Data622 - Group2 - Homework4

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Contents

Overview

In this project, we analyze a real-life mental health dataset to provide context around suicide prediction given a variety of unidentifiable demographic data. Our goals are to understand the variables relationships, identify those variables that influence our target, and develop models that can predict a patient's risk of suicide.

Approach

We will first perform exploratory data analysis (EDA) on the dataset to inform our analysis and build better models. Methods include Clustering, Principal Component Analysis, Gradient Boosting, and Support Vector Machines. This EDA step is crucial to understanding variables' relationships and identifying which variables influence our target.

Once we understand the data, we prepare it for modeling. This includes partitioning the data with a 75-25 train-test split, performing necessary imputations, relevant centering and scaling, and more as outlined in our data exploration and preparation sections. When building our models we focus on using methods that produce real-world accuracy. For this reason, we attempt to select the best generalizable model with accuracy as our primary indicator during model evaluation.

Data Exploration

The dataset with its column IDs, variable names, and variables descriptions are provided below for reference.

Columns	Variable	Description
C	Sex	Male-1, Female-2
D	Race	White-1, African American-2, Hispanic-3, Asian-4, Native American-5, Other or missing data -6
E - W	ADHD self-report scale	Never-0, rarely-1, sometimes-2, often-3, very often-4
X - AM	Mood disorder questions	No-0, yes-1; question 3: no problem-0, minor-1, moderate-2, serious-3
AN - AS	Individual substances misuse	no use-0, use-1, abuse-2, dependence-3
AT	Court Order	No-0, Yes-1
AU	Education	1-12 grade, 13+ college
AV	History of Violence	No-0, Yes-1
AW	Disorderly Conduct	No-0, Yes-1
AX	Suicide attempt	No-0, Yes-1
AY	Abuse Hx	No-0, Physical (P)-1, Sexual (S)-2, Emotional (E)-3, P&S-4, P&E-5, S&E-6, P&S&E-7
AZ	Non-substance-related Dx	0 - none; 1 - one; 2 - More than one
BA	Substance-related Dx	0 - none; 1 - one Substance-related; 2 - two; 3 - three or more

Columns	Variable	Description
BB	Psychiatric Meds	0 - none; 1 - one psychotropic med; 2 - more than one psychotropic med

Notice how the data is grouped with ADHD, Mood disorders, and Individual Substance misuse present across a range of columns. These groups are reviewed throughout the exploration process and new features are generated to attempt to improve model performance.

Data Characteristics

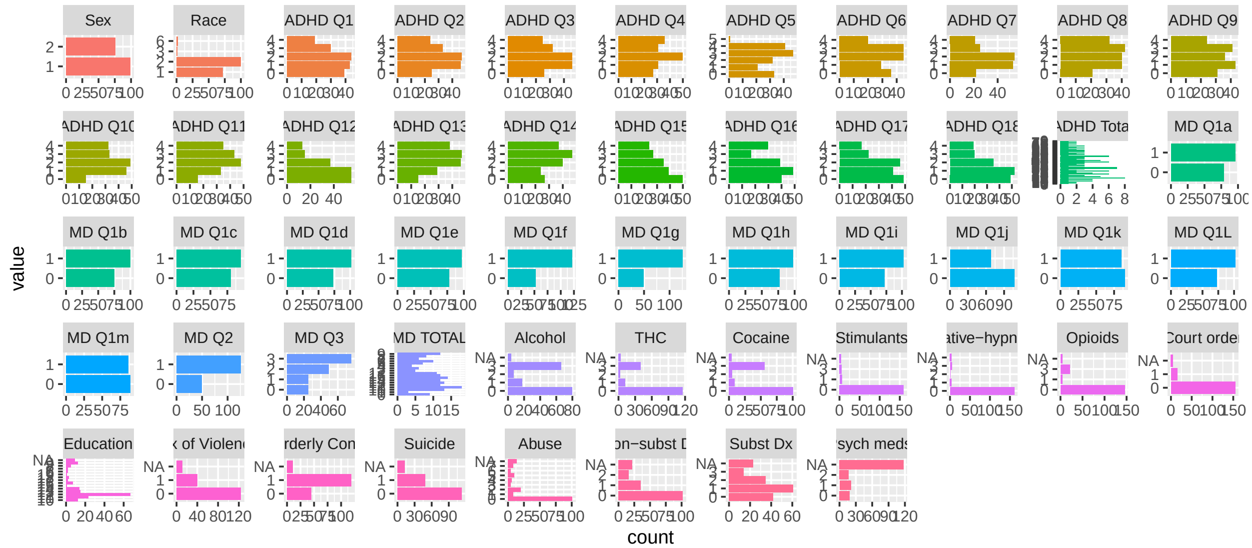
```
## [1] 53
```

The data contains 175 observations of 53 variables. We import the data from a remote repository and find that 51 of the variables should be of the factor data type given clear levels in their distributions. As is, these variables are interpreted as character strings. This will need to be converted for realistic results. The remaining variables can be numeric for our purposes.

We review one grouped variable set, known as mood disorders (MD), to show what we're working with. These contain a series of associated questions (Q1-Q3) with Q1 containing parts 'a' through 'm.'

```
## # A tibble: 175 x 15
##    `MD Q1a` `MD Q1b` `MD Q1c` `MD Q1d` `MD Q1e` `MD Q1f` `MD Q1g` `MD Q1h`
##    <fct>    <fct>    <fct>    <fct>    <fct>    <fct>    <fct>    <fct>
##  1 1        1        1        1        0        1        1        1
##  2 1        1        1        1        1        1        1        1
##  3 0        0        0        0        1        1        1        0
##  4 1        1        0        0        1        1        1        1
##  5 0        1        0        1        0        1        1        0
##  6 0        1        0        1        1        1        1        1
##  7 1        1        0        0        1        1        0        0
##  8 0        0        0        0        0        1        1        0
##  9 1        1        0        1        1        1        1        0
## 10 1        1        0        0        1        0        1        0
## # ... with 165 more rows, and 7 more variables: MD Q1i <fct>, MD Q1j <fct>,
## #   MD Q1k <fct>, MD Q1L <fct>, MD Q1m <fct>, MD Q2 <fct>, MD Q3 <fct>
```

Each part of Q1 'a' through 'm' corresponds with a specific question related to mood disorders for a single patient. In our feature engineering, it may be useful to tally these responses for a more holistic perspective of the patient's overall mood. We repeat this for the other groups to get an sense of the patient well-being which should provide insight into their risk of suicide.



Data summary

```
## Data Frame Summary
## adhd_data
## Dimensions: 175 x 53
## Duplicates: 0
##
## +----+----------------------+--------------------------+--------------------+---------+---------+
## | No | Variable             | Stats / Values           | Freqs (% of Valid) | Valid   | Missing |
## +====+======================+==========================+====================+=========+=========+
## | 1  | Age                  | Mean (sd) : 39.5 (11.2)  | 42 distinct values | 175     | 0       |
## |    | [numeric]            | min < med < max:         |                    | (100.0%) | (0.0%) |
## |    |                      | 18 < 42 < 69             |                    |         |         |
## |    |                      | IQR (CV) : 18.5 (0.3)    |                    |         |         |
## +----+----------------------+--------------------------+--------------------+---------+---------+
## | 2  | Sex                  | 1. 1                     | 99 (56.6%)         | 175     | 0       |
## |    | [factor]             | 2. 2                     | 76 (43.4%)         | (100.0%) | (0.0%) |
## +----+----------------------+--------------------------+--------------------+---------+---------+
## | 3  | Race                 | 1. 1                     |  72 (41.1%)        | 175     | 0       |
## |    | [factor]             | 2. 2                     | 100 (57.1%)        | (100.0%) | (0.0%) |
## |    |                      | 3. 3                     |   1 ( 0.6%)        |         |         |
## |    |                      | 4. 6                     |   2 ( 1.1%)        |         |         |
## +----+----------------------+--------------------------+--------------------+---------+---------+
## | 4  | ADHD Q1              | 1. 0                     | 39 (22.3%)         | 175     | 0       |
## |    | [factor]             | 2. 1                     | 43 (24.6%)         | (100.0%) | (0.0%) |
## |    |                      | 3. 2                     | 44 (25.1%)         |         |         |
## |    |                      | 4. 3                     | 30 (17.1%)         |         |         |
## |    |                      | 5. 4                     | 19 (10.9%)         |         |         |
## +----+----------------------+--------------------------+--------------------+---------+---------+
## | 5  | ADHD Q2              | 1. 0                     | 25 (14.3%)         | 175     | 0       |
## |    | [factor]             | 2. 1                     | 46 (26.3%)         | (100.0%) | (0.0%) |
## |    |                      | 3. 2                     | 47 (26.9%)         |         |         |
## |    |                      | 4. 3                     | 33 (18.9%)         |         |         |
## |    |                      | 5. 4                     | 24 (13.7%)         |         |         |
```

```
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 6  | ADHD Q3             | 1. 0                     | 26 (14.9%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 46 (26.3%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 46 (26.3%)         |          |         |
## |    |                     | 4. 3                     | 32 (18.3%)         |          |         |
## |    |                     | 5. 4                     | 25 (14.3%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 7  | ADHD Q4             | 1. 0                     | 27 (15.4%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 31 (17.7%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 50 (28.6%)         |          |         |
## |    |                     | 4. 3                     | 31 (17.7%)         |          |         |
## |    |                     | 5. 4                     | 36 (20.6%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 8  | ADHD Q5             | 1. 0                     | 33 (18.9%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 21 (12.0%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 32 (18.3%)         |          |         |
## |    |                     | 4. 3                     | 47 (26.9%)         |          |         |
## |    |                     | 5. 4                     | 41 (23.4%)         |          |         |
## |    |                     | 6. 5                     |  1 ( 0.6%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 9  | ADHD Q6             | 1. 0                     | 36 (20.6%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 29 (16.6%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 45 (25.7%)         |          |         |
## |    |                     | 4. 3                     | 45 (25.7%)         |          |         |
## |    |                     | 5. 4                     | 20 (11.4%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 10 | ADHD Q7             | 1. 0                     | 22 (12.6%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 53 (30.3%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 54 (30.9%)         |          |         |
## |    |                     | 4. 3                     | 25 (14.3%)         |          |         |
## |    |                     | 5. 4                     | 21 (12.0%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 11 | ADHD Q8             | 1. 0                     | 21 (12.0%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 40 (22.9%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 40 (22.9%)         |          |         |
## |    |                     | 4. 3                     | 42 (24.0%)         |          |         |
## |    |                     | 5. 4                     | 32 (18.3%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 12 | ADHD Q9             | 1. 0                     | 31 (17.7%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 43 (24.6%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 36 (20.6%)         |          |         |
## |    |                     | 4. 3                     | 41 (23.4%)         |          |         |
## |    |                     | 5. 4                     | 24 (13.7%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 13 | ADHD Q10            | 1. 0                     | 15 ( 8.6%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 46 (26.3%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 49 (28.0%)         |          |         |
## |    |                     | 4. 3                     | 33 (18.9%)         |          |         |
## |    |                     | 5. 4                     | 32 (18.3%)         |          |         |
## +----+---------------------+--------------------------+--------------------+----------+---------+
## | 14 | ADHD Q11            | 1. 0                     | 16 ( 9.1%)         | 175      | 0       |
## |    | [factor]            | 2. 1                     | 33 (18.9%)         | (100.0%) | (0.0%)  |
## |    |                     | 3. 2                     | 48 (27.4%)         |          |         |
## |    |                     | 4. 3                     | 43 (24.6%)         |          |         |
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## |    |                     | 5. 4                       | 35 (20.0%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 15 | ADHD Q12            | 1. 0                       | 55 (31.4%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 55 (31.4%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 37 (21.1%)            |          |          |
## |    |                     | 4. 3                       | 15 ( 8.6%)            |          |          |
## |    |                     | 5. 4                       | 13 ( 7.4%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 16 | ADHD Q13            | 1. 0                       | 15 ( 8.6%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 29 (16.6%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 46 (26.3%)            |          |          |
## |    |                     | 4. 3                       | 47 (26.9%)            |          |          |
## |    |                     | 5. 4                       | 38 (21.7%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 17 | ADHD Q14            | 1. 0                       | 27 (15.4%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 24 (13.7%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 40 (22.9%)            |          |          |
## |    |                     | 4. 3                       | 47 (26.9%)            |          |          |
## |    |                     | 5. 4                       | 37 (21.1%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 18 | ADHD Q15            | 1. 0                       | 50 (28.6%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 39 (22.3%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 35 (20.0%)            |          |          |
## |    |                     | 4. 3                       | 27 (15.4%)            |          |          |
## |    |                     | 5. 4                       | 24 (13.7%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 19 | ADHD Q16            | 1. 0                       | 40 (22.9%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 49 (28.0%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 39 (22.3%)            |          |          |
## |    |                     | 4. 3                       | 17 ( 9.7%)            |          |          |
## |    |                     | 5. 4                       | 30 (17.1%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 20 | ADHD Q17            | 1. 0                       | 49 (28.0%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 41 (23.4%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 46 (26.3%)            |          |          |
## |    |                     | 4. 3                       | 22 (12.6%)            |          |          |
## |    |                     | 5. 4                       | 17 ( 9.7%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 21 | ADHD Q18            | 1. 0                       | 49 (28.0%)            | 175      | 0        |
## |    | [factor]            | 2. 1                       | 52 (29.7%)            | (100.0%) | (0.0%)   |
## |    |                     | 3. 2                       | 35 (20.0%)            |          |          |
## |    |                     | 4. 3                       | 20 (11.4%)            |          |          |
## |    |                     | 5. 4                       | 19 (10.9%)            |          |          |
## +----+---------------------+----------------------------+-----------------------+----------+----------+
## | 22 | ADHD Total          | 1. 0                       |   1 ( 0.6%)           | 175      | 0        |
## |    | [factor]            | 2. 1                       |   2 ( 1.1%)           | (100.0%) | (0.0%)   |
## |    |                     | 3. 3                       |   1 ( 0.6%)           |          |          |
## |    |                     | 4. 5                       |   1 ( 0.6%)           |          |          |
## |    |                     | 5. 6                       |   3 ( 1.7%)           |          |          |
## |    |                     | 6. 7                       |   2 ( 1.1%)           |          |          |
## |    |                     | 7. 8                       |   1 ( 0.6%)           |          |          |
## |    |                     | 8. 9                       |   2 ( 1.1%)           |          |          |
## |    |                     | 9. 10                      |   2 ( 1.1%)           |          |          |
## |    |                     | 10. 11                     |   1 ( 0.6%)           |          |          |
```

