Drug Consumption

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1 Introduction

Drug use is a significant risk behavior with serious health consequences for individuals and society. Multiple factors contribute to initial drug use, including psychological, social, individual, environmental, and economic elements, as well as personality traits. While legal substances like sugar, alcohol, and tobacco cause more premature deaths, illegal recreational drugs still create substantial social and personal problems.

In this data science project, we aim to identify factors and patterns potentially explaining drug use behaviors through machine learning techniques. By analyzing demographic, psychological, and social variables in our dataset, we'll aim to uncover potential predictors, use machine learning methods to understand the complex relationships surrounding drug consumption, demonstrating how machine learning can reveal insights into behavioral patterns. While our findings won't directly inform interventions, this project showcases how data-driven approaches can enhance our understanding of complex social phenomena and provide valuable practice in applying machine learning to real-world datasets.

The database contains records for 1,885 respondents with 12 attributes including personality measurements (NEO-FFI-R, BIS-11, ImpSS), demographics (education, age, gender, country, ethnicity), and self-reported usage of 18 drugs plus one fictitious drug (Semeron). Drug use is classified into seven categories ranging from "Never Used" to "Used in Last Day." All input attributes are quantified as real values, creating 18 distinct classification problems corresponding to each drug. A detailed description of the variables can be found in the Column Decsription text file.

2 Cleaning and Formatting the Dataset

2.1 Fomatting the Dataset

The original data set had all the values for most of the variables set to a random floating number representing a specific categorical value, we believe this was done in order to remove bias from the dataset. As the requirements of this project is different form the data set's original intention we had to replace these values with the original values in order to complete all the required steps for our project.

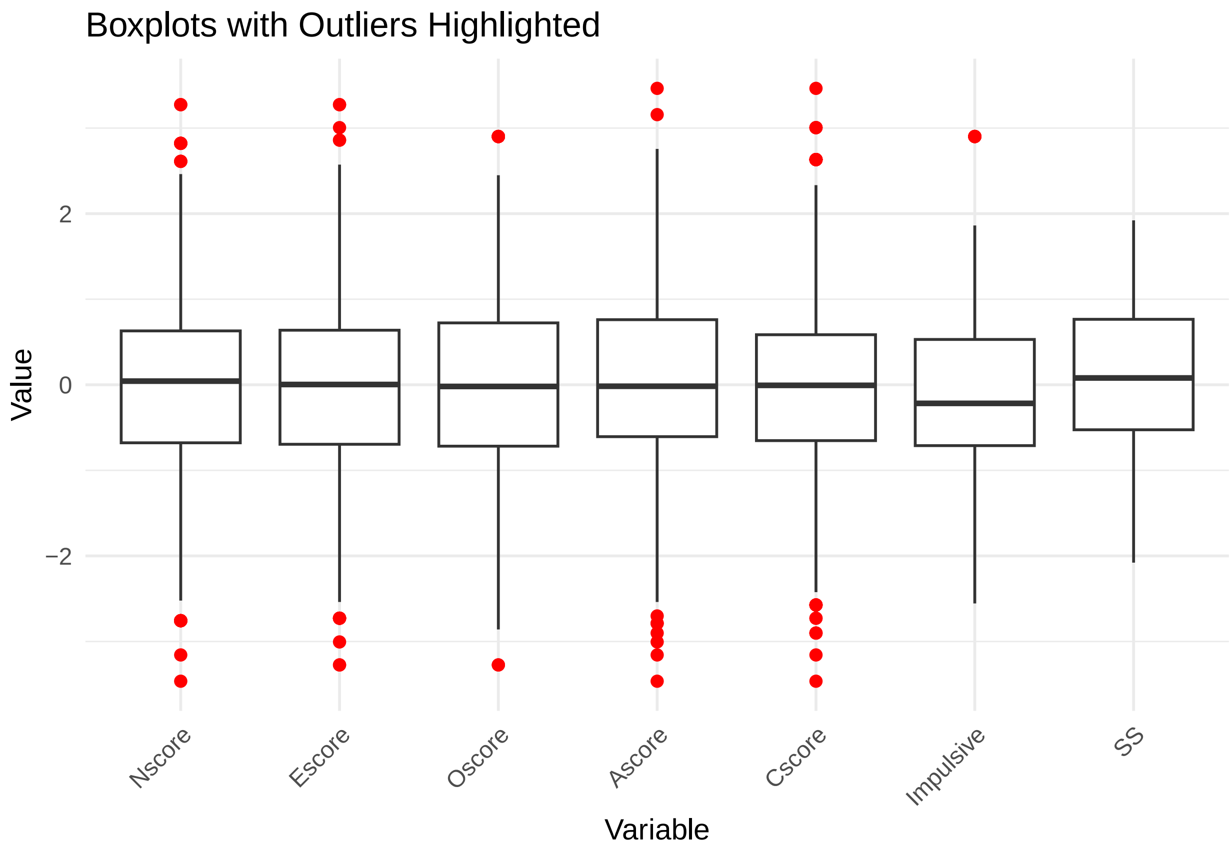
2.2 Investigating Missing Values

```
## NA values by column:

## Education Ethnicity
##        99        83
```

