

```
In [1]:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
In [2]:
dating_data = pd.read_csv('d:\python programs\speed_dating.csv')
```

```
In [3]:
dating_data.head()
```

Out[3]:

	has_null	wave	gender	age	age_o	d_age	d_d_age	race	race_o	sam
0	0	1	female	21.0	27.0	6	[4-6]	asian/pacific islander/asian-american	european/caucasian-american	
1	0	1	female	21.0	22.0	1	[0-1]	asian/pacific islander/asian-american	european/caucasian-american	
2	1	1	female	21.0	22.0	1	[0-1]	asian/pacific islander/asian-american	asian/pacific islander/asian-american	
3	0	1	female	21.0	23.0	2	[2-3]	asian/pacific islander/asian-american	european/caucasian-american	
4	0	1	female	21.0	24.0	3	[2-3]	asian/pacific islander/asian-american	latino/hispanic american	

5 rows × 123 columns

```
In [4]:
dating_data.tail()
```

Out[4]:

	has_null	wave	gender	age	age_o	d_age	d_d_age	race	race_o s
8373	1	21	male	25.0	26.0	1	[0-1]	european/caucasian-american	latino/hispanic american
8374	1	21	male	25.0	24.0	1	[0-1]	european/caucasian-american	other
8375	1	21	male	25.0	29.0	4	[4-6]	european/caucasian-american	latino/hispanic american
8376	1	21	male	25.0	22.0	3	[2-3]	european/caucasian-american	asian/pacific islander/asian-american
8377	1	21	male	25.0	22.0	3	[2-3]	european/caucasian-american	asian/pacific islander/asian-american

5 rows × 123 columns

```
In [5]:
dating_data.shape
```

Out[5]:

(8378, 123)

```
In [6]:
dating_data.columns
```

Out[6]:

```
Index(['has_null', 'wave', 'gender', 'age', 'age_o', 'd_age', 'd_d_age',
      'race', 'race_o', 'samerace',
      ...,
      'd_expected_num_interested_in_me', 'd_expected_num_matches', 'like',
      'guess_prob_liked', 'd_like', 'd_guess_prob_liked', 'met', 'decision',
      'decision_o', 'match'],
      dtype='object', length=123)
```

```
In [7]:
dating_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8378 entries, 0 to 8377
Columns: 123 entries, has_null to match
dtypes: float64(57), int64(7), object(59)
memory usage: 7.9+ MB
```

```
In [8]:  
dating_data.describe()
```

Out[8]:

	has_null	wave	age	age_o	d_age	samerace	importance_
count	8378.00000	8378.000000	8283.000000	8274.000000	8378.000000	8378.000000	8
mean	0.87491	11.350919	26.358928	26.364999	4.185605	0.395799	
std	0.33084	5.995903	3.566763	3.563648	4.596171	0.489051	
min	0.00000	1.000000	18.000000	18.000000	0.000000	0.000000	
25%	1.00000	7.000000	24.000000	24.000000	1.000000	0.000000	
50%	1.00000	11.000000	26.000000	26.000000	3.000000	0.000000	
75%	1.00000	15.000000	28.000000	28.000000	5.000000	1.000000	
max	1.00000	21.000000	55.000000	55.000000	37.000000	1.000000	

8 rows × 64 columns

In [9]:

```
with open('d:\python programs\speed_dating.txt') as f:  
    contents = f.read()  
    print(contents)
```

```

* gender: Gender of self
* age: Age of self
* age_o: Age of partner
* d_age: Difference in age
* race: Race of self
* race_o: Race of partner
* samerace: Whether the two persons have the same race or not.
* importance_same_race: How important is it that partner is of same race?
* importance_same_religion: How important is it that partner has same religio
n?
* field: Field of study
* pref_o_attractive: How important does partner rate attractiveness
* pref_o_sincere: How important does partner rate sincerity
* pref_o_intelligence: How important does partner rate intelligence
* pref_o_funny: How important does partner rate being funny
* pref_o_ambitious: How important does partner rate ambition
* pref_o_shared_interests: How important does partner rate having shared inter
ests
* attractive_o: Rating by partner (about me) at night of event on attractivene
ss
* sincere_o: Rating by partner (about me) at night of event on sincerity
* intelligence_o: Rating by partner (about me) at night of event on intelligen
ce
* funny_o: Rating by partner (about me) at night of event on being funny
* ambitious_o: Rating by partner (about me) at night of event on being ambitiou
s
* shared_interests_o: Rating by partner (about me) at night of event on shared
interest
* attractive_important: What do you look for in a partner - attractiveness
* sincere_important: What do you look for in a partner - sincerity
* intelligence_important: What do you look for in a partner - intelligence
* funny_important: What do you look for in a partner - being funny
* ambition_important: What do you look for in a partner - ambition
* shared_interests_important: What do you look for in a partner - shared inter
ests
* attractive: Rate yourself - attractiveness
* sincere: Rate yourself - sincerity
* intelligence: Rate yourself - intelligence
* funny: Rate yourself - being funny
* ambition: Rate yourself - ambition
* attractive_partner: Rate your partner - attractiveness
* sincere_partner: Rate your partner - sincerity
* intelligence_partner: Rate your partner - intelligence
* funny_partner: Rate your partner - being funny
* ambition_partner: Rate your partner - ambition
* shared_interests_partner: Rate your partner - shared interests
* sports: Your own interests [1-10]
* tvsports
* exercise
* dining
* museums
* art
* hiking
* gaming
* clubbing
* reading
* tv
* theater
* movies
* concerts
* music
* shopping

