zodiac sign when this information is not available? Knowing the zodiac sign of each individual is key since many users think that their astrological sign has an important role when choosing a romatic partner.

Therefore, this project defines the problem to solve as the request to build a machine learning model for OKCupid to predict the missing zodiac signs as accurately as possible, by selecting the dataset variables of more relevance to increase the model accuracy.

1.3.2 Data

The dataset used for the project analysis (`profiles.csv`) has been provided by Codecademy.com. Before having any modifications from the project side, it contains 59946 rows and 31 columns in csv format, which will be transformed into a dataframe. This dataset contains information about the age, body type, variety of diet, drinking frequency, drugs-consumption frequency, education level, topic of essays 0 to 9, ethnicity, height, income, job, last time online, location, whether they have children or not, sexual orientation, pets, religion, sex, zodiac sign, whether smoker or not, language and current status.

1.3.3 Analysis

This project will leverage on descriptive statistics and visualization tools to fully understand the data before building 4 different machine learning classification algorithms (K-Nearest Neighbors, Decision Tree, Random Forest, and Naive Bayes) to obtain zodiac sign predictions based of the data from the remaining columns.

1.3.4 Evaluation

Finally, this project will evaluate the accuracy of the 4 different ML models to select the one with the highest accuracy. Recommendations for improving the study, as well as next steps, will also be mentioned.

1.4 Data

1.4.1 Project Setup

[52]:
```python
# Importing basic Python libraries:
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns

# Reading csv files as pandas dataframe:
profiles = pd.read_csv('profiles.csv')

# Printing original dataset first 5 rows:
profiles.head()
```

[52]:
```
   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]
```

1.4.2 Initial Data Exploration

[53]:
```python
# Basic characteristics per column:
profiles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59946 entries, 0 to 59945
Data columns (total 31 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   age          59946 non-null  int64
 1   body_type    54650 non-null  object
 2   diet         35551 non-null  object
 3   drinks       56961 non-null  object
 4   drugs        45866 non-null  object
 5   education    53318 non-null  object
 6   essay0       54458 non-null  object
 7   essay1       52374 non-null  object
 8   essay2       50308 non-null  object
 9   essay3       48470 non-null  object
 10  essay4       49409 non-null  object
 11  essay5       49096 non-null  object
 12  essay6       46175 non-null  object
 13  essay7       47495 non-null  object
 14  essay8       40721 non-null  object
 15  essay9       47343 non-null  object
 16  ethnicity    54266 non-null  object
 17  height       59943 non-null  float64
 18  income       59946 non-null  int64
 19  job          51748 non-null  object
 20  last_online  59946 non-null  object
 21  location     59946 non-null  object
```

```
 22  offspring    24385 non-null  object
 23  orientation  59946 non-null  object
 24  pets         40025 non-null  object
 25  religion     39720 non-null  object
 26  sex          59946 non-null  object
 27  sign         48890 non-null  object
 28  smokes       54434 non-null  object
 29  speaks       59896 non-null  object
 30  status       59946 non-null  object
dtypes: float64(1), int64(2), object(28)
memory usage: 14.2+ MB
```

The `profiles` dataset has 59946 rows and 31 columns, only 3 of them are numerical (`age`, `height` and `income`). The project will start by getting some statistics about the numerical variables, then proceeding to explore the categorical variables, and even performing some data cleaning in case necessary.

[54]:
```
profiles.sign.value_counts()
```

[54]:
```
gemini and it&rsquo;s fun to think about         1782
scorpio and it&rsquo;s fun to think about        1772
leo and it&rsquo;s fun to think about            1692
libra and it&rsquo;s fun to think about          1649
taurus and it&rsquo;s fun to think about         1640
cancer and it&rsquo;s fun to think about         1597
pisces and it&rsquo;s fun to think about         1592
sagittarius and it&rsquo;s fun to think about    1583
virgo and it&rsquo;s fun to think about          1574
aries and it&rsquo;s fun to think about          1573
aquarius and it&rsquo;s fun to think about       1503
virgo but it doesn&rsquo;t matter                1497
leo but it doesn&rsquo;t matter                  1457
cancer but it doesn&rsquo;t matter               1454
gemini but it doesn&rsquo;t matter               1453
taurus but it doesn&rsquo;t matter               1450
libra but it doesn&rsquo;t matter                1408
aquarius but it doesn&rsquo;t matter             1408
capricorn and it&rsquo;s fun to think about      1376
sagittarius but it doesn&rsquo;t matter          1375
aries but it doesn&rsquo;t matter                1373
capricorn but it doesn&rsquo;t matter            1319
pisces but it doesn&rsquo;t matter               1300
scorpio but it doesn&rsquo;t matter              1264
leo                                              1159
libra                                            1098
cancer                                           1092
virgo                                            1029
scorpio                                          1020
```

```
gemini                                        1013
taurus                                        1001
aries                                          996
pisces                                         992
aquarius                                       954
sagittarius                                    937
capricorn                                      833
scorpio and it matters a lot                    78
leo and it matters a lot                        66
aquarius and it matters a lot                   63
cancer and it matters a lot                     63
pisces and it matters a lot                     62
gemini and it matters a lot                     62
libra and it matters a lot                      52
taurus and it matters a lot                     49
sagittarius and it matters a lot                47
aries and it matters a lot                      47
capricorn and it matters a lot                  45
virgo and it matters a lot                      41
Name: sign, dtype: int64
```

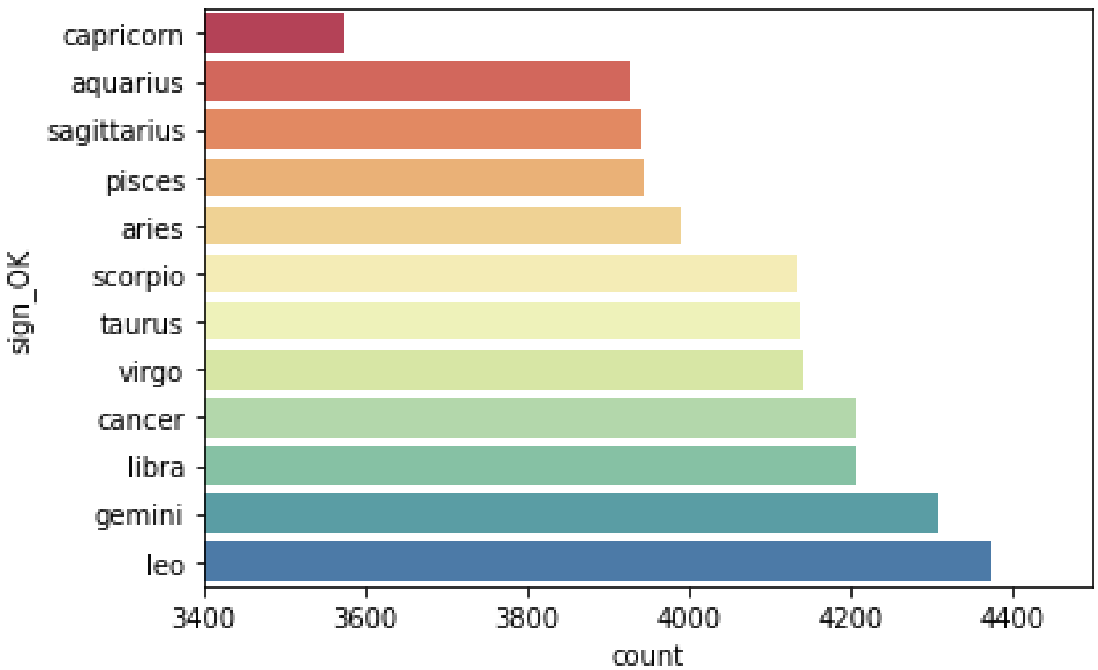
This column requires some cleaning since there are only 12 signs, luckily it can be noticed that the first word is always the sign. Therefore, a new column with the correct signs, called `sign_OK`, will be created.

[55]:
```
# Splitting 'sign' column by space:
str_split = profiles.sign.str.split(' ')
profiles['sign_OK'] = str_split.str.get(0)
profiles.sign_OK.value_counts()
```

[55]:
```
leo            4374
gemini         4310
libra          4207
cancer         4206
virgo          4141
taurus         4140
scorpio        4134
aries          3989
pisces         3946
sagittarius    3942
aquarius       3928
capricorn      3573
Name: sign_OK, dtype: int64
```

Since there are so many variables, this project believes it is worth it to analyze and plot it one by one. The firs one will be `sign_OK` as it is the variable that ML model will have to predict. #### Signs

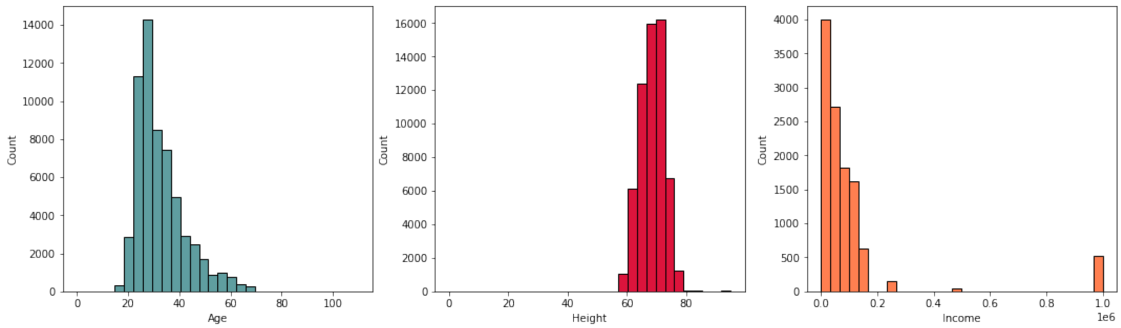
```
[56]: # Using Seaborn bar countplot:
ax = sns.countplot(y=profiles['sign_OK'], order=profiles["sign_OK"].
                   value_counts(ascending=True).index, palette='Spectral')
ax.set(xlim=(3400,4500))
plt.show()
```



