

# 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

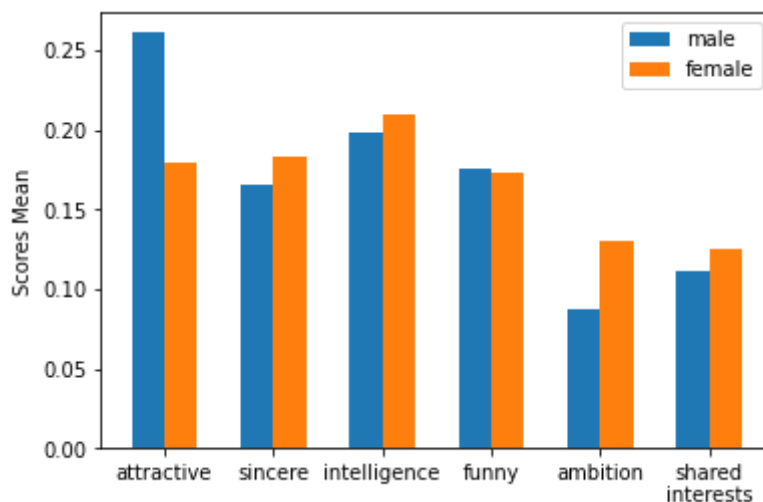
```
In [ ]: %run -i preprocess.py {DATA_RAW} {DATA_NORMAILZED}
```

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

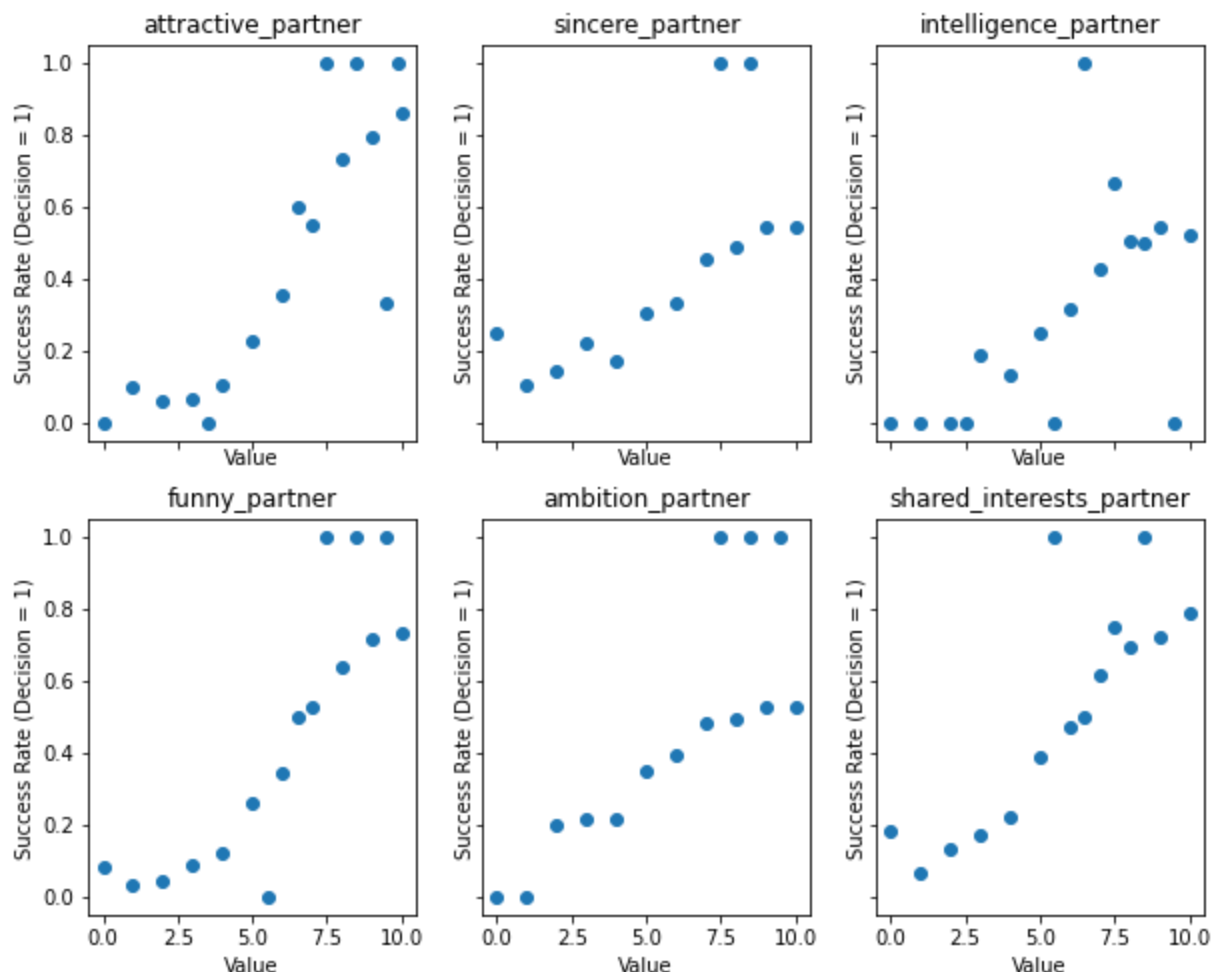
```
In [ ]: %run -i 2_1.py {DATA_NORMAILZED}
```