```

```
* yoga
* interests_correlate: Correlation between participant's and partner's ratings of interests.
* expected_happy_with_sd_people: How happy do you expect to be with the people you meet during the speed-dating event?
* expected_num_interested_in_me: Out of the 20 people you will meet, how many do you expect will be interested in dating you?
* expected_num_matches: How many matches do you expect to get?
* like: Did you like your partner?
* guess_prob_liked: How likely do you think it is that your partner likes you?
* met: Have you met your partner before?
* decision: Decision at night of event.
* decision_o: Decision of partner at night of event.
* match: Match (yes/no)
```

In [10]:

```
dating_data.duplicated().sum()
```

Out[10]:

0

In [11]:

```
dating_data.isnull().sum()
```

Out[11]:

```
has_null      0
wave          0
gender        0
age          95
age_o        104
...
d_guess_prob_liked  0
met              375
decision         0
decision_o       0
match           0
Length: 123, dtype: int64
```

In [12]:

```
dating_data.nunique()
```

Out[12]:

```
has_null      2
wave         21
gender        2
age          24
age_o        24
..
d_guess_prob_liked  3
met              7
decision         2
decision_o       2
match           2
Length: 123, dtype: int64
```

```
In [13]:
dating_categorical = ['gender', 'race', 'race_o', 'field']
dating_numerical = ['has_null', 'wave', 'age', 'age_o', 'd_age', 'samerace', 'importance_sam
'importance_same_religion', 'pref_o_attractive', 'pref_o_sincere', 'pref_o_intelligence', '
'pref_o_ambitious', 'pref_o_shared_interests', 'attractive_o', 'sinsere_o', 'intelligence_o
'ambitious_o', 'shared_interests_o', 'attractive_important', 'sincere_important', 'intellige
'funny_important', 'ambtition_important', 'shared_interests_important', 'attractive', 'sinc
'funny', 'ambition', 'attractive_partner', 'sincere_partner', 'intelligence_partner', 'funn
'shared_interests_partner', 'sports', 'tvsports', 'exercise', 'dining', 'museums', 'art', '
'reading', 'tv', 'theater', 'movies', 'concerts', 'music', 'shopping', 'yoga', 'interests_c
'expected_happy_with_sd_people', 'expected_num_interested_in_me', 'expected_num_matches', '
```

```
In [14]:
dating_data[dating_categorical].nunique()
```

Out[14]:

gender	2
race	5
race_o	5
field	219

dtype: int64

```
In [15]:
dating_data[dating_categorical].value_counts()
```

Out[15]:

gender	race	race_o	field
male	224	224	business
female	158	158	social work
male	135	135	mba
			law
97			
female	90	90	law
...			
male	1	1	chemistry
female	1	1	climate chan
ge	1	1	
male	1	1	business sch
ool	1	1	business [mb
a]	1	1	
	other	other	theater
1			

Length: 1386, dtype: int64

In [16]:

```
dating_data[dating_categorical].isnull().sum()
```

Out[16]:

```
gender      0
race        63
race_o      73
field       63
dtype: int64
```

In [17]:

```
dating_data[dating_numerical].nunique()
```

Out[17]:

```
has_null      2
wave          21
age           24
age_o         24
d_age         35
..
expected_num_interested_in_me  18
expected_num_matches          17
like                          18
guess_prob_liked              19
met                           7
Length: 61, dtype: int64
```

In [18]:

```
dating_data[dating_numerical].isnull().sum()
```

Out[18]:

```
has_null      0
wave          0
age           95
age_o        104
d_age         0
...
expected_num_interested_in_me  6578
expected_num_matches          1173
like                          240
guess_prob_liked              309
met                           375
Length: 61, dtype: int64
```