Only two columns contain missing values, affecting approximately 5% of the 1885 observations. Given the nature of these variables and the completeness of the rest of the data, we assume participants deliberately withheld this information. Therefore, we replaced the missing values with "Not Provided", allowing us to treat these instances as a distinct category.

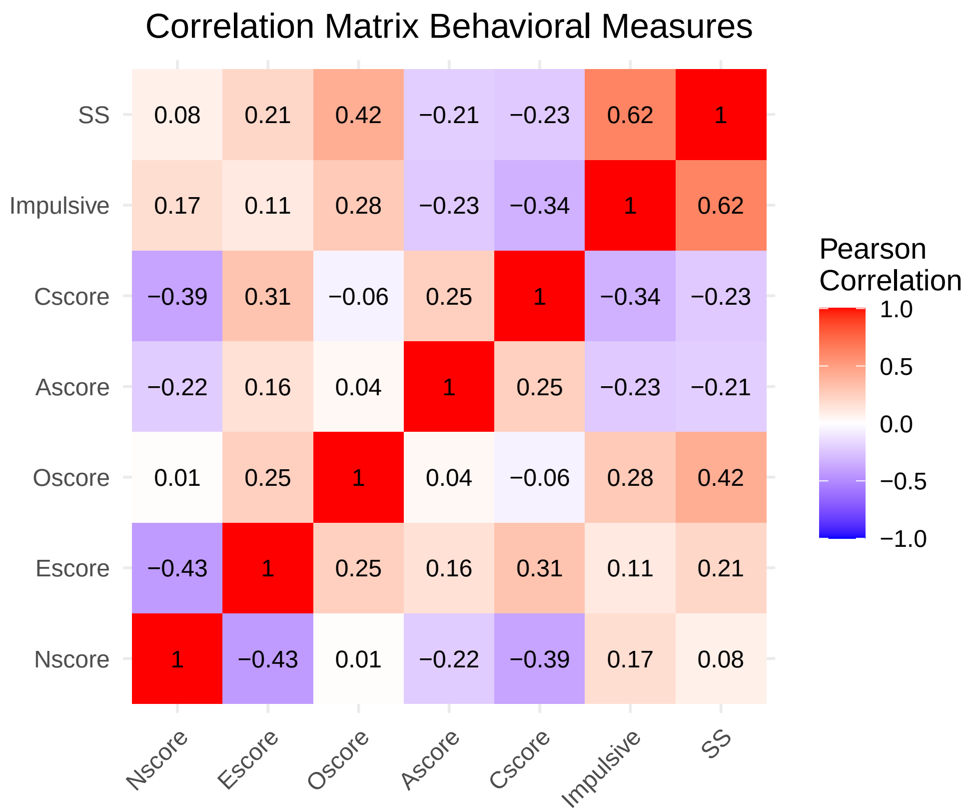
2.3 Investigating Outliers



As can be seen from the box plots our data set has some values that are outside of the upper and lower bounds. All thought these values are technically outliers they are not extreme, still fall inside of the range of our expected values and conforms to a normal distribution.

