

# 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 Description text file.

## 2 Cleaning and formatting the dataset

### 2.1 Fomattting 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.

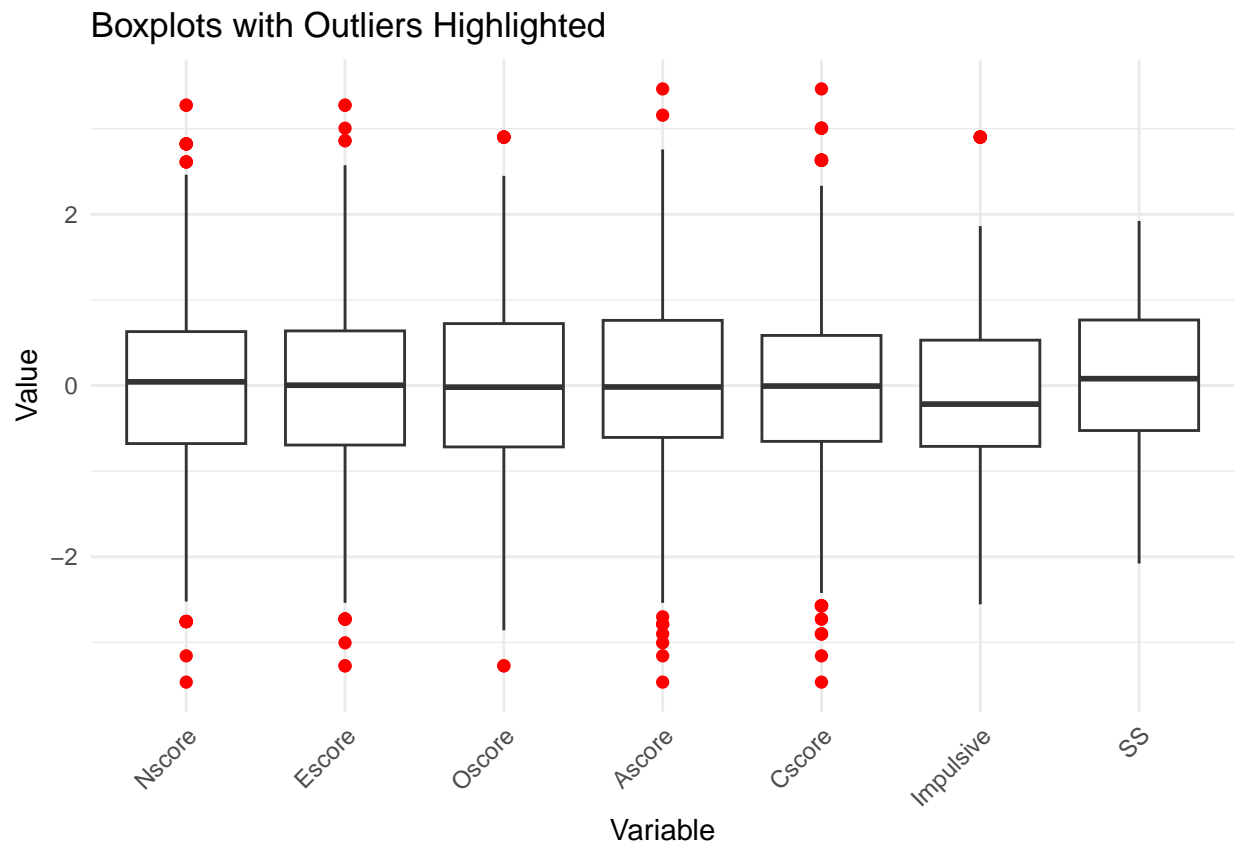
### 2.2 Investigating missing values

```
## 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.

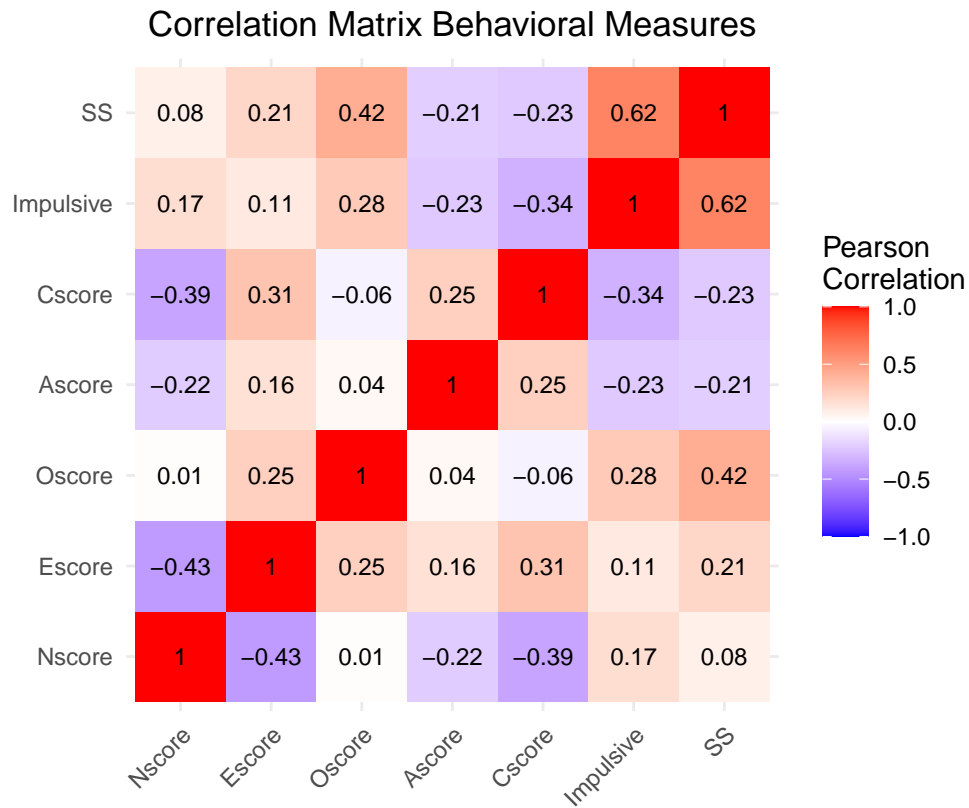
## 2.3 Investigating outliers



As can be seen from the box plots our data set has some values that are outside of the upper and lower bounds. All though 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 together. For example, SS (Sensation Seeking) has a positive correlation with Escore (Extraversion), Oscore (Openness) and Impulsive, while they in turn also have positive correlations with each other and a negative correlation to Cscore (Conscientiousness) and Ascore (Agreeableness).