Now starting with the independent variables (the ones used as input data to predict `sign_OK`), the numerical ones will be first: #### Age, Height, and Income

```
[57]: # Using histograms (since this is a numerical continuous variable):
plt.figure(figsize=(18,5))
ax = plt.subplot(1,3,1)
plt.hist(profiles.age, range=(0,110), bins=30, color='cadetblue',␣
 ↪edgecolor="black")
plt.xlabel("Age")
plt.ylabel("Count")
ax = plt.subplot(1,3,2)
plt.hist(profiles.height, range=(0,95), bins=30, color='crimson',␣
 ↪edgecolor="black")
plt.xlabel("Height")
plt.ylabel("Count")
ax = plt.subplot(1,3,3)
plt.hist(profiles.income, range=(0,1000000), bins=30, color='coral',␣
 ↪edgecolor="black")
plt.xlabel("Income")
```

```
plt.ylabel("Count")
plt.show()
```



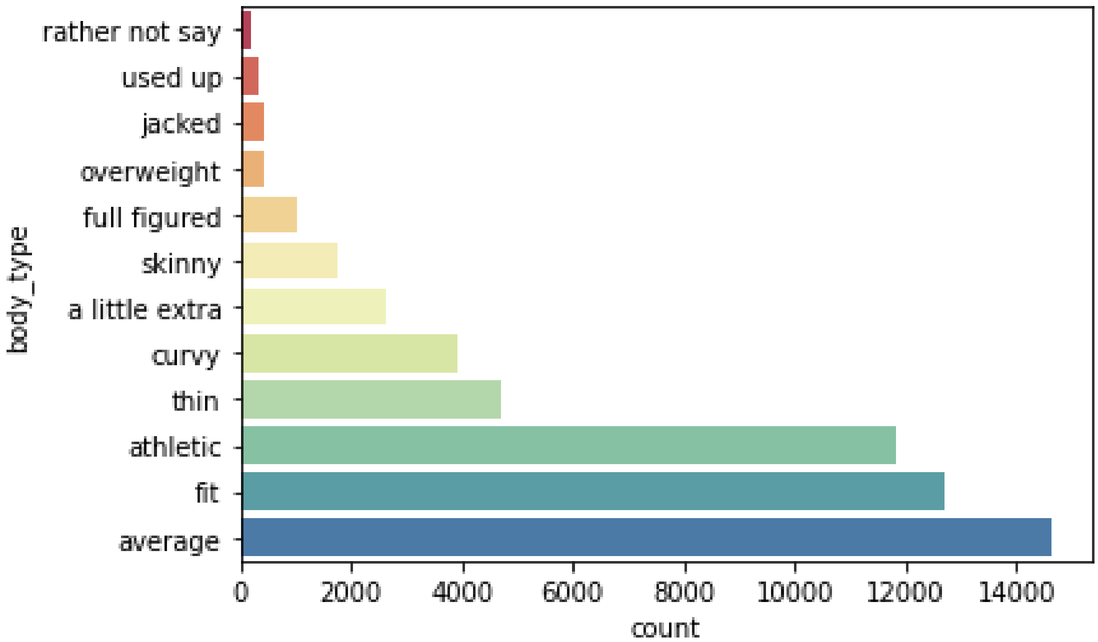
[58]:
```
# Basic statistics for numerical variables:
profiles.describe()
```

[58]:

	age	height	income
count	59946.000000	59943.000000	59946.000000
mean	32.340290	68.295281	20033.222534
std	9.452779	3.994803	97346.192104
min	18.000000	1.000000	-1.000000
25%	26.000000	66.000000	-1.000000
50%	30.000000	68.000000	-1.000000
75%	37.000000	71.000000	-1.000000
max	110.000000	95.000000	1000000.000000

As seen above, there are some outlayers in the data for all 3 variables. For `age` and `height`, it would be wise to eliminate `age` or`'height` as 110 or 1 respectively. `income` does not need any cleaning, as there is a considerable proportion of people that have ~1,000,000 USD income. #### Body_type

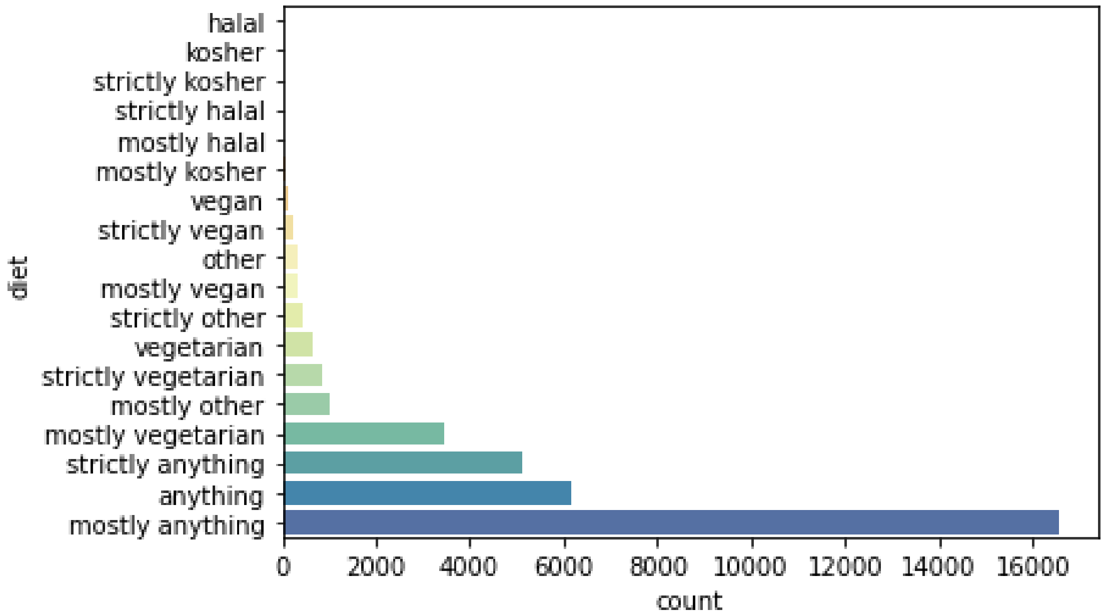
[59]:
```
ax = sns.countplot(y=profiles['body_type'], order=profiles["body_type"].
↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.body_type.value_counts()/len(profiles)
```



It can be seen that the first 5 categories (‘average’, ‘fit’, ‘athletic’, ‘thin’, ‘curvy’) group ~80% of the total data.

Diet

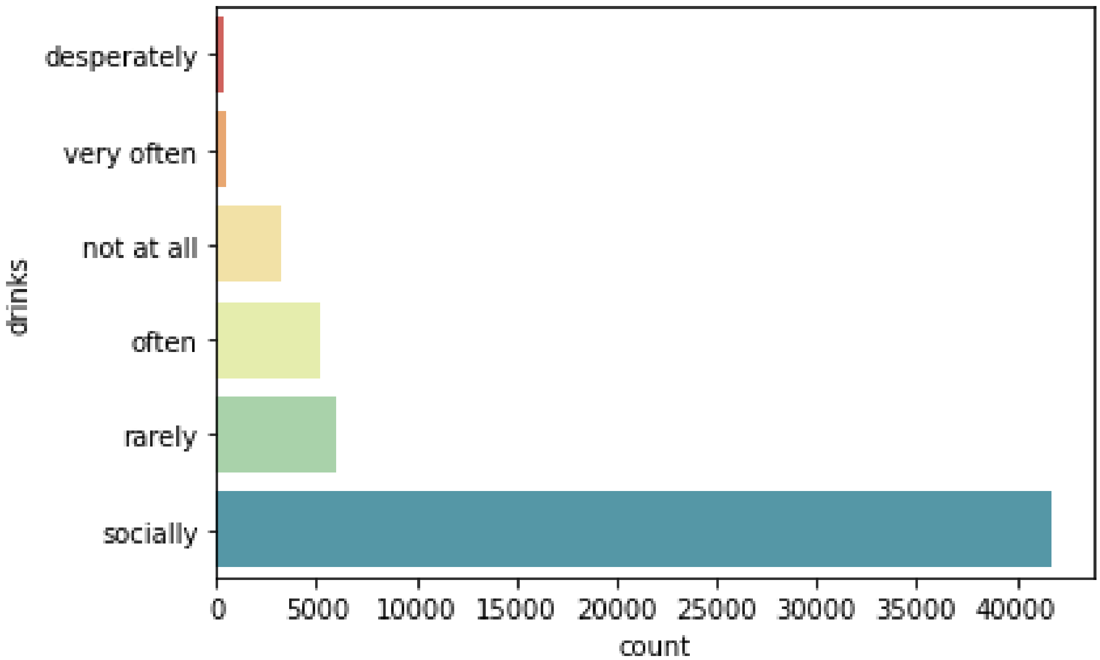
[60]:
```
ax = sns.countplot(y=profiles['diet'], order=profiles["diet"].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.diet.value_counts()/len(profiles)
```



It can be seen that the first 3 categories ('mostly anything', 'anything', 'strictly anything') belong to users who are not so strict with their diets. They group ~46% of the total data.