In [19]:

```
dating_data['field'].unique()
```

Out[19]:

```
array(['law', 'economics', 'masters in public administration',
      'masters of social work&education', 'finance', 'business',
      'political science', 'money', 'operations research',
      'tc [health ed]', 'psychology', 'social work',
      'speech language pathology', 'speech languahe pathology',
      'educational psychology', 'applied maths/econs', 'mathematics',
      'statistics', 'organizational psychology',
      'mechanical engineering', 'finanace', 'finance&economics',
      'undergrad - gs', 'mathematical finance', 'medicine', 'mba', nan,
      'german literature', 'business & international affairs',
      'mfa creative writing', 'engineering', 'electrical engineering',
      'classics', 'operations research [seas]', 'chemistry',
      'journalism', 'elementary/childhood education [ma]',
      'microbiology', 'masters of social work', 'communications',
      'marketing', 'international educational development',
      'education administration', 'business [mba]', 'computer science',
      'climate-earth and environ. science', 'financial math',
      'business- mba', 'religion', 'film', 'sociology',
      'economics; english', 'economics; sociology', 'polish', 'english',
      'psychology and english', 'biomedical engineering',
      'economics and political science', 'art history/medicine',
      'philosophy', 'marine geophysics', 'theory', 'nutrition/genetics',
      'neuroscience', 'comparative literature',
      'international relations', 'history of religion',
      'international affairs - economic development',
      'modern chinese literature', 'business; marketing',
      'physics [astrophysics]', 'physics',
      'business/ finance/ real estate', 'biochemistry', 'art education',
      'american studies [masters]', 'biology', 'cell biology', 'math',
      'international affairs/finance', 'international affairs',
      'international affairs/international finance', 'health policy',
      'english and comp lit', 'international finance and business',
      'sociomedical sciences- school of public health', 'epidemiology',
      'international business', 'medical informatics',
      'international finance; economic policy', 'law and social work',
      'international development', 'business/law', 'clinical psychology',
      'religion, gas', 'international affairs and public health',
      'history',
      'business and international affairs [mba/mia dual degree]', 'qmss',
      'climate change', 'public administration', 'ma biotechnology',
      'international affairs/business', 'ecology',
      'master in public administration', 'computational biochemsistry',
      'neurobiology', 'mathematics phd', 'history [gsas - phd]',
      'biomedicine', 'master of international affairs',
      'sociology and education', 'elementary education',
      'american studies', 'arts administration', 'conservation biology',
      'japanese literature', 'biotechnology',
      'earth and environmental science', 'philosophy [ph.d.]',
      'physics', 'nutrition', 'ma science education',
      'genetics', 'law and english literature [j.d./ph.d.]', 'french',
      'nutrition', 'gs postbacc premed', 'art history',
      'molecular biology', 'genetics & development', 'electrical engg.',
      'business school', 'international politics',
      'mba / master of international affairs [sipa]',
      'medicine and biochemistry', 'social studies education',
      'ma teaching social studies', 'education policy',
      'education- literacy specialist', 'anthropology/education',
      'bilingual education', 'speech pathology', 'education',
      'math education', 'tesol', 'cognitive studies in education',
      'finance/economics', 'museum anthropology',
      'environmental engineering', 'business administration',
      'curriculum and teaching/giftedness', 'anthropology',
```

In [20]:
 Out[20]:
 business and international affairs [mba/mia dual degree], 'qmss',
 'climate change', 'public administration', 'ma biotechnology',
 'international affairs/business', 'ecology',
 'master in public administration', 'computational biochemsistry',
 'neurobiology', 'mathematics phd', 'history [gsas - phd]',
 'biomedicine', 'master of international affairs',
 'sociology and education', 'elementary education',
 'american studies', 'arts administration', 'conservation biology',
 'japanese literature', 'biotechnology',
 'earth and environmental science', 'philosophy [ph.d.]',
 'physics', 'nutrition', 'ma science education',
 'genetics', 'law and english literature [j.d./ph.d.]', 'french',
 'nutrition', 'gs postbacc premed', 'art history',
 'molecular biology', 'genetics & development', 'electrical engg.',
 'business school', 'international politics',
 'mba / master of international affairs [sipa]',
 'medicine and biochemistry', 'social studies education',
 'ma teaching social studies', 'education policy',
 'education- literacy specialist', 'anthropology/education',
 'bilingual education', 'speech pathology', 'education',
 'math education', 'tesol', 'cognitive studies in education',
 'finance/economics', 'museum anthropology',
 'environmental engineering', 'business administration',
 'curriculum and teaching/giftedness', 'anthropology',

```

'instructional tech & media', 'school psychology',
In [21]: 'instructional media and technology', 'sipa / mia',
'english education', 'ma in quantitative methods',
plt.figure(figsize=(15,6))
sns.countplot('field', data=dating_data.head(2000))
plt.xticks(rotation=90)
plt.title('international security policy - sipa',
plt.show()
'applied physiology & nutrition', 'music education',
'counseling psychology', 'communications in education',