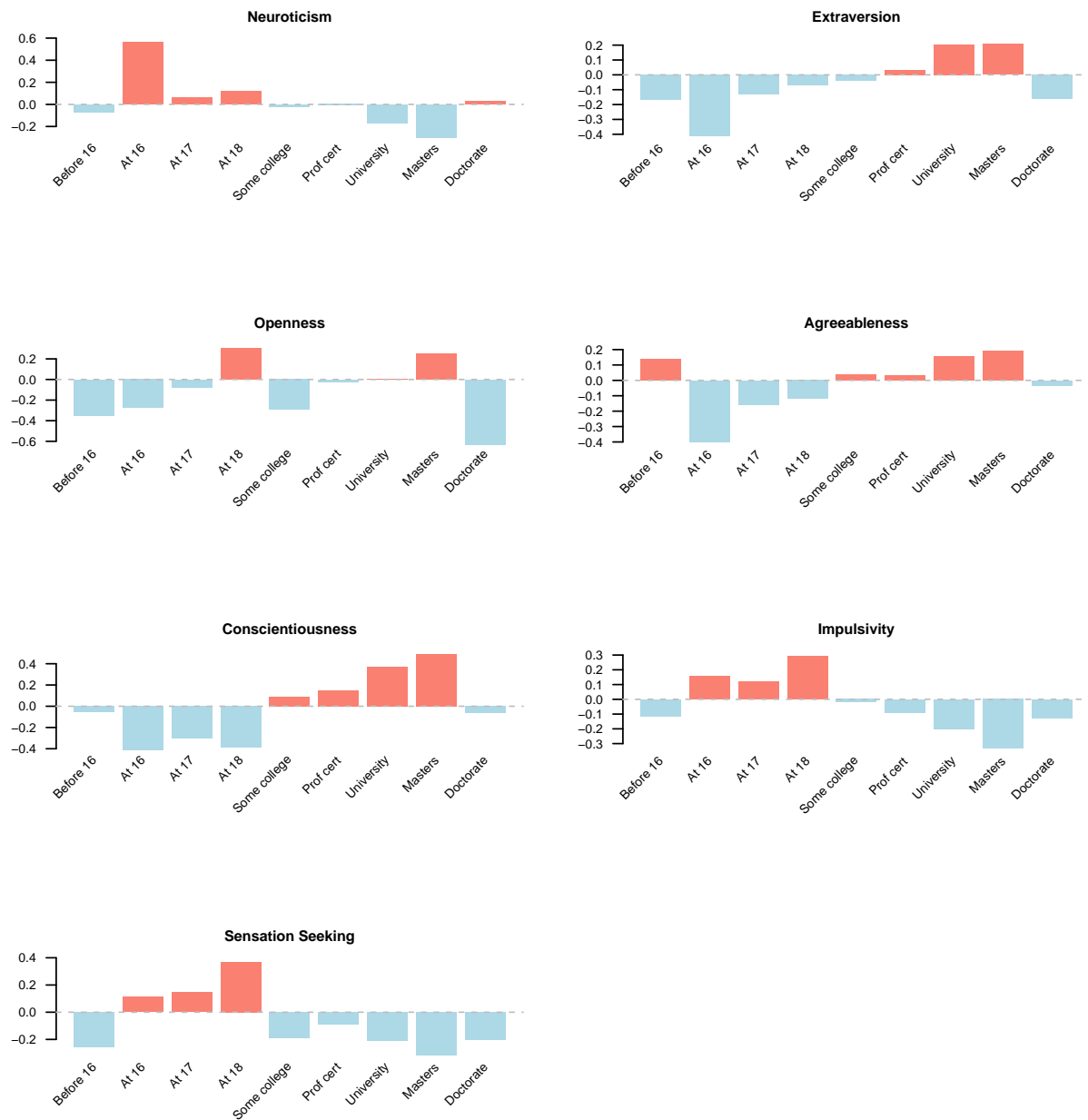
### 3.2 Comparing Behavioral Measure For Gender



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

#### Personality Traits by Education Level



It is not very clear at first glance but when you study the table closely it becomes clear that traits that can be perceived as bad like Neuroticism, Impulsivity and Sensation Seeking is more prevalent with lower education levels including 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%      |

Seremon is a non existing drug that was introduced to the questionnaire. With only 0.42% of respondents 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 Source

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