Data Science as a Field Project

Kate Borden, Evan McCormick, Paige Phillips

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Statement of question and interest

Question: **What factors in personality and prior drug use are predominantly associated with the use of specific drugs – especially hard drugs?**

For our project we are interested in drug consumption and the association to personality and behavior. For instance, we want to further evaluate the different types of risk to be for each drug. We can split up the drugs based on how they are scheduled or classified as controlled substances. We are primarily interested in distinguishing which factors in personality and prior drug use are predominantly associated with the use of specific drugs. Secondly, we want to assess which factors are predominantly associated with hard drugs.

Source & Dataset Description

We got our database from here, see Drug Consumptions (UCI)

You can access our data here, see GitHub

Dataset Contents:

There are 12 attributes that are categorized based on their background demographic and personality measurements. These attributes are assessed across 18 central nervous system (CNS) psychoactive drugs. The drugs selected includes both illicit and licit.

Featured Attributes for Quantified Data

- *ID*: total number of 1885 records in this database
- *Age*: participant's age
- *Gender*: binary of only fale or female
- *Education*: participant's level of education
- *Country*: participant's country of origin
- *Ethnicity*: participant's ethnicity

Featured Attributes for Personality measurements (NEO-FFI-R)

- *Nscore*: neuroticism
- *Escore*: extraversion
- *Oscore*: openness to experience.
- *Ascore*: agreeableness.
- *Cscore*: conscientiousness.
- *Impulsive*: impulsiveness (measured by BIS-11)
- *SS*: sensation seeing (measured by ImpSS)

Consumption usage of 18 legal and illegal drugs

1. *Alcohol*: alcohol consumption
2. *Amphet*: amphetamines consumption
3. *Amyl*: nitrite consumption
4. *Benzos*: benzodiazepine consumption
5. *Caff*: caffeine consumption
6. *Cannabis*: marijuana consumption
7. *Choc*: chocolate consumption
8. *Coke*: cocaine consumption
9. *Crack*: crack cocaine consumption
10. Ecstasy: ecstasy consumption
11. *Heroin*: heroin consumption
12. *Ketamine*: ketamine consumption
13. *Legalh*: legal highs consumption
14. *LSD*: LSD consumption
15. *Meth*: methadone consumption
16. *Mushroom*: magic mushroom consumption
17. *Nicotine*: nicotine consumption
18. *Semer*: class of fictitious drug Semeron consumption (i.e. control)
19. *VSA*: class of volatile substance abuse consumption

Rating's for Drug Use

- 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

Examining the Data

Subset dataframe

Alcohol	Amphet	Amyl	Benzos	Cannabis	Coke	Crack	Ecstasy	Heroin	Ketamine	Legalh	LSD	Meth	Mushrooms	Nicotine	VSA
CL5	CL2	CL2	CL0	CL4	CL3	CL0	CL4	CL0	CL2	CL0	CL2	CL3	CL0	CL4	CL0
CL6	CL0	CL0	CL0	CL3	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL1	CL0	CL0
CL4	CL0	CL0	CL3	CL2	CL2	CL0	CL0	CL0	CL2	CL0	CL0	CL0	CL0	CL2	CL0
CL4	CL1	CL1	CL0	CL3	CL0	CL0	CL1	CL0	CL0	CL1	CL0	CL0	CL2	CL2	CL0
CL2	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL6	CL0
CL6	CL0	CL0	CL0	CL1	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL0	CL6	CL0

Cleaning the data

Alcohol	Amphet	Amyl	Benzos	Cannabis	Coke	Crack	Ecstasy	Heroin	Ketamine	Legalh	LSD	Meth	Mushrooms	Nicotine	VSA	Psychedelics	Sedatives	Stimulants
1	1	1	0	1	1	0	1	0	1	0	1	1	0	1	0	1	1	1
1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
1	0	0	1	1	1	0	0	0	1	0	0	0	0	1	0	0	1	1
1	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	1	1	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0