Drinks

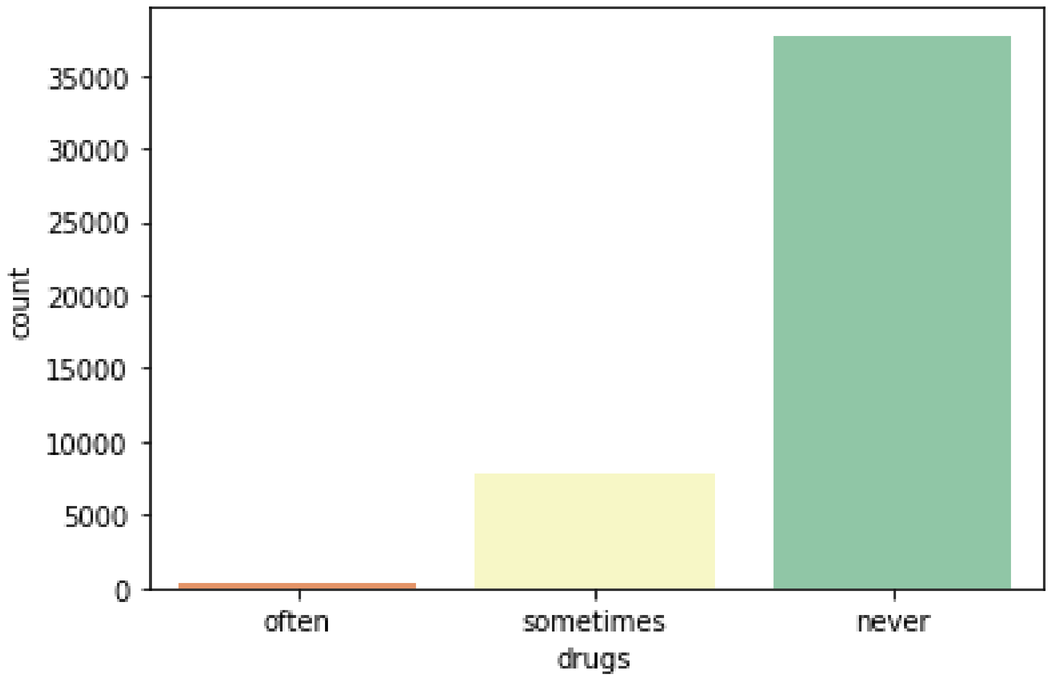
[61]:
```
ax = sns.countplot(y=profiles['drinks'], order=profiles["drinks"].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.drinks.value_counts()/len(profiles)
```



The first category, ‘socially’, groups ~70% of the data. This indicates that the OKCupid users do not drink much; as ‘often’, ‘very often’, and ‘desperately’ group only ~10% of the data.

Drugs

[62]:
```
ax = sns.countplot(x=profiles['drugs'], order=profiles["drugs"].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
profiles.drugs.value_counts()/len(profiles)
```

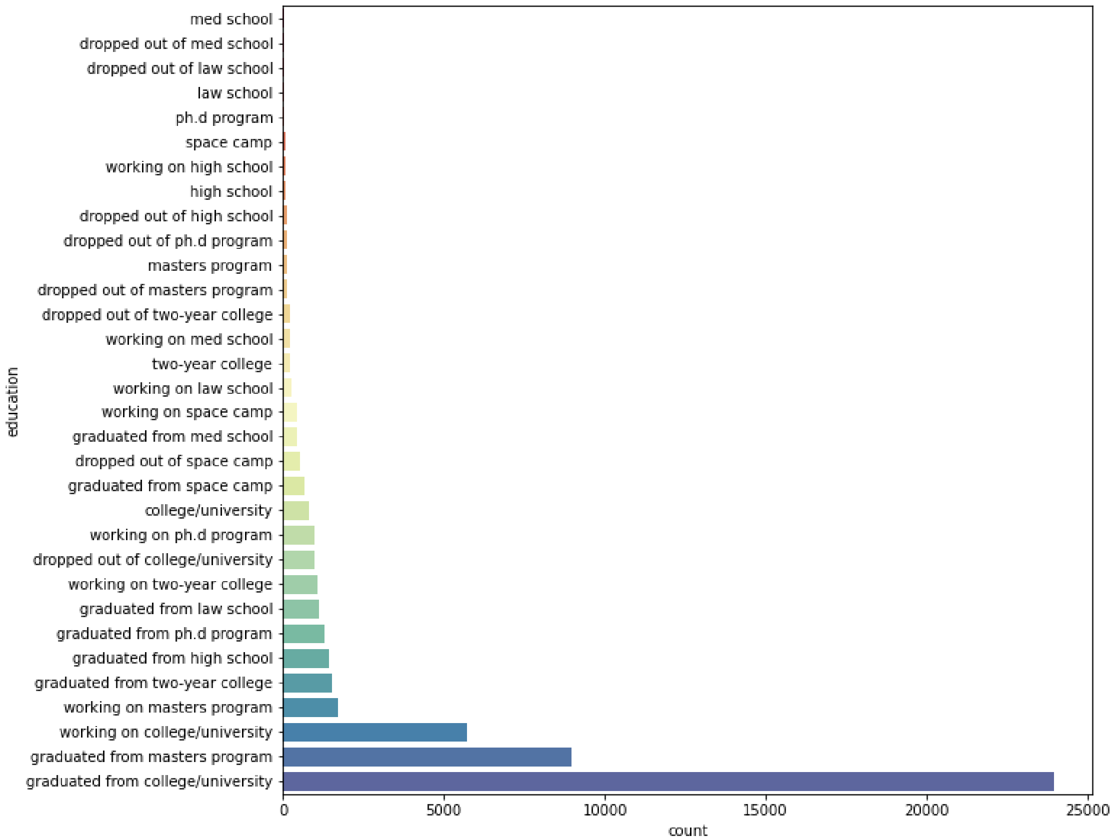


[62]:
```
never        0.629300
sometimes    0.128983
often        0.006839
Name: drugs, dtype: float64
```

The vast majority of the OKCupid users say that they never use drugs (~63%), yet ~25% did not answer the question.

Education

[63]:
```
plt.figure(figsize=(10, 10))
ax = sns.countplot(y=profiles['education'], order=profiles['education'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.education.value_counts()/len(profiles)
```



The biggest category is 'graduated from college/university' which groups 40% of the data.

Ethnicity

[64]:
```
profiles.ethnicity.value_counts()
```

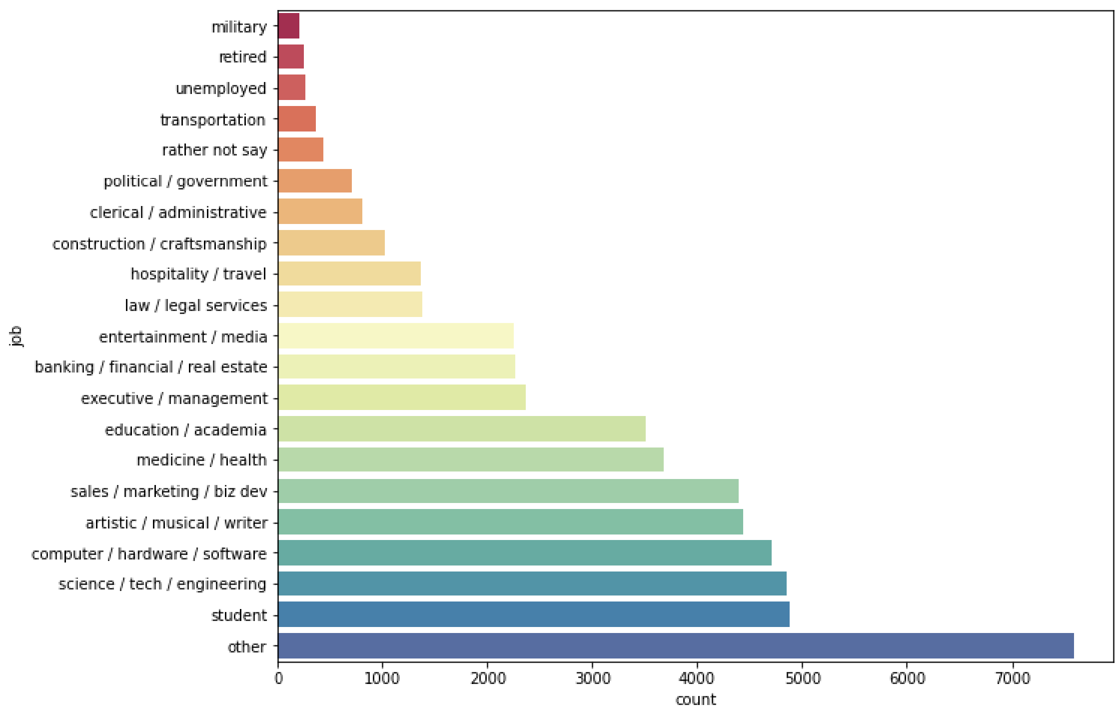
[64]:
```
white
32831
asian
6134
hispanic / latin
2823
black
2008
other
1706
                                 …
asian, middle eastern, black, native american, hispanic / latin, white
1
asian, middle eastern, indian, hispanic / latin
1
```

```
black, native american, pacific islander, white, other
1
asian, middle eastern, black, pacific islander
1
middle eastern, black, native american, indian, pacific islander, hispanic /
latin, white, other        1
Name: ethnicity, Length: 217, dtype: int64
```

Since there are 217 different categories in the `ethnicity` variable, for the moment this variable will not be considered for the analysis.

