CS 57300 Data Mining Assignment 2

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In [ ]:

```
DATA_RAW = 'dating-full.csv'
DATA_NORMAILZED = 'dating.csv'
DATA_BINNED = 'dating-binned.csv'
TEST_SET = 'testSet.csv'
TRAINING_SET = 'trainingSet.csv'
```

Preprocessing

In [ ]:

```
%run -i preprocess.py {DATA_RAW} {DATA_NORMAILZED}
```

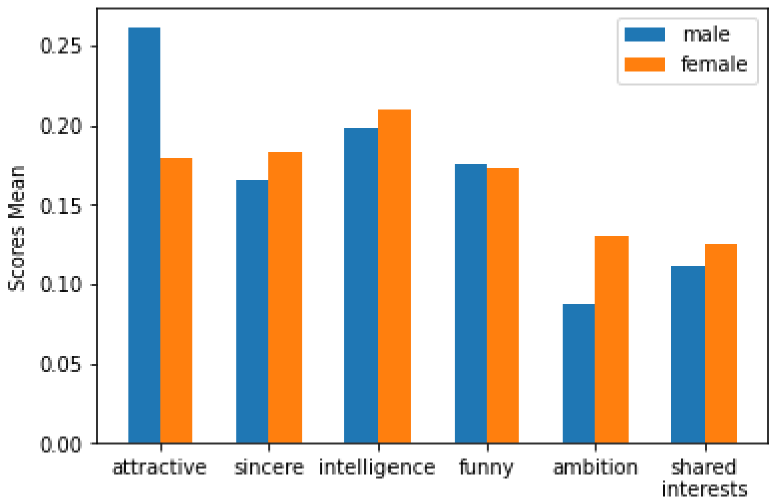
```
Quotes removed from 8316 cells.
Standardized 5707 cells to lower case.
Value assigned for male in column gender: 1.
Value assigned for European/Caucasian-American in column race: 2.
Value assigned for Latino/Hispanic American in column race_o: 3.
Value assigned for law in column field: 121.
Mean of attractive_important: 0.22.
Mean of sincere_important: 0.17.
Mean of intelligence_important: 0.20.
Mean of funny_important: 0.17.
Mean of ambition_important: 0.11.
Mean of shared_interests_important: 0.12.
Mean of pref_o_attractive: 0.22.
Mean of pref_o_sincere: 0.17.
Mean of pref_o_intelligence: 0.20.
Mean of pref_o_funny: 0.17.
Mean of pref_o_ambitious: 0.11.
Mean of pref_o_shared_interests: 0.12.
```