3 Exploratory Data Analysis

3.1 Correlation between Behavioral Measures



The correlation matrix shows that certain personality traits tend to cluster thougher for example SS (Sensation Seeking) has a positive correlation with Escore (Extraversion), Oscore (Openness) and Impulsive while they in turn also have positive correlations which other and a negative correlation to Cscore (Conscientiousness) and Ascore (Agreeableness) while they have a positive correlation with each other.

3.2 Comparing Behavioral Measure for Gender

The mean of all the Behavioral Measures is 0, the chart show the mean score broken down by gender for each Behavioral Measures. That chart shows that males tend to be more sensation seeking and impulsive but also more open, where females tend to be more impulsive but also more agreeable and conscientious.

3.3 Comparing Education Level with Behavioral Measures

It is not very clear at first glance but when you study the table closely it becomes clear that traits that can be precived as bad like Neuroticism, Impulsivity and Sensation Seeking is more prevelent with lower education levels inccluding Not Provided and steadily decrease as the level of education increases.

3.4 Analysis of Seremon Usage

Table 1: Semeron Usage Categories

Usage Category	**Count**	**Percentage**
Never Used	1877	99.58%
Used in Last Decade	3	0.16%
Used in Last Year	2	0.11%
Used over a Decade Ago	2	0.11%
Used in Last Month	1	0.05%

Semeron is a non exsisting drug that was introduced to the questonaire. With only 0.42% of resopndents reporting usage of Semeron. This would indicate that the survey data is likely of good quality, with most respondents providing attentive and truthful answers regarding their substance use.

4 Prepraring the Dataset for Machine Learning

Since the main focus of the project is implementing machine learning models we decided to prepare our data for this purpose. Just like we converted our original dataset to be more human readable for data exploration we have changed our dataset dataset to be more machine readable. The sex column was changed to binary data and for all the Drug columns, Education and Age we converted the data to ordinal data.

For the Ethnicity and Country columns we used a technique called One-Hot Encoding, where we transforms a categorical variable with multiple possible values into multiple binary (0 or 1) columns. Each new column represents one possible category from the original variable, and for each observation, exactly one of these new columns will have the value 1 (hence “one-hot”) while all others will be 0.

It prevents the machine learning algorithm from assuming an arbitrary numerical relationship between categories. For example, if you simply encoded “USA”=1, “UK”=2, “Canada”=3, the algorithm might incorrectly assume that “Canada” is somehow “greater than” or “three times more important than” “USA”.