Job

[65]:
```
plt.figure(figsize=(10, 8))
ax = sns.countplot(y=profiles['job'], order=profiles['job'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.job.value_counts()/len(profiles)
```



Job-wise, the data is quite spreaded, being the biggest category 'other' with 13% of the data; and 'student' and 'science / tech / engineering' with 8% of the data.

Last online

[66]:
```
profiles.last_online.value_counts()/len(profiles)
```

[66]:
```
2012-06-29-22-56    0.000400
2012-06-30-22-09    0.000384
2012-06-30-23-27    0.000384
2012-06-30-22-56    0.000384
2012-06-30-21-51    0.000384
                      …
2012-05-28-12-28    0.000017
2012-06-06-20-54    0.000017
2012-06-30-05-50    0.000017
2011-12-25-22-13    0.000017
2012-06-15-23-22    0.000017
Name: last_online, Length: 30123, dtype: float64
```

Since there are 30123 different categories in the `last_online` variable, this variable will not be considered for the analysis.

Location

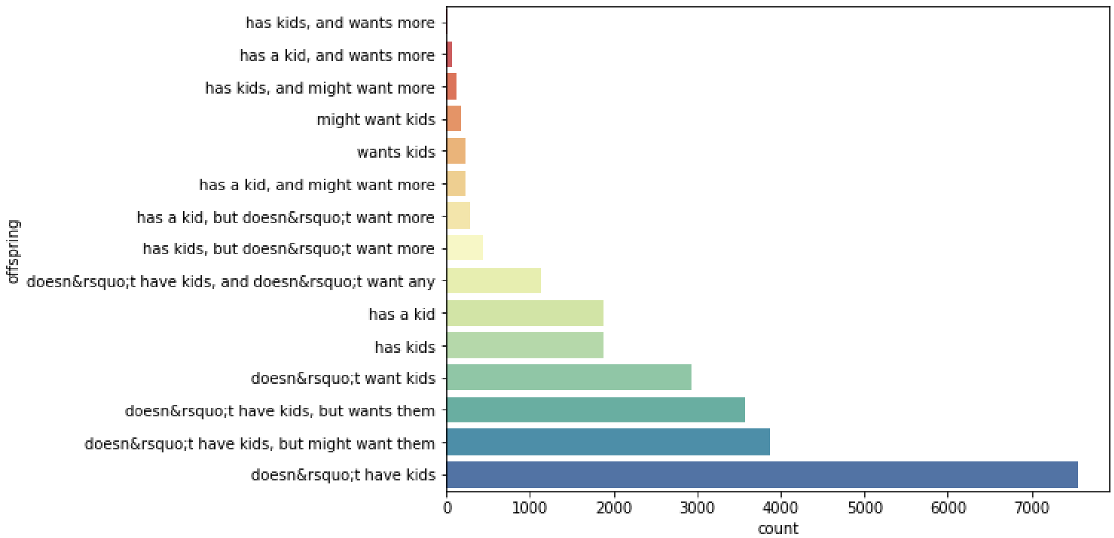
[67]:
```
profiles.location.value_counts()/len(profiles)
```

[67]:
```
san francisco, california      0.518200
oakland, california            0.120342
berkeley, california           0.070263
san mateo, california          0.022203
palo alto, california          0.017749
                                 …
cincinnati, ohio               0.000017
nevada city, california        0.000017
leander, texas                 0.000017
oakley, california             0.000017
san luis obispo, california    0.000017
Name: location, Length: 199, dtype: float64
```

Since there are 199 different categories in the `location` variable, for the moment we will not consider this variable for the analysis.

Offspring

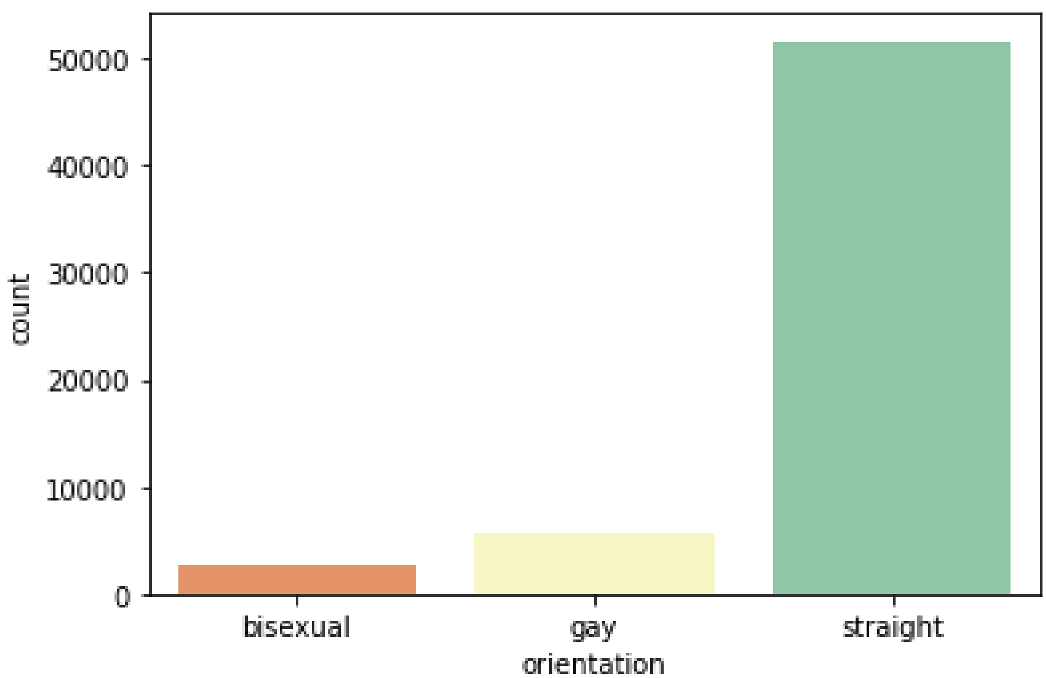
[68]:
```
plt.figure(figsize=(8, 6))
ax = sns.countplot(y=profiles['offspring'], order=profiles['offspring'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.offspring.value_counts()/len(profiles)
```



The first 4 categories group ~30% of the data, corresponding to the users that do not have kids (the majority).

Orientation

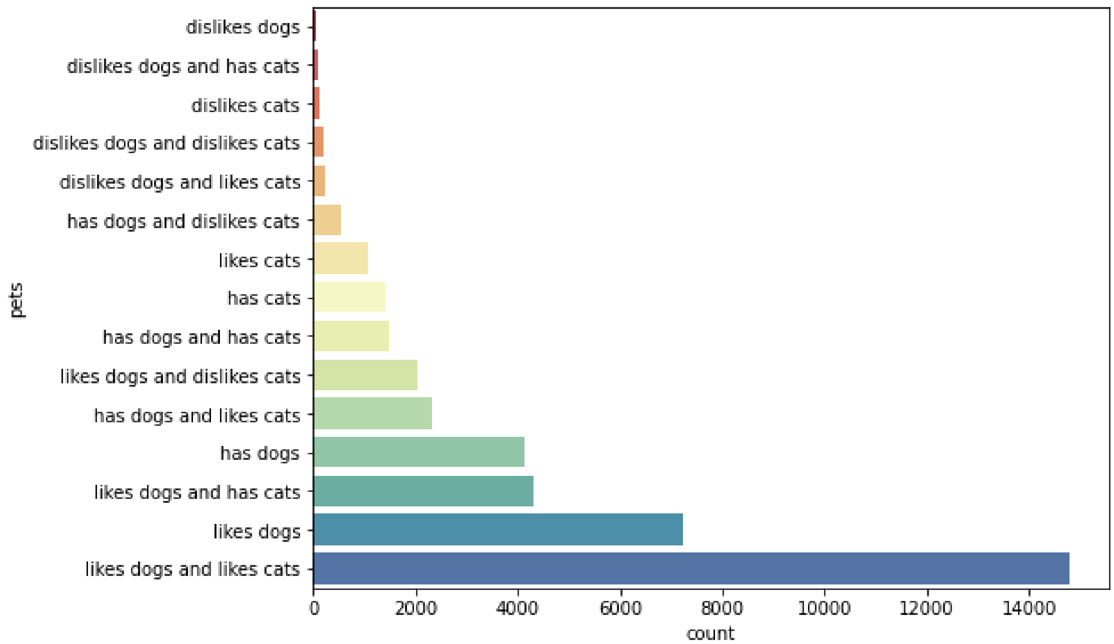
[69]:
```
ax = sns.countplot(x=profiles['orientation'], order=profiles['orientation'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.orientation.value_counts()/len(profiles)
```



The big majority (86% of the total) have declared to be straight.