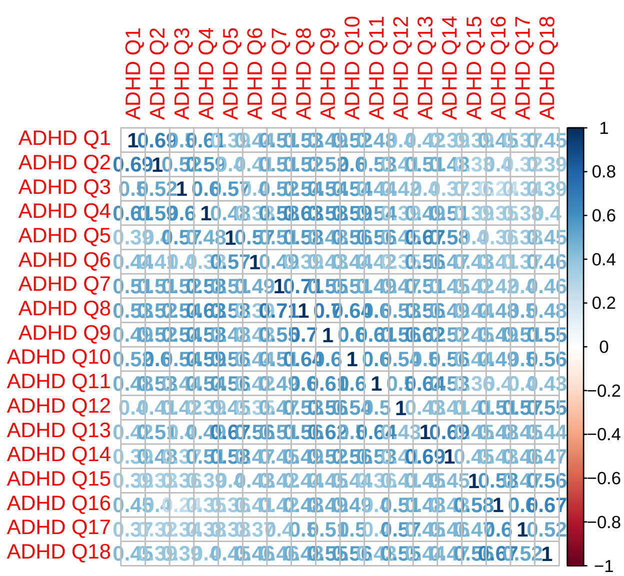
```
## |    |                       | [ 52 others ]            | 159 (90.9%)          |          |         |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 23 | MD Q1a                | 1. 0                     | 79 (45.1%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 96 (54.9%)           | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 24 | MD Q1b                | 1. 0                     |  75 (42.9%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 100 (57.1%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 25 | MD Q1c                | 1. 0                     | 80 (45.7%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 95 (54.3%)           | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 26 | MD Q1d                | 1. 0                     |  73 (41.7%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 102 (58.3%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 27 | MD Q1e                | 1. 0                     | 78 (44.6%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 97 (55.4%)           | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 28 | MD Q1f                | 1. 0                     |  53 (30.3%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 122 (69.7%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 29 | MD Q1g                | 1. 0                     |  49 (28.0%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 126 (72.0%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 30 | MD Q1h                | 1. 0                     | 77 (44.0%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 98 (56.0%)           | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 31 | MD Q1i                | 1. 0                     |  72 (41.1%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 103 (58.9%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 32 | MD Q1j                | 1. 0                     | 107 (61.1%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     |  68 (38.9%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 33 | MD Q1k                | 1. 0                     | 90 (51.4%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 85 (48.6%)           | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 34 | MD Q1L                | 1. 0                     |  73 (41.7%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 102 (58.3%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 35 | MD Q1m                | 1. 0                     | 89 (50.9%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 86 (49.1%)           | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 36 | MD Q2                 | 1. 0                     |  49 (28.0%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     | 126 (72.0%)          | (100.0%) | (0.0%)  |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 37 | MD Q3                 | 1. 0                     | 25 (14.3%)           | 175      | 0       |
## |    | [factor]              | 2. 1                     | 25 (14.3%)           | (100.0%) | (0.0%)  |
## |    |                       | 3. 2                     | 49 (28.0%)           |          |         |
## |    |                       | 4. 3                     | 76 (43.4%)           |          |         |
## +----+-----------------------+--------------------------+---------------------+----------+---------+
## | 38 | MD TOTAL              | 1. 0                     |   9 ( 5.1%)          | 175      | 0       |
## |    | [factor]              | 2. 1                     |   3 ( 1.7%)          | (100.0%) | (0.0%)  |
## |    |                       | 3. 2                     |   5 ( 2.9%)          |          |         |
## |    |                       | 4. 3                     |   6 ( 3.4%)          |          |         |
## |    |                       | 5. 4                     |   4 ( 2.3%)          |          |         |
```

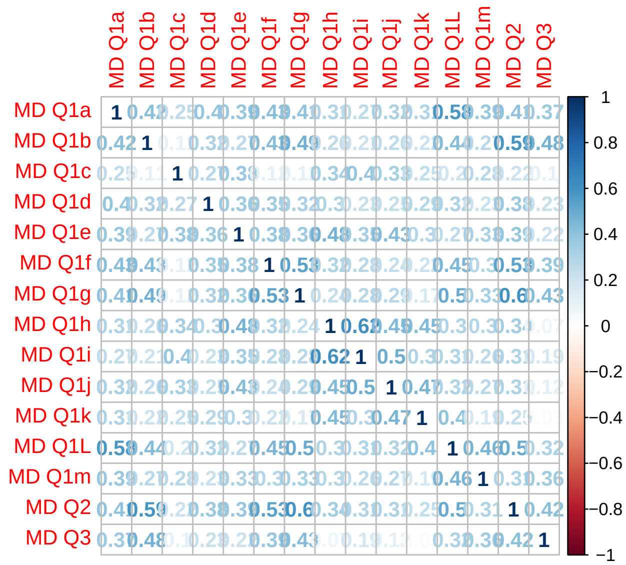
```
## |    |                     | 6. 5                        |   7 ( 4.0%)         |          |         |
## |    |                     | 7. 6                        |  10 ( 5.7%)         |          |         |
## |    |                     | 8. 7                        |   6 ( 3.4%)         |          |         |
## |    |                     | 9. 8                        |   8 ( 4.6%)         |          |         |
## |    |                     | 10. 9                       |  12 ( 6.9%)         |          |         |
## |    |                     | [ 8 others ]                | 105 (60.0%)         |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 39 | Alcohol             | 1. 0                        | 80 (46.8%)          | 171      | 4       |
## |    | [factor]            | 2. 1                        | 18 (10.5%)          | (97.7%)  | (2.3%)  |
## |    |                     | 3. 2                        |  7 ( 4.1%)          |          |         |
## |    |                     | 4. 3                        | 66 (38.6%)          |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 40 | THC                 | 1. 0                        | 116 (67.8%)         | 171      | 4       |
## |    | [factor]            | 2. 1                        |  12 ( 7.0%)         | (97.7%)  | (2.3%)  |
## |    |                     | 3. 2                        |   3 ( 1.8%)         |          |         |
## |    |                     | 4. 3                        |  40 (23.4%)         |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 41 | Cocaine             | 1. 0                        | 101 (59.1%)         | 171      | 4       |
## |    | [factor]            | 2. 1                        |   9 ( 5.3%)         | (97.7%)  | (2.3%)  |
## |    |                     | 3. 2                        |   5 ( 2.9%)         |          |         |
## |    |                     | 4. 3                        |  56 (32.7%)         |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 42 | Stimulants          | 1. 0                        | 160 (93.6%)         | 171      | 4       |
## |    | [factor]            | 2. 1                        |   6 ( 3.5%)         | (97.7%)  | (2.3%)  |
## |    |                     | 3. 3                        |   5 ( 2.9%)         |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 43 | Sedative-hypnotics  | 1. 0                        | 161 (94.2%)         | 171      | 4       |
## |    | [factor]            | 2. 1                        |   4 ( 2.3%)         | (97.7%)  | (2.3%)  |
## |    |                     | 3. 2                        |   1 ( 0.6%)         |          |         |
## |    |                     | 4. 3                        |   5 ( 2.9%)         |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 44 | Opioids             | 1. 0                        | 146 (85.4%)         | 171      | 4       |
## |    | [factor]            | 2. 1                        |   4 ( 2.3%)         | (97.7%)  | (2.3%)  |
## |    |                     | 3. 3                        |  21 (12.3%)         |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 45 | Court order         | 1. 0                        | 155 (91.2%)         | 170      | 5       |
## |    | [factor]            | 2. 1                        |  15 ( 8.8%)         | (97.1%)  | (2.9%)  |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 46 | Education           | 1. 6                        |  2 ( 1.2%)          | 166      | 9       |
## |    | [factor]            | 2. 7                        |  2 ( 1.2%)          | (94.9%)  | (5.1%)  |
## |    |                     | 3. 8                        |  5 ( 3.0%)          |          |         |
## |    |                     | 4. 9                        | 12 ( 7.2%)          |          |         |
## |    |                     | 5. 10                       | 12 ( 7.2%)          |          |         |
## |    |                     | 6. 11                       | 23 (13.9%)          |          |         |
## |    |                     | 7. 12                       | 67 (40.4%)          |          |         |
## |    |                     | 8. 13                       | 15 ( 9.0%)          |          |         |
## |    |                     | 9. 14                       | 14 ( 8.4%)          |          |         |
## |    |                     | 10. 15                      |  1 ( 0.6%)          |          |         |
## |    |                     | [ 4 others ]                | 13 ( 7.8%)          |          |         |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 47 | Hx of Violence      | 1. 0                        | 124 (75.6%)         | 164      | 11      |
## |    | [factor]            | 2. 1                        |  40 (24.4%)         | (93.7%)  | (6.3%)  |
## +----+---------------------+-----------------------------+---------------------+----------+---------+
## | 48 | Disorderly Conduct  | 1. 0                        |  45 (27.4%)         | 164      | 11      |
```

```
## |    | [factor]             | 2. 1                    | 119 (72.6%)          | (93.7%)  | (6.3%)   |
## +----+----------------------+-------------------------+----------------------+----------+----------+
## | 49 | Suicide              | 1. 0                    | 113 (69.8%)          | 162      | 13       |
## |    | [factor]             | 2. 1                    |  49 (30.2%)          | (92.6%)  | (7.4%)   |
## +----+----------------------+-------------------------+----------------------+----------+----------+
## | 50 | Abuse                | 1. 0                    | 101 (62.7%)          | 161      | 14       |
## |    | [factor]             | 2. 1                    |   8 ( 5.0%)          | (92.0%)  | (8.0%)   |
## |    |                      | 3. 2                    |  20 (12.4%)          |          |          |
## |    |                      | 4. 3                    |   4 ( 2.5%)          |          |          |
## |    |                      | 5. 4                    |   6 ( 3.7%)          |          |          |
## |    |                      | 6. 5                    |  10 ( 6.2%)          |          |          |
## |    |                      | 7. 6                    |   4 ( 2.5%)          |          |          |
## |    |                      | 8. 7                    |   8 ( 5.0%)          |          |          |
## +----+----------------------+-------------------------+----------------------+----------+----------+
## | 51 | Non-subst Dx         | 1. 0                    | 102 (66.7%)          | 153      | 22       |
## |    | [factor]             | 2. 1                    |  35 (22.9%)          | (87.4%)  | (12.6%)  |
## |    |                      | 3. 2                    |  16 (10.5%)          |          |          |
## +----+----------------------+-------------------------+----------------------+----------+----------+
## | 52 | Subst Dx             | 1. 0                    | 42 (27.6%)           | 152      | 23       |
## |    | [factor]             | 2. 1                    | 61 (40.1%)           | (86.9%)  | (13.1%)  |
## |    |                      | 3. 2                    | 35 (23.0%)           |          |          |
## |    |                      | 4. 3                    | 14 ( 9.2%)           |          |          |
## +----+----------------------+-------------------------+----------------------+----------+----------+
## | 53 | Psych meds.          | 1. 0                    | 19 (33.3%)           | 57       | 118      |
## |    | [factor]             | 2. 1                    | 21 (36.8%)           | (32.6%)  | (67.4%)  |
## |    |                      | 3. 2                    | 17 (29.8%)           |          |          |
## +----+----------------------+-------------------------+----------------------+----------+----------+
```

Coorelation

Next we will see the correlation among ADHD questions and MD questions. As we can deduce from below 2 correlation plots, ADHD questions are highly correlated and MD questions comparatively shows moderate correlation.





