

PYTHON FOR DATA ANALYSIS

DRUG CONSUMPTION ANALYSIS AND PREDICTION

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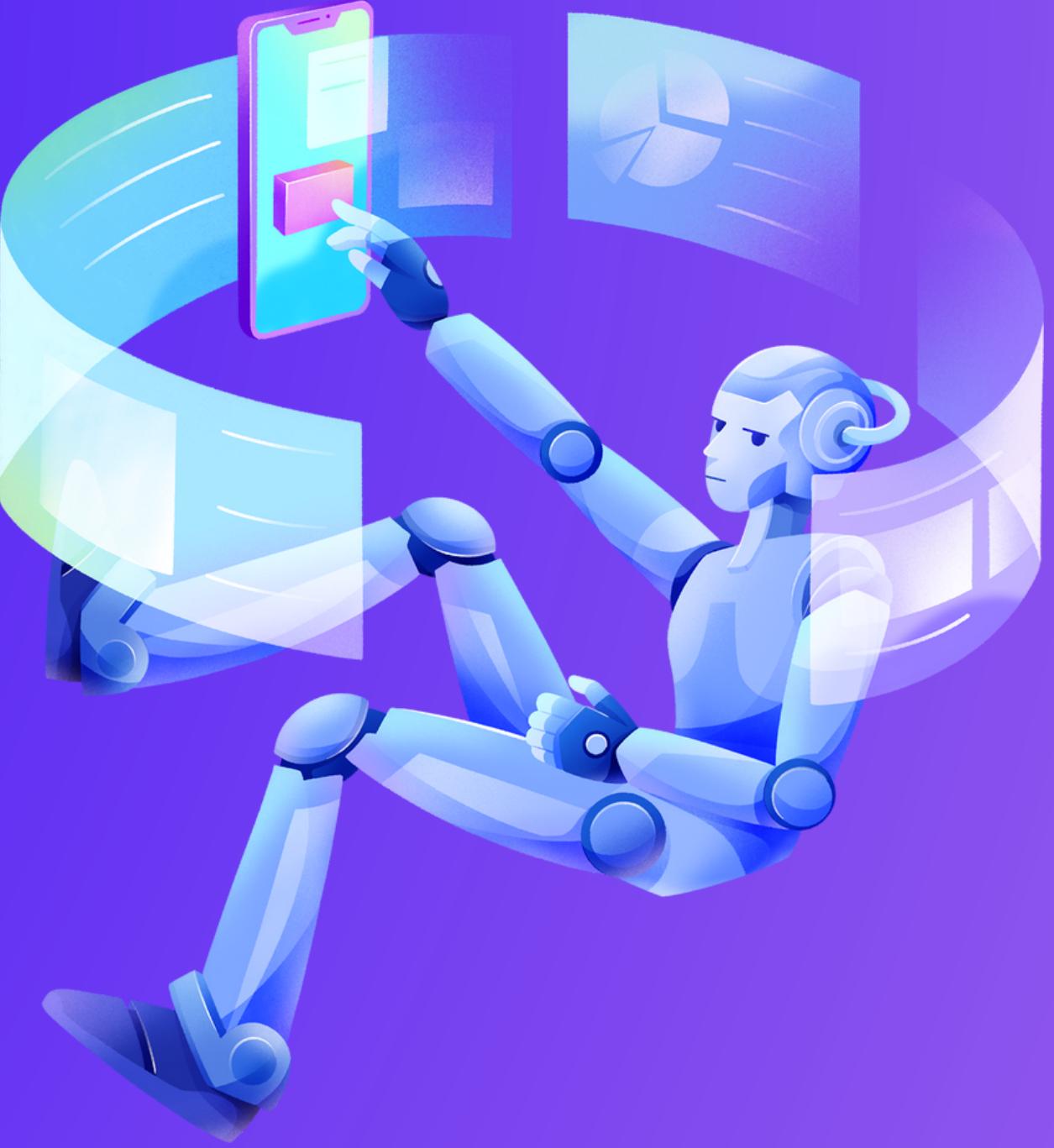
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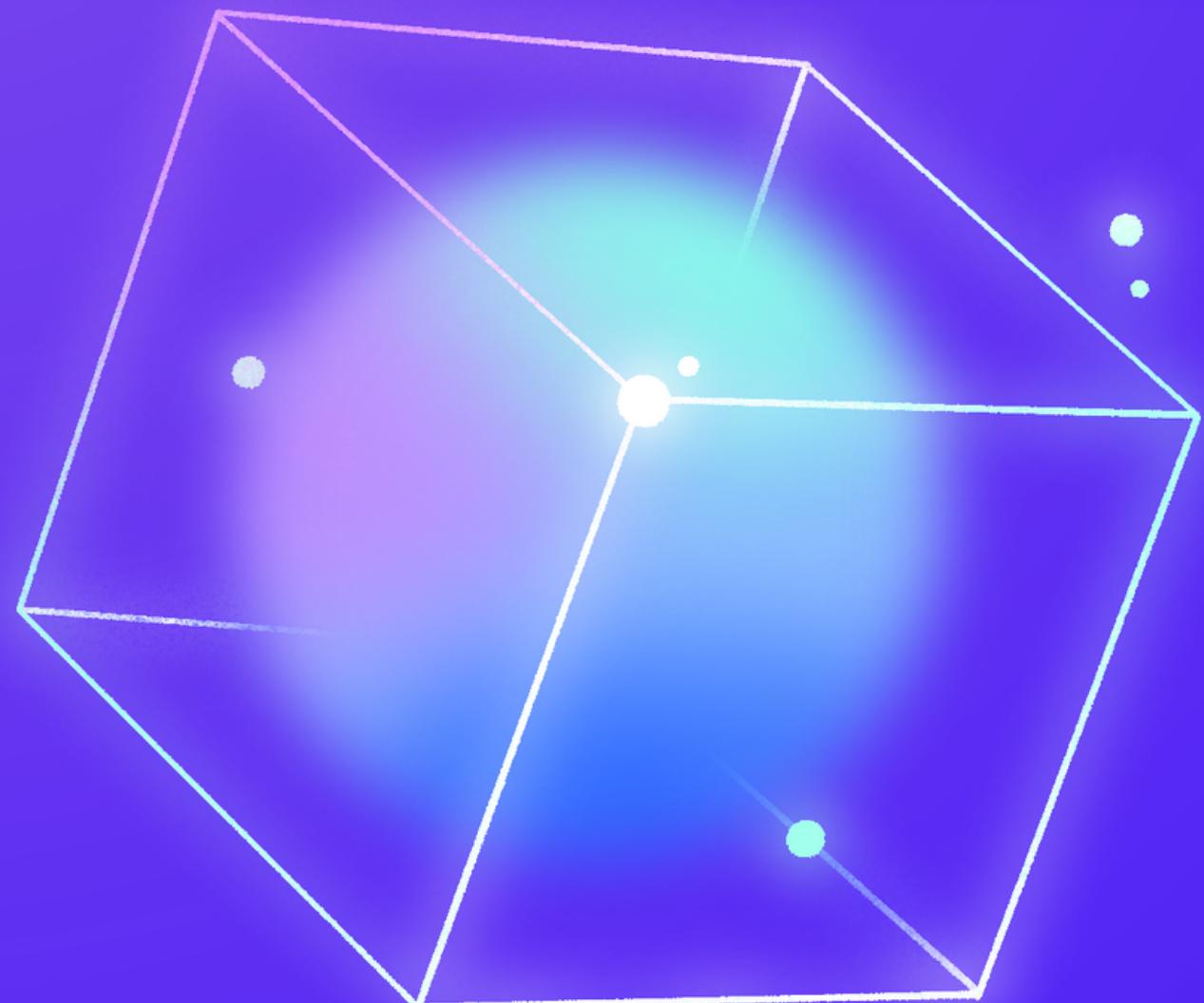


INTRODUCTION

- Developing a model to forecast drug consumption patterns
- Examining demographic, psychological, physical, and educational attributes to understand their influence on drugs use
- Demonstration of statistical relationships between contributing factors and drug use.