Pets

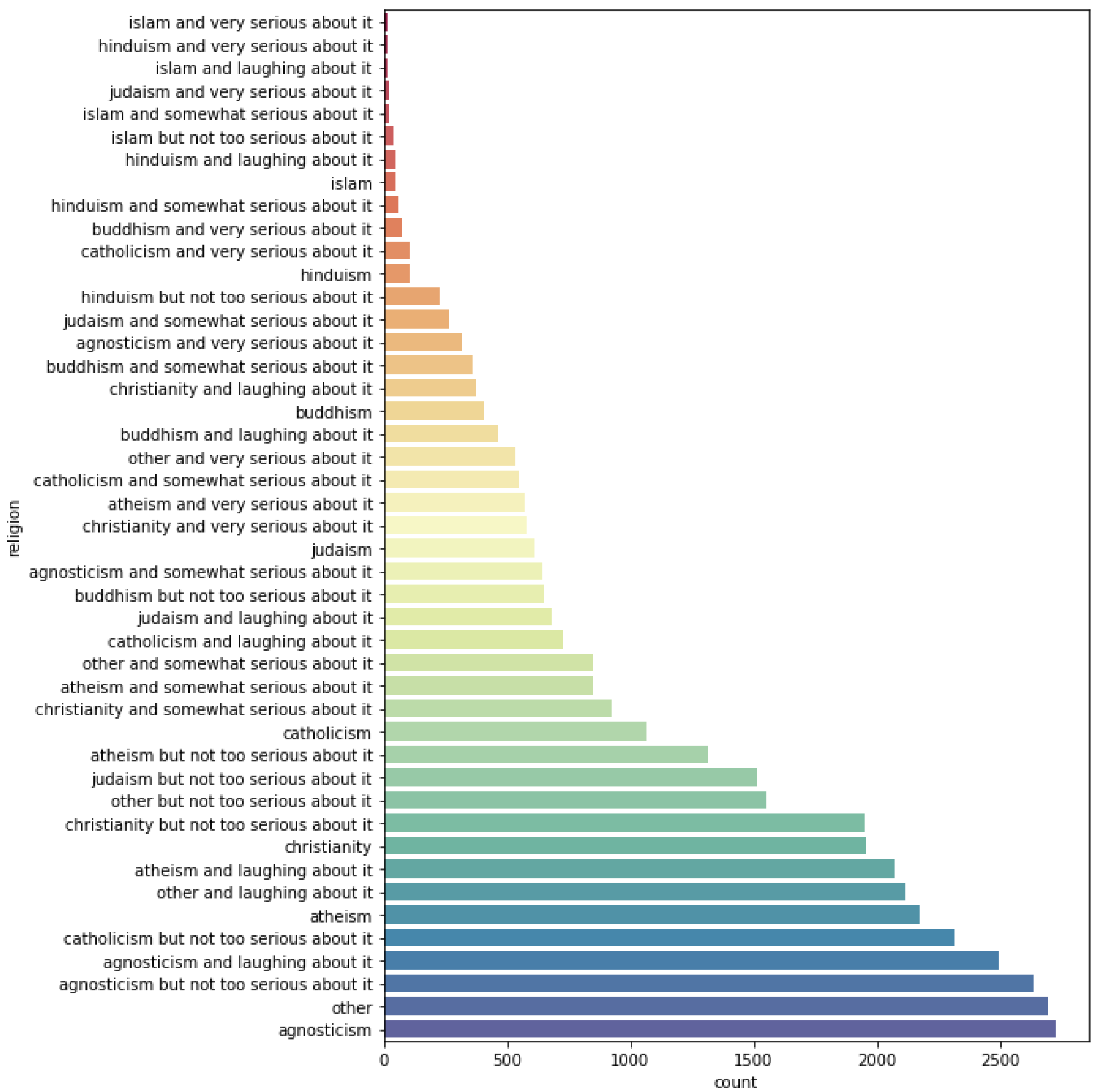
[70]:
```
plt.figure(figsize=(8, 6))
ax = sns.countplot(y=profiles['pets'], order=profiles['pets'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.pets.value_counts()/len(profiles)
```



The majority of users either has dogs or likes dogs (compared to cats).

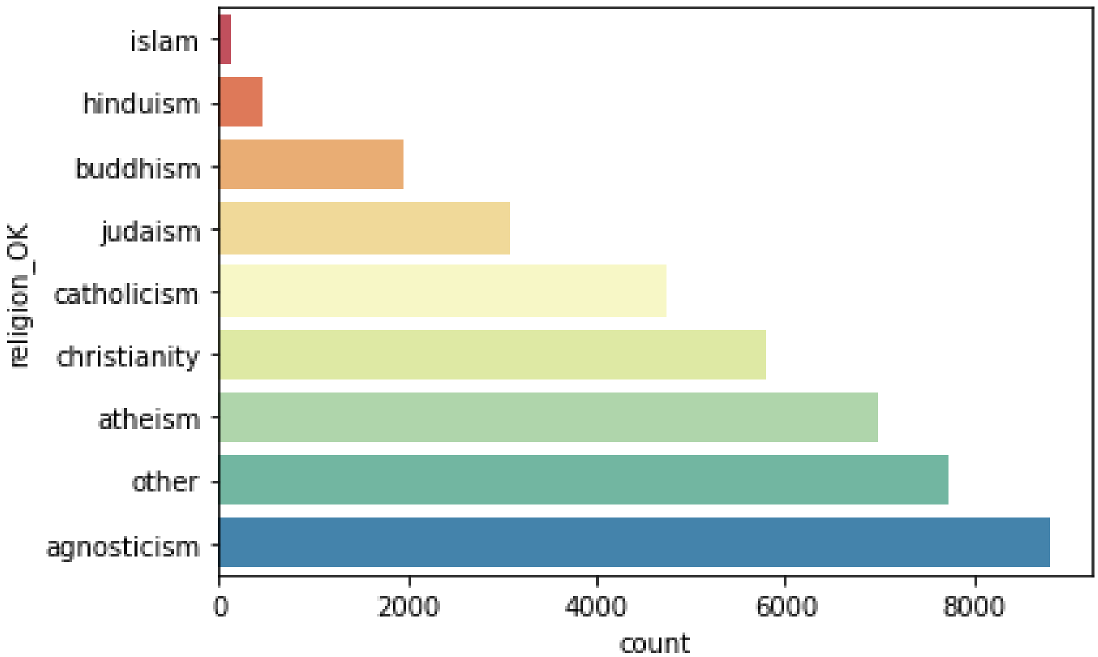
Religion

[71]:
```
plt.figure(figsize=(8, 12))
ax = sns.countplot(y=profiles['religion'], order=profiles['religion'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.religion.value_counts()/len(profiles)
```



This data will be cleaned by taking only the first word, as it was done for `sign`.

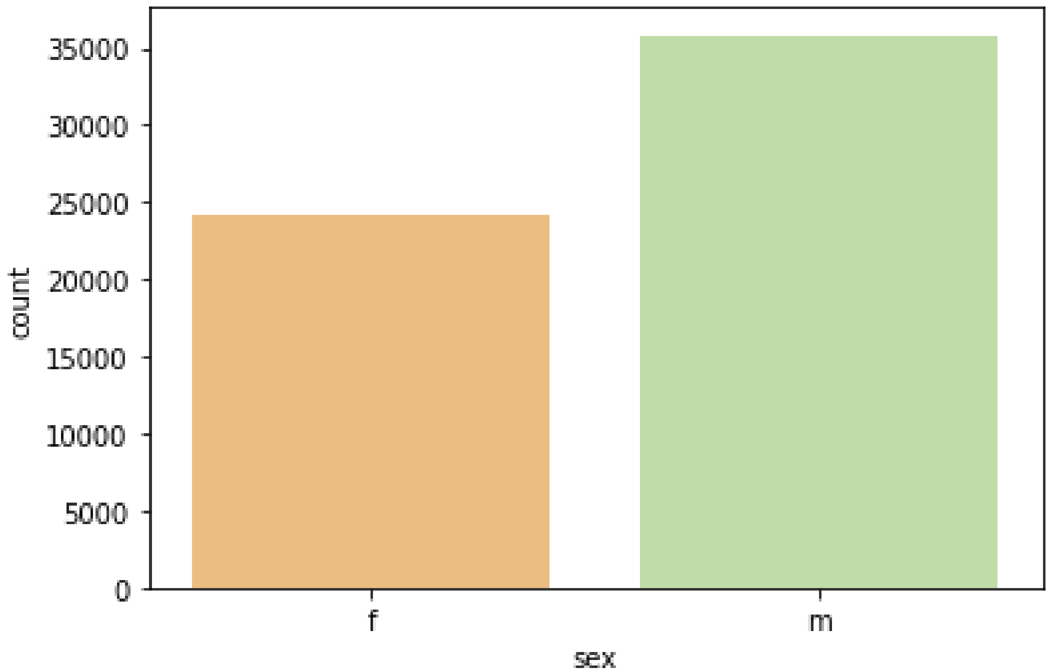
[72]:
```
# Splitting 'religion' column by space:
str_split_1 = profiles.religion.str.split(' ')
profiles['religion_OK'] = str_split_1.str.get(0)
# Plotting:
ax = sns.countplot(y=profiles['religion_OK'], order=profiles['religion_OK'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.religion_OK.value_counts()/len(profiles)
```



15% of the users declare to be agnostic, and 13% do not declare any religion. Therefore, the majority does not mention affiliation with any religion. The mean age in the dataset is 32 years, which might imply some relationship with the `religion` variable, as younger generations appear less interested in it.