Data Preparation

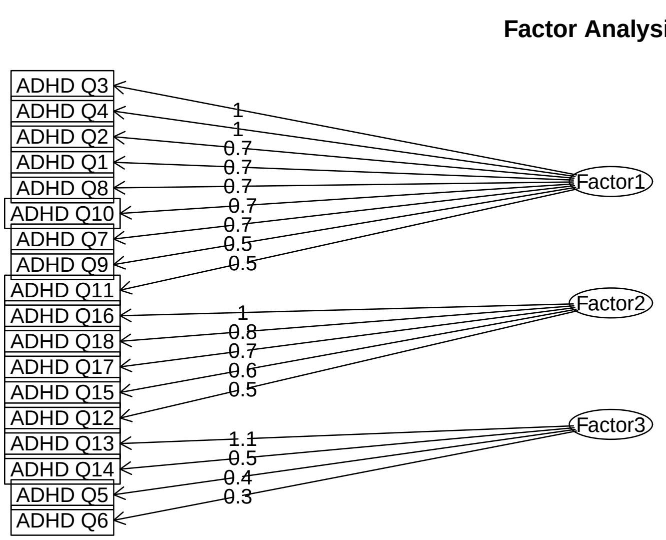
Factor Analysis

Like PCA, Factor Analysis too, reduces larger number of variables into smaller number of variables, called latent variables.It is used to identify underlying factors that explain the correlation among set of variables. Factor analysis is a great tool for treating multivariate questionnaire studies.

For ADHD questions, test of the hypothesis that 3 factors are sufficient. The chi square statistic is 197.3 on 102 degrees of freedom. The p-value is 0.0000000476. We have used regression factor scores here as they predict the location of each individual on the factor.

```
##
## Call:
## factanal(x = sapply(adhd_data[, c(4:21)], as.numeric), factors = 3,     scores = "regression", rotat
##
## Uniquenesses:
##  ADHD Q1  ADHD Q2  ADHD Q3  ADHD Q4  ADHD Q5  ADHD Q6  ADHD Q7  ADHD Q8
##    0.493    0.470    0.447    0.360    0.454    0.605    0.457    0.344
##  ADHD Q9 ADHD Q10 ADHD Q11 ADHD Q12 ADHD Q13 ADHD Q14 ADHD Q15 ADHD Q16
##    0.378    0.372    0.444    0.516    0.008    0.460    0.538    0.266
## ADHD Q17 ADHD Q18
##    0.496    0.360
##
## Loadings:
##          Factor1 Factor2 Factor3
## ADHD Q1   0.738   0.102  -0.142
## ADHD Q2   0.743
## ADHD Q3   0.972  -0.186  -0.144
## ADHD Q4   0.967  -0.164
## ADHD Q5   0.379           0.447
## ADHD Q6   0.173   0.185   0.332
## ADHD Q7   0.675
```

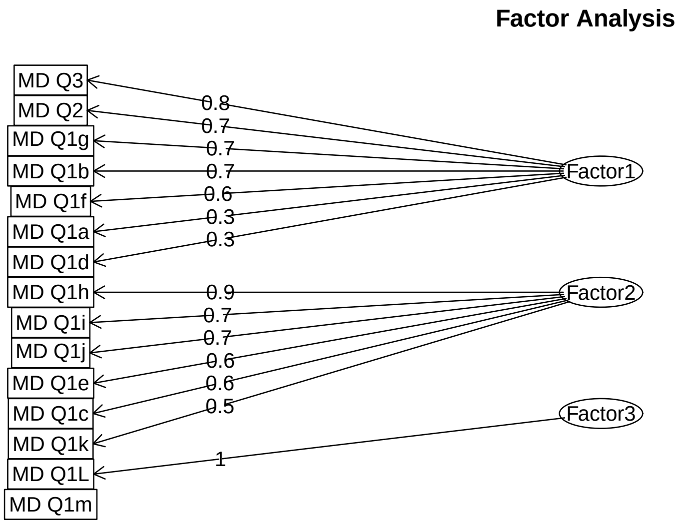
```
## ADHD Q8   0.731   0.110
## ADHD Q9   0.500   0.194   0.159
## ADHD Q10  0.687   0.237  -0.113
## ADHD Q11  0.480           0.327
## ADHD Q12  0.302   0.511
## ADHD Q13 -0.163           1.142
## ADHD Q14  0.158   0.122   0.512
## ADHD Q15          0.638
## ADHD Q16 -0.241   1.014
## ADHD Q17          0.682
## ADHD Q18          0.823  -0.116
##
##                Factor1 Factor2 Factor3
## SS loadings      5.298   3.079   2.095
## Proportion Var   0.294   0.171   0.116
## Cumulative Var   0.294   0.465   0.582
##
## Factor Correlations:
##         Factor1 Factor2 Factor3
## Factor1   1.000   0.765  -0.685
## Factor2   0.765   1.000  -0.748
## Factor3  -0.685  -0.748   1.000
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 197.3 on 102 degrees of freedom.
## The p-value is 4.76e-08
```



For MD questions we could see that 1st MD question has multiple sub questions as compared to 2nd and 3rd question. Now for these set of MD questions too, we will apply similar factor analysis as of ADHD questions. Test of the hypothesis that 3 factors are sufficient. The chi square statistic is 88.82 on 63 degrees of freedom. The p-value is 0.0178.

```
##
## Call:
```

```
## factanal(x = sapply(adhd_data[, c(23:37)], as.numeric), factors = 3,     scores = "regression", rota
##
## Uniquenesses:
## MD Q1a MD Q1b MD Q1c MD Q1d MD Q1e MD Q1f MD Q1g MD Q1h MD Q1i MD Q1j MD Q1k
##  0.562  0.506  0.736  0.735  0.564  0.536  0.446  0.388  0.507  0.567  0.638
## MD Q1L MD Q1m  MD Q2  MD Q3
##  0.005  0.719  0.394  0.601
##
## Loadings:
##        Factor1 Factor2 Factor3
## MD Q1a  0.345   0.117   0.308
## MD Q1b  0.732
## MD Q1c          0.565
## MD Q1d  0.342   0.257
## MD Q1e  0.283   0.568  -0.194
## MD Q1f  0.632
## MD Q1g  0.735
## MD Q1h          0.856
## MD Q1i          0.738
## MD Q1j          0.662
## MD Q1k -0.172   0.515   0.265
## MD Q1L  0.133  -0.124   0.981
## MD Q1m  0.228   0.158   0.240
## MD Q2   0.738
## MD Q3   0.751  -0.184
##
##                Factor1 Factor2 Factor3
## SS loadings      3.009   2.790   1.241
## Proportion Var   0.201   0.186   0.083
## Cumulative Var   0.201   0.387   0.469
##
## Factor Correlations:
##         Factor1 Factor2 Factor3
## Factor1   1.000   0.550  -0.587
## Factor2   0.550   1.000  -0.563
## Factor3  -0.587  -0.563   1.000
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 88.82 on 63 degrees of freedom.
## The p-value is 0.0178
```

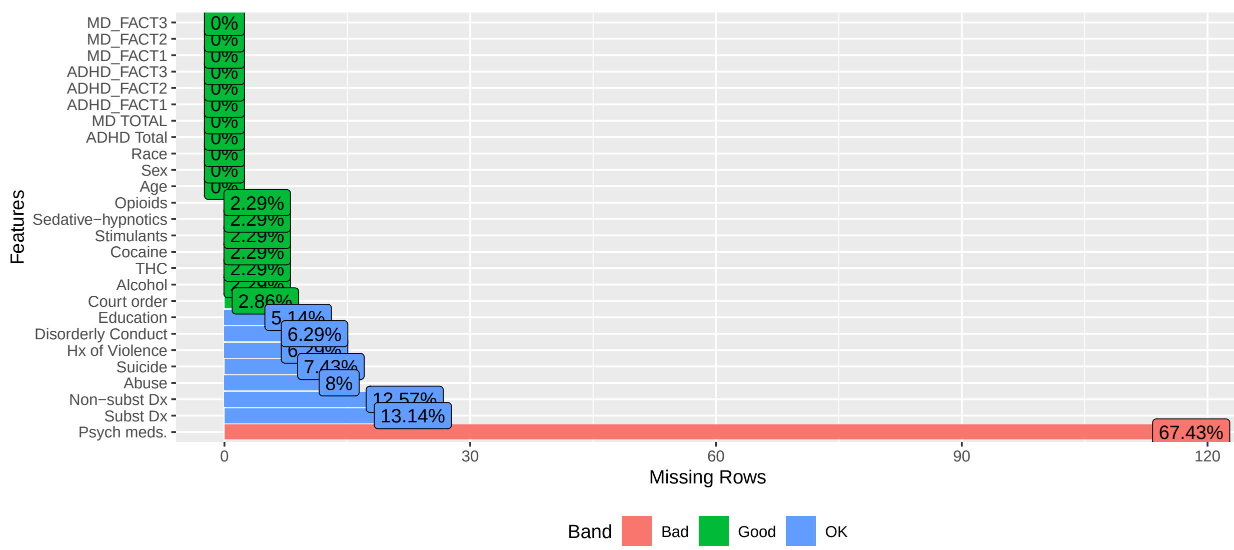


In the next step we will remove all ADHD Question columns, ADHD Total, MD questions columns and MD TOTAL columns. Then we will add the new factors found above for ADHD and MD questions.

Here is glimpse of new set of data.

```
##   Age Sex Race ADHD Total MD TOTAL Alcohol THC Cocaine Stimulants
## 1  24   1    1         40       15       1   1       1          0
## 2  48   2    1         55       14       0   0       0          0
## 3  51   2    1         31        5       0   0       0          0
## 4  43   1    1         45       13       1   1       1          1
## 5  34   1    1         48        7       1   1       0          0
## 6  39   2    1         55       14       1   0       0          0
##   Sedative-hypnotics Opioids Court order Education Hx of Violence
## 1                  0       0           1        11              0
## 2                  0       0           0        14              0
## 3                  0       0           0        12              0
## 4                  0       0           0        12              0
## 5                  0       0           1         9              1
## 6                  0       0           0        11              0
##   Disorderly Conduct Suicide Abuse Non-subst Dx Subst Dx Psych meds. ADHD_FACT1
## 1                  1       1     0            2        0           2  1.6922046
## 2                  0       1     4            1        0           1  2.0799334
## 3                  0       0     6            2        0           1 -0.5301540
## 4                  0       1     7            2        0           2  0.9321586
## 5                  1       1     0            2        0           0  2.5823393
## 6                  1       1     2            0        0           0 -0.8422991
##   ADHD_FACT2 ADHD_FACT3  MD_FACT1    MD_FACT2   MD_FACT3
## 1  1.6740898 -3.3243648 1.3855809  1.59853502 -2.8509956
## 2  1.5195976 -2.6626233 0.7973360 -0.08361024  0.3704740
## 3  0.3261461 -0.1297720 0.4673052 -0.80624391 -1.0898824
## 4 -0.5385242  0.2275811 0.8725442 -0.45310917  0.5084134
## 5 -1.6535142 -0.2129593 2.1105464 -1.37884110 -1.8594994
## 6  1.3342893  1.0827141 0.2816620  0.44486489  0.4402313
```

Handling missing values



We can see from this chart that `Psych meds.` contributes to 67.43% of missing data which is maximum among all missing data in other columns. We will remove this column before imputation. We then impute values using MICE (Multivariate Imputation by Chained Equations) for columns having missing values.

```
##  Alcohol THC     Cocaine Stimulants Sedative_hypnotics Opioids Court_order
##  0:80    0:118   0:102   0:163      0:162              0:147   0:158
##  1:21    1: 13   1: 10   1:  7      1:  5              1:  6   1: 17
##  2: 8    2:  4   2:  7   3:  5      2:  1              3: 22
##  3:66    3: 40   3: 56              3:  7
##
##
##
##    Education   Hx_of_Violence Disorderly_Conduct Suicide     Abuse
##  12      :68   0:132          0: 47              0:124   0      :108
##  11      :25   1: 43          1:128              1: 51   2      : 21
##  13      :16                                             5      : 12
##  14      :14                                             7      : 11
##  9       :13                                             1      :  8
##  10      :13                                             4      :  6
##  (Other):26                                              (Other):  9
##  Non_subst_Dx Subst_Dx
##  0:114        0:51
##  1: 39        1:66
##  2: 22        2:38
##               3:20
##
##
##

##   Alcohol THC Cocaine Stimulants Sedative_hypnotics Opioids Court_order
## 1       1   1       1          0                  0       0           1
## 2       0   0       0          0                  0       0           0
```

```
## 3       0   0       0          0                  0       0           0
## 4       1   1       1          1                  0       0           0
## 5       1   1       0          0                  0       0           1
## 6       1   0       0          0                  0       0           0
##   Education Hx_of_Violence Disorderly_Conduct Suicide Abuse Non_subst_Dx
## 1        11              0                  1       1     0            2
## 2        14              0                  0       1     4            1
## 3        12              0                  0       0     6            2
## 4        12              0                  0       1     7            2
## 5         9              1                  1       1     0            2
## 6        11              0                  1       1     2            0
##   Subst_Dx ADHD_Total ADHD_FACT1 ADHD_FACT2 ADHD_FACT3 MD_Total  MD_FACT1
## 1        0         40  1.6922046  1.6740898 -3.3243648       15 1.3855809
## 2        0         55  2.0799334  1.5195976 -2.6626233       14 0.7973360
## 3        0         31 -0.5301540  0.3261461 -0.1297720        5 0.4673052
## 4        0         45  0.9321586 -0.5385242  0.2275811       13 0.8725442
## 5        0         48  2.5823393 -1.6535142 -0.2129593        7 2.1105464
## 6        0         55 -0.8422991  1.3342893  1.0827141       14 0.2816620
##      MD_FACT2   MD_FACT3 Race Sex Age
## 1  1.59853502 -2.8509956    1   1  24
## 2 -0.08361024  0.3704740    1   2  48
## 3 -0.80624391 -1.0898824    1   2  51
## 4 -0.45310917  0.5084134    1   1  43
## 5 -1.37884110 -1.8594994    1   1  34
## 6  0.44486489  0.4402313    1   2  39
```