Analysis

Using Frequency Pattern Analysis to find common patterns in drug use.

```
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.9    0.1    1 none FALSE            TRUE       5     0.4      2
 maxlen target  ext
     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 753
```

```
set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[16 item(s), 1884 transaction(s)] done [0.00s].
sorting and recoding items ... [5 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 done [0.00s].
writing ... [3 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

    lhs                        rhs       support   confidence coverage  lift
[1] {Nicotine}           => {Alcohol} 0.6560510 0.9786223  0.6703822 1.015267
[2] {Cannabis}           => {Alcohol} 0.6576433 0.9794466  0.6714437 1.016122
[3] {Cannabis, Nicotine} => {Alcohol} 0.5594480 0.9850467  0.5679406 1.021932
    count
[1] 1236
[2] 1239
[3] 1054

Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.9    0.1    1 none FALSE            TRUE       5    0.18      2
 maxlen target  ext
     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 339

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[13 item(s), 1884 transaction(s)] done [0.00s].
sorting and recoding items ... [10 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 done [0.00s].
writing ... [5 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

    lhs                             rhs         support   confidence coverage
[1] {Benzos, LSD}              => {Mushrooms} 0.1820594 0.9122340  0.1995754
```

```
[2] {Amphet, LSD}             => {Ecstasy}   0.1942675 0.9081886  0.2139066
[3] {Coke, LSD}               => {Ecstasy}   0.1910828 0.9326425  0.2048832
[4] {Ecstasy, Legalh, LSD}    => {Mushrooms} 0.1863057 0.9046392  0.2059448
[5] {Amphet, Coke, Mushrooms} => {Ecstasy}   0.1804671 0.9264305  0.1947983
    lift     count
[1] 2.476439 343
[2] 2.278332 366
[3] 2.339678 360
[4] 2.455822 351
[5] 2.324095 340

Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.9    0.1    1 none FALSE            TRUE       5    0.11      2
 maxlen target  ext
     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 207

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[11 item(s), 1884 transaction(s)] done [0.00s].
sorting and recoding items ... [10 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 5 done [0.00s].
writing ... [4 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

    lhs                         rhs      support   confidence coverage  lift
[1] {Coke, Meth}           => {Benzos} 0.1406582 0.9330986  0.1507431 2.289007
[2] {Amphet, Meth}         => {Benzos} 0.1475584 0.9084967  0.1624204 2.228656
[3] {Amphet, Coke, Meth}   => {Benzos} 0.1210191 0.9500000  0.1273885 2.330469
[4] {Amphet, Legalh, Meth} => {Benzos} 0.1157113 0.9159664  0.1263270 2.246980
    count
[1] 265
[2] 278
[3] 228
```

```
[4] 218

Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.9    0.1    1 none FALSE            TRUE       5     0.4      2
 maxlen target  ext
     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 753

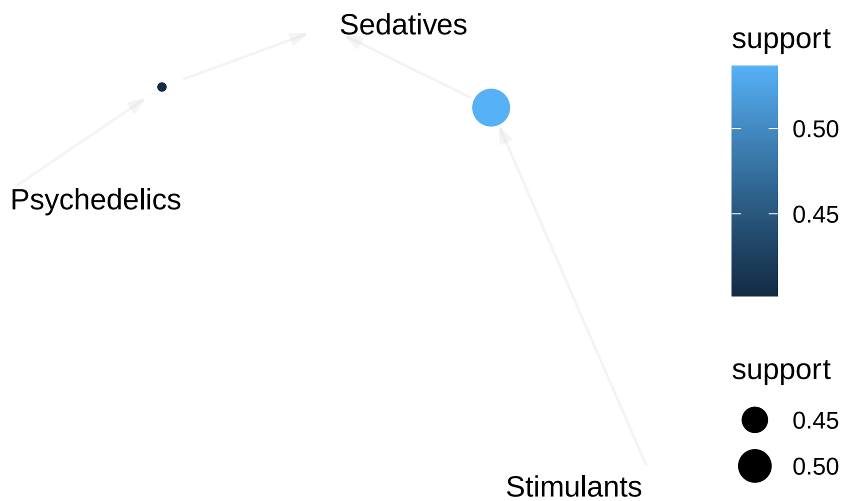
set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[3 item(s), 1884 transaction(s)] done [0.00s].
sorting and recoding items ... [3 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 done [0.00s].
writing ... [2 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

    lhs                rhs         support   confidence coverage  lift     count
[1] {Psychedelics} => {Sedatives} 0.4018047 0.9908377  0.4055202 1.017296  757
[2] {Stimulants}   => {Sedatives} 0.5366242 0.9931238  0.5403397 1.019643 1011
```