Sex

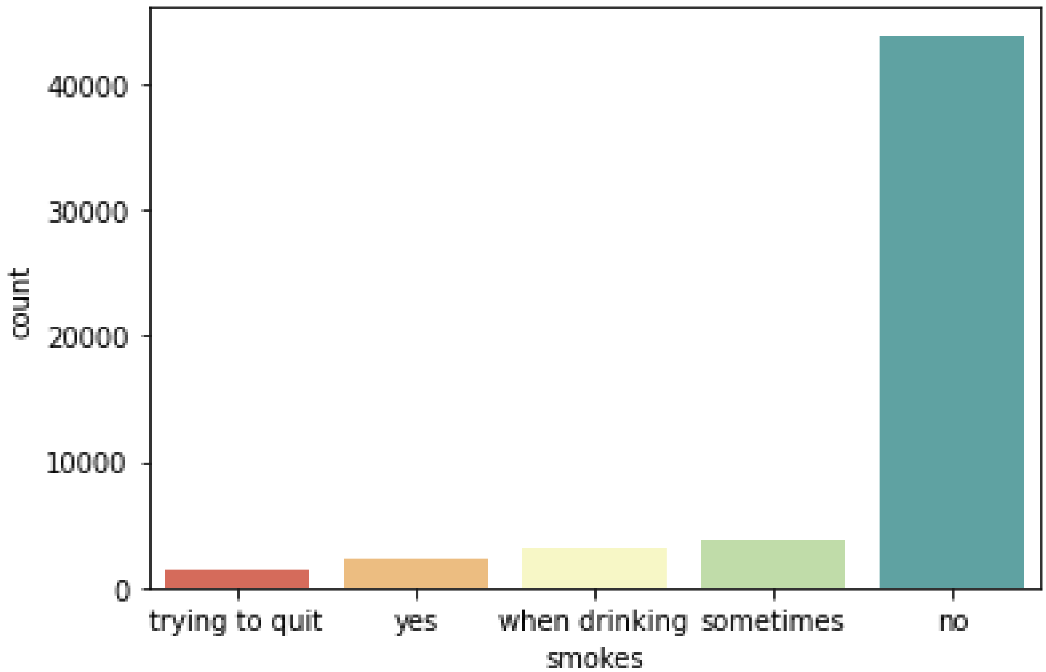
[73]:
```
ax = sns.countplot(x=profiles['sex'], order=profiles['sex'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.sex.value_counts()/len(profiles)
```



60% of the users are male vs 40% who are female.

Smokes

[74]:
```
ax = sns.countplot(x=profiles['smokes'], order=profiles['smokes'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.smokes.value_counts()/len(profiles)
```



More than 73% of the users declares that they do not smoke.

Speaks

[75]:
```
profiles.speaks.value_counts()
```

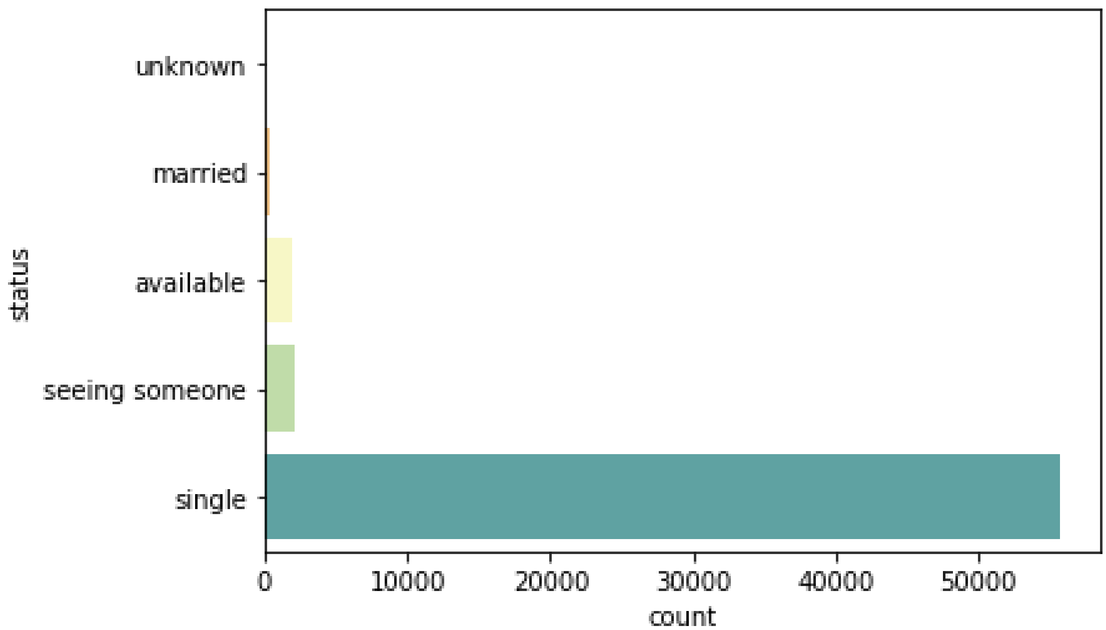
[75]:
```
english
21828
english (fluently)
6628
english (fluently), spanish (poorly)
2059
english (fluently), spanish (okay)
1917
english (fluently), spanish (fluently)
1288
                                                                            …
english, spanish (okay), italian (okay), korean (poorly), hebrew (poorly)
1
english (fluently), bengali (fluently), french (fluently), spanish (okay)
1
english (fluently), spanish (poorly), tagalog (okay), french (poorly)
1
english (fluently), tagalog (okay), cebuano (okay)
1
english (fluently), spanish (okay), bengali (poorly)
```

```
1
Name: speaks, Length: 7647, dtype: int64
```

Since there are 7647 different categories in the `speaks` variable, this variable will not be considered for the analysis.

Status

[76]:
```
ax = sns.countplot(y=profiles['status'], order=profiles['status'].
 ↪value_counts(ascending=True).index, palette='Spectral')
plt.show()
# profiles.status.value_counts()/len(profiles)
```



93% of the total users are 'single', which intuitively sense since this is a dating platform.

1.4.3 Data Cleaning

Before beginning the analysis and ML classifiers design, this project will prepare/clean the data and create the required subsets. The first step is to identify the missing values in the `profiles` dataset columns (e.g. we notices that in the `drugs` column an important proportion of data was missing).

[77]:
```
profiles.isnull().sum()
np.sum(profiles.isnull())
```

[77]:
```
age              0
body_type     5296
diet         24395
```

```
drinks            2985
drugs            14080
education         6628
essay0            5488
essay1            7572
essay2            9638
essay3           11476
essay4           10537
essay5           10850
essay6           13771
essay7           12451
essay8           19225
essay9           12603
ethnicity         5680
height               3
income               0
job               8198
last_online          0
location             0
offspring        35561
orientation          0
pets             19921
religion         20226
sex                  0
sign             11056
smokes            5512
speaks              50
status               0
sign_OK          11056
religion_OK      20226
dtype: int64
```

Now, the variables that will be considered to classify the users per zodiac sign can be chosen. The criteria for selecting them is that the variables should be related to the preferences of the users, disregarding the ones that are 'forced' to them by external factors or circumstances, such as `age`, `height` or `education`. A new subset that has only the selected features columns + the label column (`sign_OK`) will be created.

Note: `drugs` and `diet` were not considered due to the huge amount of blanks as per the previous information.

[78]:
```python
# Defining features, labels and signs list (to index answers):
features_and_labels = ['body_type','orientation','pets','sex','religion_OK',
                       'job','drinks','smokes','sign_OK']
signs =␣
 ↪['capricorn','aquarius','pisces','aries','taurus','gemini','cancer','leo',
         'virgo','libra','scorpio','sagittarius']
```

```
# Creating subset (df) with only the corresponding columns:
df = profiles[features_and_labels]
```

Since the project objective is to predict the **sign** value for the rows that do not have it, we will separate the dataframe in 2 big groups: dataset with sign (`df_with_sign`) and dataset without sign (`df_no_sign`). We will use the first dataset to train and test our models, and the second dataset will be left for trying prediction exercises if the project can find a suitable ML model.

[79]:
```
# Creating the mentioned dataframes:
df_with_sign = df[df.sign_OK.notnull()]
df_no_sign = df[df.sign_OK.isnull()]
print(len(df_with_sign), len(df_no_sign))
```

```
48890 11056
```

Then, the rows from each of our subsets that do not have data in the features columns are removed, as the ML models would need this information to make the predictions.

[80]:
```
# Dropping rows with empty values:
df_with_sign = df_with_sign.dropna()

# For this df we do not want to drop the empty values for the 'sign_OK' value,␣
↪because the df would be empty
df_no_sign = df_no_sign.dropna(subset=[n for n in df_no_sign if n != 'sign_OK'])
print(len(df_with_sign), len(df_no_sign), '\n')

# Checking if sample used for analysis will still have representation for all␣
↪zodiac signs (all OK):
print(df_with_sign.sign_OK.value_counts())
```

```
22404 2069

leo            2033
gemini         2012
virgo          1963
cancer         1920
taurus         1896
scorpio        1876
libra          1862
aries          1819
sagittarius    1794
pisces         1787
aquarius       1774
capricorn      1668
Name: sign_OK, dtype: int64
```

The selected variables are going to require some work in order to be ready for the models, mainly the creation of dummies to account for the several options available that do not follow a particular order (ordinal).