Preprocess using transformation

In this transformation, we would first use dummyVars to create dummy variables for categorical features. Next we use center and scaling transformation.

```
##    Alcohol.0  Alcohol.1 Alcohol.2  Alcohol.3     THC.0      THC.1      THC.2
## 1 -0.9150373  2.7002645 -0.218244 -0.7759153 -1.434694  3.5199900 -0.1525062
## 2  1.0866068 -0.3682179 -0.218244 -0.7759153  0.693030 -0.2824683 -0.1525062
## 3  1.0866068 -0.3682179 -0.218244 -0.7759153  0.693030 -0.2824683 -0.1525062
## 4 -0.9150373  2.7002645 -0.218244 -0.7759153 -1.434694  3.5199900 -0.1525062
## 5 -0.9150373  2.7002645 -0.218244 -0.7759153 -1.434694  3.5199900 -0.1525062
## 6 -0.9150373  2.7002645 -0.218244 -0.7759153  0.693030 -0.2824683 -0.1525062
##        THC.3  Cocaine.0  Cocaine.1  Cocaine.2  Cocaine.3 Stimulants.0
## 1 -0.5427736 -1.1786755  4.0503968 -0.2035401 -0.6840315     0.270553
## 2 -0.5427736  0.8435619 -0.2454786 -0.2035401 -0.6840315     0.270553
## 3 -0.5427736  0.8435619 -0.2454786 -0.2035401 -0.6840315     0.270553
## 4 -0.5427736 -1.1786755  4.0503968 -0.2035401 -0.6840315    -3.675012
## 5 -0.5427736  0.8435619 -0.2454786 -0.2035401 -0.6840315     0.270553
## 6 -0.5427736  0.8435619 -0.2454786 -0.2035401 -0.6840315     0.270553
##   Stimulants.1 Stimulants.3 Sedative_hypnotics.0 Sedative_hypnotics.1
## 1   -0.2035401   -0.1710079            0.2824683           -0.1710079
## 2   -0.2035401   -0.1710079            0.2824683           -0.1710079
## 3   -0.2035401   -0.1710079            0.2824683           -0.1710079
## 4    4.8849623   -0.1710079            0.2824683           -0.1710079
## 5   -0.2035401   -0.1710079            0.2824683           -0.1710079
## 6   -0.2035401   -0.1710079            0.2824683           -0.1710079
##   Sedative_hypnotics.2 Sedative_hypnotics.3 Opioids.0  Opioids.1  Opioids.3
```

```
## 1          -0.07559289           -0.2035401  0.435187 -0.1878832 -0.3781127
## 2          -0.07559289           -0.2035401  0.435187 -0.1878832 -0.3781127
## 3          -0.07559289           -0.2035401  0.435187 -0.1878832 -0.3781127
## 4          -0.07559289           -0.2035401  0.435187 -0.1878832 -0.3781127
## 5          -0.07559289           -0.2035401  0.435187 -0.1878832 -0.3781127
## 6          -0.07559289           -0.2035401  0.435187 -0.1878832 -0.3781127
##   Court_order.0 Court_order.1 Education.6 Education.7 Education.8 Education.9
## 1    -3.0399027     3.0399027  -0.1316898   -0.107213  -0.1878832  -0.2824683
## 2     0.3270781    -0.3270781  -0.1316898   -0.107213  -0.1878832  -0.2824683
## 3     0.3270781    -0.3270781  -0.1316898   -0.107213  -0.1878832  -0.2824683
## 4     0.3270781    -0.3270781  -0.1316898   -0.107213  -0.1878832  -0.2824683
## 5    -3.0399027     3.0399027  -0.1316898   -0.107213  -0.1878832   3.5199900
## 6     0.3270781    -0.3270781  -0.1316898   -0.107213  -0.1878832  -0.2824683
##   Education.10 Education.11 Education.12 Education.13 Education.14 Education.15
## 1   -0.2824683    2.4424812   -0.7949104    -0.316313   -0.2940402  -0.07559289
## 2   -0.2824683   -0.4070802   -0.7949104    -0.316313    3.3814621  -0.07559289
## 3   -0.2824683   -0.4070802    1.2508149    -0.316313   -0.2940402  -0.07559289
## 4   -0.2824683   -0.4070802    1.2508149    -0.316313   -0.2940402  -0.07559289
## 5   -0.2824683   -0.4070802   -0.7949104    -0.316313   -0.2940402  -0.07559289
## 6   -0.2824683    2.4424812   -0.7949104    -0.316313   -0.2940402  -0.07559289
##   Education.16 Education.17 Education.18 Education.19 Hx_of_Violence.0
## 1    -0.218244    -0.107213   -0.1316898  -0.07559289        0.5691187
## 2    -0.218244    -0.107213   -0.1316898  -0.07559289        0.5691187
## 3    -0.218244    -0.107213   -0.1316898  -0.07559289        0.5691187
## 4    -0.218244    -0.107213   -0.1316898  -0.07559289        0.5691187
## 5    -0.218244    -0.107213   -0.1316898  -0.07559289       -1.7470621
## 6    -0.218244    -0.107213   -0.1316898  -0.07559289        0.5691187
##   Hx_of_Violence.1 Disorderly_Conduct.0 Disorderly_Conduct.1    Abuse.0
## 1       -0.5691187           -0.6042262            0.6042262  0.7853823
## 2       -0.5691187            1.6455522           -1.6455522 -1.2659894
## 3       -0.5691187            1.6455522           -1.6455522 -1.2659894
## 4       -0.5691187            1.6455522           -1.6455522 -1.2659894
## 5        1.7470621           -0.6042262            0.6042262  0.7853823
## 6       -0.5691187           -0.6042262            0.6042262 -1.2659894
##     Abuse.1    Abuse.2    Abuse.3    Abuse.4   Abuse.5    Abuse.6    Abuse.7
## 1 -0.218244 -0.3682179 -0.1710079 -0.1878832 -0.270553 -0.1525062 -0.2582439
## 2 -0.218244 -0.3682179 -0.1710079  5.2920425 -0.270553 -0.1525062 -0.2582439
## 3 -0.218244 -0.3682179 -0.1710079 -0.1878832 -0.270553  6.5196407 -0.2582439
## 4 -0.218244 -0.3682179 -0.1710079 -0.1878832 -0.270553 -0.1525062  3.8501813
## 5 -0.218244 -0.3682179 -0.1710079 -0.1878832 -0.270553 -0.1525062 -0.2582439
## 6 -0.218244  2.7002645 -0.1710079 -0.1878832 -0.270553 -0.1525062 -0.2582439
##   Non_subst_Dx.0 Non_subst_Dx.1 Non_subst_Dx.2 Subst_Dx.0 Subst_Dx.1 Subst_Dx.2
## 1     -1.3631483      -0.533972      2.6296017   1.554824 -0.7759153 -0.5251545
## 2     -1.3631483       1.862056     -0.3781127   1.554824 -0.7759153 -0.5251545
## 3     -1.3631483      -0.533972      2.6296017   1.554824 -0.7759153 -0.5251545
## 4     -1.3631483      -0.533972      2.6296017   1.554824 -0.7759153 -0.5251545
## 5     -1.3631483      -0.533972      2.6296017   1.554824 -0.7759153 -0.5251545
## 6      0.7294039      -0.533972     -0.3781127   1.554824 -0.7759153 -0.5251545
##   Subst_Dx.3 ADHD_Total.0 ADHD_Total.1 ADHD_Total.3 ADHD_Total.5 ADHD_Total.6
## 1 -0.3581828  -0.07559289    -0.107213  -0.07559289  -0.07559289   -0.1316898
## 2 -0.3581828  -0.07559289    -0.107213  -0.07559289  -0.07559289   -0.1316898
## 3 -0.3581828  -0.07559289    -0.107213  -0.07559289  -0.07559289   -0.1316898
## 4 -0.3581828  -0.07559289    -0.107213  -0.07559289  -0.07559289   -0.1316898
## 5 -0.3581828  -0.07559289    -0.107213  -0.07559289  -0.07559289   -0.1316898
```

```
## 6 -0.3581828  -0.07559289    -0.107213  -0.07559289  -0.07559289   -0.1316898
##   ADHD_Total.7 ADHD_Total.8 ADHD_Total.9 ADHD_Total.10 ADHD_Total.11
## 1    -0.107213  -0.07559289    -0.107213     -0.107213   -0.07559289
## 2    -0.107213  -0.07559289    -0.107213     -0.107213   -0.07559289
## 3    -0.107213  -0.07559289    -0.107213     -0.107213   -0.07559289
## 4    -0.107213  -0.07559289    -0.107213     -0.107213   -0.07559289
## 5    -0.107213  -0.07559289    -0.107213     -0.107213   -0.07559289
## 6    -0.107213  -0.07559289    -0.107213     -0.107213   -0.07559289
##   ADHD_Total.12 ADHD_Total.13 ADHD_Total.14 ADHD_Total.16 ADHD_Total.17
## 1    -0.1525062   -0.07559289    -0.1525062   -0.07559289     -0.218244
## 2    -0.1525062   -0.07559289    -0.1525062   -0.07559289     -0.218244
## 3    -0.1525062   -0.07559289    -0.1525062   -0.07559289     -0.218244
## 4    -0.1525062   -0.07559289    -0.1525062   -0.07559289     -0.218244
## 5    -0.1525062   -0.07559289    -0.1525062   -0.07559289     -0.218244
## 6    -0.1525062   -0.07559289    -0.1525062   -0.07559289     -0.218244
##   ADHD_Total.18 ADHD_Total.19 ADHD_Total.20 ADHD_Total.21 ADHD_Total.23
## 1   -0.07559289    -0.1710079    -0.1316898    -0.1316898   -0.07559289
## 2   -0.07559289    -0.1710079    -0.1316898    -0.1316898   -0.07559289
## 3   -0.07559289    -0.1710079    -0.1316898    -0.1316898   -0.07559289
## 4   -0.07559289    -0.1710079    -0.1316898    -0.1316898   -0.07559289
## 5   -0.07559289    -0.1710079    -0.1316898    -0.1316898   -0.07559289
## 6   -0.07559289    -0.1710079    -0.1316898    -0.1316898   -0.07559289
##   ADHD_Total.24 ADHD_Total.25 ADHD_Total.26 ADHD_Total.27 ADHD_Total.28
## 1    -0.1878832    -0.1525062   -0.07559289     -0.107213    -0.1878832
## 2    -0.1878832    -0.1525062   -0.07559289     -0.107213    -0.1878832
## 3    -0.1878832    -0.1525062   -0.07559289     -0.107213    -0.1878832
## 4    -0.1878832    -0.1525062   -0.07559289     -0.107213    -0.1878832
## 5    -0.1878832    -0.1525062   -0.07559289     -0.107213    -0.1878832
## 6    -0.1878832    -0.1525062   -0.07559289     -0.107213    -0.1878832
##   ADHD_Total.29 ADHD_Total.30 ADHD_Total.31 ADHD_Total.32 ADHD_Total.33
## 1     -0.107213    -0.1316898    -0.2035401    -0.2035401    -0.1316898
## 2     -0.107213    -0.1316898    -0.2035401    -0.2035401    -0.1316898
## 3     -0.107213    -0.1316898     4.8849623    -0.2035401    -0.1316898
## 4     -0.107213    -0.1316898    -0.2035401    -0.2035401    -0.1316898
## 5     -0.107213    -0.1316898    -0.2035401    -0.2035401    -0.1316898
## 6     -0.107213    -0.1316898    -0.2035401    -0.2035401    -0.1316898
##   ADHD_Total.34 ADHD_Total.35 ADHD_Total.36 ADHD_Total.37 ADHD_Total.38
## 1   -0.07559289    -0.1316898    -0.1316898     -0.107213    -0.1316898
## 2   -0.07559289    -0.1316898    -0.1316898     -0.107213    -0.1316898
## 3   -0.07559289    -0.1316898    -0.1316898     -0.107213    -0.1316898
## 4   -0.07559289    -0.1316898    -0.1316898     -0.107213    -0.1316898
## 5   -0.07559289    -0.1316898    -0.1316898     -0.107213    -0.1316898
## 6   -0.07559289    -0.1316898    -0.1316898     -0.107213    -0.1316898
##   ADHD_Total.39 ADHD_Total.40 ADHD_Total.41 ADHD_Total.42 ADHD_Total.43
## 1    -0.1316898     5.2920425    -0.1316898    -0.1710079    -0.1316898
## 2    -0.1316898    -0.1878832    -0.1316898    -0.1710079    -0.1316898
## 3    -0.1316898    -0.1878832    -0.1316898    -0.1710079    -0.1316898
## 4    -0.1316898    -0.1878832    -0.1316898    -0.1710079    -0.1316898
## 5    -0.1316898    -0.1878832    -0.1316898    -0.1710079    -0.1316898
## 6    -0.1316898    -0.1878832    -0.1316898    -0.1710079    -0.1316898
##   ADHD_Total.44 ADHD_Total.45 ADHD_Total.46 ADHD_Total.47 ADHD_Total.48
## 1     -0.107213    -0.1316898    -0.1316898    -0.1316898    -0.1878832
## 2     -0.107213    -0.1316898    -0.1316898    -0.1316898    -0.1878832
## 3     -0.107213    -0.1316898    -0.1316898    -0.1316898    -0.1878832
```

```
## 4     -0.107213     7.5502129    -0.1316898    -0.1316898    -0.1878832
## 5     -0.107213    -0.1316898    -0.1316898    -0.1316898     5.2920425
## 6     -0.107213    -0.1316898    -0.1316898    -0.1316898    -0.1878832
##   ADHD_Total.49 ADHD_Total.50 ADHD_Total.51 ADHD_Total.52 ADHD_Total.53
## 1    -0.1878832    -0.1316898     -0.107213    -0.1316898   -0.07559289
## 2    -0.1878832    -0.1316898     -0.107213    -0.1316898   -0.07559289
## 3    -0.1878832    -0.1316898     -0.107213    -0.1316898   -0.07559289
## 4    -0.1878832    -0.1316898     -0.107213    -0.1316898   -0.07559289
## 5    -0.1878832    -0.1316898     -0.107213    -0.1316898   -0.07559289
## 6    -0.1878832    -0.1316898     -0.107213    -0.1316898   -0.07559289
##   ADHD_Total.54 ADHD_Total.55 ADHD_Total.56 ADHD_Total.57 ADHD_Total.58
## 1    -0.1316898    -0.1316898    -0.1316898     -0.107213   -0.07559289
## 2    -0.1316898     7.5502129    -0.1316898     -0.107213   -0.07559289
## 3    -0.1316898    -0.1316898    -0.1316898     -0.107213   -0.07559289
## 4    -0.1316898    -0.1316898    -0.1316898     -0.107213   -0.07559289
## 5    -0.1316898    -0.1316898    -0.1316898     -0.107213   -0.07559289
## 6    -0.1316898     7.5502129    -0.1316898     -0.107213   -0.07559289
##   ADHD_Total.62 ADHD_Total.63 ADHD_Total.65 ADHD_Total.67 ADHD_Total.69
## 1     -0.107213   -0.07559289    -0.1316898   -0.07559289   -0.07559289
## 2     -0.107213   -0.07559289    -0.1316898   -0.07559289   -0.07559289
## 3     -0.107213   -0.07559289    -0.1316898   -0.07559289   -0.07559289
## 4     -0.107213   -0.07559289    -0.1316898   -0.07559289   -0.07559289
## 5     -0.107213   -0.07559289    -0.1316898   -0.07559289   -0.07559289
## 6     -0.107213   -0.07559289    -0.1316898   -0.07559289   -0.07559289
##   ADHD_Total.71 ADHD_Total.72 ADHD_FACT1 ADHD_FACT2  ADHD_FACT3 MD_Total.0
## 1   -0.07559289     -0.107213  1.0783202  1.2371956 -2.13013067 -0.2321789
## 2   -0.07559289     -0.107213  1.3253918  1.1230219 -1.70611102 -0.2321789
## 3   -0.07559289     -0.107213 -0.3378290  0.2410304 -0.08315315 -0.2321789
## 4   -0.07559289     -0.107213  0.5939976 -0.3979833  0.14582561 -0.2321789
## 5   -0.07559289     -0.107213  1.6455389 -1.2219897 -0.13645646 -0.2321789
## 6   -0.07559289     -0.107213 -0.5367366  0.9860743  0.69376338 -0.2321789
##   MD_Total.1 MD_Total.2 MD_Total.3 MD_Total.4 MD_Total.5 MD_Total.6 MD_Total.7
## 1 -0.1316898 -0.1710079 -0.1878832 -0.1525062 -0.2035401 -0.2454786 -0.1878832
## 2 -0.1316898 -0.1710079 -0.1878832 -0.1525062 -0.2035401 -0.2454786 -0.1878832
## 3 -0.1316898 -0.1710079 -0.1878832 -0.1525062  4.8849623 -0.2454786 -0.1878832
## 4 -0.1316898 -0.1710079 -0.1878832 -0.1525062 -0.2035401 -0.2454786 -0.1878832
## 5 -0.1316898 -0.1710079 -0.1878832 -0.1525062 -0.2035401 -0.2454786  5.2920425
## 6 -0.1316898 -0.1710079 -0.1878832 -0.1525062 -0.2035401 -0.2454786 -0.1878832
##   MD_Total.8 MD_Total.9 MD_Total.10 MD_Total.11 MD_Total.12 MD_Total.13
## 1  -0.218244  -0.270553  -0.2824683  -0.3376308   -0.270553  -0.2824683
## 2  -0.218244  -0.270553  -0.2824683  -0.3376308   -0.270553  -0.2824683
## 3  -0.218244  -0.270553  -0.2824683  -0.3376308   -0.270553  -0.2824683
## 4  -0.218244  -0.270553  -0.2824683  -0.3376308   -0.270553   3.5199900
## 5  -0.218244  -0.270553  -0.2824683  -0.3376308   -0.270553  -0.2824683
## 6  -0.218244  -0.270553  -0.2824683  -0.3376308   -0.270553  -0.2824683
##   MD_Total.14 MD_Total.15 MD_Total.16 MD_Total.17  MD_FACT1    MD_FACT2
## 1   -0.270553   3.3814621   -0.270553  -0.2582439 1.2270551  1.42214452
## 2    3.675012  -0.2940402   -0.270553  -0.2582439 0.7061119 -0.07438426
## 3   -0.270553  -0.2940402   -0.270553  -0.2582439 0.4138403 -0.71727885
## 4   -0.270553  -0.2940402   -0.270553  -0.2582439 0.7727155 -0.40311079
## 5   -0.270553  -0.2940402   -0.270553  -0.2582439 1.8690765 -1.22669275
## 6    3.675012  -0.2940402   -0.270553  -0.2582439 0.2494367  0.39577623
##     MD_FACT3   Race.1    Race.2      Race.3    Race.6      Sex.1      Sex.2
## 1 -2.2790099 1.192636 -1.151397 -0.07559289 -0.107213  0.8736647 -0.8736647
```

```
## 2  0.2961471 1.192636 -1.151397 -0.07559289 -0.107213 -1.1380633  1.1380633
## 3 -0.8712229 1.192636 -1.151397 -0.07559289 -0.107213 -1.1380633  1.1380633
## 4  0.4064121 1.192636 -1.151397 -0.07559289 -0.107213  0.8736647 -0.8736647
## 5 -1.4864343 1.192636 -1.151397 -0.07559289 -0.107213  0.8736647 -0.8736647
## 6  0.3519091 1.192636 -1.151397 -0.07559289 -0.107213 -1.1380633  1.1380633
##           Age Suicide
## 1 -1.38522071       1
## 2  0.76320137       1
## 3  1.03175413       0
## 4  0.31561343       1
## 5 -0.49004485       1
## 6 -0.04245691       1
```

