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DSC 680

Final Project 2

Background/History and our Business Problem

```
The war on drugs has always been at the forefront of this nation.
Aside from the political aspect of this so-called
war, one thing remains bipartisan and that is the effects that many
drugs can have on people. Legal or illegal drug
use has been researched far and wide. We have been told time and time
again about the physical repercussions of
different drugs. We've been told from an early age that smoking
causes lung cancer and to say no to drugs. But how
much are we taught when it comes to the mental and possibly emotional
effects that drugs can have on the human brain?
Can drugs affect your personality? During use yes and it has been
proven. Especially when used in addictive behavior
(Gateway Foundation, 2024).

As drug use and specific drugs are becoming legal in more and more
places, people are constantly having access to
different narcotics at record rates. It's important to look at the
different effects that these drugs can have on
people. While extensive research has been done on how drugs can
affect the human body physically, there is a noticeably
lower amount of research done on exactly how different drugs might
affect a person's personality.

The main problem that I want to explore is whether we can determine
what kind of personality attributes (variables
neuroticism, extraversion, openness to experience, agreeableness,
conscientiousness, impulsivity, sensation seeking)
based on how often a person uses specific drugs. The goal is to
possibly make some kind of model or series of models
to build a personality profile for the individual.
```

Data Explanation (Data Prep, Data Dictionary, etc)

```
The data that we will be using a data set found on Kaggle.com titled
"Drug Consumptions (UCI)".
The data set contains information and records for 1885 different
individuals who chose to respond to a questionnaire.
```

```
For each respondent, 12 different personality attributes are known
(neuroticism, extraversion, openness to experience,
agreeableness, conscientiousness, impulsivity, sensation seeking,
level of education, age, gender, country of
residence, and ethnicity. The participants were also asked to provide
information on any past drug use (both legal
and illegal drugs are included in the data set). The drugs included
are alcohol, amphetamines, amyl nitrite,
benzodiazepine, cannabis, chocolate, cocaine, caffeine, crack,
ecstasy, heroin, ketamine, legal highs, LSD, methadone,
mushrooms, nicotine and volatile substance abuse, and Semeron. For
each drug, each participant listened to how long
ago they had used the drug which shines a light on how often an
individual is using and what sort of effects you can
expect.
```

About the Data and Variables and Drug Codes:

```
ID:-------is a number of records in an original database. Cannot be
related to the participant.
Age: ------is the age of participant
Gender:----Male or Female
Education:-level of education of participant
Country:---country of origin of the participant
Ethnicity:-ethnicity of participant
Nscore:----is NEO-FFI-R Neuroticism (TARGET)
Escore:----is NEO-FFI-R Extraversion (TARGET)
Oscore:----is NEO-FFI-R Openness to experience. (TARGET)
Ascore:----is NEO-FFI-R Agreeableness. (TARGET)
Cscore:----is NEO-FFI-R Conscientiousness. (TARGET)
Impulsive:-is impulsiveness measured by BIS-11 (TARGET)
SS:--------is sensation seeing measured by ImpSS (TARGET)
Alcohol:---alcohol consumption
Amphet:----amphetamines consumption
Amyl:------nitrite consumption
Benzos:----benzodiazepine consumption
Caff:------caffeine consumption
Cannabis:--marijuana consumption
Choc:------chocolate consumption
Coke:------cocaine consumption
Crack:-----crack cocaine consumption
Ecstasy:---ecstasy consumption
Heroin:----heroin consumption
Ketamine:--ketamine consumption
Legalh:----legal highs consumption
LSD:-------LSD consumption
Meth:------methadone consumption
Mushrooms:--magic mushroom consumption
Nicotine:--nicotine consumption
Semer:-----class of fictitious drug Semeron consumption (i.e.
control)
```

```
VSA:-------class of volatile substance abuse consumption
```

Drug Use Codes:

```
CL0:-------Never Used
CL1:-------Used over a Decade Ago
CL2:-------Used in Last Decade
CL3:-------Used in Last Year 59
CL4:-------Used in Last Month
CL5:-------Used in Last Week
CL6:-------Used in Last Day
```

Importing Data and Main Packages

```
Before we can begin to build our model we must first load our data. A
view of what the data looks like can be found
in the appendix at the end of this report. Our data will be saved
into a dataframe object 'drugdata'.
```

In [1]:
```
#Importing Data and Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

drugdata = pd.read_csv('drug.csv')
drugdata = pd.DataFrame(drugdata)
```

Examining and Cleaning Data

```
Once our data has been loaded and saved in a dataframe, we can start
examining the data more closely. Then we can
see what we need to do in order to clean and prepare the data for our
analysis.

The first thing that we did was get rid of the ID variable. We get
rid of this values since we aren't necessarily
concerned with specific individuaul's observed data. Each instance
can also be refered to by their index in the
dataframe.
```

In [2]:
```
drugdata = drugdata.drop(columns=['ID'])
```

```
In this next portion of the code we want to see all the different
unique values for each of the categorical
variables, which would be all of our predicting varaibles. This will
help us decide if there are any other varaibles
that we might want to consider getting rid of before moving onto our
model-building process. We can also get an idea
of all the different types of unique values for each variable as well
```

as the spread in terms of frequency of those values.

In [3]:
```
#Unique Values for Age
print(drugdata['Age'].value_counts())
```

```
Age
18-24    643
25-34    481
35-44    355
45-54    294
55-64     93
65+       18
Name: count, dtype: int64
```

In [4]:
```
#Unique Values for Gender
print(drugdata['Gender'].value_counts())
```

```
Gender
M    943
F    941
Name: count, dtype: int64
```

In [5]:
```
#Unique Values for Education
print(drugdata['Education'].value_counts())
```

```
Education
Some college or university, no certificate or degree    506
University degree                                       480
Masters degree                                          283
Professional certificate/ diploma                       269
Left school at 18 years                                 100
Left school at 16 years                                  99
Doctorate degree                                         89
Left school at 17 years                                  30
Left school before 16 years                              28
Name: count, dtype: int64
```

In [6]:
```
#Unique Values for Country
print(drugdata['Country'].value_counts())
```

```
Country
UK                     1043
USA                     557
Other                   118
Canada                   87
Australia                54
Republic of Ireland      20
New Zealand               5
Name: count, dtype: int64
```

