masculinity

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1 Masculinity Survey

In this project we will focus on clustering algorithms, notably KMeans. We'll use data from a masculinity survey FiveThirtyEight, which can be found in `masculinity-survey.pdf`. The raw responses can be found in `masculinity.csv`.

1.0.1 Imports

Our imports are pandas, matplotlib, and sklearns.

[12]:
```
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.cluster import KMeans
```

Let's import the csv into a dataframe and take a look at the first few values. We'll also see how long the dataset is and what the columns are.

[13]:
```
survey = pd.read_csv('masculinity.csv')
print(f'The columns are:\n{survey.columns}')
print(f'The length of the set is:\n{len(survey)}')
print(survey['q0007_0001'].value_counts())
print(survey.head())
```

```
The columns are: Index(['Unnamed: 0', 'StartDate', 'EndDate', 'q0001', 'q0002',
'q0004_0001',
       'q0004_0002', 'q0004_0003', 'q0004_0004', 'q0004_0005', 'q0004_0006',
       'q0005', 'q0007_0001', 'q0007_0002', 'q0007_0003', 'q0007_0004',
       'q0007_0005', 'q0007_0006', 'q0007_0007', 'q0007_0008', 'q0007_0009',
       'q0007_0010', 'q0007_0011', 'q0008_0001', 'q0008_0002', 'q0008_0003',
       'q0008_0004', 'q0008_0005', 'q0008_0006', 'q0008_0007', 'q0008_0008',
       'q0008_0009', 'q0008_0010', 'q0008_0011', 'q0008_0012', 'q0009',
       'q0010_0001', 'q0010_0002', 'q0010_0003', 'q0010_0004', 'q0010_0005',
       'q0010_0006', 'q0010_0007', 'q0010_0008', 'q0011_0001', 'q0011_0002',
       'q0011_0003', 'q0011_0004', 'q0011_0005', 'q0012_0001', 'q0012_0002',
       'q0012_0003', 'q0012_0004', 'q0012_0005', 'q0012_0006', 'q0012_0007',
       'q0013', 'q0014', 'q0015', 'q0017', 'q0018', 'q0019_0001', 'q0019_0002',
       'q0019_0003', 'q0019_0004', 'q0019_0005', 'q0019_0006', 'q0019_0007',
       'q0020_0001', 'q0020_0002', 'q0020_0003', 'q0020_0004', 'q0020_0005',
       'q0020_0006', 'q0021_0001', 'q0021_0002', 'q0021_0003', 'q0021_0004',
```

```
       'q0022', 'q0024', 'q0025_0001', 'q0025_0002', 'q0025_0003', 'q0026',
       'q0028', 'q0029', 'q0030', 'q0034', 'q0035', 'q0036', 'race2',
       'racethn4', 'educ3', 'educ4', 'age3', 'kids', 'orientation', 'weight'],
      dtype='object')
The length of the set is: 1189
Sometimes                      537
Rarely                         324
Often                          142
Never, but open to it          123
Never, and not open to it       53
No answer                       10
Name: q0007_0001, dtype: int64
   Unnamed: 0     StartDate       EndDate               q0001  \
0           1  5/10/18 4:01  5/10/18 4:06  Somewhat masculine
1           2  5/10/18 6:30  5/10/18 6:53  Somewhat masculine
2           3  5/10/18 7:02  5/10/18 7:09      Very masculine
3           4  5/10/18 7:27  5/10/18 7:31      Very masculine
4           5  5/10/18 7:35  5/10/18 7:42      Very masculine

                q0002                  q0004_0001                  q0004_0002  \
0  Somewhat important                Not selected                Not selected
1  Somewhat important  Father or father figure(s)                Not selected
2   Not too important  Father or father figure(s)                Not selected
3   Not too important  Father or father figure(s)  Mother or mother figure(s)
4      Very important                Not selected                Not selected

             q0004_0003    q0004_0004    q0004_0005  …               q0035  \
0          Not selected   Pop culture  Not selected  …     Middle Atlantic
1          Not selected  Not selected  Not selected  …  East North Central
2          Not selected  Not selected  Not selected  …  East North Central
3  Other family members  Not selected  Not selected  …  East North Central
4  Other family members  Not selected  Not selected  …  East North Central

                    q0036      race2  racethn4            educ3  \
0  Windows Desktop / Laptop  Non-white  Hispanic  College or more
1        iOS Phone / Tablet      White     White     Some college
2  Windows Desktop / Laptop      White     White  College or more
3  Windows Desktop / Laptop      White     White     Some college
4  Windows Desktop / Laptop      White     White  College or more

             educ4       age3          kids   orientation    weight
0  College or more    35 - 64   No children  Gay/Bisexual  1.714026
1     Some college  65 and up  Has children      Straight  1.247120
2  College or more    35 - 64  Has children      Straight  0.515746
3     Some college  65 and up  Has children     No answer  0.600640
4  College or more    35 - 64   No children      Straight  1.033400

[5 rows x 98 columns]
```