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 *\_attractivepartner*, *\_funnypartner* and *\_shared\_interestspartner* 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} {TRAINING_SET} {TEST_SET}
```

## Implement a Naive Bayes Classifier

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

```
In [ ]: %run -i 5_1.py
```

```

Training Accuracy: 0.78
Testing Accuracy: 0.75

```

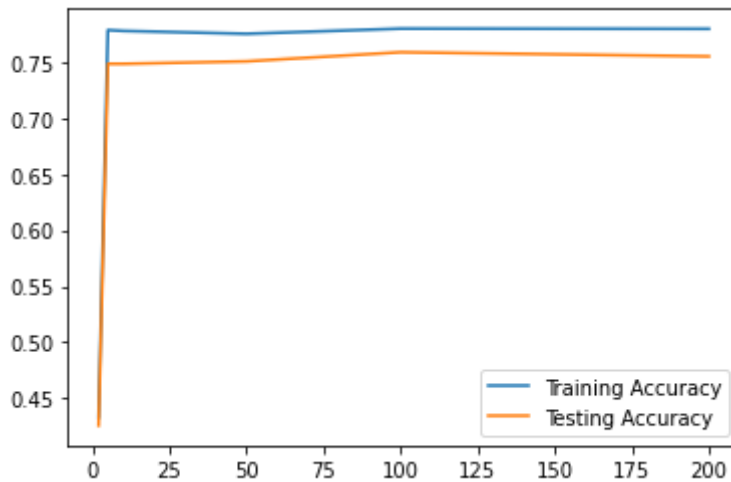
```
nbc(t_frac=1, bin_size)
```

```
In [ ]: %run -i 5_2.py
```

```

Bin size: 2
Training Accuracy: 0.43
Testing Accuracy: 0.43
Bin size: 5
Training Accuracy: 0.78
Testing Accuracy: 0.75
Bin size: 10
Training Accuracy: 0.78
Testing Accuracy: 0.75
Bin size: 50
Training Accuracy: 0.78
Testing Accuracy: 0.75
Bin size: 100
Training Accuracy: 0.78
Testing Accuracy: 0.76
Bin size: 200
Training Accuracy: 0.78
Testing Accuracy: 0.76

```



With different bin sizes, we can see that the accuracy increases when the bin size increases. This is because a small bin size will "blur" the trait of each data, which makes the classification harder. A large bin size, e.g. 200, would be better to model the trait of the data.

```
nbc(frac_t, bin_size=5)
```

In [ ]:

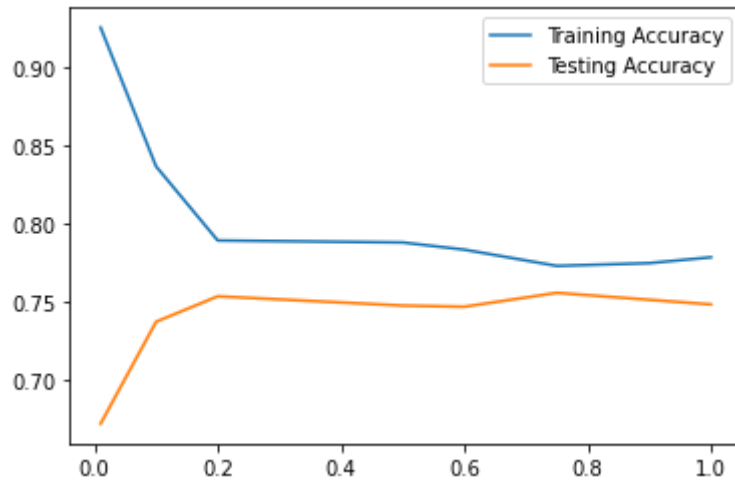
```
%run -i 5_3.py
```

```

frac: 0.01
Training Accuracy: 0.93
Testing Accuracy: 0.67
frac: 0.1
Training Accuracy: 0.84
Testing Accuracy: 0.74
frac: 0.2
Training Accuracy: 0.79
Testing Accuracy: 0.75
frac: 0.5
Training Accuracy: 0.79
Testing Accuracy: 0.75
frac: 0.6
Training Accuracy: 0.78
Testing Accuracy: 0.75
frac: 0.75
Training Accuracy: 0.77
Testing Accuracy: 0.76
frac: 0.9
Training Accuracy: 0.78

```

Testing Accuracy: 0.75  
frac: 1  
Training Accuracy: 0.78  
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.