In [7]:
```
#Unique Values for Ethnicity
print(drugdata['Ethnicity'].value_counts())
```

```
Ethnicity
White                 1720
Other                   63
Black                   33
Asian                   26
Mixed-White/Black       20
Mixed-White/Asian       19
Mixed-Black/Asian        3
Name: count, dtype: int64
```

In [8]:
```python
#Unique Values for Alcohol
print(drugdata['Alcohol'].value_counts())
```

```
Alcohol
CL5    758
CL6    505
CL4    287
CL3    198
CL2     68
CL1     34
CL0     34
Name: count, dtype: int64
```

In [9]:
```python
#Unique Values for amphetamines
print(drugdata['Amphet'].value_counts())
```

```
Amphet
CL0    976
CL2    242
CL1    230
CL3    198
CL6    102
CL4     75
CL5     61
Name: count, dtype: int64
```

In [10]:
```python
#Unique Values for nitrite
print(drugdata['Amyl'].value_counts())
```

```
Amyl
CL0    1304
CL2     237
CL1     210
CL3      92
CL4      24
CL5      14
CL6       3
Name: count, dtype: int64
```

In [11]:
```python
#Unique Values for benzodiazepine
print(drugdata['Benzos'].value_counts())
```

```
Benzos
CL0    1000
CL3     236
CL2     233
CL4     120
CL1     116
CL6      95
CL5      84
Name: count, dtype: int64
```

In [12]:
```
#Unique Values for Caffeine
print(drugdata['Caff'].value_counts())
```

```
Caff
CL6    1384
CL5     273
CL4     106
CL3      60
CL0      27
CL2      24
CL1      10
Name: count, dtype: int64
```

In [13]:
```
#Unique Values for Cannabis
print(drugdata['Cannabis'].value_counts())
```

```
Cannabis
CL6    463
CL0    412
CL2    266
CL3    211
CL1    207
CL5    185
CL4    140
Name: count, dtype: int64
```

In [14]:
```
#Unique Values for Chocolate
print(drugdata['Choc'].value_counts())
```

```
Choc
CL6    807
CL5    682
CL4    296
CL3     54
CL0     32
CL2     10
CL1      3
Name: count, dtype: int64
```

In [15]:
```
#Unique Values for Cocaine
print(drugdata['Coke'].value_counts())
```

```
Coke
CL0    1037
CL2     270
CL3     258
CL1     160
CL4      99
CL5      41
CL6      19
Name: count, dtype: int64
```

In [16]:
```
#Unique Values for Crack Cocaine
print(drugdata['Crack'].value_counts())
```

```
Crack
CL0    1626
CL2     112
CL1      67
CL3      59
CL5       9
CL4       9
CL6       2
Name: count, dtype: int64
```

In [17]:
```
#Unique Values for Ecstasy
print(drugdata['Ecstasy'].value_counts())
```

```
Ecstasy
CL0    1020
CL3     277
CL2     234
CL4     156
CL1     113
CL5      63
CL6      21
Name: count, dtype: int64
```

In [18]:
```
#Unique Values for Heroin
print(drugdata['Heroin'].value_counts())
```

```
Heroin
CL0    1604
CL2      94
CL1      68
CL3      65
CL4      24
CL5      16
CL6      13
Name: count, dtype: int64
```

In [19]:
```
#Unique Values for Ketamine
print(drugdata['Ketamine'].value_counts())
```

```
Ketamine
CL0    1489
CL2     142
CL3     129
CL1      45
CL4      42
CL5      33
CL6       4
Name: count, dtype: int64
```

In [20]:
```
#Unique Values for Legalh
print(drugdata['Legalh'].value_counts())
```

```
Legalh
CL0    1093
CL3     323
CL2     198
CL4     110
CL6      67
CL5      64
CL1      29
Name: count, dtype: int64
```

In [21]:
```
#Unique Values for LSD
print(drugdata['LSD'].value_counts())
```

```
LSD
CL0    1068
CL1     259
CL3     214
CL2     177
CL4      97
CL5      56
CL6      13
Name: count, dtype: int64
```

In [22]:
```
#Unique Values for Meth
print(drugdata['Meth'].value_counts())
```

```
Meth
CL0    1428
CL3     149
CL2      97
CL6      73
CL4      50
CL5      48
CL1      39
Name: count, dtype: int64
```

In [23]:
```
#Unique Values for Mushroom
print(drugdata['Mushrooms'].value_counts())
```

```
Mushrooms
CL0    981
CL3    275
CL2    260
CL1    209
CL4    115
CL5     40
CL6      4
Name: count, dtype: int64
```

In [24]:
```
#Unique Values for Nicotine
print(drugdata['Nicotine'].value_counts())
```

```
Nicotine
CL6    610
CL0    428
CL2    203
CL1    193
CL3    185
CL5    157
CL4    108
Name: count, dtype: int64
```

In [25]:
```
#Unique Values for Semer
print(drugdata['Semer'].value_counts())
```

```
Semer
CL0    1876
CL2       3
CL3       2
CL1       2
CL4       1
Name: count, dtype: int64
```

In [26]:
```
#Unique Values for VSA
print(drugdata['VSA'].value_counts())
```

```
VSA
CL0    1454
CL1     200
CL2     135
CL3      61
CL5      14
CL4      13
CL6       7
Name: count, dtype: int64
```

Now based on the results, we might want to get rid of some varaibles that do not have adequate amounts of observations for all categories in the varaible. We will also be getting rid of Caffeine and Chocolate due to the fact that they are often consumed by average people who don't use the substances in an addictive behavior. Typical effects of both substances are also not of high risk. Then we move on to some additional data cleaning. Removing duplicates and missing values from our data.