2 Mapping the Data

For our KMeans Algorithm, we need to transform some of these responses from ordinal to numerical data. The answers to question 7 are a series of responses: - 'Often' - 'Sometimes' - 'Rarely' - 'Never, but open to it' - 'Never, and not open to it'

We could perform similar mappings with question 28 (`racethn4`) and question 29 (`educ4`).

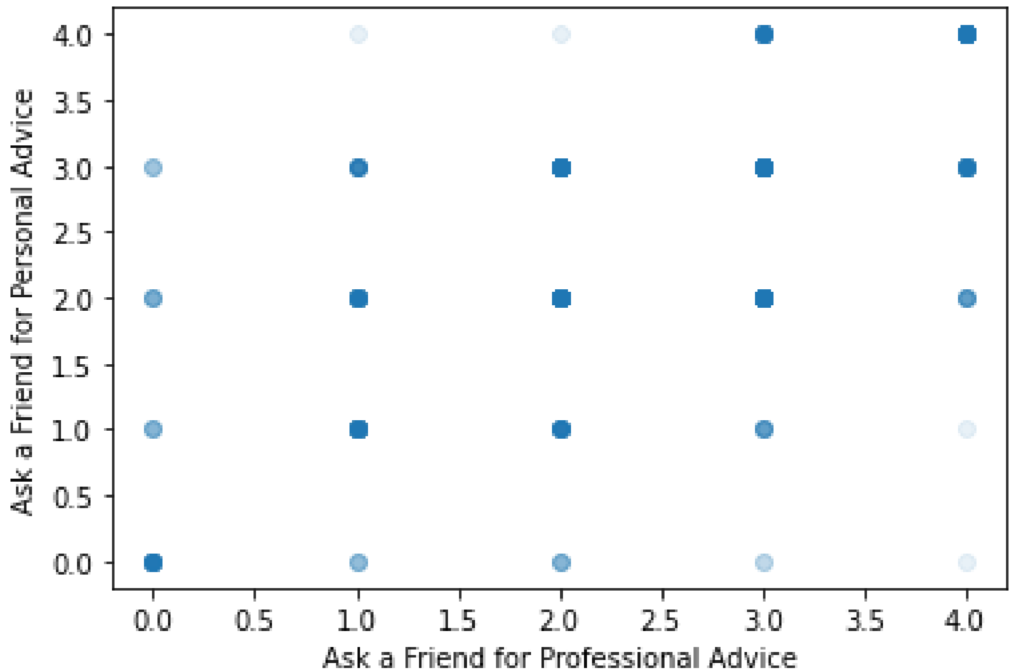
[14]:
```
# getting the sub-questions of question 7
cols_to_map = ["q0007_0001", "q0007_0002", "q0007_0003", "q0007_0004",
       "q0007_0005", "q0007_0006", "q0007_0007", "q0007_0008", "q0007_0009",
       "q0007_0010", "q0007_0011"]

# changing the answers to numerical responses
for col in cols_to_map:
        survey[col] = survey[col].map({'Often': 4,
                                       'Sometimes': 3,
                                       'Rarely': 2,
                                       'Never, but open to it': 1,
                                       'Never, and not open to it': 0})

# checking for success
print(survey['q0007_0001'].head())
print(survey['q0007_0001'].value_counts())
```

```
0    4.0
1    2.0
2    3.0
3    2.0
4    3.0
Name: q0007_0001, dtype: float64
3.0    537
2.0    324
4.0    142
1.0    123
0.0     53
Name: q0007_0001, dtype: int64
```