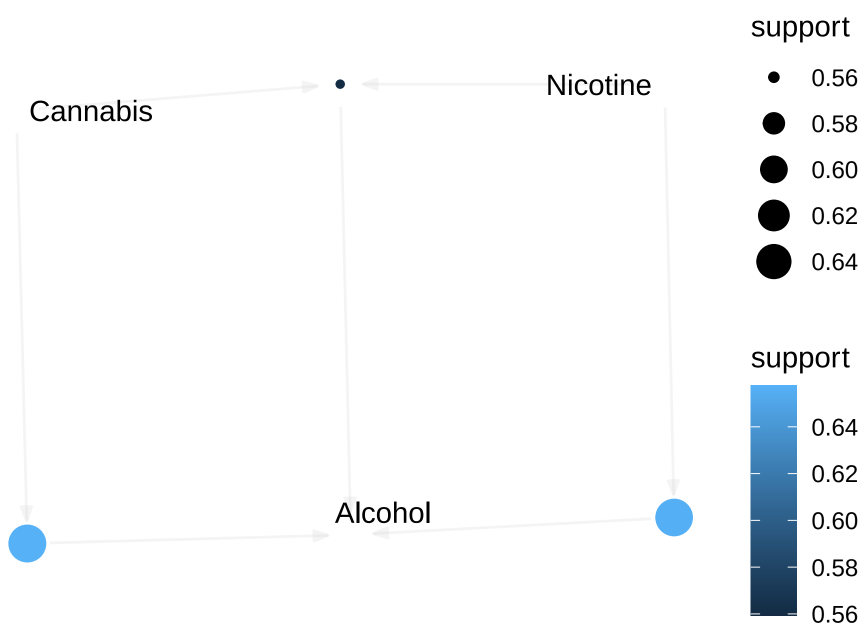
Conclusion

One pattern found in the data is that people's drug use tends to cluster around specific groups of drugs. Using Frequency Pattern (FP) analysis, popular drug groupings are found at various levels of popularity.

```
Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```




```
Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```



When looking at all drug relations, the most common 'basket' of drugs used in combination is the three most common drugs used: Alcohol, Cannabis, and Nicotine. While these three are often used together, they are also found to be the main drug used in combination with other, less common drugs. This shows their status as "gateway" drugs. Nearly everyone who uses some of the harder, less common drugs also uses one of these three.