DATA PREPROCESSING



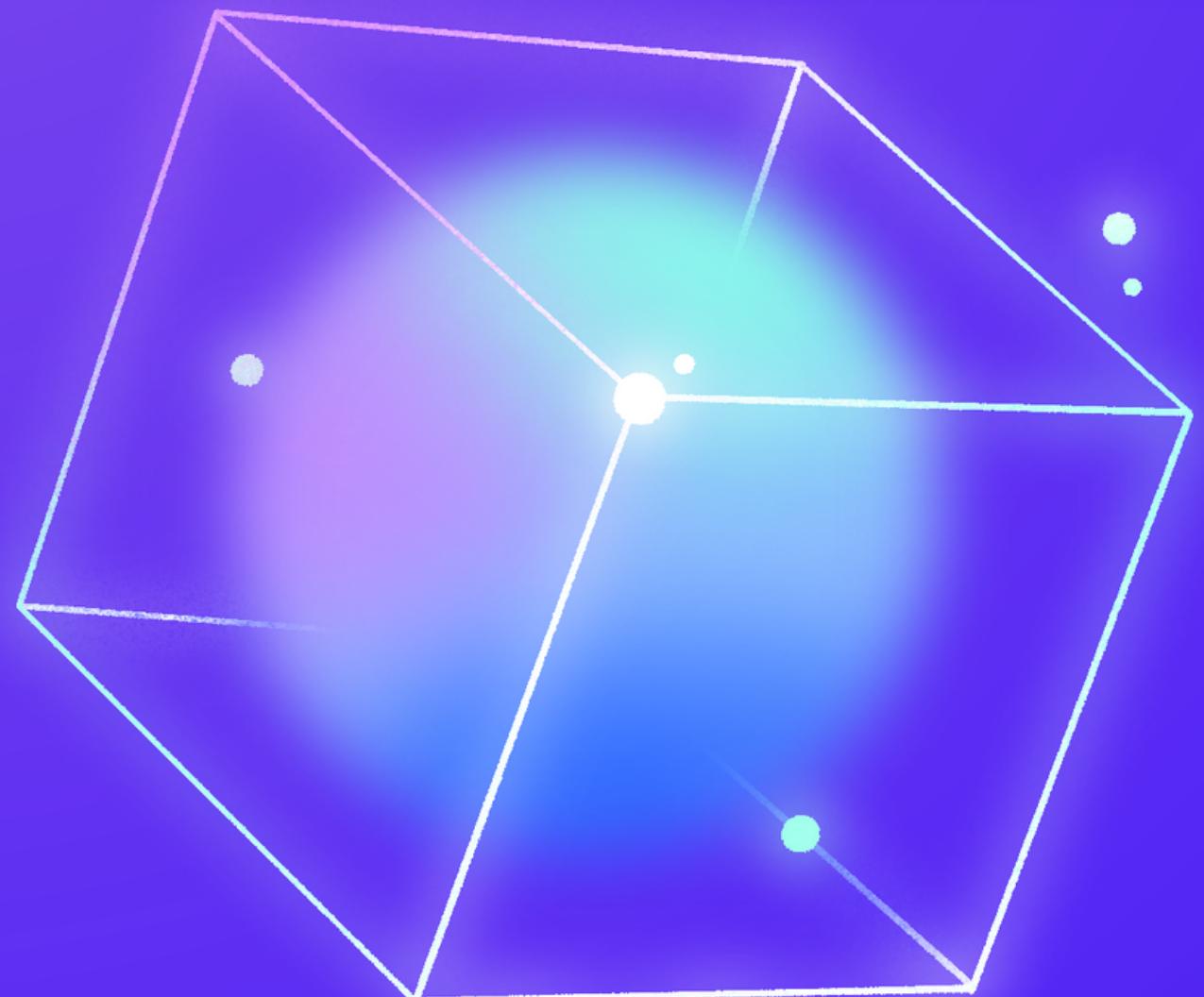
Objective

To prepare and refine a comprehensive dataset for analysis.

Approach

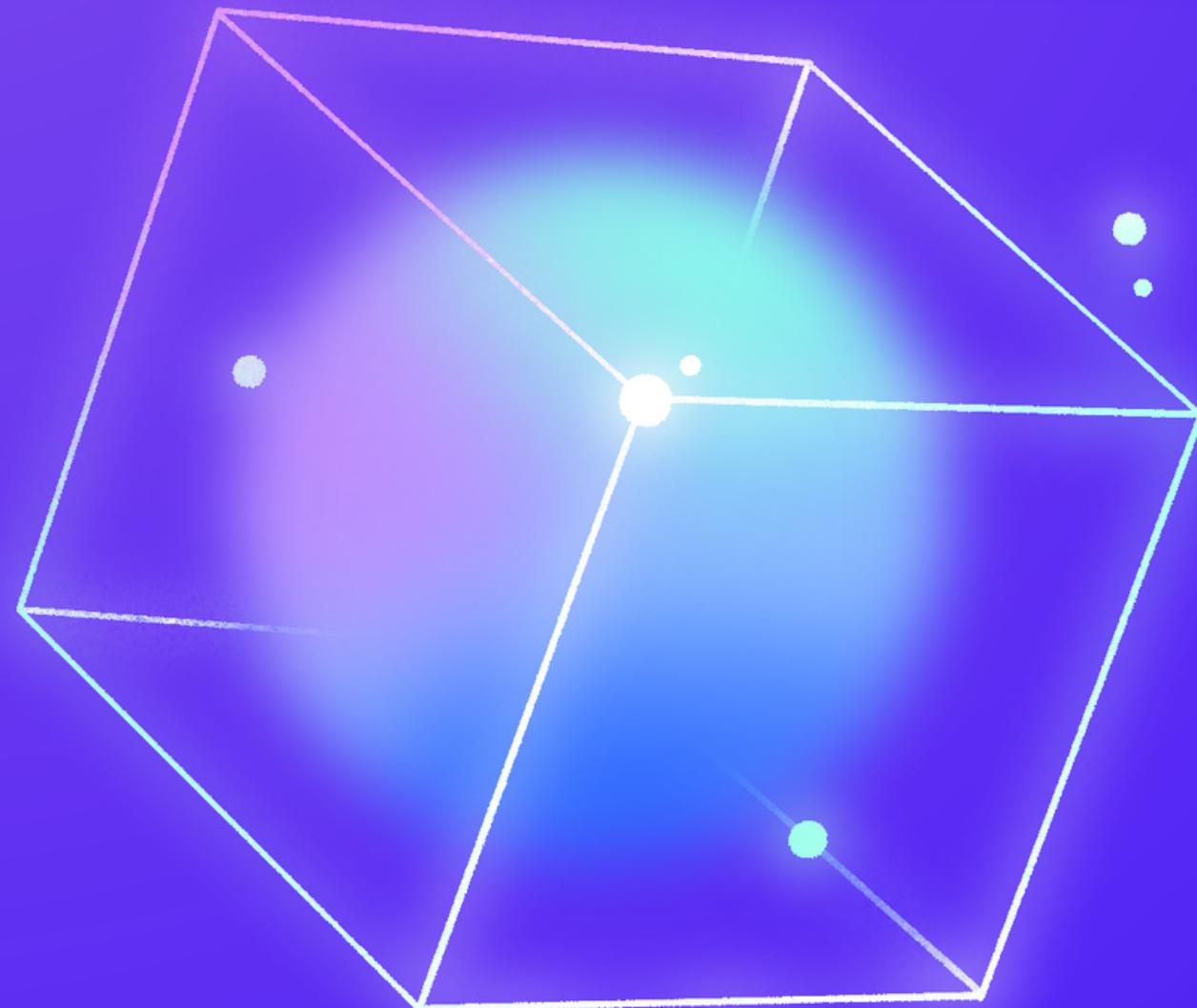
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DATA PREPROCESSING