5 Machine Learning Models

5.1 Linear Model

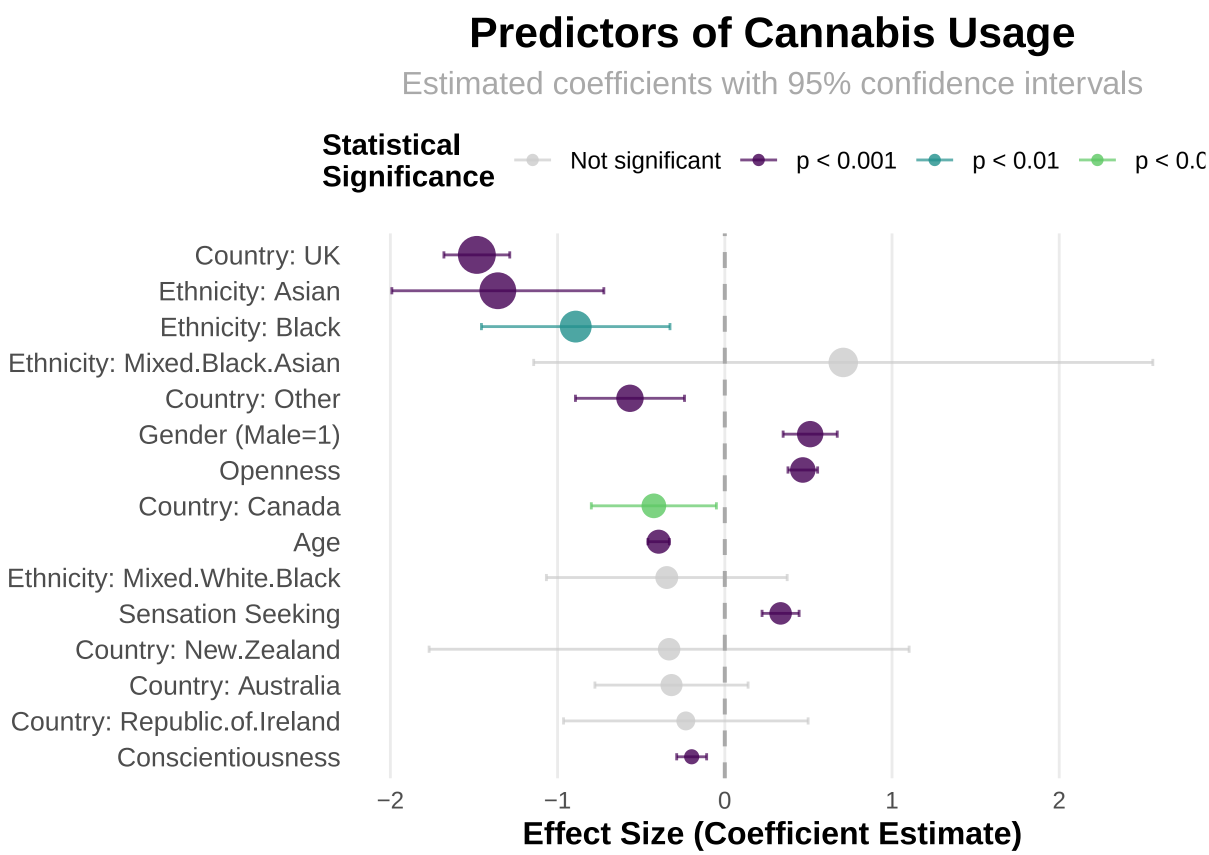
As linear regression is not the ideal model for our dataset when making predictions we decided to use linear regression to better understand what factors influences drug use and focus in the better suited models on making predictions.