In [27]:
```
drugdata = drugdata.drop(columns=['VSA'])
drugdata = drugdata.drop(columns=['Semer'])
drugdata = drugdata.drop(columns=['Choc'])
drugdata = drugdata.drop(columns=['Caff'])
```

In [28]:
```
#Getting Rid of Duplicates: keeping first duplicate row
drugdata = drugdata.drop_duplicates()

#Getting Rid of Missing Value Rows: Based on NA values
drugdata = drugdata.dropna()
drugdata
```

Out[28]:

	Age	Gender	Education	Country	Ethnicity	Nscore	Escore	Oscore	AScore	Cscore
0	25-34	M	Doctorate degree	UK	White	-0.67825	1.93886	1.43533	0.76096	-0.14277
1	35-44	M	Professional certificate/ diploma	UK	White	-0.46725	0.80523	-0.84732	-1.62090	-1.01450
2	18-24	F	Masters degree	UK	White	-0.14882	-0.80615	-0.01928	0.59042	0.58489
3	35-44	F	Doctorate degree	UK	White	0.73545	-1.63340	-0.45174	-0.30172	1.30612
4	65+	F	Left school at 18 years	Canada	White	-0.67825	-0.30033	-1.55521	2.03972	1.63088
...	...	...	...	...	...	...	...	...	...	...
1879	18-24	F	Some college or university, no certificate or ...	USA	White	-1.19430	1.74091	1.88511	0.76096	-1.13788
1880	18-24	M	Some college or university, no certificate or ...	USA	White	-0.24649	1.74091	0.58331	0.76096	-1.51840
1881	25-34	F	University degree	USA	White	1.13281	-1.37639	-1.27553	-1.77200	-1.38502
1882	18-24	F	Some college or university, no certificate or ...	USA	White	0.91093	-1.92173	0.29338	-1.62090	-2.57309
1883	18-24	M	Some college or university, no certificate or ...	Republic of Ireland	White	-0.46725	2.12700	1.65653	1.11406	0.41594

1884 rows × 27 columns

Methods

```
Before getting into the model building process, we first conducted
some exploratory data analysis on our data to
investigate what kind of patterns and relationships we can find in
```

```
the data before we create a model. It is in this
state that we explored each varaible's relationship with our target
varaible, including categorical variables. The
purpose of those steps was to be able to give us a hint as to what
varaibles should or shouldn't be included in
the model building process as well as to shine a light on what
varaibles are most important in the model.

Since we ideally want to be able to predict a multitude of different
personality attributes of a person, we might want
to consider multivariate multiple regression or even something like
multi-output regression which involves neural
networks. As far as investigating the data we could see how each
variable individually is related to our target
variables or even how the target ariables correspond with each other.

Afterwhich, we can finally get into our model creation process.
Although, before we can use our data to train
a model we first had to convert all of our categorical varaibles to
dummy varaible in order to be used for linear
regression in the model building process.

We then split that new dataframe with dummy varaibles instead of
categorical varaibles into training and testing
sets of the original data. We built our model with the training
dataset and then later evaluated that model using
the RMSE value of our testing set compared to the model predictions.
```

Analysis and Model Creation

In [29]:

```python
#Getting Predicting Variables (Dropping targets from the Dataset)
X = drugdata
X = X.drop(columns=['Nscore'])
X = X.drop(columns=['Escore'])
X = X.drop(columns=['Oscore'])
X = X.drop(columns=['AScore'])
X = X.drop(columns=['Cscore'])
X = X.drop(columns=['Impulsive'])
X = X.drop(columns=['SS'])
X
```

Out[29]:

	Age	Gender	Education	Country	Ethnicity	Alcohol	Amphet	Amyl	Benzos	Cannabis	Cok
0	25-34	M	Doctorate degree	UK	White	CL5	CL2	CL2	CL0	CL4	CL
1	35-44	M	Professional certificate/ diploma	UK	White	CL6	CL0	CL0	CL0	CL3	CL
2	18-24	F	Masters degree	UK	White	CL4	CL0	CL0	CL3	CL2	CL
3	35-44	F	Doctorate degree	UK	White	CL4	CL1	CL1	CL0	CL3	CL
4	65+	F	Left school at 18 years	Canada	White	CL2	CL0	CL0	CL0	CL0	CL
...	...	...	...	...	...	...	...	...	...	...	.
1879	18-24	F	Some college or university, no certificate or ...	USA	White	CL5	CL0	CL0	CL0	CL5	CL
1880	18-24	M	Some college or university, no certificate or ...	USA	White	CL5	CL0	CL0	CL0	CL3	CL
1881	25-34	F	University degree	USA	White	CL4	CL6	CL5	CL5	CL6	CL
1882	18-24	F	Some college or university, no certificate or ...	USA	White	CL5	CL0	CL0	CL0	CL6	CL
1883	18-24	M	Some college or university, no certificate or ...	Republic of Ireland	White	CL4	CL3	CL0	CL3	CL3	CL

1884 rows × 20 columns

```
After creating a dataframe with only our predicting varaibles, we now
want to double check that these variables are
of the right class in order to be transformed into dummy variables
appropriately.
```

In [30]:
```
result = X.dtypes

print("Output:")
print(result)
```

```
Output:
Age          object
Gender       object
Education    object
Country      object
Ethnicity    object
Alcohol      object
Amphet       object
Amyl         object
Benzos       object
Cannabis     object
Coke         object
Crack        object
Ecstasy      object
Heroin       object
Ketamine     object
Legalh       object
LSD          object
Meth         object
Mushrooms    object
Nicotine     object
dtype: object
```

In [31]:
```
#Transforming Categorical Varaibles to Dummy Variables
X = pd.get_dummies(X)
dummy_vars = X
```

In [32]:
```
#Splitting Training and Testing Sets

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

#Different target variables
y1nscore = drugdata['Nscore']
y2escore = drugdata['Escore']
y3oscore = drugdata['Oscore']
y4ascore = drugdata['AScore']
y5cscore = drugdata['Cscore']
y6impuls = drugdata['Impulsive']
y7ss = drugdata['SS']
```

In [33]:
```
#Model for Nscore
# split the dataset
X_train, X_test, y1_train, y1_test = train_test_split(X, y1nscore, test_size=0.05, rar

#Creating Linear Regression Model
import sklearn.metrics as metrics
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(X_train, y1_train)
y1_pred = model.predict(X_test)
```

```
# RMSE
print(np.sqrt(metrics.mean_squared_error(y1_test, y1_pred)))
```

1.0565506615171463

In [34]:
```
#Model for Escore
# split the dataset
X_train, X_test, y2_train, y2_test = train_test_split(X, y2escore, test_size=0.05, rar

model = LinearRegression()
model.fit(X_train, y1_train)
y2_pred = model.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y2_test, y2_pred)))
```

1.123676856879238

In [35]:
```
#Model for Oscore
# split the dataset
X_train, X_test, y3_train, y3_test = train_test_split(X, y3oscore, test_size=0.05, rar

model = LinearRegression()
model.fit(X_train, y1_train)
y3_pred = model.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y3_test, y3_pred)))
```

1.0668135577362854

In [36]:
```
#Model for Ascore
# split the dataset
X_train, X_test, y4train, y4_test = train_test_split(X, y4ascore, test_size=0.05, ranc

model = LinearRegression()
model.fit(X_train, y1_train)
y4_pred = model.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y4_test, y4_pred)))
```