Feature	Description
ID	Identification
Age	Age range of participant
Gender	Male or Female
Education	Level of education
Country	Country of origin
Ethnicity	Ethnicity/Race of participant
Nscore	Quantified NEO Five-Factor Inventory Neuroticism score
Escore	Quantified NEO Five-Factor Inventory Extraversion score
Oscore	Quantified NEO Five-Factor Inventory Openness to experience score
Ascore	Quantified NEO Five-Factor Inventory Agreeableness score
Cscore	Quantified NEO Five-Factor Inventory Conscientiousness score
Impulsive	Quantified BIS-11 impulsiveness score
SS	Quantified Impulsive Sensation Seeking score
Drug	Various drugs were examined and measured in terms of frequency of use

DATA PREPROCESSING



ACTIONS REALIZED ON THE DATA

- SET THE COLUMN'S TITLES
- CHECK FOR MISSING VALUES
- CHECK FOR DUPLICATE VALUES
- SET THE DATA LABELS

DATA VISUALISATION



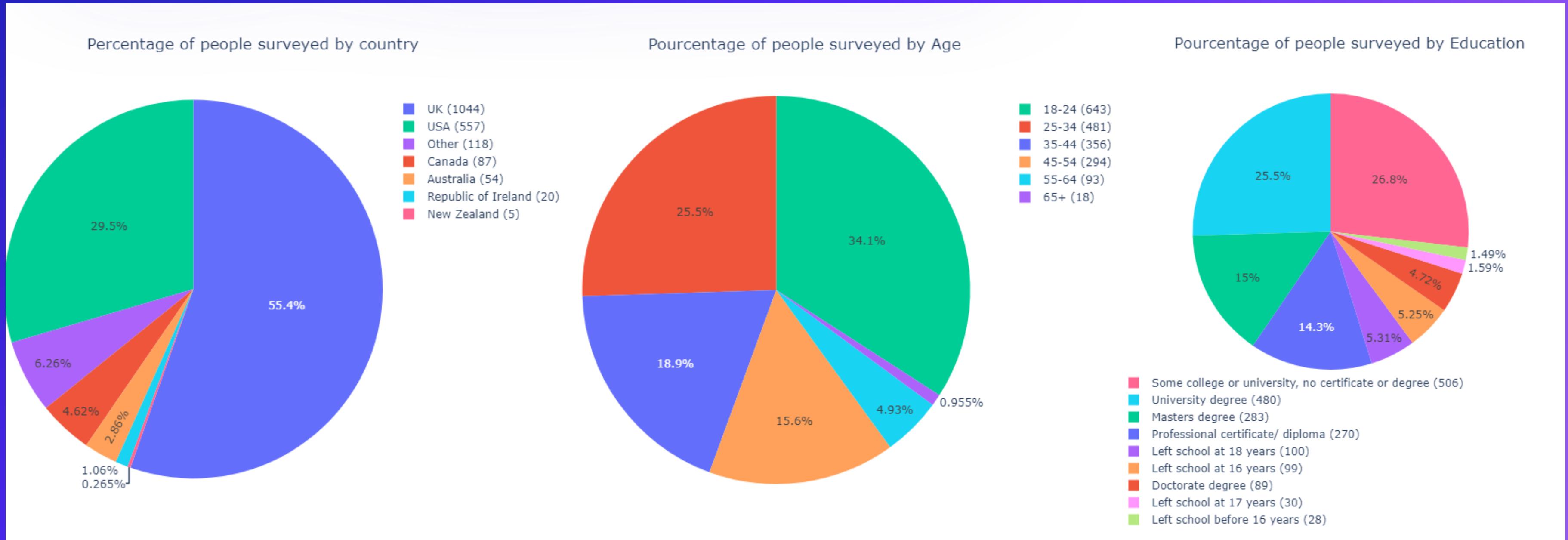
Objective

To translate the dataset into understandable and insightful visual formats.

Approach

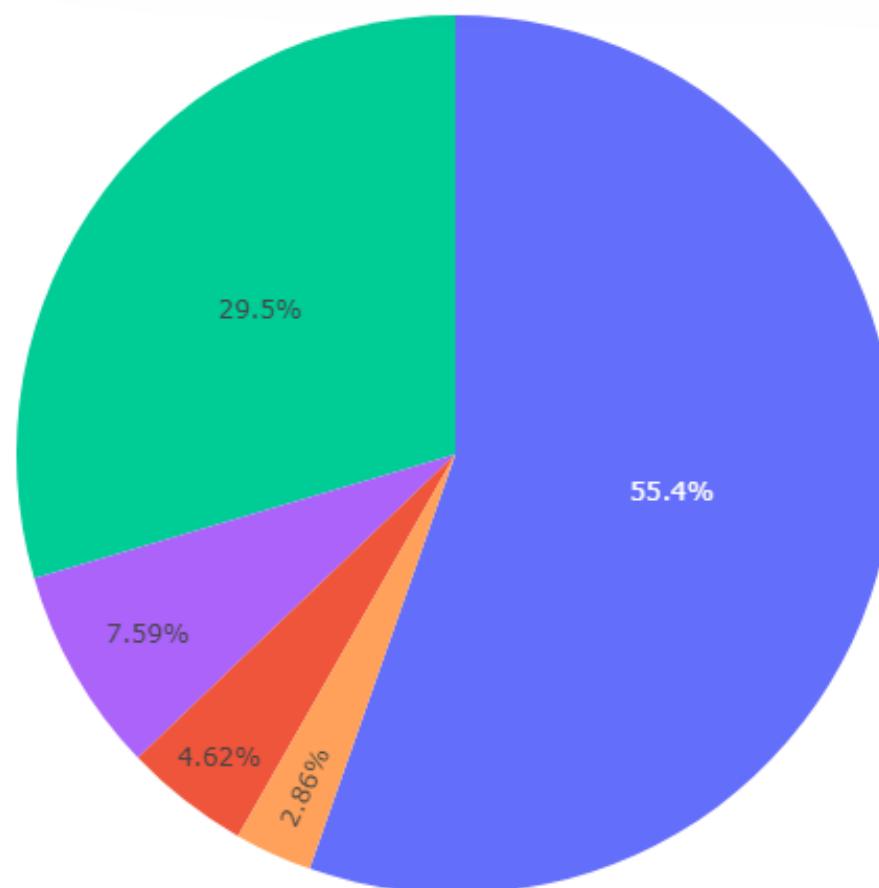
We aim to uncover hidden trends and patterns, making the data accessible and interpretable for both technical and non-technical audiences.