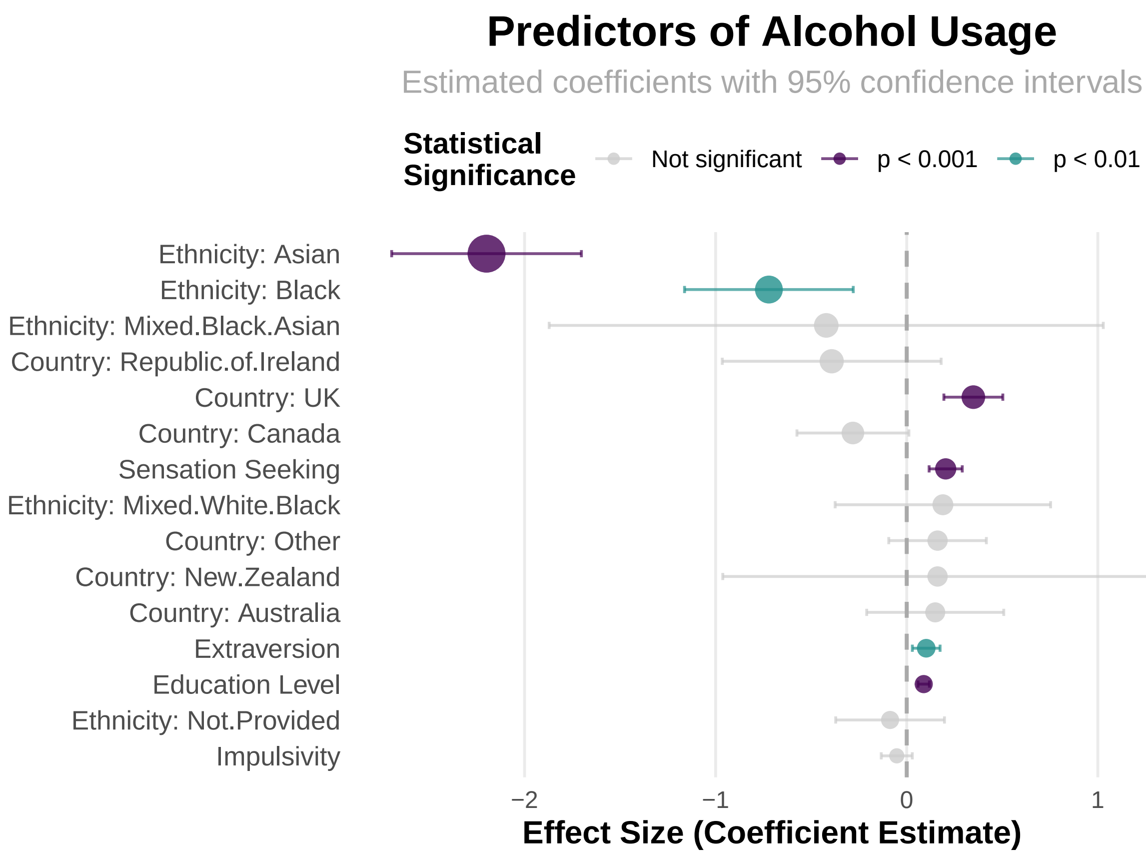
Table 2: Linear Regression Models for Drug Usage (Usage Level 0-6)

	Drug Models				
Variable	Cannabis	Alcohol	Nicotine	Coke	Ecstasy
Intercept	5.387***	3.929***	4.925***	1.588***	2.295***
Age	-0.396***	-0.031	-0.216***	-0.095***	-0.307***
Gender (Male=1)	0.511***	0.043	0.377***	0.216**	0.344***
Education Level	-0.116***	0.089***	-0.160***	-0.005	-0.026
Neuroticism	-0.112*	0.049	0.109	0.123**	-0.002
Extraversion	-0.098*	0.102**	0.009	0.113**	0.113**
Openness	0.467***	-0.040	0.158**	0.029	0.175***

Agreeableness	-0.037	-0.031	0.010	-0.144***	-0.026
Conscientiousness	-0.198***	-0.031	-0.198**	-0.095*	-0.169***
Impulsivity	0.017	-0.052	0.128	0.035	-0.003
Sensation Seeking	0.334***	0.204***	0.293***	0.272***	0.257***
N	1885	1885	1885	1885	1885
R^2	0.499	0.094	0.197	0.195	0.291
Adjusted R^2	0.494	0.083	0.188	0.186	0.283
F-statistic	88.484	9.151	21.715	21.454	36.412

Significance levels: * * p<0.05; ** p<0.01; *** p<0.001




Predictors of Alcohol Usage
Estimated coefficients with 95% confidence intervals
Statistical Significance
Not significant
p < 0.001
p < 0.01
Ethnicity: Asian
Ethnicity: Black
Ethnicity: Mixed.Black.Asian
Country: Republic.of.Ireland
Country: UK
Country: Canada
Sensation Seeking
Ethnicity: Mixed.White.Black
Country: Other
Country: New.Zealand
Country: Australia
Extraversion
Education Level
Ethnicity: Not.Provided
Impulsivity
−2
−1
0
1
Effect Size (Coefficient Estimate)