1.264388987720511

In [37]:
```
#Model for Cscore
# split the dataset
X_train, X_test, y5_train, y5_test = train_test_split(X, y5cscore, test_size=0.05, rar

model = LinearRegression()
model.fit(X_train, y1_train)
y5_pred = model.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y5_test, y5_pred)))
```

0.96895875249846

In [38]:
```
#Model for Impusivity
# split the dataset
X_train, X_test, y6_train, y6_test = train_test_split(X, y6impuls, test_size=0.05, rar
```

```
model = LinearRegression()
model.fit(X_train, y1_train)
y6_pred = model.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y6_test, y6_pred)))
```

```
1.0446526943387267
```

In [39]:

```
#Model for Sscore
# split the dataset
X_train, X_test, y7_train, y7_test = train_test_split(X, y7ss, test_size=0.05, random_

model = LinearRegression()
model.fit(X_train, y1_train)
y7_pred = model.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y7_test, y7_pred)))
```

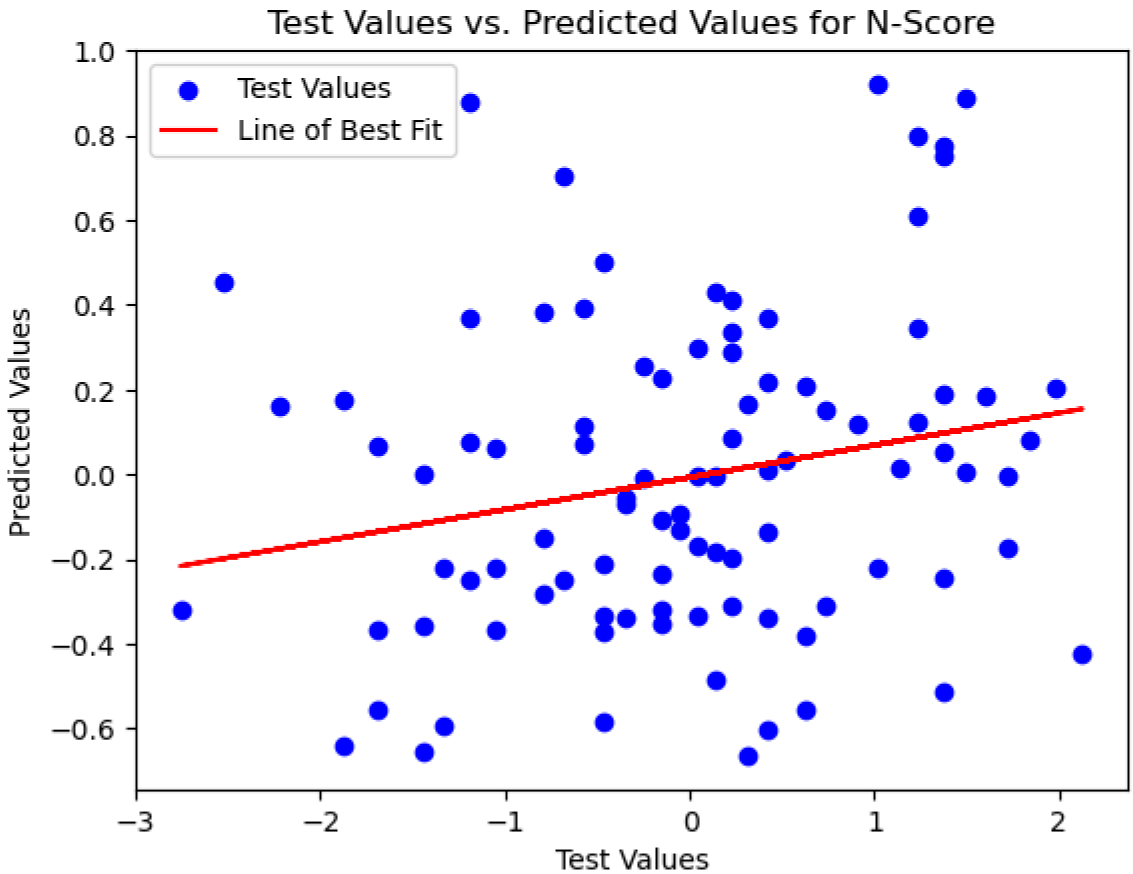
```
0.8561731776406374
```

Results

In [40]:

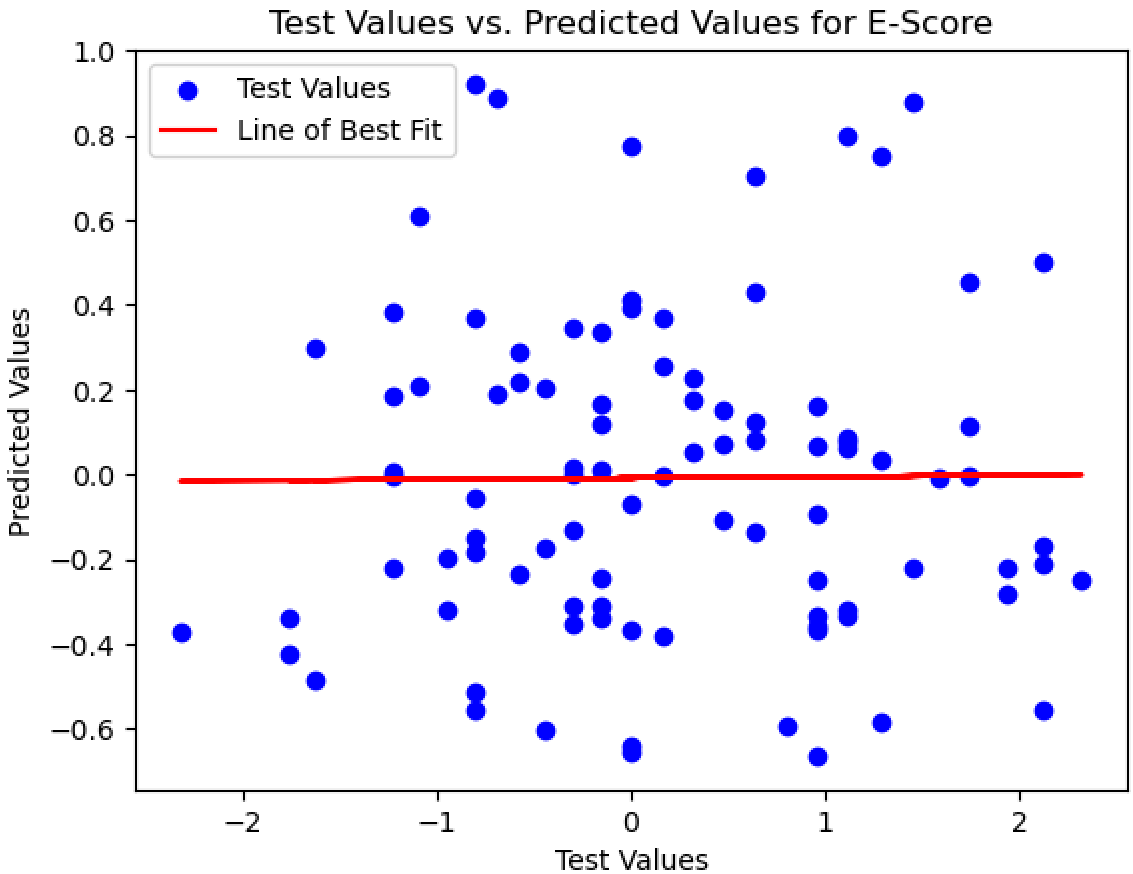
```
slope, intercept = np.polyfit(y1_test, y1_pred, 1)
def line1(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y1_test, y1_pred, color="blue", label="Test Values")
ax.plot(y1_test, line1(y1_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for N-Score")
ax.legend()
plt.show()
```