2.1 Plotting the Data

Let's look at our features before putting them in the algorithm. We'll compare question 7-1 and 7-2.

[15]:
```
# graphing the values before k-means
plt.scatter(survey['q0007_0001'], survey['q0007_0002'], alpha=0.1)
plt.xlabel('Ask a Friend for Professional Advice')
plt.ylabel('Ask a Friend for Personal Advice')
plt.show()
```



2.2 Building the Model

For question 7, the first four sub-questions are not traditionally seen as masculine: - Ask a friend for professional advice - Ask a friend for personal advice - Express physical affection to male friends, like hugging, rubbing shoulders - Cry

Whereas 7-5, 7-8, and 7-9 are usually viewed as masculine: - Get in a physical fight with another person - Watch sports of any kind - Work out

Let's take these features (traditionally non-masculine vs masculine) and compare them with KMeans Clustering.

[16]:
```
# dropping nan values
cols = ["q0007_0001", "q0007_0002", "q0007_0003", "q0007_0004",
        "q0007_0005", "q0007_0008", "q0007_0009"]
rows_to_cluster = survey.dropna(subset=cols)

# creating kmeans object
classifier = KMeans(n_clusters = 2)
classifier.fit(rows_to_cluster[["q0007_0001", "q0007_0002", "q0007_0003",␣
 ↪"q0007_0004",
        "q0007_0005", "q0007_0008", "q0007_0009"]])

# showing the center of the cluster
print(classifier.cluster_centers_)
```

```
[[1.87830688 1.84391534 0.85185185 1.72486772 0.57142857 2.64021164
  1.97089947]
 [2.84548105 2.81632653 2.84110787 2.39941691 0.69387755 3.06997085
  2.90087464]]
```

2.3 Separating the Clusters

A higher number indicates that a person was more likely to 'often' Let's look at the labels of the set to see who fell into each cluster, where each row is a person.