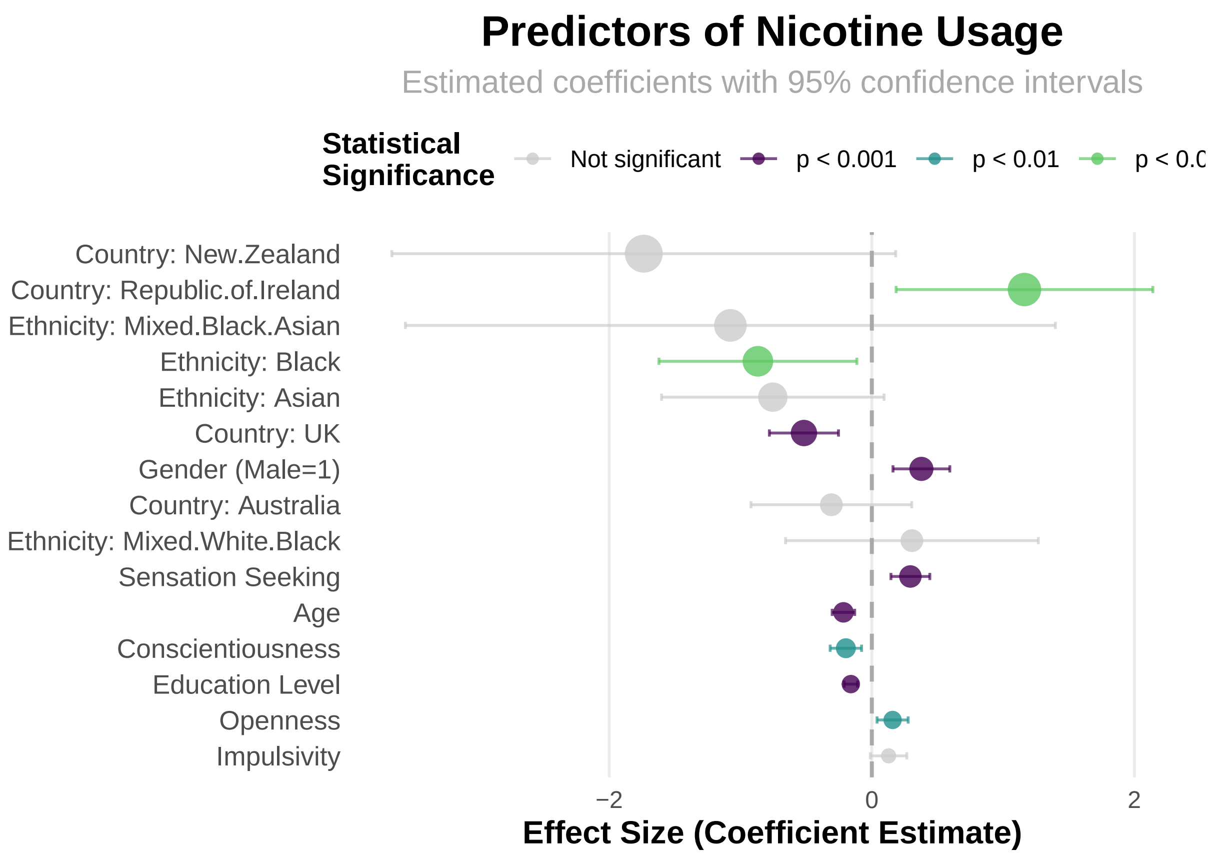


Table 3: Significant Predictors of Drug Usage

	Drug	Predictor	Coefficient	StdError	P_Value
EthnicityAsian1	Alcohol	EthnicityAsian	-2.199	0.253	<0.001
EthnicityBlack1	Alcohol	EthnicityBlack	-0.721	0.225	0.001
CountryUK1	Alcohol	CountryUK	0.349	0.079	<0.001
SS1	Alcohol	SS	0.204	0.044	<0.001
Escore1	Alcohol	Escore	0.102	0.037	0.006
Education1	Alcohol	Education	0.089	0.015	<0.001
CountryUK	Cannabis	CountryUK	-1.483	0.100	<0.001
EthnicityAsian	Cannabis	EthnicityAsian	-1.357	0.323	<0.001
EthnicityBlack	Cannabis	EthnicityBlack	-0.892	0.288	0.002
CountryOther	Cannabis	CountryOther	-0.567	0.166	<0.001
Gender	Cannabis	Gender	0.511	0.083	<0.001
Oscore	Cannabis	Oscore	0.467	0.045	<0.001
CountryCanada	Cannabis	CountryCanada	-0.424	0.191	0.026
Age	Cannabis	Age	-0.396	0.033	<0.001
SS	Cannabis	SS	0.334	0.057	<0.001
Cscore	Cannabis	Cscore	-0.198	0.046	<0.001
Education	Cannabis	Education	-0.116	0.019	<0.001
Nscore	Cannabis	Nscore	-0.112	0.046	0.015
Escore	Cannabis	Escore	-0.098	0.047	0.038
EthnicityAsian2	Coke	EthnicityAsian	-0.642	0.271	0.018
CountryUK3	Coke	CountryUK	-0.448	0.084	<0.001