Visualizing Interesting Trends in Data

Relation between Gender and Preference Scores of Participant

In [ ]:

```
%run -i 2_1.py {DATA_NORMAILZED}
```

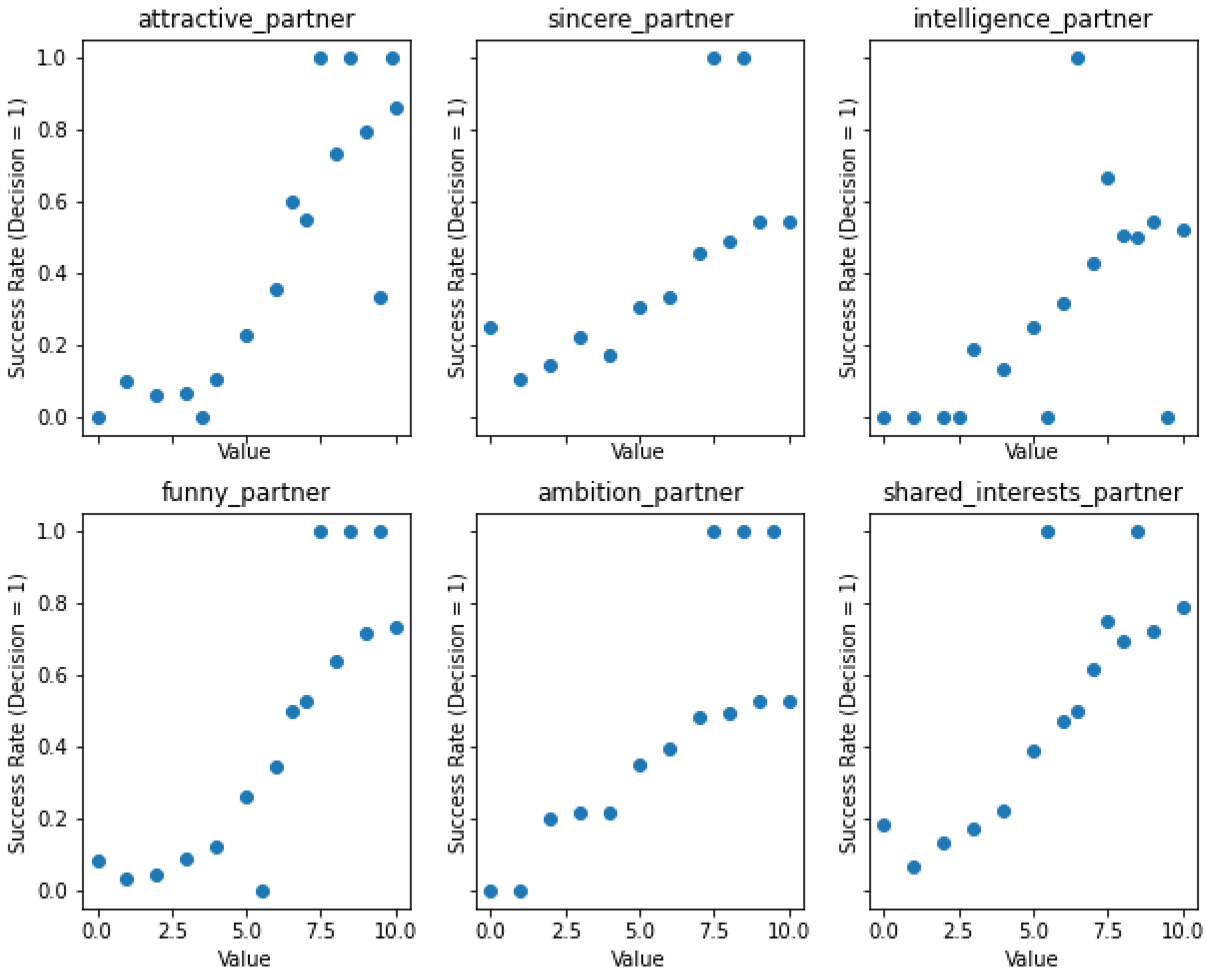


From the visualization, we can see that, for men, attractiveness is relatively more important compared to the importance to women. On the other hand, women tend to value the ambition of participants more than men. Overall, the score means from women is usually higher than the scores from men.

Relation between Success Rate and Ratings of Partner from Participant

In [ ]:

```
%run -i 2_2.py {DATA_NORMAILZED}
```



For all six different ratings, the success rates are positively correlated to the value of the rating. If you draw the regression line for each subplot, you will see that the slopes of _attractive*partner*, _funny*partner* and _shared_interests*partner* are relatively higher than other subplots, which may indicate that these 3 ratings impact more on the success rate. People tend to care about these 3 ratings more than others.

Convert Continuous Attributes to Categorical Attributes

In [ ]:

```
%run -i discretize.py {DATA_NORMAILZED} {DATA_BINNED}
```

```
age: [3710 2932   97    0    5]
age_o: [3704 2899  136    0    5]
importance_same_race: [2980 1213  977 1013  561]
importance_same_religion: [3203 1188 1110  742  501]
pref_o_attractive: [4333 1987  344   51   29]
pref_o_sincere: [5500 1225   19    0    0]
pref_o_intelligence: [4601 2062   81    0    0]
```

```
pref_o_funny: [5616 1103   25    0    0]
pref_o_ambitious: [6656   88    0    0    0]
pref_o_shared_interests: [6467  277    0    0    0]
attractive_important: [4323 2017  328   57   19]
sincere_important: [5495 1235   14    0    0]
intelligence_important: [4606 2071   67    0    0]
funny_important: [5588 1128   28    0    0]
ambition_important: [6644  100    0    0    0]
shared_interests_important: [6494  250    0    0    0]
attractive: [  18  276 1462 4122  866]
sincere: [  33  117  487 2715 3392]
intelligence: [  34  185 1049 3190 2286]
funny: [   0   19  221 3191 3313]
ambition: [  84  327 1070 2876 2387]
attractive_partner: [ 284  948 2418 2390  704]
sincere_partner: [  94  353 1627 3282 1388]
intelligence_partner: [  36  193 1509 3509 1497]
funny_partner: [ 279  733 2296 2600  836]
ambition_partner: [ 119  473 2258 2804 1090]
shared_interests_partner: [ 701 1269 2536 1774  464]
sports: [ 650  961 1369 2077 1687]
tvsports: [2151 1292 1233 1383  685]
exercise: [ 619  952 1775 2115 1283]
dining: [  39  172 1118 2797 2618]
museums: [ 117  732 1417 2737 1741]
art: [ 224  946 1557 2500 1517]
hiking: [ 963 1386 1575 1855  965]
gaming: [2565 2338 1598  168   75]
clubbing: [ 912 1068 1668 2193  903]
reading: [ 131  833 1642 4089   49]
tv: [1188 1216 1999 1642  699]
theater: [ 288  811 1585 2300 1760]
movies: [  45  248  843 2783 2825]
concerts: [ 222  777 1752 2282 1711]
music: [  62  196 1106 2583 2797]
shopping: [1093 1098 1709 1643 1201]
yoga: [2285 1392 1369 1056  642]
interests_correlate: [  18  758 2520 2875  573]
expected_happy_with_sd_people: [ 321 1262 3292 1596  273]
like: [ 273  865 2539 2560  507]
```