Training and Test Partition

In this step for data preparation we will partition the training dataset in training and validation sets using `createDataPartition` method from `caret` package. We will reserve 75% for training and rest 25% for validation purpose.

Principal Component Analysis

Principal Compenent Analysis (PCA) is one way for which we can reduce the dimensionality of a data set which would help increase the interpretability of the data while minimizing information loss. We're going to perform PCA for ADHD and MD response questions below while using scree plots to determine the numberof PCA's to keep. The Scree plot will display the eigenvalues in a downward curve, and order them from largest to smallest.

Groups: - All ADHD Questions - All MD Questions

ADHD

First we will use the prcomp function to perform a prinicpal component analysis on the adhd response questions. We will also center and scale this dataset to ensure normality.

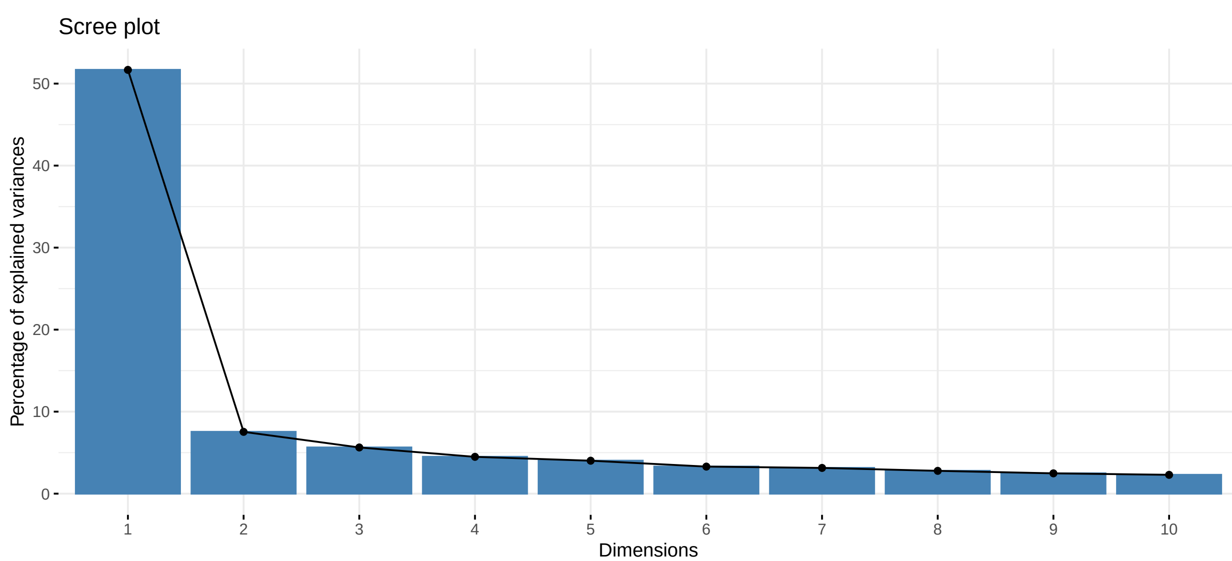
We will use the factoextra library to display the results of our PCA. this library specializes in extracting and visualizing the out put of exploratory multivariate analysis. Through this and a correlation table we can see the relationship between each ADHD response score and the Prinicple Components. The list of PC's (sorted by descending impact on the variance of score) whos us the components that are the most impactful in grouping the respondents. By viewing the associated plots and correlations we can see the ADHd response questions 4,8,9,10,16,17,18 are the most impactful on plot of PC1 and PC2 which indicates they should be used in initial modeling of this dataset. We can also see the factors that are most impactful for other principal components below.

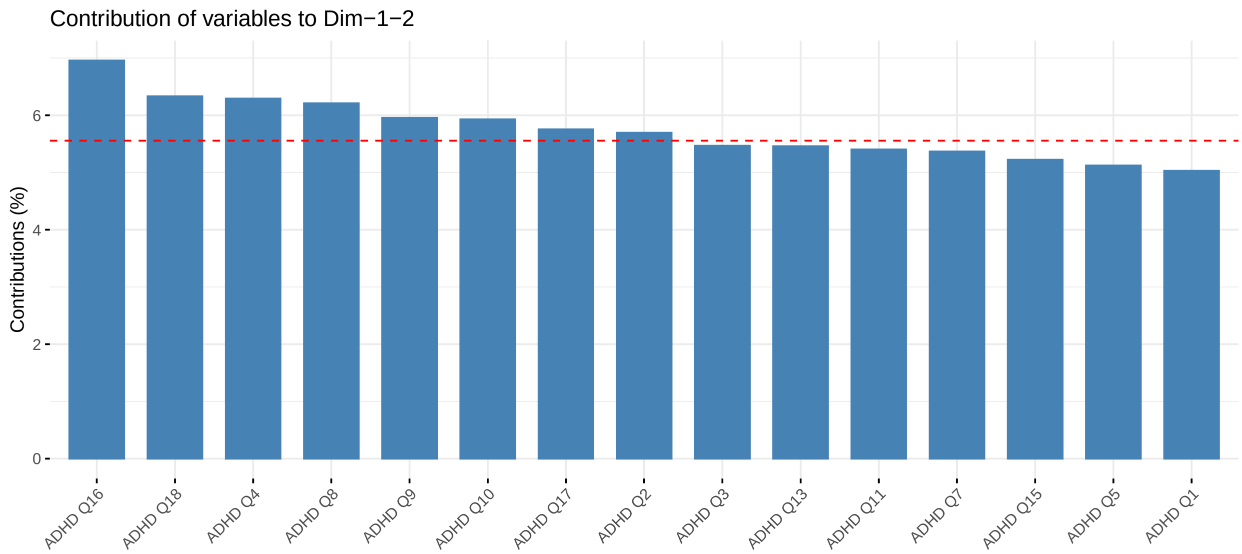
```
## Importance of components:
##                           PC1     PC2     PC3    PC4     PC5    PC6     PC7
## Standard deviation     3.0498 1.16471 1.00693 0.8990 0.85050 0.7707 0.75154
## Proportion of Variance 0.5168 0.07536 0.05633 0.0449 0.04019 0.0330 0.03138
## Cumulative Proportion  0.5168 0.59211 0.64844 0.6933 0.73353 0.7665 0.79791
##                            PC8     PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation     0.70763 0.66788 0.64291 0.63647 0.60782 0.59495 0.53747
## Proportion of Variance 0.02782 0.02478 0.02296 0.02251 0.02052 0.01966 0.01605
## Cumulative Proportion  0.82573 0.85051 0.87347 0.89598 0.91650 0.93617 0.95222
```