Features to convert to dummies: `body_type`, `orientation`, `pets`, `religion_OK`, `sex`, `job`, `drinks`, `smokes`.

```
[81]: # Applying One-Hot Encoding:
df_with_sign = pd.get_dummies(data=df_with_sign,
                                                    ␣
 ↪columns=['body_type','orientation','pets','religion_OK',
                                        'sex','job','drinks','smokes'])
df_with_sign.head()
```

```
[81]:       sign_OK  body_type_a little extra  body_type_athletic  \
0       gemini                         1                   0
1       cancer                         0                   0
5       taurus                         0                   0
7  sagittarius                         0                   0
9       cancer                         0                   1

   body_type_average  body_type_curvy  body_type_fit  body_type_full figured  \
0                  0                0              0                       0
1                  1                0              0                       0
5                  1                0              0                       0
7                  1                0              0                       0
9                  0                0              0                       0

   body_type_jacked  body_type_overweight  body_type_rather not say  …  \
0                 0                     0                         0  …
1                 0                     0                         0  …
5                 0                     0                         0  …
7                 0                     0                         0  …
9                 0                     0                         0  …

   drinks_not at all  drinks_often  drinks_rarely  drinks_socially  \
0                  0             0              0                1
1                  0             1              0                0
5                  0             0              0                1
7                  0             0              0                1
9                  1             0              0                0

   drinks_very often  smokes_no  smokes_sometimes  smokes_trying to quit  \
0                  0          0                 1                      0
1                  0          1                 0                      0
5                  0          1                 0                      0
7                  0          1                 0                      0
9                  0          1                 0                      0

   smokes_when drinking  smokes_yes
0                     0           0
```

```
1                          0             0
5                          0             0
7                          0             0
9                          0             0

[5 rows x 74 columns]
```

1.4.4 Creating training and test sets

The next step is to create the training and test sets for the model from our dataset (`df_with_sign`). These sets should have 2 parts: features and labels.

[82]:
```python
# Defining features and labels:
features = df_with_sign[[n for n in df_with_sign if n != 'sign_OK']]
labels = df_with_sign['sign_OK']

from sklearn.model_selection import train_test_split

# Defining training and testing data and labels
train_data, test_data, train_labels, test_labels = train_test_split(features, labels, test_size=0.20, random_state=0)
print('Number of datapoints in train_data, test_data, train_labels, test_labels: ' +
      str(len(train_data)) + ', ' + str(len(test_data)) + ', ' +
      str(len(train_labels)) + ', ' + str(len(test_labels)))

# Transforming 'train_labels' and 'test_labels' to 1D horizontal arrays:
train_labels = train_labels.to_numpy().ravel()
test_labels = test_labels.to_numpy().ravel()
```

```
Number of datapoints in train_data, test_data, train_labels, test_labels: 17923,
4481, 17923, 4481
```

1.5 Analysis

1.5.1 K-Nearest Neighbors

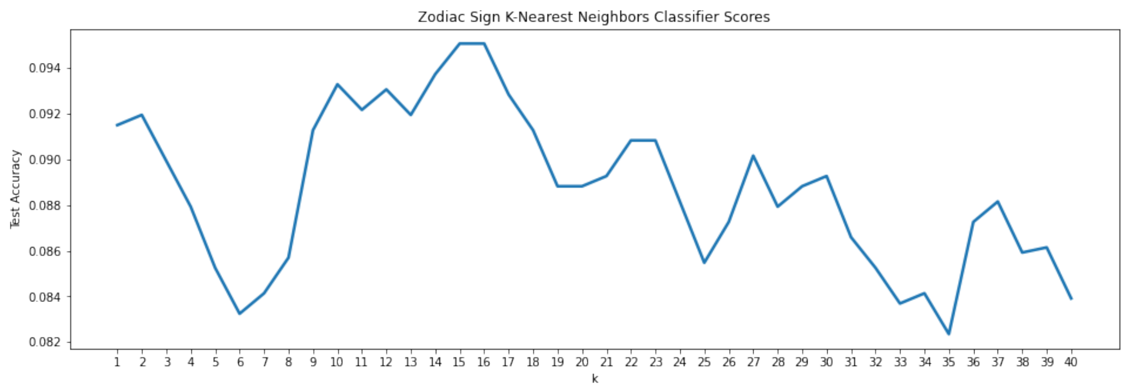
The first model that the project will try is the K-Nearest Neighbors ML Classification Model. Since this model relies heavily on finding the right k-number that maximizes the accuracy score, a plot showing all scores obtained by different k-numbers (from k=1 to 40) will be created to visually select the k that maximizes the score value. Then, this k-number will be used to generate a Classification Report to assess the overall prediction score on the test data (precision, recall and overall f1-score).

[83]:
```python
#Creating ML K-Nearest Neighbors model:
from sklearn.neighbors import KNeighborsClassifier

k_accuracies = []
```

```
for k in range(1,41):
    k_classifier = KNeighborsClassifier(n_neighbors = k)
    k_classifier.fit(train_data, train_labels)
    k_accuracies.append(k_classifier.score(test_data, test_labels))
```

[84]:
```
# Plotting accuracy vs k
k_list = range(1,41)
plt.figure(figsize=(16,5))
ax = plt.subplot()
plt.plot(range(len(k_list)), k_accuracies, linewidth=2.5)
ax.set_xticks(range(len(k_list)))
ax.set_xticklabels(k_list)
plt.xlabel('k')
plt.ylabel('Test Accuracy')
plt.title('Zodiac Sign K-Nearest Neighbors Classifier Scores')
plt.show()
```



As the graph tells, the maximum score obtained by the model is 9.5% for k=15 when using the model on the test data. By guessing without the help of any ML model, our accuracy would be 8.3% (100%/12 possible outcomes). Therefore, it seems that the KNN model does not increase much the chance of predicting zodiac signs correctly based on the features data. Below the project shows the obtained Classification Report for k=15 to have more information on the precision, recall and f1-score values.

[85]:
```
# Obtaining Classification Report for precision, recall and f1-score (using␣
 ↪k=15):
from sklearn.metrics import classification_report
k15_classifier = KNeighborsClassifier(n_neighbors = 15).fit(train_data,␣
 ↪train_labels)
k15_classifier_predictions = k15_classifier.predict(test_data)
print(classification_report(test_labels, k15_classifier_predictions))
```

```
              precision    recall  f1-score   support
```

```
     aquarius       0.10      0.17      0.12       346
        aries       0.08      0.13      0.10       353
       cancer       0.12      0.14      0.13       404
    capricorn       0.08      0.07      0.08       334
       gemini       0.11      0.11      0.11       407
          leo       0.09      0.10      0.10       393
        libra       0.11      0.11      0.11       351
       pisces       0.08      0.07      0.08       361
  sagittarius       0.10      0.07      0.09       361
      scorpio       0.09      0.07      0.08       361
       taurus       0.08      0.05      0.06       376
        virgo       0.09      0.05      0.07       434

     accuracy                           0.10      4481
    macro avg       0.09      0.10      0.09      4481
 weighted avg       0.09      0.10      0.09      4481
```

The overall f1-score for the KNN model is around 10% when used for the test data. Overall this model is not recommended for predicting zodiac signs based on the given `profiles` data.

1.5.2 Decision Tree

Although the KNN Classifier model results were dissapointing, there are still other tools to try. Another option would be to use Decision Trees, which are known to be able to create accurate models for multiclass classification (which is this project's case). As seen before, one of the main challenges here is that we need to classify amongst 12 different options, so trying de Decision Tree ML model might be worth it. The tool will be tested with the same features and labels that were used for the KNN model.

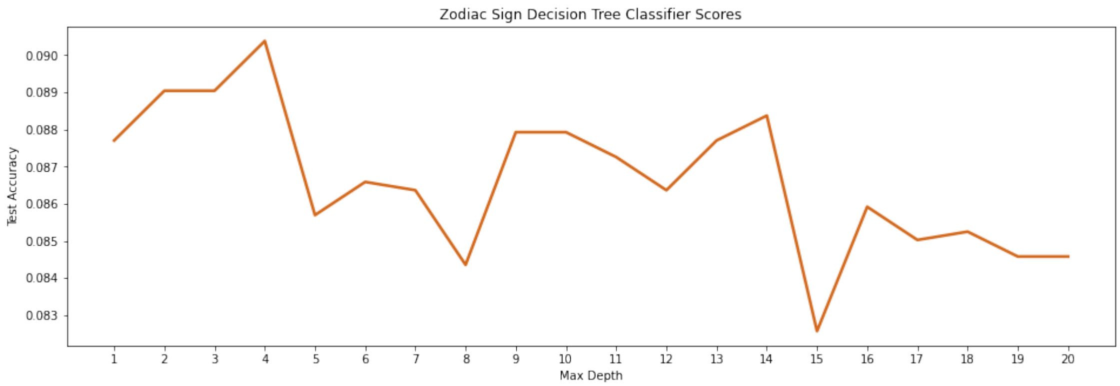
Since this model relies heavily on finding the right amount of branches, the project will test via pruning (changing the max_depth factor) the number of branches that maximizes the accuracy score. For this, a plot chart between accuracy and max_depth will be created.

[86]:
```python
from sklearn.tree import DecisionTreeClassifier

tree_scores = []
for i in range(1,21):
    tree_classifier = DecisionTreeClassifier(random_state=1, max_depth=i)
    tree_classifier.fit(train_data, train_labels)
    score = tree_classifier.score(test_data, test_labels)
    tree_scores.append(score)
```

[87]:
```python
# Plotting accuracy vs k
tree_list = range(1,21)
plt.figure(figsize=(16,5))
ax = plt.subplot()
plt.plot(range(len(tree_list)), tree_scores, linewidth=2.5, color='chocolate')
ax.set_xticks(range(len(tree_list)))
```

```
ax.set_xticklabels(tree_list)
plt.xlabel('Max Depth')
plt.ylabel('Test Accuracy')
plt.title('Zodiac Sign Decision Tree Classifier Scores')
plt.show()
```



The maximum score obtained by the model is 9.1% for max_depth=4 when using the model on the test data. Again, compared with the accuracy of ramdom guessing (8.3%), this model also does not seem to be performing well. Below the project calculated the Classification Report for max_depth=4 to have more information on the precision, recall and f1-score values.