```



```

In [22]: 'climate dynamics'], dtype=object)

```

```

import string
import re

```

```

In [23]:

```

```

dating_data['race'] = dating_data['race'].str.lower()
dating_data['race'] = dating_data['race'].str.replace("'", "", regex=False)
dating_data['race'] = dating_data['race'].str.replace(" ", "_", regex=False)
dating_data['race_o'] = dating_data['race_o'].str.lower()
dating_data['race_o'] = dating_data['race_o'].str.replace("'", "", regex=False)
dating_data['race_o'] = dating_data['race_o'].str.replace(" ", "_", regex=False)

```

```

In [24]:

```

```

dating_data.race = dating_data.race.fillna('Not Available')
dating_data.race_o = dating_data.race_o.fillna('Not Available')
dating_data.field = dating_data.field.fillna('Not Available')

```

In [25]:

```
dating_data[dating_categorical].isnull().sum()
```

Out[25]:

```
gender    0
race      0
race_o    0
field     0
dtype: int64
```

In [26]:

```
dating_data.drop(columns=['expected_num_interested_in_me'],inplace=True)
```

In [27]:

```
dating_numerical.remove('expected_num_interested_in_me')
```

In [28]:

```
for i in dating_numerical:
    dating_data[i] = dating_data[i].fillna(dating_data[i].mean())
```

In [29]:

```
dating_data[dating_numerical].isnull().sum()
```

Out[29]:

In [32]:

```
match = dating_data[dating_data['match']==1]
not_match = dating_data[dating_data['match']==0]
```

In [33]:

```
match.groupby('gender')['match'].count()
```

Out[33]:

```
gender
female    690
male      690
Name: match, dtype: int64
```

In [34]:

```
not_match.groupby('gender')['match'].count()
```

Out[34]:

```
gender
female    3494
male      3504
Name: match, dtype: int64
```

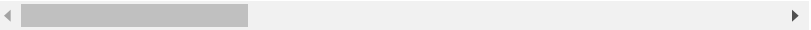
In [35]:

```
dating_data.corr()
```

Out[35]:

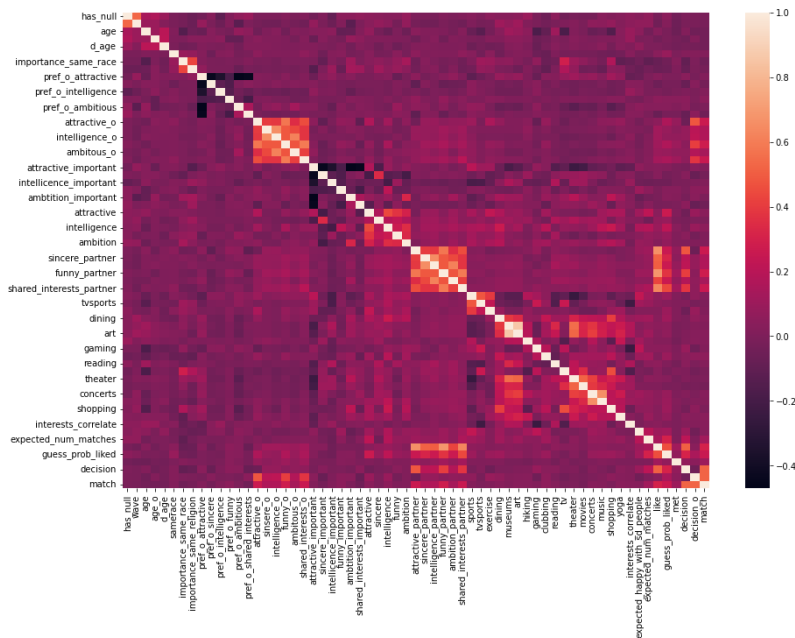
	has_null	wave	age	age_o	d_age	samerace	importance_sar
has_null	1.000000	0.529313	0.144285	0.165107	0.094874	-0.016382	-0
wave	0.529313	1.000000	0.094523	0.092863	0.022024	-0.014967	-0
age	0.144285	0.094523	1.000000	0.099012	0.202476	0.007107	-0
age_o	0.165107	0.092863	0.099012	1.000000	0.208846	0.005737	-0
d_age	0.094874	0.022024	0.202476	0.208846	1.000000	-0.006238	-0
...
guess_prob_liked	0.041519	0.021093	-0.012547	-0.009376	-0.019391	0.082328	-0
met	-0.035000	-0.054883	-0.059553	-0.028931	-0.036715	-0.002383	0
decision	-0.002146	-0.011598	0.015801	-0.049065	-0.026940	0.023036	-0
decision_o	-0.009000	-0.010831	-0.047566	0.015043	-0.028545	0.023626	-0
match	-0.013011	-0.017404	-0.034832	-0.035632	-0.038239	0.013028	-0