Training-Test Split

In [ ]:

```
%run -i split.py {DATA_BINNED} {TEST_SET} {TRAINING_SET}
```

Implement a Naive Bayes Classifier

`nbc(t_frac=1, bin_size=5)`

In [ ]:

```
%run -i 5_1.py
```

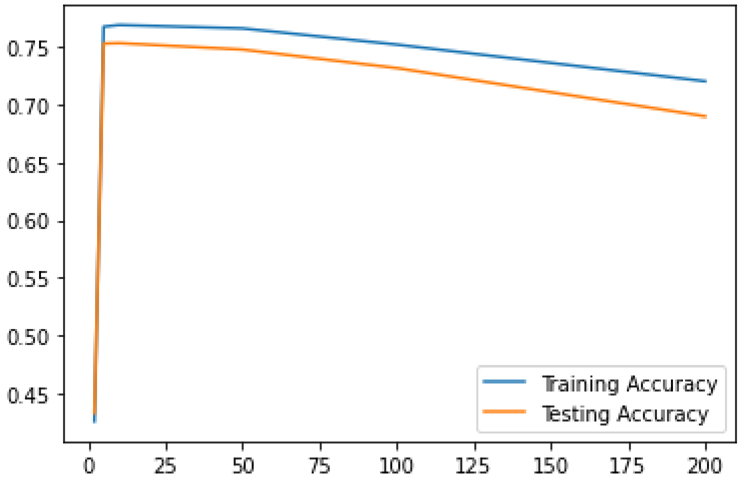
```
Training Accuracy: 0.77
Testing Accuracy: 0.75
```

`nbc(t_frac=1, bin_size)`

In [ ]:

```
%run -i 5_2.py
```

```
Bin size: 2
Training Accuracy: 0.43
Testing Accuracy: 0.43
Bin size: 5
Training Accuracy: 0.77
Testing Accuracy: 0.75
Bin size: 10
Training Accuracy: 0.77
Testing Accuracy: 0.75
Bin size: 50
Training Accuracy: 0.77
Testing Accuracy: 0.75
Bin size: 100
Training Accuracy: 0.75
Testing Accuracy: 0.73
Bin size: 200
Training Accuracy: 0.72
Testing Accuracy: 0.69
```



With different bin sizes, we can see that when the bin size is approximately 10, the accuracies for both training and test data are the best. The accuracy decreases when the bin size increases. That is because when the bin size is large, the bins are sparse arrays, and the uniform smoothing (Laplace Correction) we added greatly impacts the accuracy. On the other hand, if the bin size is too small (e.g. 2), the feature of the data becomes too blur to train an accurate prediction model.

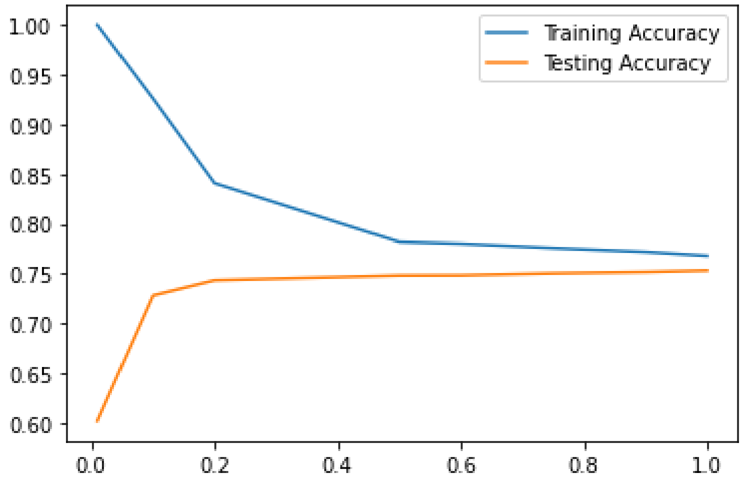
`nbc(frac_t, bin_size=5)`

In [ ]:

```
%run -i 5_3.py
```

```
frac: 0.01
Training Accuracy: 1.00
Testing Accuracy: 0.60
frac: 0.1
Training Accuracy: 0.93
Testing Accuracy: 0.73
frac: 0.2
Training Accuracy: 0.84
Testing Accuracy: 0.74
frac: 0.5
Training Accuracy: 0.78
Testing Accuracy: 0.75
frac: 0.6
Training Accuracy: 0.78
Testing Accuracy: 0.75
frac: 0.75
```

```
Training Accuracy: 0.78
Testing Accuracy: 0.75
frac: 0.9
Training Accuracy: 0.77
Testing Accuracy: 0.75
frac: 1
Training Accuracy: 0.77
Testing Accuracy: 0.75
```



With different sample rates (fractions), we can see that the test accuracy increases but training accuracy decreases when the size of training is larger (higher `frac`). Both accuracies converge with the size of the training set increasing. This is because when the size of the training set is too small, the trained model is overfitting, which results in extremely high training accuracy but poor performance on the test data, which is unseen to the classifier.