[88]:
```
# Obtaining Classification Report for precision, recall and f1-score (using␣
↪max_depth=4):
from sklearn.metrics import classification_report
tree_classifier = DecisionTreeClassifier(random_state=1, max_depth=4)
tree_classifier.fit(train_data, train_labels)
tree_classifier_predictions = tree_classifier.predict(test_data)
print(classification_report(test_labels, tree_classifier_predictions))
```

```
              precision    recall  f1-score   support

    aquarius       0.00      0.00      0.00       346
       aries       0.11      0.00      0.01       353
      cancer       0.08      0.03      0.04       404
   capricorn       0.00      0.00      0.00       334
      gemini       0.09      0.20      0.13       407
         leo       0.09      0.67      0.16       393
       libra       0.00      0.00      0.00       351
      pisces       0.00      0.00      0.00       361
 sagittarius       0.07      0.02      0.03       361
     scorpio       0.00      0.00      0.00       361
      taurus       0.00      0.00      0.00       376
       virgo       0.11      0.09      0.10       434
```

```
    accuracy                           0.09      4481
   macro avg       0.05      0.08      0.04      4481
weighted avg       0.05      0.09      0.04      4481


/Library/Frameworks/Python.framework/Versions/3.9/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Library/Frameworks/Python.framework/Versions/3.9/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Library/Frameworks/Python.framework/Versions/3.9/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

The overall f1-score for the Decision Trees model is around 9% when used for the test data. Overall this model is not recommended for predicting zodiac signs based on the given `profiles` data, in fact, it is less accurate than our previous KNN model. Still, the project will give it another go to the Decision Trees powered by Random Forests.

1.5.3 Random Forest

Despite the fact that the Decision Tree ML model score results were also dissapointing, its low accuracy could be partially related with overfitting. To discard this (and maybe come up with a better model), the project will also try to create a random forest model with 1000 trees (forest large enough to ensure that no overfitting is affecting the model) and setting features bagging to 'sqrt' as standard in ML.

[89]:
```python
from sklearn.ensemble import RandomForestClassifier

RF_classifier = RandomForestClassifier(n_estimators=1000, random_state=1,␣
 ↪max_features='sqrt')
RF_classifier.fit(train_data, train_labels)
RF_score = RF_classifier.score(test_data, test_labels)
print(RF_score)
```

```
0.09395224280294577
```

[90]:
```python
# Obtaining Classification Report for precision, recall and f1-score (using␣
 ↪k=15):
from sklearn.metrics import classification_report
RF_classifier_predictions = RF_classifier.predict(test_data)
print(classification_report(test_labels, RF_classifier_predictions))
```

```
              precision    recall  f1-score   support

    aquarius       0.10      0.10      0.10       346
       aries       0.10      0.10      0.10       353
      cancer       0.10      0.11      0.11       404
   capricorn       0.08      0.07      0.07       334
      gemini       0.08      0.08      0.08       407
         leo       0.11      0.13      0.12       393
       libra       0.10      0.11      0.11       351
      pisces       0.11      0.09      0.10       361
 sagittarius       0.10      0.09      0.09       361
     scorpio       0.07      0.06      0.06       361
      taurus       0.09      0.09      0.09       376
       virgo       0.09      0.08      0.09       434

    accuracy                           0.09      4481
   macro avg       0.09      0.09      0.09      4481
weighted avg       0.09      0.09      0.09      4481
```

As seen above, the predictions did not get more accurate when applying Random Forest (accuracy still ~9%). This project will give it a final shot by implementing the Naive Bayers Classifier to find a better sign prediction tool than to just simply random guessing (accuracy=8.3%).

1.5.4 Naive Bayes

The Naive Bayes classifier will require a different set of data. Instead of trying to predict zodiac signs based on `body_types`, or `religion`, the project will use the essay columns to find patterns in the text written by the people in each essay to see if the NB ML model can find a better correlation between the words and the users' signs.

First step will be to prepare the data for implementing Naive Bayes.

[116]:
```python
# Creating function for preparing required datasets:
essay_df = profiles[['essay0', 'sign_OK']]
essay_df = essay_df.dropna()
print(len(essay_df))

# Creating dataframes (1 per sign):
aries_essays = essay_df[essay_df.sign_OK == 'aries']
taurus_essays = essay_df[essay_df.sign_OK == 'taurus']
gemini_essays = essay_df[essay_df.sign_OK == 'gemini']
cancer_essays = essay_df[essay_df.sign_OK == 'cancer']
leo_essays = essay_df[essay_df.sign_OK == 'leo']
virgo_essays = essay_df[essay_df.sign_OK == 'virgo']
libra_essays = essay_df[essay_df.sign_OK == 'libra']
scorpio_essays = essay_df[essay_df.sign_OK == 'scorpio']
sagittarius_essays = essay_df[essay_df.sign_OK == 'sagittarius']
capricorn_essays = essay_df[essay_df.sign_OK == 'capricorn']
```

```
aquarius_essays = essay_df[essay_df.sign_OK == 'aquarius']
pisces_essays = essay_df[essay_df.sign_OK == 'pisces']
```

44796

[117]:
```
# Creating lists for model:
aries_text = aries_essays['essay0'].tolist()
taurus_text = taurus_essays['essay0'].tolist()
gemini_text = gemini_essays['essay0'].tolist()
cancer_text = cancer_essays['essay0'].tolist()
leo_text = leo_essays['essay0'].tolist()
virgo_text = virgo_essays['essay0'].tolist()
libra_text = libra_essays['essay0'].tolist()
scorpio_text = scorpio_essays['essay0'].tolist()
sagittarius_text = sagittarius_essays['essay0'].tolist()
capricorn_text = capricorn_essays['essay0'].tolist()
aquarius_text = aquarius_essays['essay0'].tolist()
pisces_text = pisces_essays['essay0'].tolist()

# Combining tweets into 1 list:
text_lists =␣
 ↪[aries_text,taurus_text,gemini_text,cancer_text,leo_text,virgo_text,libra_text,
          ␣
 ↪scorpio_text,sagittarius_text,capricorn_text,aquarius_text,pisces_text]
all_texts = []
labels = []
for i in range(len(text_lists)):
    all_texts += text_lists[i]
    labels += [i]*len(text_lists[i])
print(len(all_texts))
print(len(labels))
```

44796
44796

[122]:
```
# Creating the model:
train_tdata, test_tdata, train_tlabels, test_tlabels =␣
 ↪train_test_split(all_texts, labels,
                                                                        ␣
 ↪random_state=1, test_size=0.2)
print(len(train_tdata))
print(len(test_tdata))
```

35836
8960

[119]:
```
# Creating and fitting the counter:
from sklearn.feature_extraction.text import CountVectorizer
```

```
counter = CountVectorizer()
counter.fit(train_tdata)
train_tcounts = counter.transform(train_tdata)
test_tcounts = counter.transform(test_tdata)
```

[120]:
```
# Creating and fitting the classifier:
from sklearn.naive_bayes import MultinomialNB
NB_classifier = MultinomialNB()
NB_classifier.fit(train_tcounts, train_tlabels)
NB_predictions = NB_classifier.predict(test_tcounts)
```

[121]:
```
# Testing the model accuracy:
from sklearn.metrics import accuracy_score
print(accuracy_score(test_tlabels, NB_predictions))
```

```
0.09174107142857142
```

Again, when using the `essay0` column (essay column with the largest amount of data), the project still could not find a model with an accuracy for predicting signs beyond 9%. Regardless of this, some conclusions can be drawn and will be presented in the next section.

1.6 Evaluation

1.6.1 Conclusions

The goal of this project was to accurately predict the zodiac signs of the OKCupid users by implementing a supervised machine learning classification model. 4 different algorithms were tested (K-Nearest Neighbor, Decision Trees, Random Forests and Naive Bayes classifier), but none of then provided an acceptable improvement to just random guessing the sign without any model.

The model that achieved the highest accuracy on the test dataset was the KNN model (acc=10%). Since this results are not very satisfying, some recommendations to further investigate are given in the next section.

1.6.2 Recommendations and next steps

The main challenge posed by this project was the requirement of accurately classifying the outcomes in 12 different options (zodiac signs). For this purpose, the provided data did not prove to be enough. The recommendations for increasing the change of finding better predictions models are: * Increase the provided dataset to provide more data to the model to learn the differences between the features associated with 12 classes * Reduce the number of classes. It is not possible to reduce the number of zodiac signs, but changing the question to a yes/no binary question (like: is this user a 'libra' or not?) could make things easier for the ML models.

1.6.3 ML Models not used (and why)

- Logistic Regression: this ML tool works only for classifying between 2 possible outcomes (binary). It is possible to implement (although quite complex) by transforming the problem into a yes/no question for every sign and then comparing the probability that each datapoint has for each sign and choosing the highest one as the model prediction

- Support Vector Machines: similar to Logistic Regression, this is a powerful ML classification tool, but is works only for classifying between 2 classes (binary) and this project needed to classify amongst 12 classes