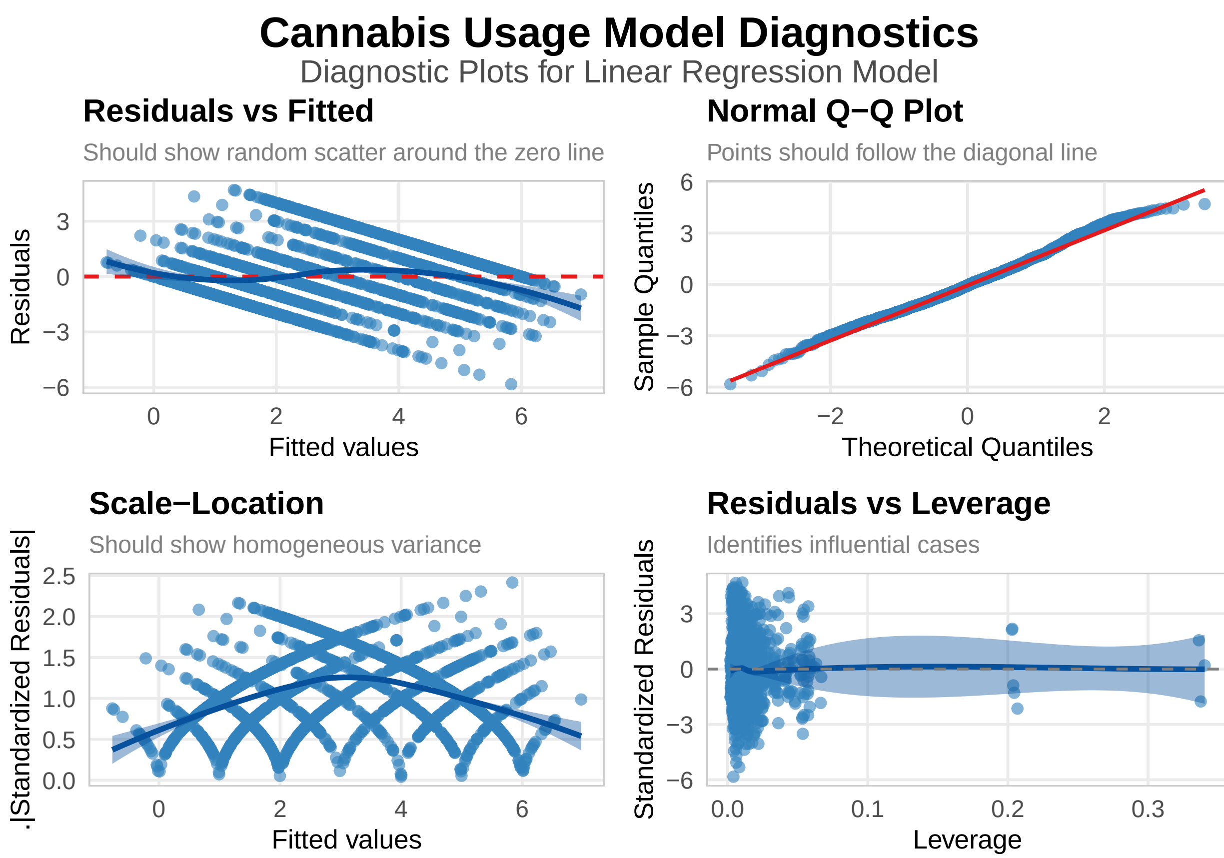
CountryOther1	Coke	CountryOther	-0.405	0.140	0.004
SS3	Coke	SS	0.272	0.047	<0.001
Gender2	Coke	Gender	0.216	0.069	0.002
Ascore	Coke	Ascore	-0.144	0.035	<0.001
Nscore1	Coke	Nscore	0.123	0.039	0.001
Escore2	Coke	Escore	0.113	0.040	0.005
Age2	Coke	Age	-0.095	0.027	<0.001
Cscore2	Coke	Cscore	-0.095	0.038	0.013
EthnicityMixed.Black.Asian	Ecstasy	EthnicityMixed.Black.Asian	-1.885	0.810	0.02
EthnicityBlack3	Ecstasy	EthnicityBlack	-0.536	0.247	0.03
CountryAustralia	Ecstasy	CountryAustralia	0.449	0.200	0.025
CountryUK4	Ecstasy	CountryUK	-0.429	0.086	<0.001
Gender3	Ecstasy	Gender	0.344	0.071	<0.001
Age3	Ecstasy	Age	-0.307	0.028	<0.001
SS4	Ecstasy	SS	0.257	0.048	<0.001
Oscore2	Ecstasy	Oscore	0.175	0.039	<0.001
Cscore3	Ecstasy	Cscore	-0.169	0.039	<0.001
Escore3	Ecstasy	Escore	0.113	0.041	0.005
CountryRepublic.of.Ireland	Nicotine	CountryRepublic.of.Ireland	1.162	0.499	0.02
EthnicityBlack2	Nicotine	EthnicityBlack	-0.868	0.384	0.024
CountryUK2	Nicotine	CountryUK	-0.517	0.134	<0.001
Gender1	Nicotine	Gender	0.377	0.110	<0.001
SS2	Nicotine	SS	0.293	0.076	<0.001
Age1	Nicotine	Age	-0.216	0.044	<0.001
Cscore1	Nicotine	Cscore	-0.198	0.061	0.001
Education2	Nicotine	Education	-0.160	0.026	<0.001
Oscore1	Nicotine	Oscore	0.158	0.060	0.009

```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: `stat_contour()`: Zero contours were generated
```

```
## Warning in min(x): no non-missing arguments to min; returning Inf
```

```
## Warning in max(x): no non-missing arguments to max; returning -Inf
```




```
## TableGrob (2 x 1) "arrange": 2 grobs
##   z     cells    name            grob
## 1 1 (1-1,1-1) arrange gtable[arrange]
## 2 2 (2-2,1-1) arrange gtable[arrange]
```

```
##
## ======= SUMMARY OF DRUG CONSUMPTION ANALYSIS =======
```

```
## Linear regression models were fit for 5 drugs
```

```
## The best-fitting model was for Cannabis with Adjusted R² = 0.494
##
## Key personality traits predicting drug use:
## -  Nscore : significant predictor for 2 drugs
## -  Escore : significant predictor for 4 drugs
## -  Oscore : significant predictor for 3 drugs
## -  Ascore : significant predictor for 1 drugs
## -  Cscore : significant predictor for 4 drugs
## -  SS : significant predictor for 5 drugs
```

6 Source

https://archive.ics.uci.edu/dataset/373/drug+consumption+quantified