[17]:
```python
# showing the cluster labels and getting the indices of each
print(classifier.labels_)
cluster_zero_indices = []
cluster_one_indices = []

for i in range(len(classifier.labels_)):
        if classifier.labels_[i] == 0:
                cluster_zero_indices.append(i)
        elif classifier.labels_[i] == 1:
                cluster_one_indices.append(i)

print(cluster_zero_indices)
```

```
[1 0 1 … 0 0 0]
[1, 4, 6, 7, 9, 10, 12, 14, 17, 18, 19, 24, 29, 35, 39, 42, 49, 51, 52, 53, 54,
55, 57, 58, 62, 63, 65, 66, 75, 78, 79, 82, 84, 86, 87, 88, 89, 90, 92, 94, 95,
97, 98, 101, 106, 107, 109, 113, 116, 117, 118, 119, 123, 128, 129, 130, 131,
132, 134, 139, 142, 143, 154, 172, 175, 176, 178, 179, 180, 181, 184, 187, 189,
195, 196, 198, 199, 201, 209, 212, 222, 229, 230, 231, 233, 236, 237, 240, 241,
247, 248, 249, 250, 256, 260, 261, 263, 264, 272, 275, 281, 283, 284, 286, 288,
291, 296, 297, 299, 300, 301, 305, 310, 311, 325, 328, 331, 336, 337, 340, 341,
343, 347, 350, 351, 353, 361, 367, 369, 377, 378, 390, 391, 392, 393, 394, 396,
397, 398, 399, 409, 410, 411, 412, 415, 417, 418, 419, 425, 428, 429, 432, 449,
454, 455, 457, 459, 461, 463, 468, 470, 471, 476, 477, 478, 484, 489, 490, 493,
494, 496, 498, 499, 502, 508, 509, 510, 515, 516, 521, 523, 525, 526, 529, 531,
533, 542, 546, 549, 555, 556, 559, 560, 562, 563, 564, 566, 567, 570, 577, 579,
580, 585, 588, 589, 592, 593, 599, 603, 610, 616, 617, 619, 620, 622, 625, 626,
629, 631, 634, 636, 637, 638, 639, 649, 651, 654, 655, 656, 659, 662, 669, 677,
681, 683, 685, 686, 687, 691, 692, 696, 697, 702, 710, 718, 719, 720, 721, 722,
723, 726, 728, 730, 736, 738, 741, 744, 745, 748, 749, 750, 751, 758, 759, 762,
766, 768, 769, 772, 775, 776, 777, 778, 782, 783, 787, 788, 789, 790, 792, 794,
795, 797, 799, 800, 801, 803, 805, 810, 814, 821, 826, 827, 831, 837, 839, 843,
848, 849, 853, 856, 858, 860, 868, 871, 872, 874, 875, 879, 880, 882, 883, 884,
886, 892, 894, 895, 896, 897, 898, 900, 901, 902, 904, 911, 914, 918, 919, 922,
923, 924, 929, 932, 936, 939, 943, 948, 954, 958, 961, 962, 963, 967, 968, 970,
971, 974, 978, 982, 985, 987, 989, 991, 993, 998, 1000, 1003, 1007, 1011, 1013,
1014, 1016, 1025, 1036, 1037, 1038, 1039, 1042, 1045, 1046, 1048, 1050, 1054,
1055, 1057, 1061, 1062, 1063]
```

2.4 Investigating the Clusters

Now that we have our indices and our clusters, we can determine where the items (people) in each cluster would fall on other factors. For example, we can now look at the ages of those each cluster and what education they have obtained. It cam sometimes be beneficial to break these down by percentage, as the number of members in each cluster can differ.

[18]:
```
cluster_zero_df = rows_to_cluster.iloc[cluster_zero_indices]
cluster_one_df = rows_to_cluster.iloc[cluster_one_indices]

print('\nCluster Zero: Age Breakdown')
print(cluster_zero_df.age3.value_counts()/len(cluster_zero_df))
print('\nCluster Zero: Educational Attainment Breakdown')
print(cluster_zero_df.educ4.value_counts()/len(cluster_zero_df))
print('\nCluster One: Age Breakdown')
print(cluster_one_df.age3.value_counts()/len(cluster_one_df))
print('\nCluster One: Educational Attainment Breakdown')
print(cluster_one_df.educ4.value_counts()/len(cluster_one_df))
```

```
Cluster Zero: Age Breakdown
65 and up    0.502646
35 - 64      0.433862
18 - 34      0.060847
Name: age3, dtype: float64

Cluster Zero: Educational Attainment Breakdown
Some college            0.314815
College or more         0.285714
Post graduate degree    0.251323
High school or less     0.145503
Name: educ4, dtype: float64

Cluster One: Age Breakdown
35 - 64      0.478134
65 and up    0.454810
18 - 34      0.067055
Name: age3, dtype: float64

Cluster One: Educational Attainment Breakdown
Post graduate degree    0.365889
College or more         0.330904
Some college            0.230321
High school or less     0.072886
Name: educ4, dtype: float64
```

2.5 Conclusion

In this project we were able to successfully differentiate respondents into clusters and derive demographic information about them. In a similar vein, we could perform an analysis on other parts of the set and use this data to build comprehensive predictive profiles based on their other survey responses.

Data Sources Data was provided by FiveThirtyEight.