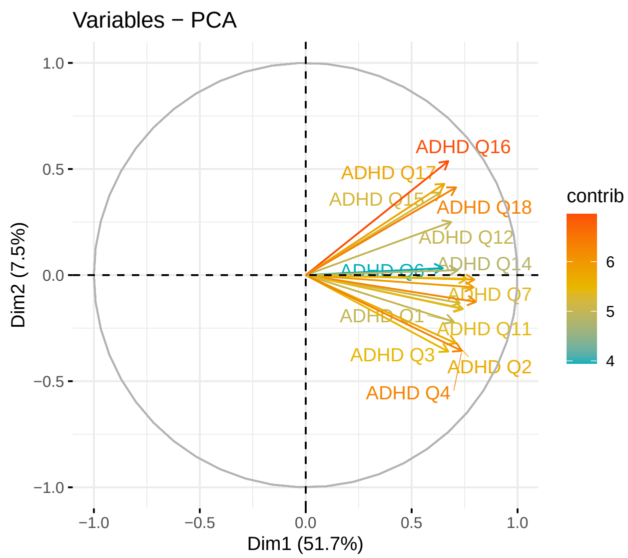
Table 2: ADHD Correlations

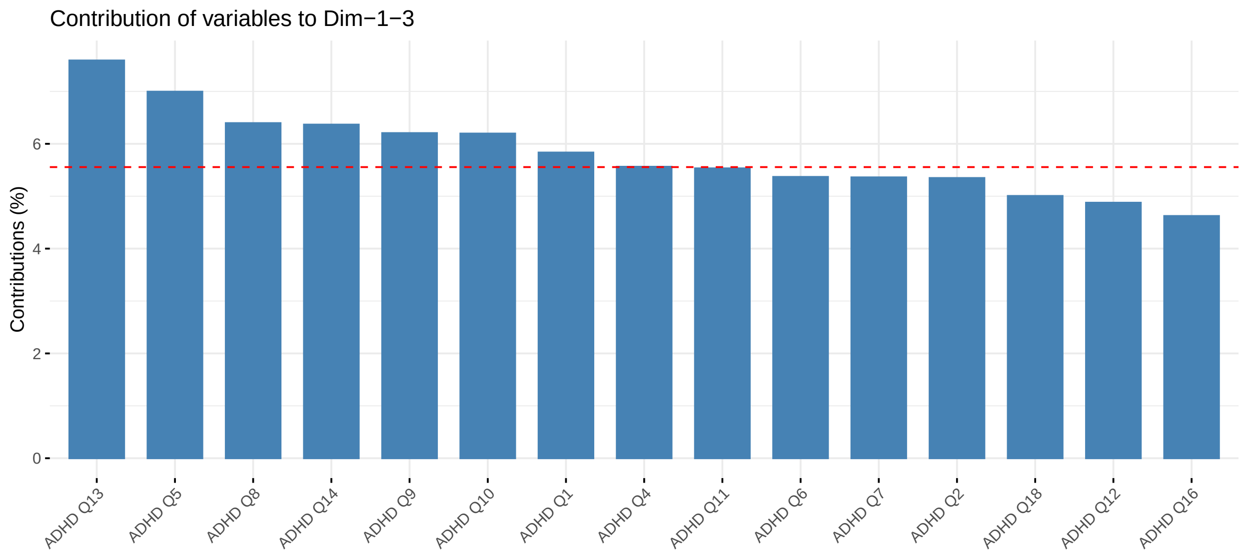
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
ADHD Q1	0.6985307	-0.2193486	0.3373110	-0.3701134	0.1620365	-0.0553265	-0.1155856	0.0634832	-0.
ADHD Q2	0.7094961	-0.3217329	0.2195271	-0.2415871	0.3149977	-0.1249863	-0.0479395	0.0317923	-0.
ADHD Q3	0.6729396	-0.3603530	0.1289838	0.0346323	-0.4064821	-0.2440550	0.2269925	0.0498093	-0.
ADHD Q4	0.7369016	-0.3570819	0.1752141	-0.0289810	0.0048257	0.1540025	0.2389656	0.0989201	0.
ADHD Q5	0.7270038	-0.1316262	-0.4393256	0.0626412	-0.2317282	-0.1653866	0.0161188	-0.0428040	0.
ADHD Q6	0.6478223	0.0330650	-0.3661242	-0.4081271	-0.2010428	-0.1415404	-0.2965562	0.1158451	-0.
ADHD Q7	0.7397991	-0.1570714	0.0745633	-0.0177672	-0.2719875	0.3665232	-0.2695678	0.0441089	0.
ADHD Q8	0.8036604	-0.1261053	0.1172968	0.2398635	-0.1092407	0.2986436	-0.0941213	-0.0499510	0.
ADHD Q9	0.7964059	-0.0211553	0.0758966	0.2369039	0.0344579	0.1119800	-0.0114321	-0.1023371	-0.
ADHD Q10	0.7928193	-0.0575642	0.1026147	0.0988034	0.0887157	-0.2189485	0.1349158	-0.0761935	0.
ADHD Q11	0.7417771	-0.1597164	-0.1426989	0.2224023	0.2630911	-0.0408302	-0.1102323	-0.2676399	-0.
ADHD Q12	0.6870249	0.2504992	0.1759628	0.3410893	-0.0587711	-0.2751124	-0.2002291	0.0034243	-0.
ADHD Q13	0.7625738	-0.0172434	-0.4488216	0.0218549	0.1970229	0.1218555	-0.0469157	0.0246575	-0.
ADHD Q14	0.7182484	0.0234819	-0.3752626	0.0082586	0.2726111	0.0471124	0.2687958	0.1484807	0.
ADHD Q15	0.6366225	0.3890284	-0.0003455	-0.2716084	-0.1802961	0.1957894	0.3451969	-0.1635894	-0.
ADHD Q16	0.6730194	0.5370634	0.1543455	-0.1542437	0.1306438	0.0783525	-0.0724010	-0.0541541	0.
ADHD Q17	0.6545364	0.4299515	0.1096686	0.2022074	0.0183908	-0.0287934	0.0308355	0.5043290	-0.
ADHD Q18	0.7097528	0.4135904	0.1118259	-0.1089439	-0.0884321	-0.1447675	0.0202057	-0.2629143	0.

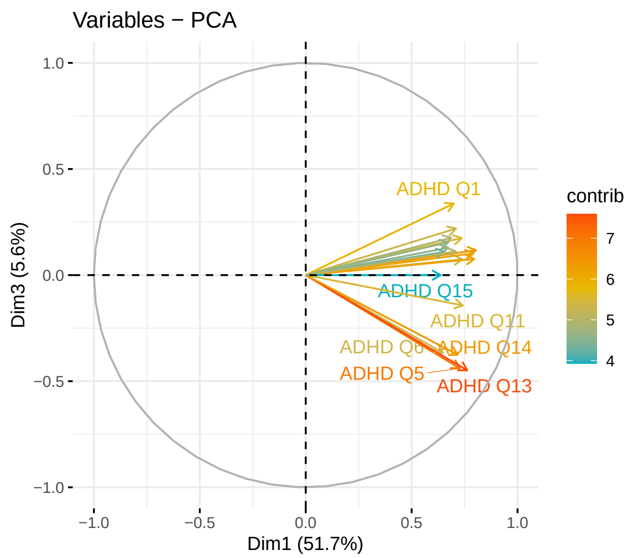
```
##                            PC15    PC16   PC17    PC18
## Standard deviation     0.52569 0.46267 0.4529 0.40566
## Proportion of Variance 0.01535 0.01189 0.0114 0.00914
## Cumulative Proportion  0.96757 0.97946 0.9909 1.00000
```

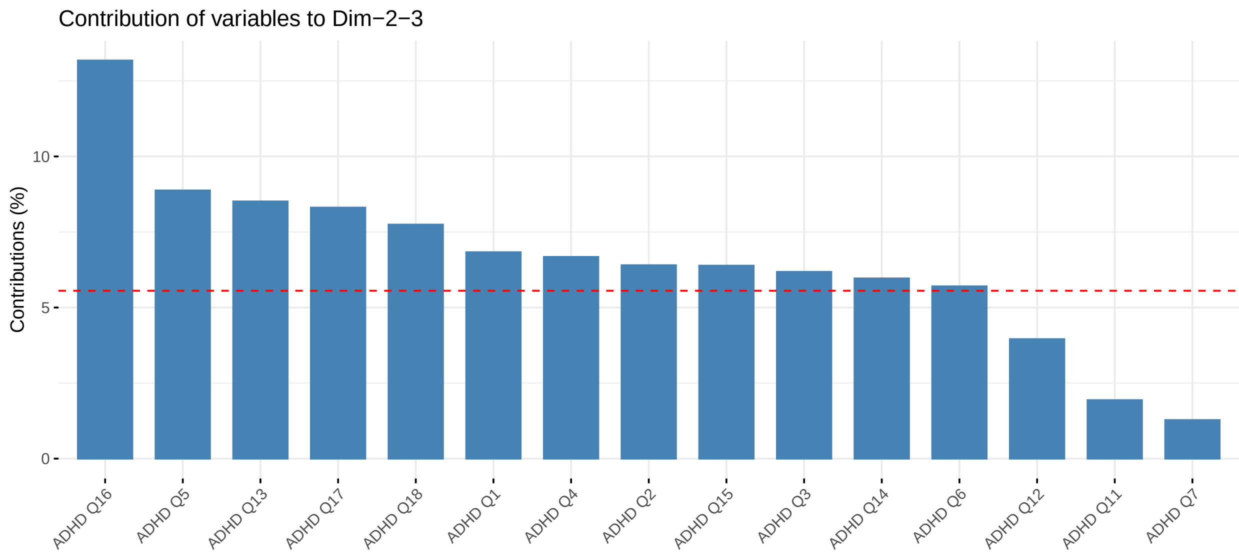


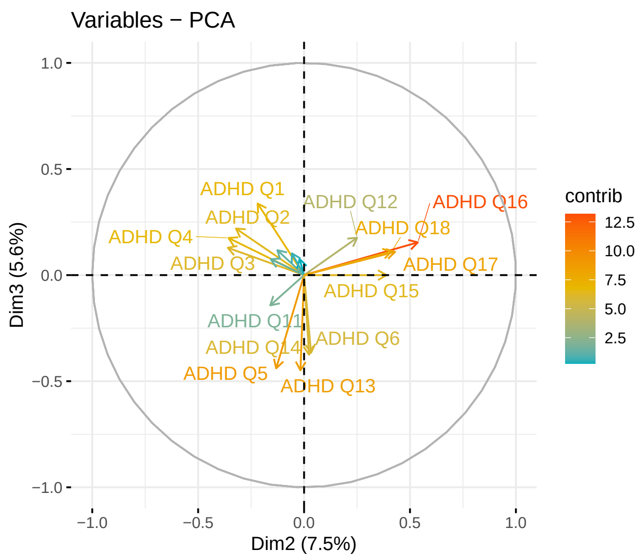

Contribution of variables to Dim−1−2
Contributions (%)
0
2
4
6
ADHD Q16
ADHD Q18
ADHD Q4
ADHD Q8
ADHD Q9
ADHD Q10
ADHD Q17
ADHD Q2
ADHD Q3
ADHD Q13
ADHD Q11
ADHD Q7
ADHD Q15
ADHD Q5
ADHD Q1


Variables − PCA
ADHD Q16
ADHD Q17
ADHD Q15
ADHD Q18
ADHD Q12
ADHD Q6
ADHD Q14
ADHD Q7
ADHD Q1
ADHD Q11
ADHD Q3
ADHD Q2
ADHD Q4
contrib
6
5
4
Dim2 (7.5%)
Dim1 (51.7%)
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0


Contribution of variables to Dim−1−3
Contributions (%)
0
2
4
6
ADHD Q13
ADHD Q5
ADHD Q8
ADHD Q14
ADHD Q9
ADHD Q10
ADHD Q1
ADHD Q4
ADHD Q11
ADHD Q6
ADHD Q7
ADHD Q2
ADHD Q18
ADHD Q12
ADHD Q16


Variables − PCA
Dim3 (5.6%)
Dim1 (51.7%)
ADHD Q1
ADHD Q15
ADHD Q11
ADHD Q6
ADHD Q14
ADHD Q5
ADHD Q13
contrib
7
6
5
4
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0





We will repeat the process above on MD response questions to get a better understanding of which of these questions are the most impactful. we can see for PC1 and PC2 MD Q1h, 1j, 1g and Q2 have the greatest impact.