DATA VISUALISATION

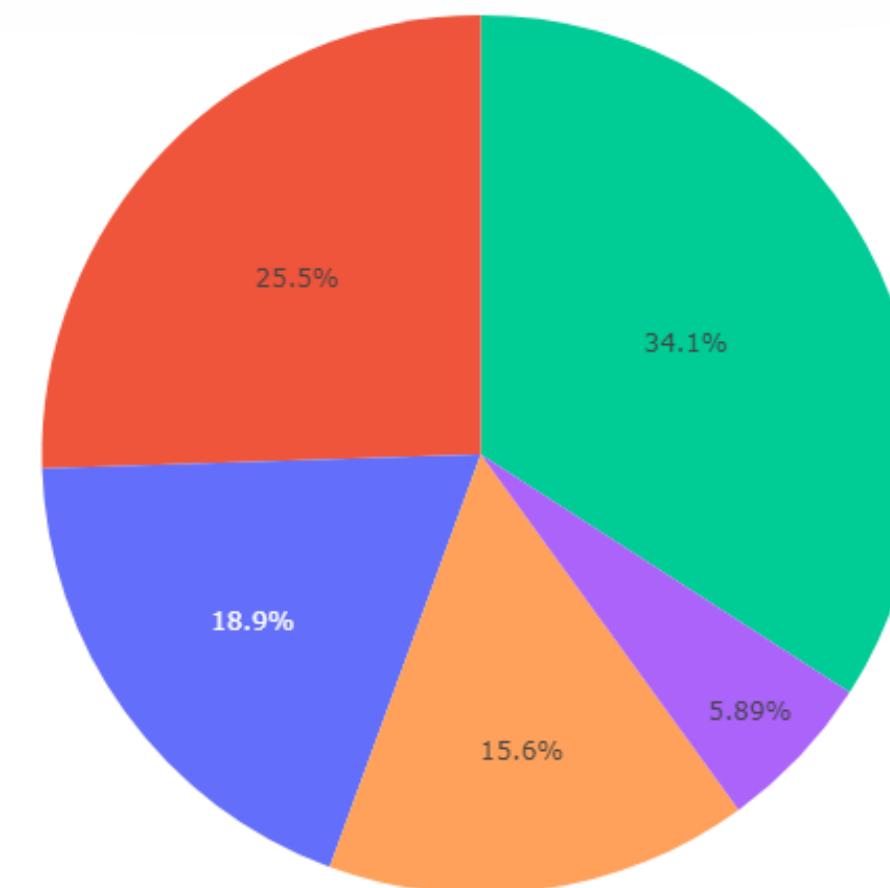


DATA VISUALISATION AFTER REARRANGEMENT

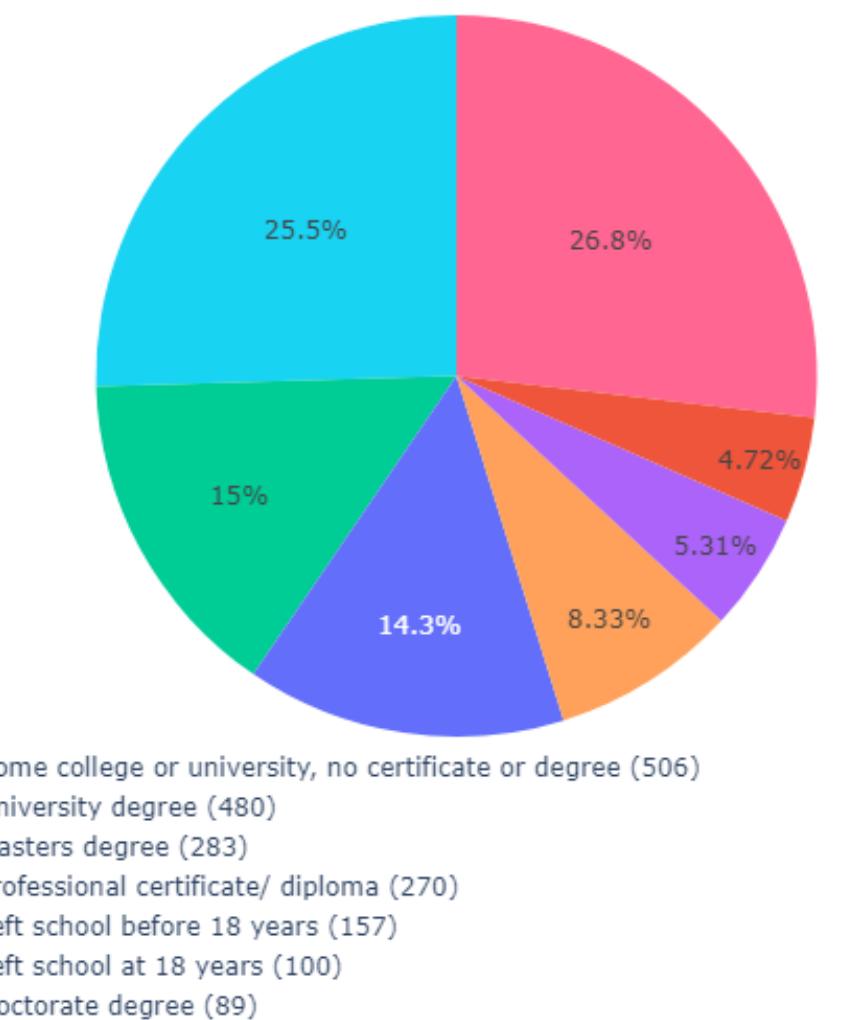
Pourcentage of people surveyed by country