63 rows × 63 columns



In [36]:

```
plt.figure(figsize=(15,10))
sns.heatmap(dating_data.corr())
plt.show()
```



In [37]:

```
from sklearn.preprocessing import StandardScaler
```

In [38]:

```
x = dating_data[dating_numerical]
y = dating_data['match']
```

In [39]:

```
x = pd.DataFrame(StandardScaler().fit_transform(x))
```

In [40]:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y,
                                                    test_size=0.15,
                                                    random_state=42)
```

In [41]:

```
from sklearn.tree import DecisionTreeClassifier
classifier= DecisionTreeClassifier(criterion='entropy', random_state=0)
classifier.fit(x_train, y_train)
```

Out[41]:

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

In [42]:

```
y_pred= classifier.predict(x_test)
```

In [43]:

```
from sklearn.metrics import confusion_matrix
cm= confusion_matrix(y_test, y_pred)
```

In [44]:

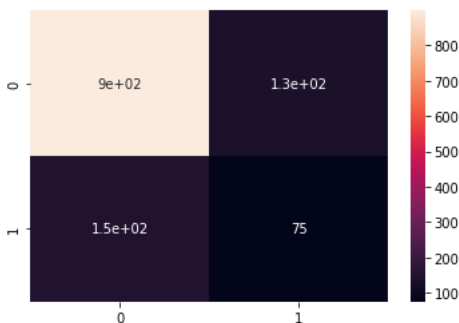
```
print('Confusion matrix : \n',cm)
```

Confusion matrix :

```
[[899 134]
 [149  75]]
```

In [45]:

```
sns.heatmap(cm, annot = True)
plt.show()
```



In [46]:

```
from sklearn import metrics
from sklearn.metrics import accuracy_score
```

In [47]:

```
print("\n Classification report for classifier %s:\n%s\n" % (classifier,
                                                           metrics.classification_report(y_test
```

```
Classification report for classifier DecisionTreeClassifier(criterion='entropy', random_state=0):
```

	precision	recall	f1-score	support
0	0.86	0.87	0.86	1033
1	0.36	0.33	0.35	224
accuracy			0.77	1257
macro avg	0.61	0.60	0.61	1257
weighted avg	0.77	0.77	0.77	1257

In [48]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [49]:

```
rfc = RandomForestClassifier(n_estimators=100, random_state=42)
```

In [50]:

```
rfc.fit(x_train, y_train)
```

Out[50]:

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In [51]:

```
y_pred = rfc.predict(x_test)
```

In [52]:

```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

Accuracy: 85.20%

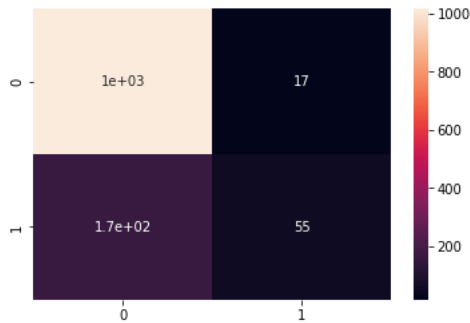
In [53]:

```
cm = confusion_matrix(y_test, y_pred)
```

```
In [54]:  
cm
```

Out[54]:
array([[1016, 17],
 [169, 55]], dtype=int64)

```
In [55]:  
sns.heatmap(cm, annot = True)  
plt.show()
```



```
In [56]:  
print("\n Classification report for classifier %s:\n%s\n" % (rfc,  
                                                            metrics.classification_report(y
```

```
Classification report for classifier RandomForestClassifier(random_state=42):
```

	precision	recall	f1-score	support
0	0.86	0.98	0.92	1033
1	0.76	0.25	0.37	224
accuracy			0.85	1257
macro avg	0.81	0.61	0.64	1257
weighted avg	0.84	0.85	0.82	1257