

Data Set

More informations: https://archive.ics.uci.edu/ml/datasets/Drug+consumption+%28quantified%29

5 Demographic Features

- Age
- Gender
- Education

- Country
- Ethnicity

7 Personality Features

- Neuroticism
- Extraversion
- Openness to experience

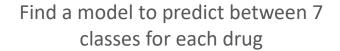
- Agreeableness
- Conscientiousness
- Impulsiveness
- Sensation seeking

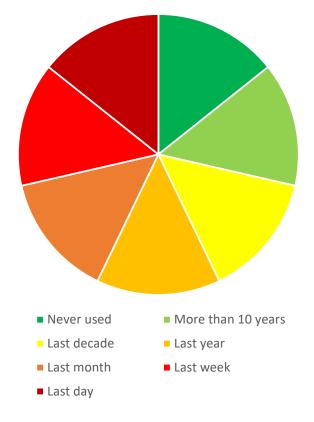
19 Drug Consumption targets

- Alcohol
- Amphetamines
- Amyl nitrite
- Benzodiazepine
- Caffeine
- Chocolate
- Cocaïne
- Crack
- Ecstasy
- Heroin

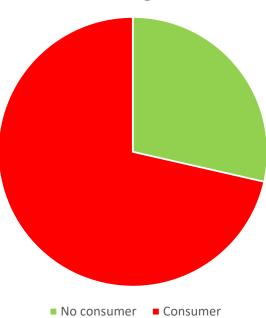
- Ketamine
- Legal highs
- Lysergic acid diethylamide
- Methadone
- Magic mushrooms
- Nicotine
- Volatile substance abuse
- Fictitious drug Semeron*

*note: that last drug is ficticious: it will be removed from the dataset as well as the participants who lied about it Problems we'll try to solve





Find a model to predict between 2 classes for each drug



Variables created

Dataframes

- **df**: contains all the dataset from the csv file
- **df_drugs**: contains all the 7 definitions of the classes (replacing 0 by 'Never used', etc.)
- **df corr**: correlation matrix of the dataframe
- **Y_drugs**: contains a binary value for each drug column: 0 for 'not user' and 1 for 'user'

Lists

- **demographic**: names of the demographic columns
- personality : names of the personality columns
- drugs: names of the drug consumption columns
- age_cat : scaled values of ages converted to category values
- gender_cat: scaled values of genders converted to category values
- education_cat : scaled values of educations converted to category values
- country_cat: scaled values of countries converted to category values
- **ethnicity cat**: scaled values of ethnicities converted to category values
- **algos**: dictionnary containing classification algorithmes we will use, and their parameters we will try
- **ests**: result of the function *predict all consumptions*

Functions

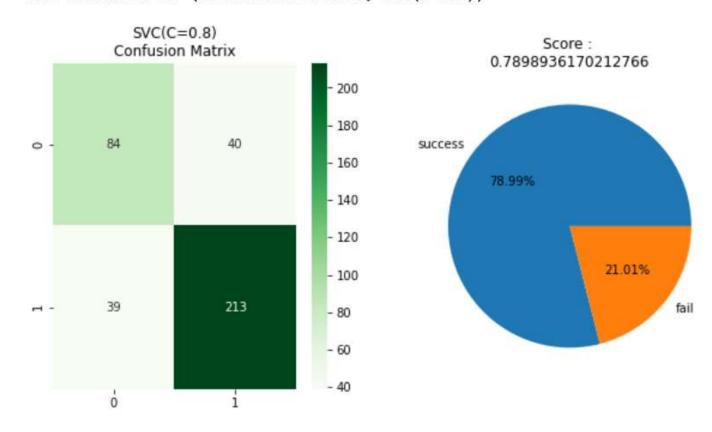
- **frequency_plots**: function to give for each column of a dataframe, a pie chart and a barplot of value counts
- plot_and_table : function to give for a given column of a dataframe, a pie chart, a barplot and a tab of value counts
- test_algo: applies a gridsearchcv and returns the best estimator and best score
- classifiers_test: returns a list of estimators for each algorithmes
- **disp_scores**: plot a confusion matrix and a pie chart of the success rate
- predict_all_consumptions : returns list of the best estimator for each target of the problem

Predicting consumer / not consumer

→ For each drug, we take the 6 most correlated features with the target and we try some algorithmes with different parameters, and we display the best estimator for each algorithm, the the best of them, and we display the confusion matrix and success rate between real test values and predicted test values. Then we save the estimator.

Cannabis consumption

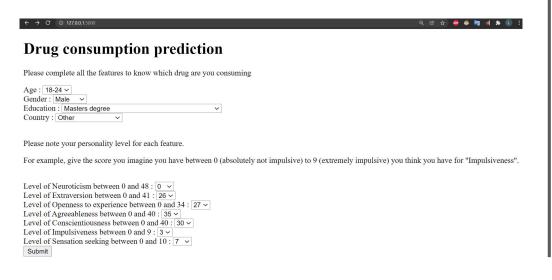
KNeighborsClassifier fitted, with score: 0.7961461794019933 SVC fitted, with score: 0.8127906976744186 LogisticRegression fitted, with score: 0.8108017718715393 RidgeClassifier fitted, with score: 0.8074706533776302 Best estimator is (0.8127906976744186, SVC(C=0.8))



API: Flask

Remarks: In the home page, you can choose some features and give yourself a score of your personality characters. When you submit, the API predicts if you are a drug consumer for each drug with the best model we saved in the notebook.

If there is an error when you press submit button, try to run app.py with anaconda



```
According to the model, there is 96.4% of chance that you ARE a Alcohol consumer
According to the model, there is 73.22% of chance that you ARE NOT a Amphetamines consumer
According to the model, there is 80.41% of chance that you ARE NOT a Amyl nitrite consumer
According to the model, there is 71.35% of chance that you ARE NOT a Benzodiazepine consumer
According to the model, there is 98.0% of chance that you ARE a Caffeine consumer
According to the model, there is 81.35% of chance that you ARE a Cannabis consumer
According to the model, there is 98.2% of chance that you ARE a Chocolate consumer
According to the model, there is 69.69% of chance that you ARE NOT a Cocaine consumer
According to the model, there is 90.14% of chance that you ARE NOT a Crack consumer
According to the model, there is 74.02% of chance that you ARE a Ecstasy consumer
According to the model, there is 89.07% of chance that you ARE NOT a Heroin consumer
According to the model, there is 81.55% of chance that you ARE NOT a Ketamine consumer
According to the model, there is 78.75% of chance that you ARE a Legal highs consumer
According to the model, there is 81.35% of chance that you ARE a Lysergic acid diethylamide consumer
According to the model, there is 80.41% of chance that you ARE NOT a Methadone consumer
According to the model, there is 77.95% of chance that you ARE a Magic mushrooms consumer
According to the model, there is 73.22% of chance that you ARE a Nicotine consumer
According to the model, there is 88.28% of chance that you ARE NOT a Volatile substance abuse consumer
```