Pourcentage of people surveyed by Age

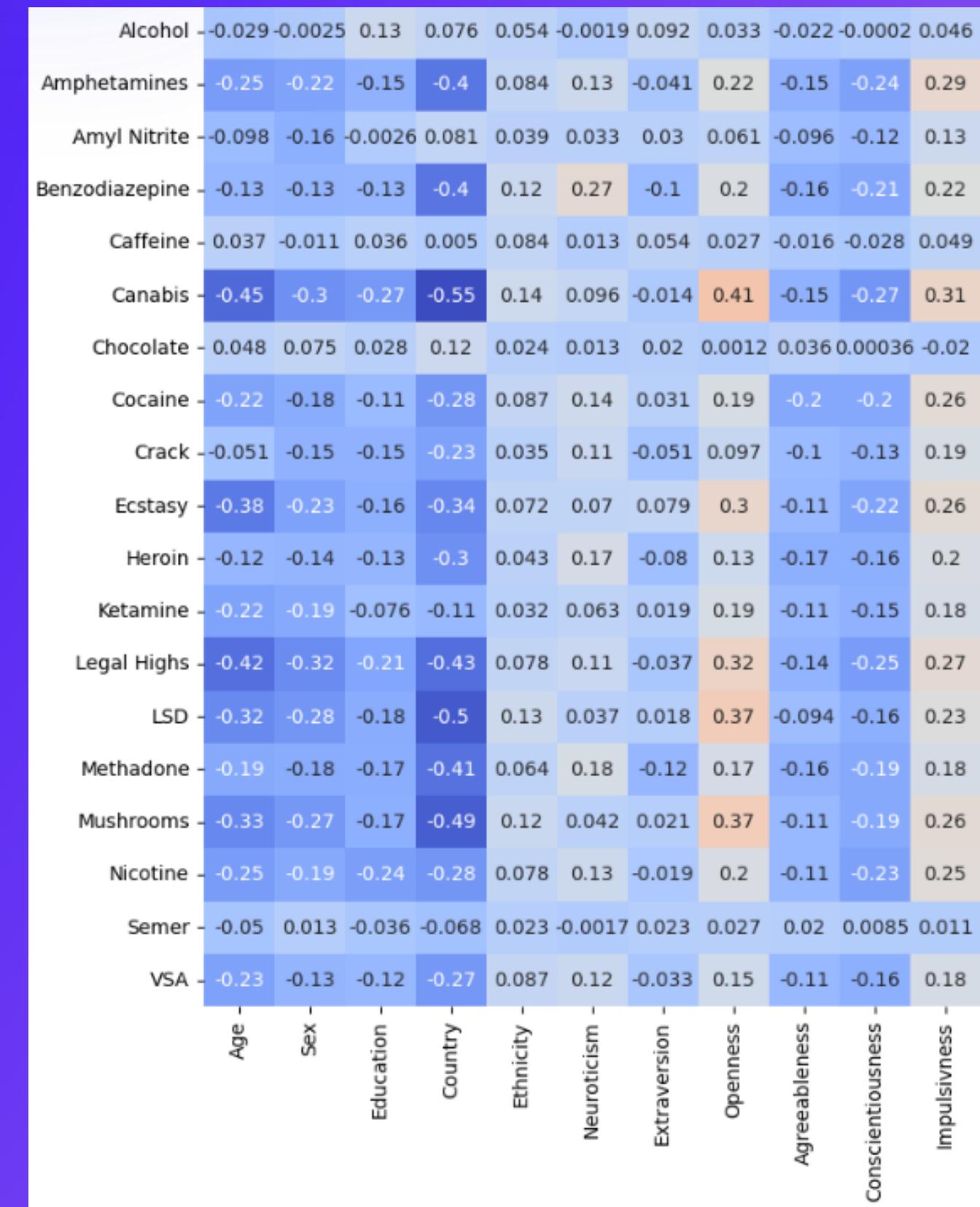


Pourcentage of people surveyed by Education

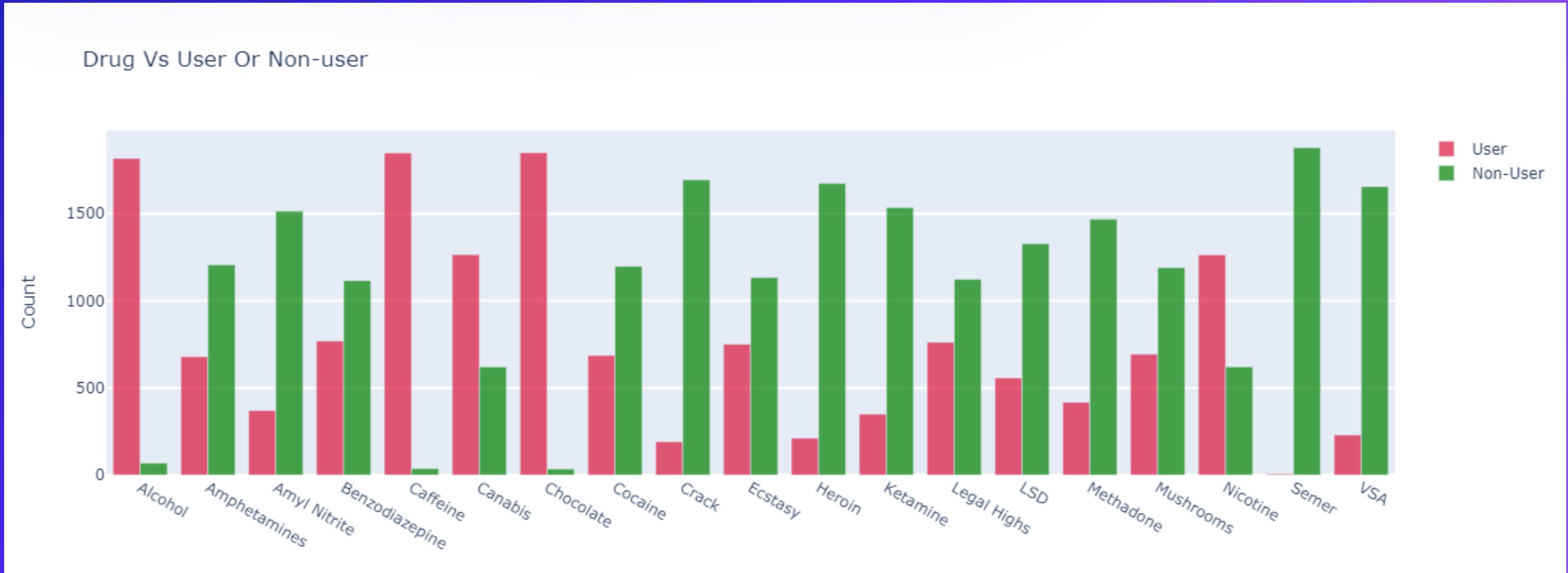


DATA VISUALISATION

Heat Map Showing the relations between
the social situation data and the drugs
consumption data



DATA VISUALISATION



DATA PREDICTION



Objective

To predict future drug consumption patterns using machine learning.

Approach

We apply RandomForestClassifier, LabelEncoder and binary encoding.

DATA PREDICTION :

DRUG USE PREDICTION MODEL BASED ON DEMOGRAPHIC, PSYCHOLOGICAL, PHYSICAL AND EDUCATIONAL FACTORS.

Profile features :

Age

Sex

Education

Country

Ethnicity

Neuroticism

Extraversion

Openness

Agreeableness

Conscientiousness

Prediction of drug consumption :

Alcohol

Amphetamines

Amyl Nitrite

Benzodiazepine

Caffeine

Canabis

Chocolate

Cocaine

Crack

Ecstasy

Heroin

Ketamine

Legal Highs

LSD Methadone

Mushrooms

Nicotine Semer

VSA

DATA PREDICTION : EXAMPLE

Profile features

Profile: Age 35-44

Sex Female

Education Professional diploma

Country UK

Ethnicity Mixed-White/Asian

Neuroticism Average

Neuroticism

Extraversion Average

Openness Average Openness

Agreeableness Average

Conscientiousness Average

Probability of having take at least one :

Alcohol: 99.50%

Amphetamines: 87.57%

Amyl Nitrite: 8.16%

Benzodiazepine: 81.85%

Caffeine: 100.00%

Canabis: 16.32%

Chocolate: 98.83%

Cocaine: 4.00%

Crack: 0.00%

Ecstasy: 2.36%

Heroin: 1.00%

Ketamine: 1.53%

Legal Highs: 2.95%

LSD: 1.83%

Methadone: 0.00%

Mushrooms: 2.30%

Nicotine: 86.50%

Semer: 0.00%

VSA: 4.25%

DATA PREDICTION :

DRUG USE PREDICTION MODEL BASED ON DEMOGRAPHIC, PSYCHOLOGICAL, PHYSICAL AND EDUCATIONAL FACTORS.