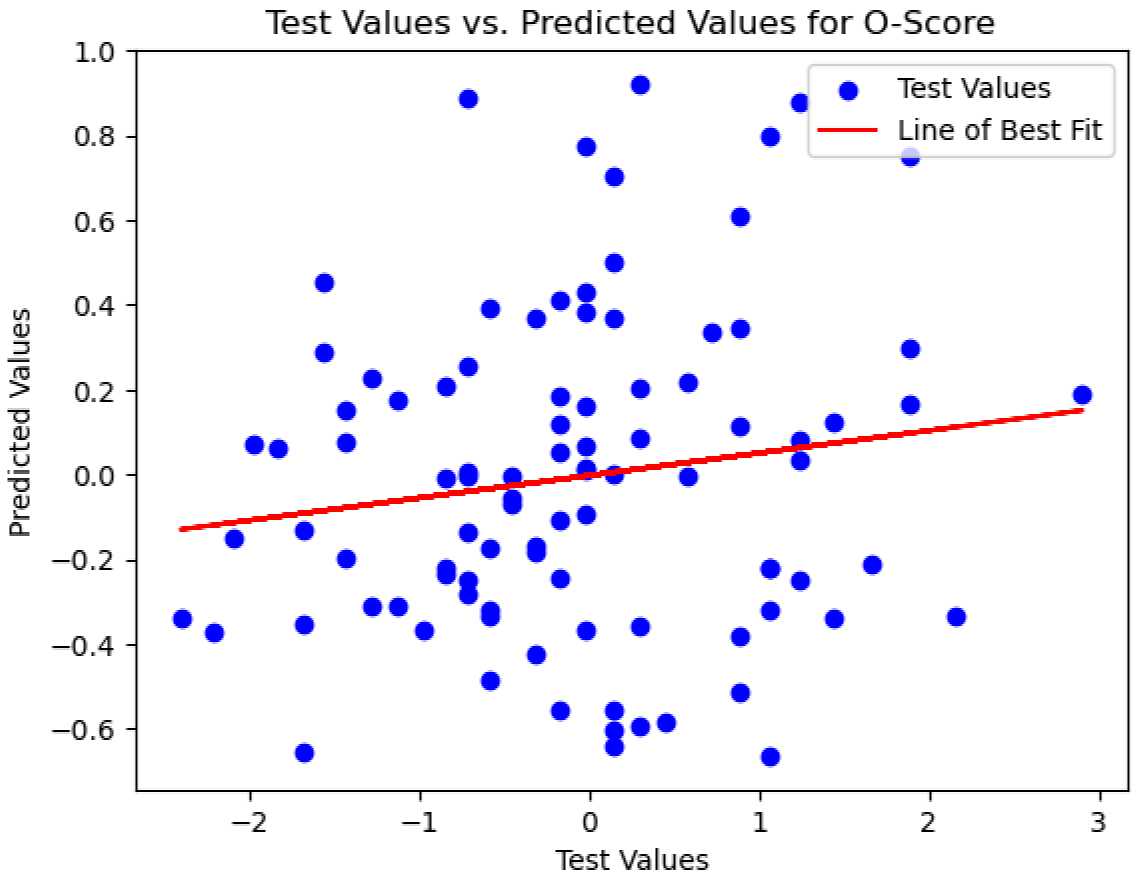
In [41]:
```
slope, intercept = np.polyfit(y2_test, y2_pred, 1)
def line2(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y2_test, y2_pred, color="blue", label="Test Values")
ax.plot(y2_test, line2(y2_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for E-Score")
ax.legend()
plt.show()
```