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Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
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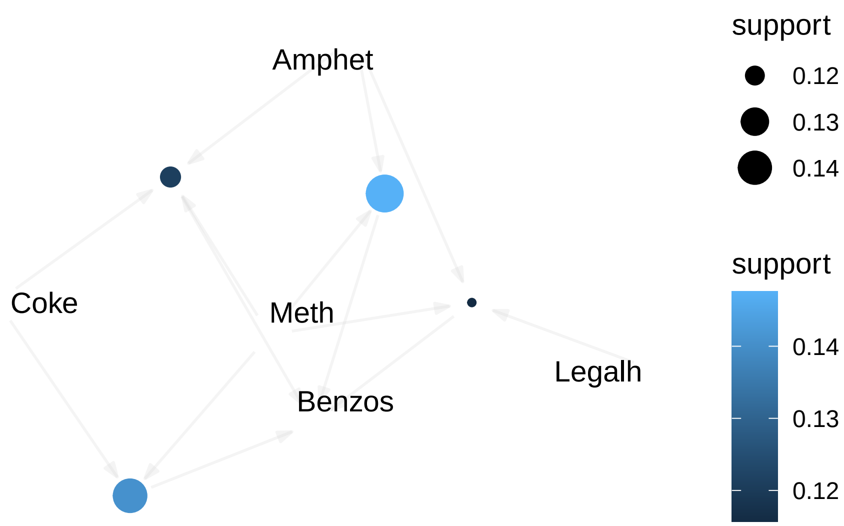
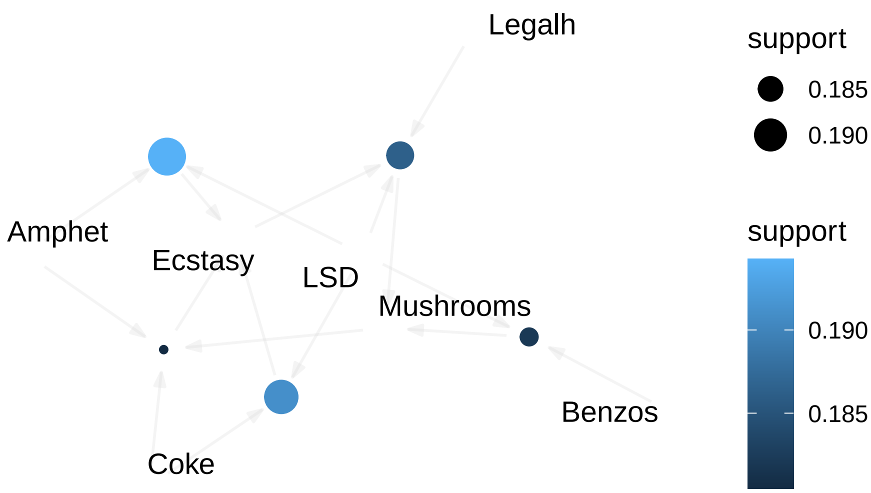


When removing the three 'gateway' drugs from the market baskets, a new pattern emerges. Around 20% of drug users use a combination of drugs including Cocaine, Amphetamine, LSD, Mushrooms, Benzos and Ecstasy (MDMA). These drugs are a varied group, and could be considered "medium" drugs, although some of them, such as Amphetamines and Benzodiazapines, are as volatile as the 'harder' drugs included in this data table. Within this group of drugs, Psilocybin and Ecstasy appear to act as the "gateway".

```
Scale for colour is already present.
Adding another scale for colour, which will replace the existing scale.
```



Group Biases -

Some personal biases that we can acknowledge from this project and dataset are the "Drugs" listed. We would have refrained from classifying a handful of the drugs presented and would not have included them in the original dataset. Precisely alcohol, caffeine, chocolate, and possibly legal highs.

A possible explanation to our bias, is due to how prevalent or not these specifics drugs are in our world. Alcohol, caffeine, chocolate, and let's say marijuana may be more accessibly available, depending on where you live, than let's say meth, heroin, or benzos, and so forth.

Another example of bias is social pressure and cultural differences. How that may influence our unconscious biases of different drugs. For example marijuana and psilocybin are becoming popular alternative drugs to use for medical and recreational purposes in the U.S., but that may not reflect the same for in the U.K. or Australia per say. How we perceive the classification and use of these drugs holds lots of bias.

Lastly, the word "drug(s)" carries a negative connotation behind it. More often than not one mind jumps to 1) illegal, 2) substance use disorder (SUD), 3) problematic. Again, a lot of these are associated with more illicit drugs like cocaine, meth, heroin, etc., not so much with alcohol, chocolate, caffeine, and marijuana. How we perceive these drugs is a bias of itself. If we were to not include some of these drugs in the dataset, that would be unethical of us as a data scientist.

SessionInfo

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R version 4.2.2 (2022-10-31)
Platform: x86_64-apple-darwin17.0 (64-bit)
Running under: macOS Big Sur ... 10.16

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.2/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.2/Resources/lib/libRlapack.dylib

locale:
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attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] arulesViz_1.5-1 arules_1.7-5    Matrix_1.5-1    forcats_0.5.2
 [5] stringr_1.4.1   dplyr_1.0.10    purrr_0.3.5     readr_2.1.3
 [9] tidyr_1.2.1     tibble_3.1.8    ggplot2_3.4.0   tidyverse_1.3.2

loaded via a namespace (and not attached):
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```