Precision for Alcohol: 99.46%

Precision for Amphetamines: 86.76%

Precision for Amyl Nitrite: 84.77%

Precision for Benzodiazepine: 88.10%

Precision for Caffeine: 99.62%

Precision for Cannabis: 93.40%

Precision for Chocolate: 99.52%

Precision for Cocaine: 84.54%

Precision for Crack: 90.24%

Precision for Ecstasy: 87.12%

Precision for Heroin: 92.34%

Precision for Ketamine: 86.88%

Precision for Legal Highs: 90.34%

Precision for LSD: 88.35%

Precision for Methadone: 83.49%

Precision for Mushrooms: 87.69%

Precision for Nicotine: 90.86%

Precision for Semer: 100.00%

Precision for VSA: 84.85%

Average Precision: 90.44%

DATA PREDICTION :

DRUG USE PREDICTION MODEL WITH COMMON DRUGS (ALCOHOL, CAFFEINE, CHOCOLATE, NICOTINE)

Profile features

Age Nicotine
Sex Chocolate
Education Caffeine
Country Alcohol
Ethnicity
Neuroticism
Extraversion
Openness
Agreeableness
Conscientiousness

Prediction of drug consumption

Amphetamines Mushrooms Nicotine
Amyl Nitrite Semer VSA
Benzodiazepine
Canabis
Cocaine
Ecstasy
Heroin
Ketamine
Legal Highs
LSD Methadone

DATA PREDICTION : EXAMPLE

DRUG USE PREDICTION MODEL WITH COMMON DRUGS (ALCOHOL, CAFFEINE, CHOCOLATE, NICOTINE)

Profile features

Age 35-44

Sex Female

Education Professional diploma

Country UK

Ethnicity Mixed-White/Asian

Neuroticism Average

Neuroticism

Extraversion Average

Openness Average Openness

Agreeableness Average

Conscientiousness Average

Alcohol Used in Last Week Caffeine

Used in Last Day Nicotine Used in

Last Decade Chocolate Used in
Last Week

Probability of having take at least one time :

Amphetamines: 84.00%

Amyl Nitrite: 9.00%

Benzodiazepine: 86.00%

Cannabis: 15.00%

Cocaine: 11.00%

Crack: 1.00%

Ecstasy: 9.00%

Heroin: 1.00%

Ketamine: 10.00%

Legal Highs: 5.00%

LSD: 8.00%

Methadone: 0.00%

Mushrooms: 7.00%

Semer: 0.00%

VSA: 8.00%

DATA PREDICTION :

DRUG USE PREDICTION MODEL WITH COMMON DRUGS (ALCOHOL, CAFFEINE, CHOCOLATE, NICOTINE)

Precision for Amphetamines: 92.70%

Precision for Amyl Nitrite: 94.24%

Precision for Benzodiazepine: 93.87%

Precision for Cannabis: 97.00%

Precision for Cocaine: 92.40%

Precision for Crack: 95.59%

Precision for Ecstasy: 92.11%

Precision for Heroin: 96.30%

Precision for Ketamine: 94.63%

Precision for Legal Highs: 94.17%

Precision for LSD: 92.87%

Precision for Methadone: 92.94%

Precision for Mushrooms: 93.44%

Precision for Semer: 100.00%

Precision for VSA: 94.81%

Average Precision: 94.47%

DATA PREDICTION :

DETERMINING THE BEST MODEL AND FEATURES

After standardizing the values in the heatmap and not taking into account specific features

Alcohol	-0.493926	Amphetamines	-0.411966
Age	-0.370167	Amyl Nitrite	0.130753
Sex	0.364151	Benzodiazepine	-0.413322
Education	0.086219	Caffeine	0.356214
Country	-0.053963	Cocaine	0.146659
Ethnicity	-0.366489	Crack	-0.468818
Neuroticism	0.161909	Ecstasy	0.056900
Extraversion	-0.478270	Heroin	-0.545480
Agreeableness	0.252624	Ketamine	0.013752
Conscientiousness	5.254320	LSD	-0.287919
Sensation Seeing	-0.357074	Methadone	-0.799265
Alcohol	-0.006619	Nicotine	-0.558521
		Semer	

DATA PREDICTION :

THREE MODELS

Random Forest Classifier

```
rf_params = {'n_estimators': [50, 100, 150],  
             'max_depth': [None, 10, 20]  
            , 'min_samples_split': [2, 5, 10],  
            'min_samples_leaf': [1, 2, 4]}
```

Scalable Linear Support Vector Machine

```
svc_params = {'C': [0.1, 1, 10],  
              'kernel': ['linear', 'rbf'],  
              'gamma': ['scale', 'auto']}
```

K-Neighbors Classifier

```
knn_params = {'n_neighbors':[3, 5, 7], 'weights':['uniform', 'distance']}
```

Drug	RFF	Best_params_rff
Alcohol	0.94164456	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 150}
Amphetamine	0.9204244	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}
Amyl Nitrite	0.93633952	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
Benzodiazepin	0.9469496	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 150}
Caffeine	0.95490716	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 150}
Canabis	0.93633952	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 150}
Chocolate	0.94429708	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Cocaine	0.92307692	{'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 50}
Crack	0.98143236	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}
Ecstasy	0.95225464	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 150}
Heroin	0.96816976	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Ketamine	0.95490716	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Legal Highs	0.90981432	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 150}
LSD	0.9602122	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 150}
Methadone	0.94960212	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}
Mushrooms	0.96816976	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 150}
Nicotine	0.92572944	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 150}
Semer	0.99734748	{'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
VSA	0.9469496	{'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 50}

Drug	KNN	Best_params_knn
Alcohol	0.59681698	{'n_neighbors': 5, 'weights': 'uniform'}
Amphetamine	0.71618037	{'n_neighbors': 7, 'weights': 'uniform'}
Amyl Nitrite	0.76392573	{'n_neighbors': 7, 'weights': 'distance'}
Benzodiazepin	0.75331565	{'n_neighbors': 3, 'weights': 'distance'}
Caffeine	0.76657825	{'n_neighbors': 3, 'weights': 'distance'}
Canabis	0.63925729	{'n_neighbors': 7, 'weights': 'distance'}
Chocolate	0.60212202	{'n_neighbors': 7, 'weights': 'uniform'}
Cocaine	0.72148541	{'n_neighbors': 5, 'weights': 'distance'}
Crack	0.89655172	{'n_neighbors': 3, 'weights': 'distance'}
Ecstasy	0.71618037	{'n_neighbors': 5, 'weights': 'distance'}
Heroin	0.90981432	{'n_neighbors': 3, 'weights': 'distance'}
Ketamine	0.85676393	{'n_neighbors': 5, 'weights': 'distance'}
Legal Highs	0.73474801	{'n_neighbors': 7, 'weights': 'distance'}
LSD	0.73740053	{'n_neighbors': 5, 'weights': 'distance'}
Methadone	0.85676393	{'n_neighbors': 5, 'weights': 'distance'}
Mushrooms	0.65517241	{'n_neighbors': 7, 'weights': 'distance'}
Nicotine	0.6259947	{'n_neighbors': 7, 'weights': 'distance'}
Semer	0.99734748	{'n_neighbors': 3, 'weights': 'uniform'}
VSA	0.80901857	{'n_neighbors': 5, 'weights': 'distance'}