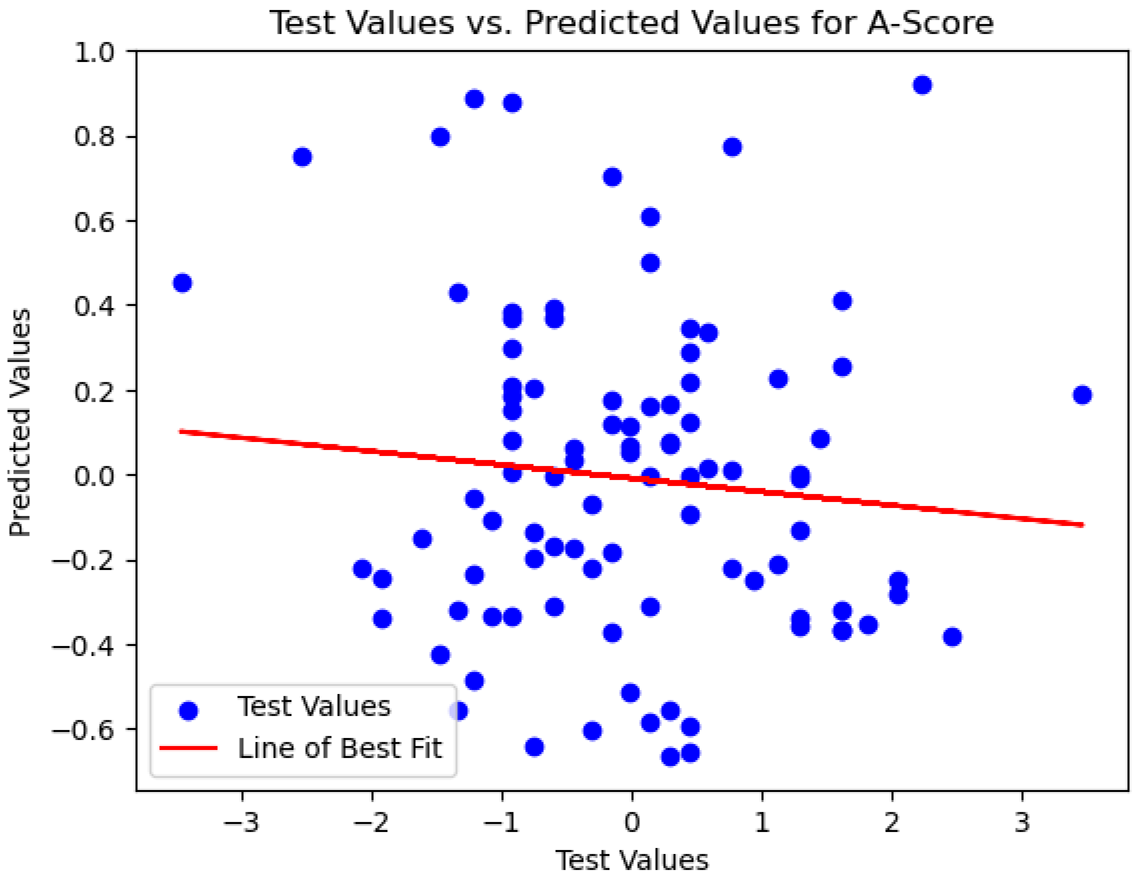
In [42]:
```
slope, intercept = np.polyfit(y3_test, y3_pred, 1)
def line3(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y3_test, y3_pred, color="blue", label="Test Values")
ax.plot(y3_test, line3(y3_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for O-Score")
ax.legend()
plt.show()
```



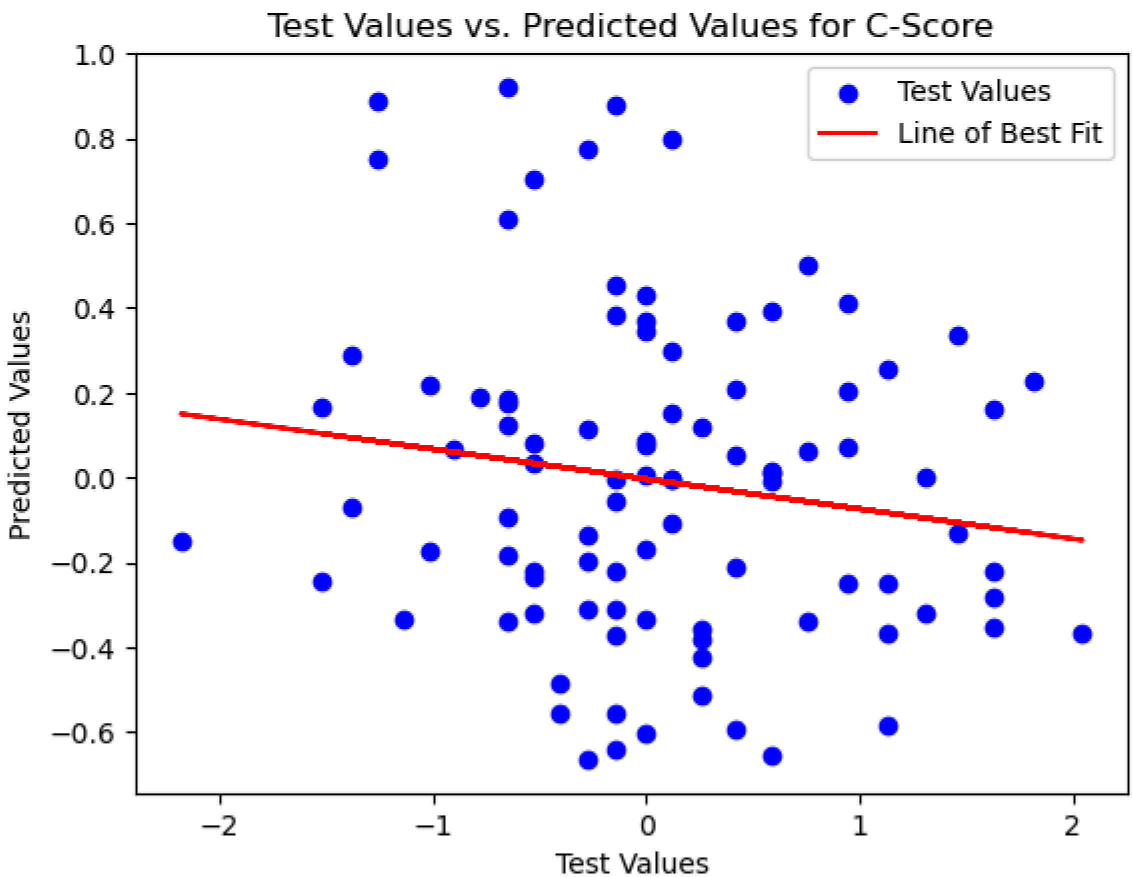
In [43]:
```
slope, intercept = np.polyfit(y4_test, y4_pred, 1)
def line4(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y4_test, y4_pred, color="blue", label="Test Values")
ax.plot(y4_test, line4(y4_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for A-Score")
ax.legend()
plt.show()
```