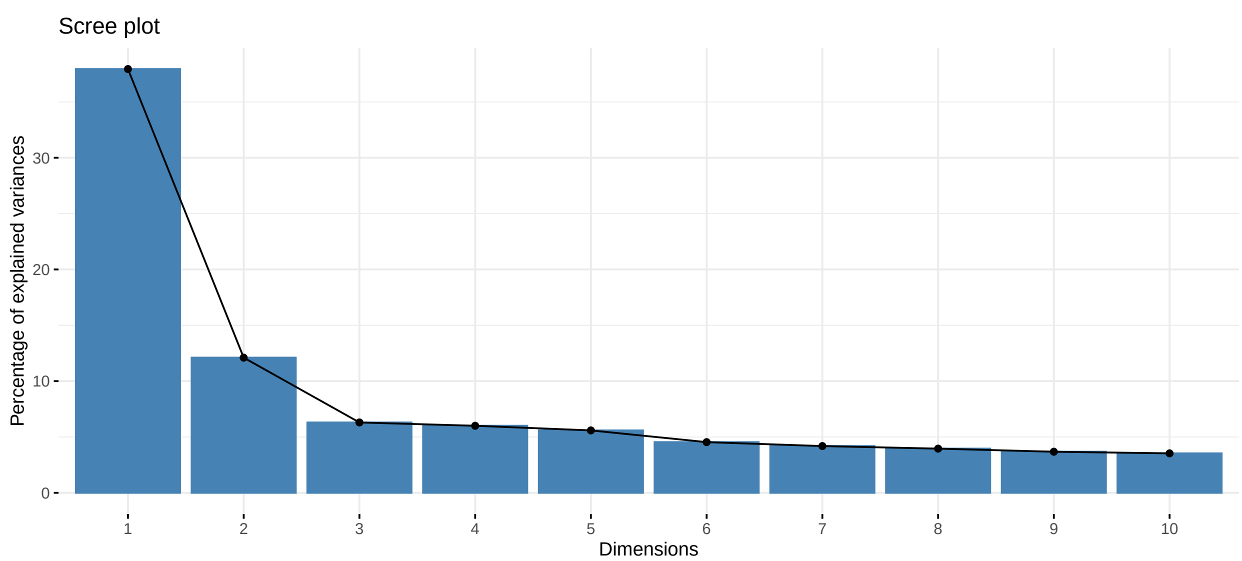
MD

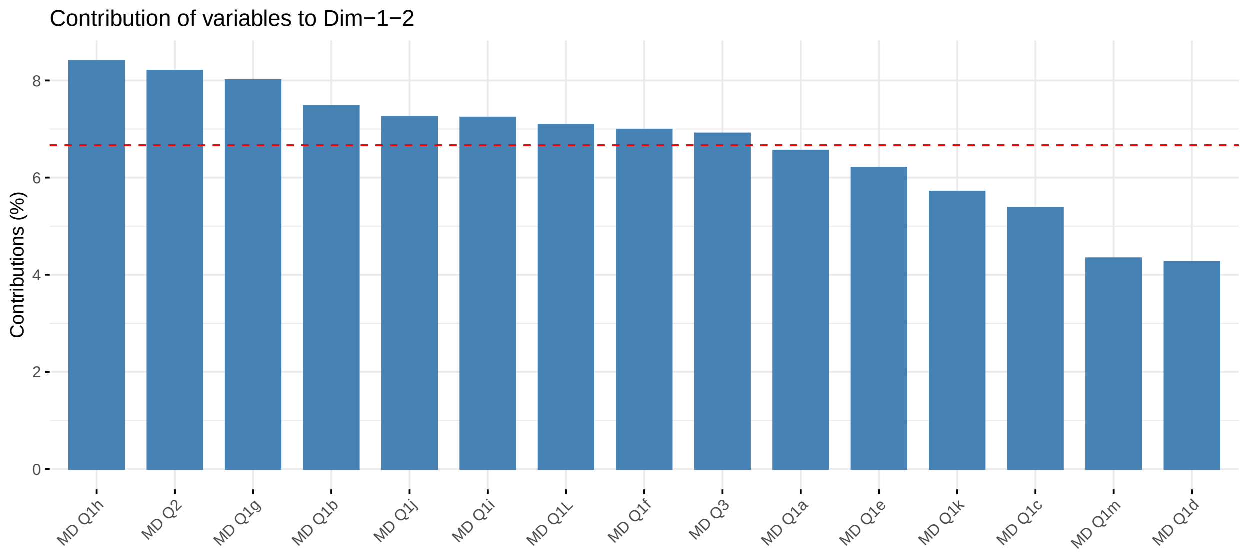
```
## Importance of components:
##                           PC1    PC2    PC3     PC4     PC5     PC6     PC7
## Standard deviation     2.3857 1.3474 0.9721 0.94891 0.91563 0.82515 0.79246
## Proportion of Variance 0.3794 0.1210 0.0630 0.06003 0.05589 0.04539 0.04187
## Cumulative Proportion  0.3794 0.5004 0.5635 0.62348 0.67937 0.72476 0.76663
##                            PC8     PC9    PC10    PC11    PC12   PC13    PC14
## Standard deviation     0.77044 0.74286 0.72814 0.70302 0.65162 0.5835 0.55685
## Proportion of Variance 0.03957 0.03679 0.03535 0.03295 0.02831 0.0227 0.02067
```

Table 3: md Correlations

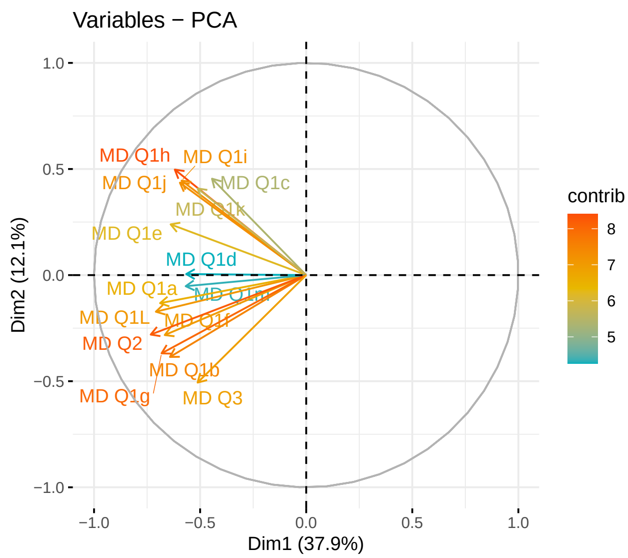
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
MD Q1a	-0.6888686	-0.1322144	0.0229725	-0.3776545	0.1155431	-0.0404785	0.0388949	-0.1162723	0.44
MD Q1b	-0.6421749	-0.3857186	0.1381774	0.1459230	-0.0448104	0.3624483	-0.0835332	-0.0859054	-0.16
MD Q1c	-0.4439895	0.4544153	-0.4763749	-0.0977568	0.2182164	0.2983609	-0.0077300	0.4015333	0.04
MD Q1d	-0.5655577	0.0049581	0.0644164	-0.0442116	0.6697469	0.0871900	0.2433963	-0.1694837	-0.11
MD Q1e	-0.6391312	0.2391336	-0.1887304	0.1745264	0.2662259	-0.3369547	-0.4017349	-0.0905138	0.01
MD Q1f	-0.6668512	-0.2825469	0.1009022	0.2032375	0.0540147	-0.3484816	0.1227297	0.0355070	0.10
MD Q1g	-0.6818994	-0.3687898	0.0536512	0.1911240	-0.0795600	-0.1339641	-0.0784985	0.2639884	0.02
MD Q1h	-0.6193596	0.4973240	0.0584859	0.2126773	-0.1071923	-0.1494907	0.2548126	-0.1564241	-0.16
MD Q1i	-0.5873223	0.4451927	-0.1405849	0.2802170	-0.3060325	0.0937060	0.3489444	-0.0655044	0.17
MD Q1j	-0.5954591	0.4356557	0.1328873	0.0517699	-0.1947518	0.1288149	-0.3882469	-0.0806025	0.16
MD Q1k	-0.5118310	0.4082574	0.5106816	-0.2784104	-0.0101545	0.1258235	-0.1131692	-0.0723359	-0.17
MD Q1L	-0.7087339	-0.1724858	0.1944088	-0.4085494	-0.1796511	-0.0457976	0.1524746	0.2247044	0.06
MD Q1m	-0.5682204	-0.0522540	-0.4267685	-0.4284171	-0.2416706	-0.2261652	-0.0162980	-0.0879603	-0.37
MD Q2	-0.7328573	-0.2802758	0.0969890	0.2440009	0.0151007	0.0994268	-0.0339440	0.2755074	-0.17
MD Q3	-0.5118573	-0.5064956	-0.3385010	0.0527350	-0.1123956	0.2676439	-0.0517879	-0.3591049	0.06

```
## Cumulative Proportion  0.80620 0.84299 0.87834 0.91128 0.93959 0.9623 0.98296
##                           PC15
## Standard deviation     0.50553
## Proportion of Variance 0.01704
## Cumulative Proportion  1.00000
```

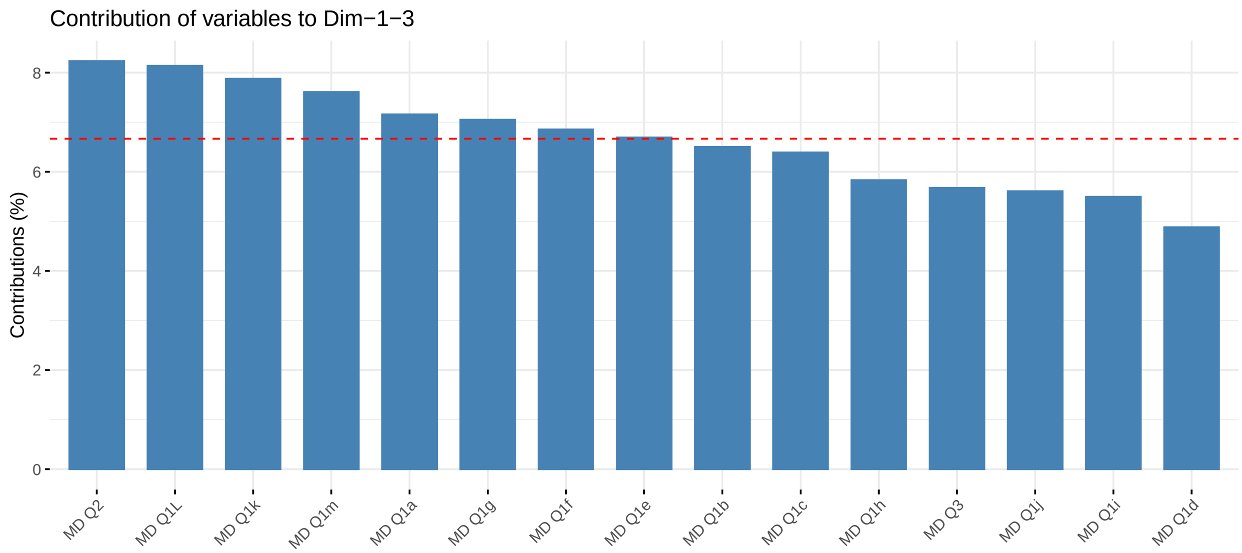


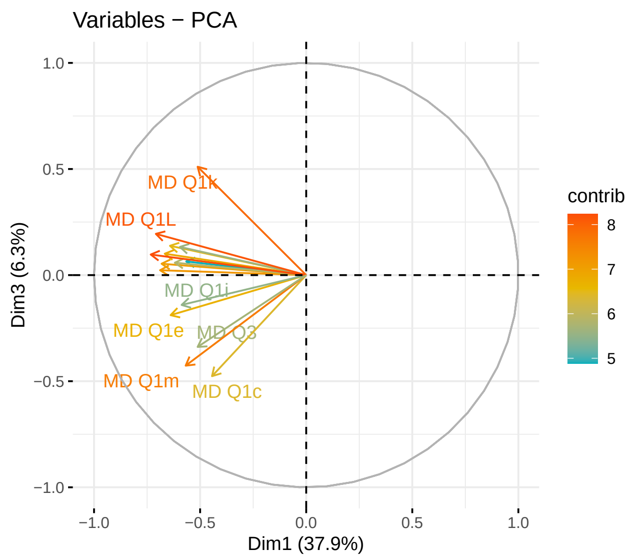


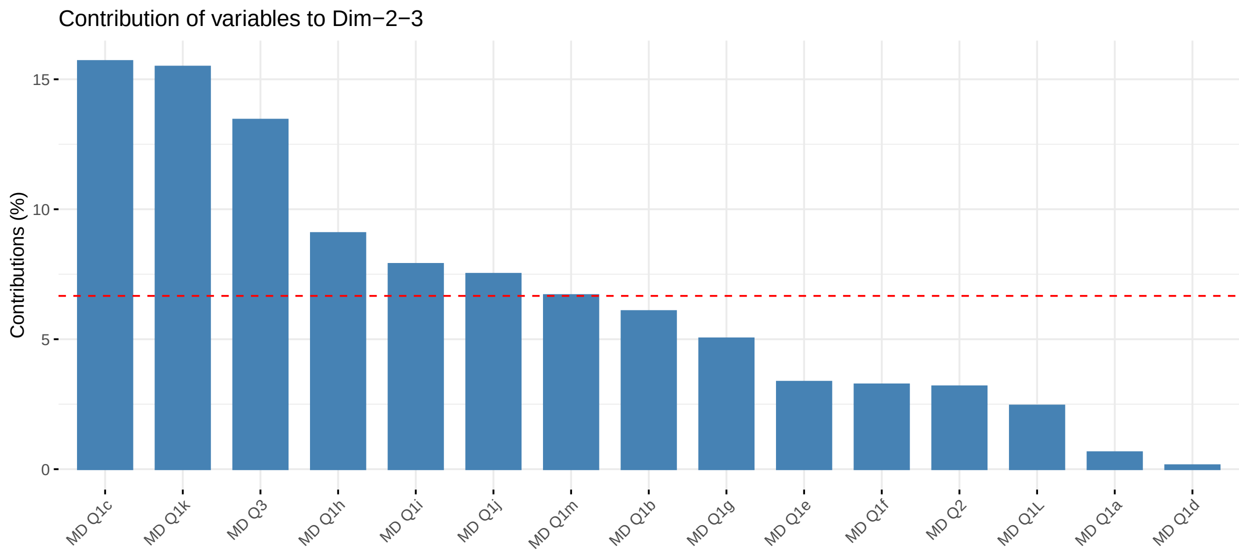
Contribution of variables to Dim−1−2
Contributions (%)
0
2
4
6
8
MD Q1h
MD Q2
MD Q1g
MD Q1b
MD Q1j
MD Q1i
MD Q1L
MD Q1f
MD Q3
MD Q1a
MD Q1e
MD Q1k
MD Q1c
MD Q1m
MD Q1d