Drug	SVC	Best_params_svc
Alcohol	1	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Amphetamine	1	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
Amyl Nitrite	0.98143236	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Benzodiazepin	1	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
Caffeine	0.99469496	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Canabis	1	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
Chocolate	0.99734748	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Cocaine	0.99734748	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Crack	0.98938992	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
Ecstasy	1	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Heroin	1	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Ketamine	0.99204244	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Legal Highs	1	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
LSD	0.99469496	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Methadone	1	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}
Mushrooms	1	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
Nicotine	1	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
Semer	0.99734748	{'C': 0.1, 'gamma': 'scale', 'kernel': 'linear'}
VSA	0.9867374	{'C': 1, 'gamma': 'scale', 'kernel': 'linear'}

DATA PREDICTION :

CLASS REPORTS COMPARISON ON ALCOHOL

RF VS KN

	Model 1	Model 2	Difference
<hr/>			
precision	0.94	0.58	0.36
recall	0.94	0.6	0.33999999999999997
f1-score	0.93	0.58	0.35000000000000001

RF VS SVC

	Model 1	Model 2	Difference
<hr/>			
precision	0.94	0.92	0.01999999999999997
recall	0.94	0.94	0.0
f1-score	0.93	0.93	0.0

KN VS SVC

	Model 1	Model 2	Difference
<hr/>			
precision	0.58	0.92	-0.34000000000000001
recall	0.6	0.94	-0.33999999999999997
f1-score	0.58	0.93	-0.35000000000000001

FLASK



Objective

Create an intuitive application to use our predictive model and display our visualizations.

Approach

We redid our preprocessing and modifying dataframes steps to be able to properly re-use our visualizations and percentage prediction model.

FLASK :

APPLICATION FOR PREDICTING DRUG USE BASED ON DEMOGRAPHIC, PSYCHOLOGICAL, PHYSICAL AND EDUCATIONAL FACTORS.

Drug Usage Form

Age Range: 18-24

Sex: Male

Education: Left school before 18 years

Country: Canada

Ethnicity: Asian

Neuroticism: Low

Extraversion: Low

Openness: Low

Agreeableness: Low

Conscientiousness: Low

Impulsiveness: Low

Sensation Seeing: Low

[Computing](#) [Country Average](#)

[Data Visualization](#)

FLASK :

RESULTS OF PREDICTION

Prediction Result

Alcohol: 71.0%

Amphetamines: 42.0%

Amyl Nitrite: 20.0%

Benzodiazepine: 36.0%

Caffeine: 84.7333333333333%

Canabis: 68.0%

Chocolate: 84.0%

Cocaine: 33.3333333333336%

Crack: 18.0%

Ecstasy: 40.0%

Heroin: 13.0%

Ketamine: 42.0%

Legal Highs: 51.0%

LSD: 31.0%

Methadone: 40.0%

Mushrooms: 36.0%

Nicotine: 50.0%

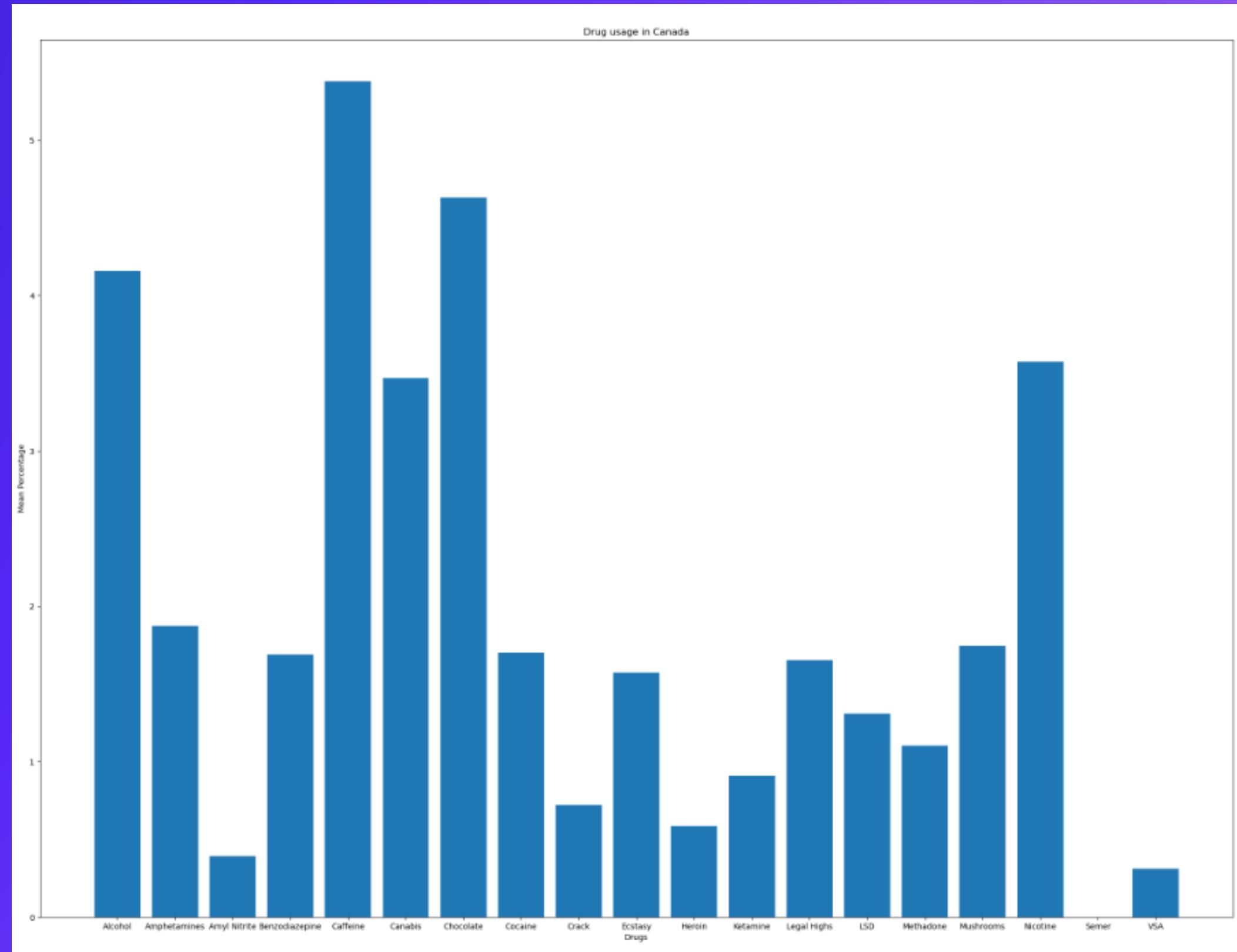
Semer: 14.00000000000002%

VSA: 34.0%

FLASK : VISUALIZATIONS

Drug Usage Graph

Select a country:



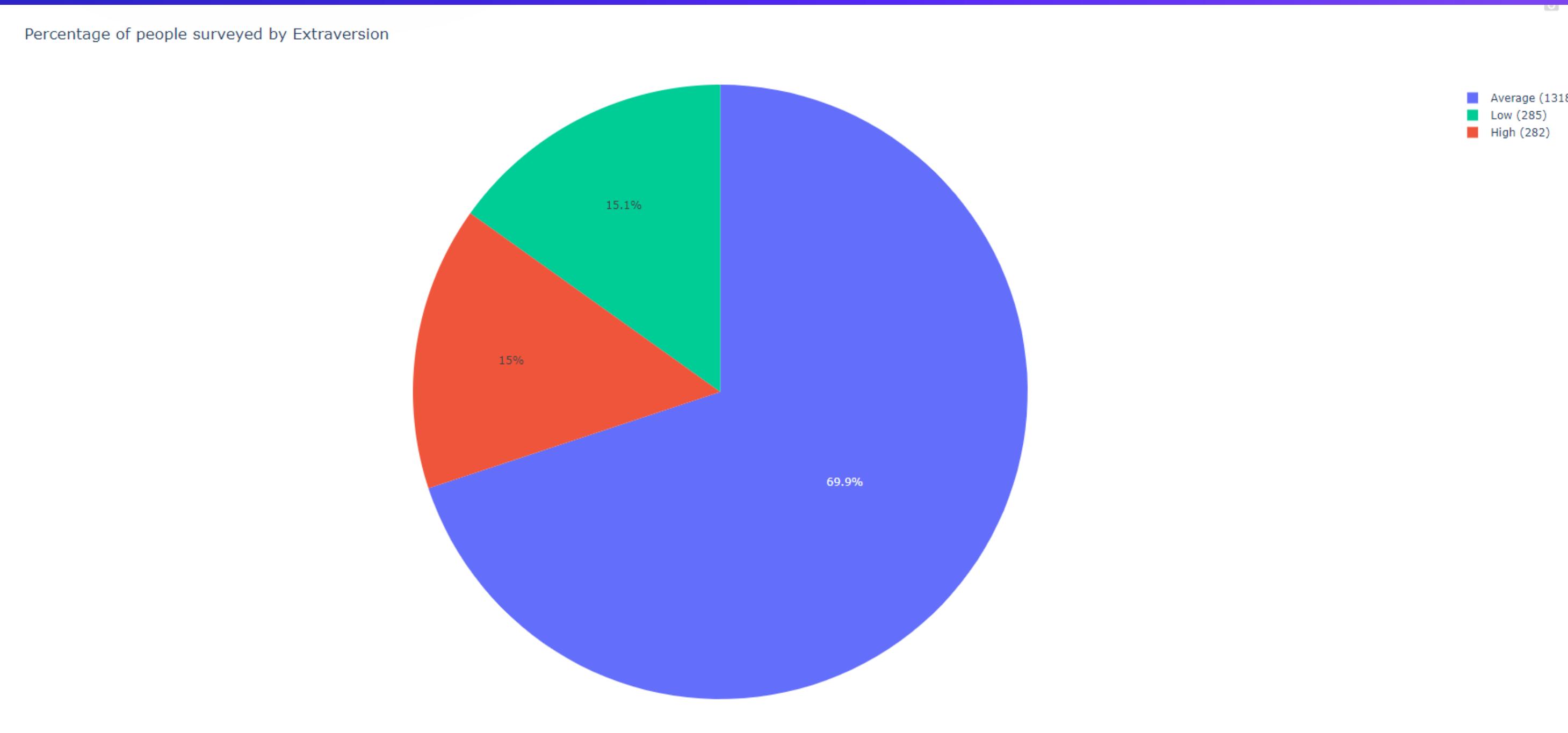
FLASK : VISUALIZATIONS

Data Visualization

Select Visualization Type: Survey Percentage

Select a Feature: Extraversion

Generate Visualization



FLASK :

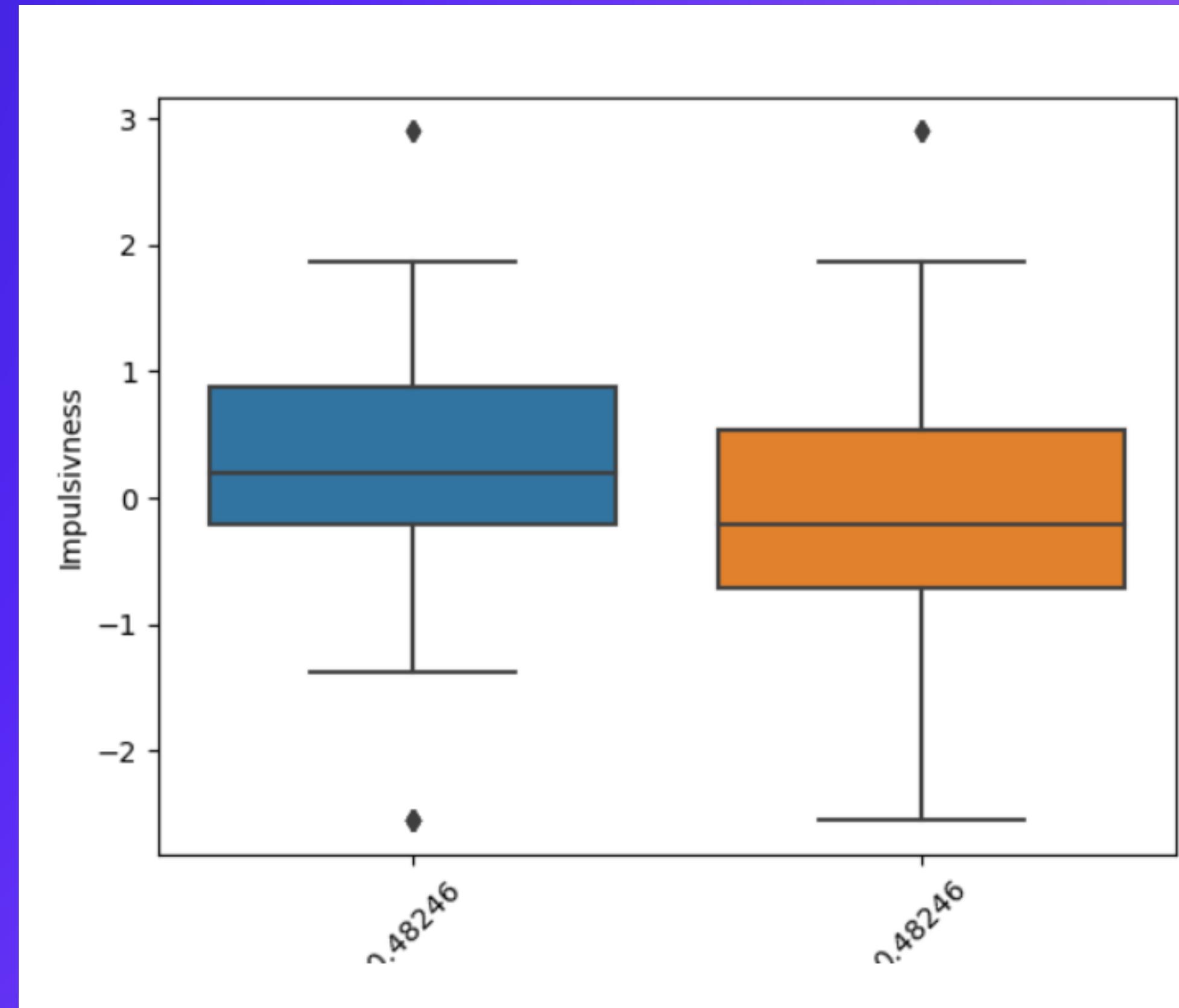
VISUALIZATIONS

Data Visualization

Select Visualization Type:

Select Feature 1:

Select Feature 2:





CONCLUSION



THANK YOU!