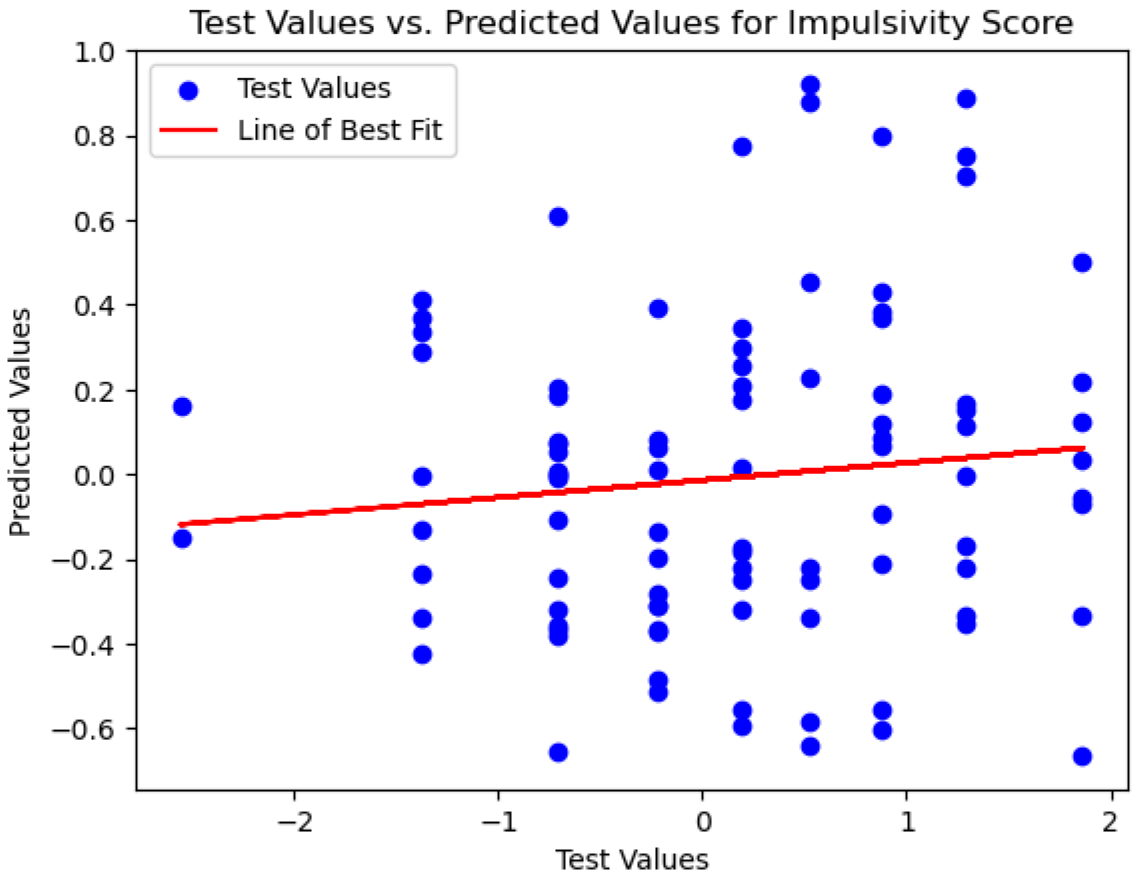
In [44]:
```
slope, intercept = np.polyfit(y5_test, y5_pred, 1)
def line5(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y5_test, y5_pred, color="blue", label="Test Values")
ax.plot(y5_test, line5(y5_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for C-Score")
ax.legend()
plt.show()
```



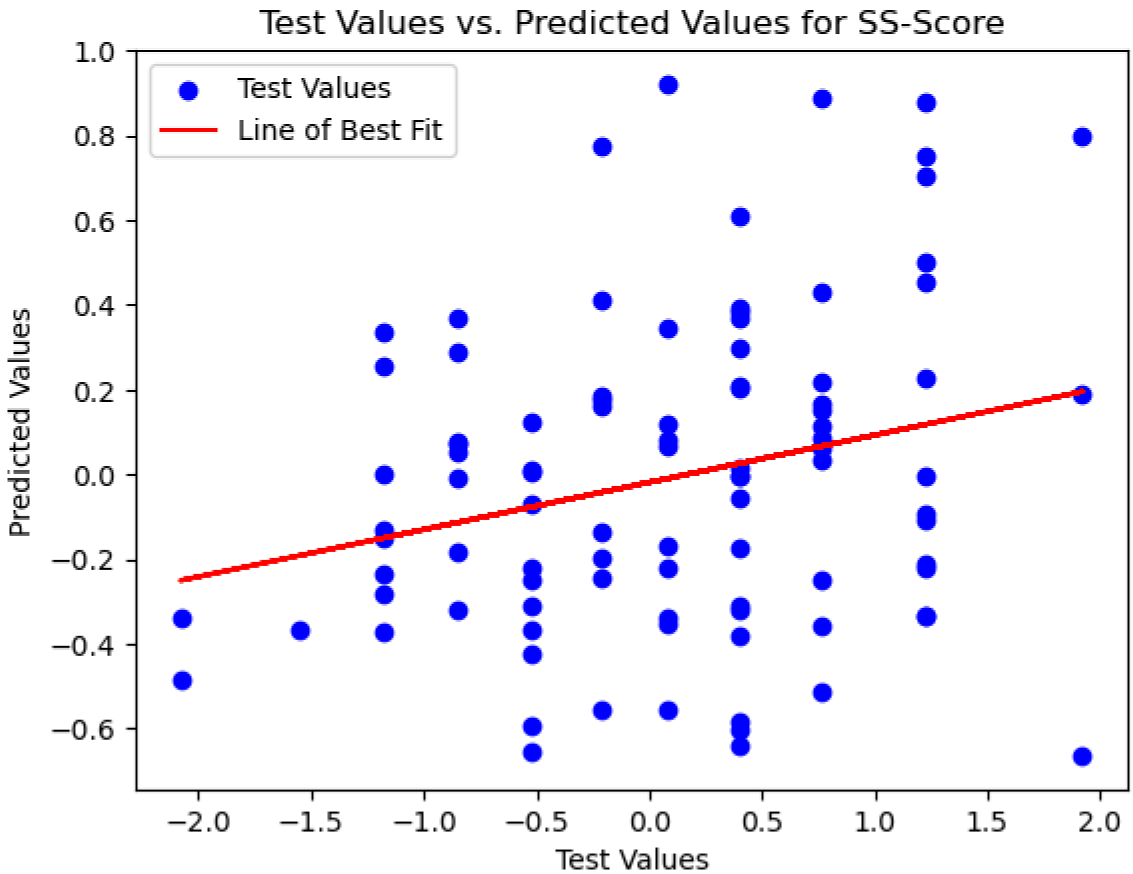
In [45]:
```
slope, intercept = np.polyfit(y6_test, y6_pred, 1)
def line6(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y6_test, y6_pred, color="blue", label="Test Values")
ax.plot(y6_test, line6(y6_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for Impulsivity Score")
ax.legend()
plt.show()
```



In [46]:
```
slope, intercept = np.polyfit(y7_test, y7_pred, 1)
def line7(x):
  return slope * x + intercept

fig, ax = plt.subplots()
ax.scatter(y7_test, y7_pred, color="blue", label="Test Values")
ax.plot(y7_test, line7(y7_test), color="red", label="Line of Best Fit")
ax.set_xlabel("Test Values")
ax.set_ylabel("Predicted Values")
ax.set_title("Test Values vs. Predicted Values for SS-Score")
ax.legend()
plt.show()
```



Conclusion

```
Now taking into account the RMSE values as well as being able to
compare the test values and predicted values visually
by looking at a scatterplot along with a line of best fit for each of
the graphs. It's easier to interpret the RMSE
results on each scale. Looking at thest results, while a lot of the
correspondance isn't stronge, the weakest model
appears to be the model for the E-Score which aims to predict
extraversion. I beleive this model performed the worst
out of all the models because extraversion, or in other words a
person's sociability, is often difficult to change
permanently. While it's known that certain substances can make it
easier for people to socialize more confidently or
feel less anxious in a social setting, those effects are far from
permanent.

In addition, the model predictions for A-Score (Agreeableness) and C-
Score (Conscienciousness) appear to be negatively
correlated to the actual results. Meaning that the model predicted a
person would be more agreeable based on their
prior drug use when in reality they might not be so agreeable. The
same goes for conscienciousness.

We make the conclusion that while these models may be able to get a
```

basis for the psychological affects of drugs use
and demographic status on a person's brain, obviously there are
millions of other factors that could contributed to
a person's personality and should be investigated further in how it
all takes place together.

Assumptions:

Independence - Observations are independent of each other and
independent of repetitive measurement

Linearity - There is a linear relationship between continuous
predictor variables and the outcome variable, and
between continuous predictor variables and the logit of the outcome
variable

Multicollinearity - There is no multicollinearity, which occurs when
two or more explanatory variables are highly
correlated to each other

Outliers - There are no strongly influential outliers

Sample size - The sample size is sufficiently large

Outcome type - The dependent/response variable is binary or
dichotomous, meaning it can only take on two possible
outcomes

Limitations:

We were very limited by the data that was aquired. The data itself
was very useful but because this was an individual
survey/questionaire it's difficult to look for extra data to
suppliment our first dataset if we wanted to look for
more trends. We were also limited by the type of variables. All the
predicting variables we used were

Challenges:

One main challenge would be the fact that there would be multiple
target variables to look at and deciding whether a
single model is optimal or splitting the targets into different
models for optimization of each attribute. It’s
possible that both methods can be attempted depending on time and
resources.

Future Uses/Additional Applications:

```
Future uses and applications at this point would be to be able to
guess exactly how specific drugs would affect a
persons personality based on how recent they used. Further research
can also be completed if more data was collected
on how LONG each drug was used by each individual. Possibilities for
a time series anlaysis on the affects of specific
drugs on a person's personality could be completed this way.
Recomendations for this project is to see if there is a
way to aquire more data and possibly more data on how long each drug
was used in addition to when the last time the
drug was used for each individual.
```

Ethical Assessment

```
As always the main ethical concern for our research projects is the
safety and privacy of individuals whose information
is included in the data. For the data set chosen, individual names
are kept anonymous. The only identifying
characteristics for each individual are level of education, age,
gender, country of residence, and ethnicity. Something
else to consider is what the results could be used for. For example,
we can find that one individual or a handful
of individuals didn’t seem to experience any negative effects of
heavy drug use. Someone reading those results could
then conclude that it is safe to use the drugs, thus spreading
misinformation on a very serious topic that can cost
people their lives. This is a huge ethical concern as well.
```

References

Gateway Foundation. (2024, April 15). 10 ways substance addiction can change your personality. https://www.gatewayfoundation.org/addiction-blog/substance-addiction-change-personality/#:~:text=Some%20personality%20changes%20are%20specific,awareness%20and%20co

Khadija. (2021, September 26). Drug Consumptions (UCI). Kaggle. https://www.kaggle.com/datasets/obeykhadija/drug-consumptions-uci

Drug fact sheets. DEA. (n.d.). https://www.dea.gov/factsheets

Appendix

Table 1: Original Dataframe

In [47]:
```
drugdata
```

Out[47]:

	Age	Gender	Education	Country	Ethnicity	Nscore	Escore	Oscore	AScore	Cscore
0	25-34	M	Doctorate degree	UK	White	-0.67825	1.93886	1.43533	0.76096	-0.14277
1	35-44	M	Professional certificate/ diploma	UK	White	-0.46725	0.80523	-0.84732	-1.62090	-1.01450
2	18-24	F	Masters degree	UK	White	-0.14882	-0.80615	-0.01928	0.59042	0.58489
3	35-44	F	Doctorate degree	UK	White	0.73545	-1.63340	-0.45174	-0.30172	1.30612
4	65+	F	Left school at 18 years	Canada	White	-0.67825	-0.30033	-1.55521	2.03972	1.63088
...	...	...	...	...	...	...	...	...	...	...
1879	18-24	F	Some college or university, no certificate or ...	USA	White	-1.19430	1.74091	1.88511	0.76096	-1.13788
1880	18-24	M	Some college or university, no certificate or ...	USA	White	-0.24649	1.74091	0.58331	0.76096	-1.51840
1881	25-34	F	University degree	USA	White	1.13281	-1.37639	-1.27553	-1.77200	-1.38502
1882	18-24	F	Some college or university, no certificate or ...	USA	White	0.91093	-1.92173	0.29338	-1.62090	-2.57309
1883	18-24	M	Some college or university, no certificate or ...	Republic of Ireland	White	-0.46725	2.12700	1.65653	1.11406	0.41594

1884 rows × 27 columns

Table 2: Dummy Variable transformation

In [48]:
```
dummy_vars
```

Out[48]:

	Age_18-24	Age_25-34	Age_35-44	Age_45-54	Age_55-64	Age_65+	Gender_F	Gender_M	Education_Doct de
0	False	True	False	False	False	False	False	True	
1	False	False	True	False	False	False	False	True	
2	True	False	False	False	False	False	True	False	
3	False	False	True	False	False	False	True	False	
4	False	False	False	False	False	True	True	False	
...	...	...	...	...	...	...	...	...	
1879	True	False	False	False	False	False	True	False	
1880	True	False	False	False	False	False	False	True	
1881	False	True	False	False	False	False	True	False	
1882	True	False	False	False	False	False	True	False	
1883	True	False	False	False	False	False	False	True	

1884 rows × 136 columns