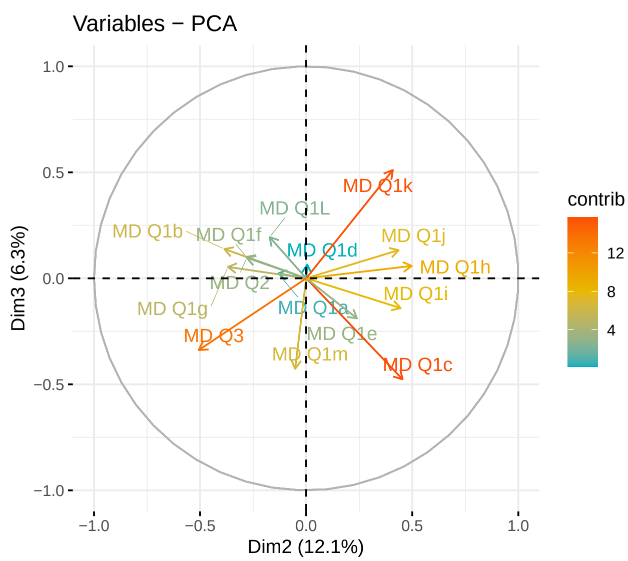


Variables − PCA
Dim2 (12.1%)
Dim1 (37.9%)
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0
MD Q1h
MD Q1i
MD Q1j
MD Q1c
MD Q1k
MD Q1e
MD Q1d
MD Q1a
MD Q1m
MD Q1L
MD Q1f
MD Q2
MD Q1b
MD Q1g
MD Q3
contrib
8
7
6
5


Contribution of variables to Dim−1−3
Contributions (%)
0
2
4
6
8
MD Q2
MD Q1L
MD Q1k
MD Q1m
MD Q1a
MD Q1g
MD Q1f
MD Q1e
MD Q1b
MD Q1c
MD Q1h
MD Q3
MD Q1j
MD Q1i
MD Q1d


Variables − PCA
Dim3 (6.3%)
Dim1 (37.9%)
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0
MD Q1k
MD Q1L
MD Q1i
MD Q1e
MD Q3
MD Q1m
MD Q1c
contrib
8
7
6
5





Gradient Boosting: Suicide

Assume you are modeling whether a patient attempted suicide (column AX). This is a binary target variable. Please use Gradient Boosting to predict whether a patient attempts suicides. Please use whatever boosting approach you deem appropriate. But please be sure to walk us through your steps.

We remove the rows null values in the target column and drop the Non-subset Dx column because it had a lot of nulls as well. XGBoost needs data to be in a matrix so we convert the dataframes to numeric matricies.

CV Split

We split the data into three folds for cross validation to imrove the ability of the model to generailze and help with overfitting. We create a function to help with parameter tunning and make use of the bayesOpt package.

https://cran.r-project.org/web/packages/ParBayesianOptimization/vignettes/tuningHyperparameters.html

```
##    Epoch Iteration max_depth min_child_weight subsample gpUtility acqOptimum
## 1:     0         1         4        16.900949 0.3980034        NA      FALSE
## 2:     0         2         9        22.465545 0.4598973        NA      FALSE
## 3:     0         3         4         2.543344 0.3380428        NA      FALSE
## 4:     0         4         7         8.946161 0.2773560        NA      FALSE
## 5:     1         5         2         1.601433 0.4039243 0.5941911       TRUE
## 6:     2         6        10         1.000000 0.5000000 0.5294463       TRUE
## 7:     3         7        10         1.000000 0.2500000 0.3537376       TRUE
##    inBounds Elapsed    Score nrounds errorMessage
## 1:     TRUE   0.060 0.500000       1           NA
## 2:     TRUE   0.033 0.500000       1           NA
## 3:     TRUE   0.043 0.722162      24           NA
## 4:     TRUE   0.013 0.500000       1           NA
## 5:     TRUE   0.058 0.732463      22           NA
## 6:     TRUE   0.040 0.762502      16           NA
## 7:     TRUE   0.020 0.646280       2           NA
```

```
## $max_depth
## [1] 10
##
## $min_child_weight
## [1] 1
##
## $subsample
## [1] 0.5
```

Build Models

Clustering Method

We use K-nearest neighbor (KNN) to identify clusters of patients that share similar patterns that could help us predict our target variable. KNN works by identifying the “k” closest neighbors in the dataset. This works particularly well for classification.

```
## [1] <NA>
## Levels: 0 1 2
```

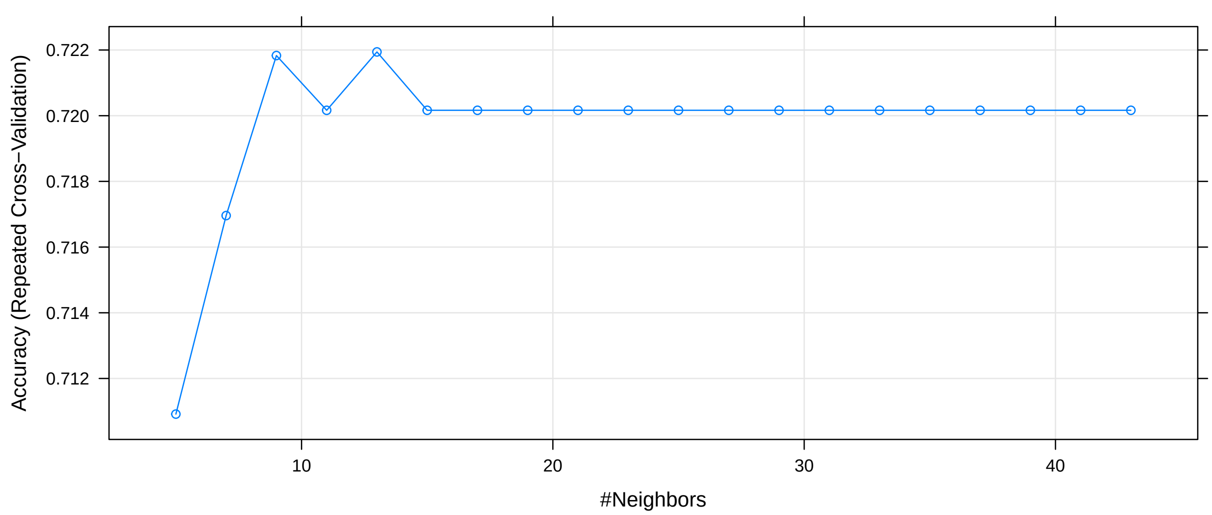
```
## [1] 0
```

```
## [1] <NA>
## Levels: 0 1 2
```

```
## [1] 0
```

```
## k-Nearest Neighbors
##
## 132 samples
```

```
##  50 predictor
##   2 classes: '0', '1'
##
## Pre-processing: centered (157), scaled (157)
## Resampling: Cross-Validated (10 fold, repeated 5 times)
## Summary of sample sizes: 119, 119, 119, 118, 119, 118, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    5  0.7109158  0.0329247345
##    7  0.7169597  0.0002244742
##    9  0.7218315  0.0085714286
##   11  0.7201648  0.0000000000
##   13  0.7219414  0.0123065729
##   15  0.7201648  0.0000000000
##   17  0.7201648  0.0000000000
##   19  0.7201648  0.0000000000
##   21  0.7201648  0.0000000000
##   23  0.7201648  0.0000000000
##   25  0.7201648  0.0000000000
##   27  0.7201648  0.0000000000
##   29  0.7201648  0.0000000000
##   31  0.7201648  0.0000000000
##   33  0.7201648  0.0000000000
##   35  0.7201648  0.0000000000
##   37  0.7201648  0.0000000000
##   39  0.7201648  0.0000000000
##   41  0.7201648  0.0000000000
##   43  0.7201648  0.0000000000
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 13.
```




```
## [1] 0.7209302
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 31 12
##          1  0  0
##
##                Accuracy : 0.7209
##                  95% CI : (0.5633, 0.8467)
##     No Information Rate : 0.7209
##     P-Value [Acc > NIR] : 0.576988
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : 0.001496
##
##             Sensitivity : 1.0000
##             Specificity : 0.0000
##          Pos Pred Value : 0.7209
##          Neg Pred Value :    NaN
##              Prevalence : 0.7209
##          Detection Rate : 0.7209
##    Detection Prevalence : 1.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : 0
##
```

Our KNN model accuracy comes out to 72.1%

Support Vector Machine

The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space (N being the number of features) that classifies the data points. Hyperplanes are decision boundaries to classify the data points. Data points that falls on either side of the hyperplane can be qualified for different classes. Support vectors are data points that are closer to the hyperplane and effect the position and orientation of the hyperplane. Using these support vectors, we do maximize the margin of the classifier.

There are number of R packages available to implement SVM. The train function can be used for SVM using methods as svmRadial, svmLinear and svmPoly that fit different kernels.

```
##
## Call:
## summary.resamples(object = svm_resamps)
##
## Models: Linear, Radial, Poly
## Number of resamples: 10
##
## Accuracy
##             Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## Linear 0.5714286 0.6282051 0.6923077 0.6902930 0.6923077 0.9230769    0
## Radial 0.5384615 0.6428571 0.7321429 0.7057692 0.7692308 0.8461538    0
## Poly   0.5384615 0.6282051 0.7307692 0.7463370 0.8887363 0.9285714    0
```

```
##
## Kappa
##              Min.      1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## Linear -0.0500000  0.157205698 0.2752525 0.2649674 0.3438347 0.8059701    0
## Radial -0.2580645  0.007462687 0.1698842 0.1639568 0.3157895 0.5806452    0
## Poly   -0.2580645 -0.066302119 0.2419355 0.2943945 0.7089552 0.8108108    0
```

We can see out Support Vector Machine Linear, Radial, and Poly fit had median accuracy rates of .631, .769 and .769 respectively indicating of radial or poly SVM should be chosen for future modeling.

Gradient Boosted

We use the information from the above function to fit our final model, make predictions, and evaluate results.

```
## Confusion Matrix and Statistics
##
##        y_label_test
## xgbpred  0  1
##       0 27  8
##       1  1  4
##
##                Accuracy : 0.775
##                  95% CI : (0.6155, 0.8916)
##     No Information Rate : 0.7
##     P-Value [Acc > NIR] : 0.1959
##
##                   Kappa : 0.3571
##
##  Mcnemar's Test P-Value : 0.0455
##
##             Sensitivity : 0.9643
##             Specificity : 0.3333
##          Pos Pred Value : 0.7714
##          Neg Pred Value : 0.8000
##              Prevalence : 0.7000
##          Detection Rate : 0.6750
##    Detection Prevalence : 0.8750
##       Balanced Accuracy : 0.6488
##
##        'Positive' Class : 0
##
```

This produced an accuracy rate of 77.5%

Model Performance

We can see that model SVM models has the best accuracy at 77.5% when applied to the test dataset. We could improve these models through more through feature selection via PCA or other methods and by focusing on feature engineering by using what was identified by these methods.

Conclusion

Through the use of feature engineering and different models we can see that there are numerous ways to approach a dataset such as this. Both models were better at predicting when a patient would not attempt to commit suicide, and not nearly as good at predicting when a patient would. Going forward it would be best to modify the model to focus on predicting when someone would attempt suicide. It is much more beneficial given the problem at hand to be over cautious and less accurate then to be more accurate but less cautious. Potentially using principle components could improve the model and focusing on feature engineering in regards to “positive” cases where the patient atttempted suicide.

References

https://towardsdatascience.com/what-is-the-difference-between-pca-and-factor-analysis-5362ef6fa6f9

https://scholarworks.umass.edu/cgi/viewcontent.cgi?article=1226&context=pare

http://www.sthda.com/english/articles/31-principal-component-methods-in-r-practical-guide/118-principal-component-analysis-in-r-prcomp-vs-princomp/

https://rdrr.io/r/stats/prcomp.html

Code Appendix

```
knitr::opts_chunk$set(echo=FALSE, error=FALSE, warning=FALSE, message=FALSE, fig.align="center", fig.wi
# Libraries
library(summarytools)
library(tidyverse)
library(DataExplorer)
library(reshape2)
library(mice)
library(caret)
library(MASS)
library(e1071)
library(tree)
library(corrplot)
library(kableExtra)
library(htmltools)
library(readxl)
library(psych)
library(xgboost)
library(ParBayesianOptimization)
library(factoextra)
set.seed(622)
# read data
adhd_data <- read_excel("ADHD_data.xlsx", sheet = "Data") %>% na_if("") %>% dplyr::select(-1)
#columns <- list(dimnames(adhd_data)[2])
#df <- adhd_data[,2:53]
adhd_data[,2:53] <- lapply(adhd_data[,2:53], factor)
adhd_data.dims <- dim(adhd_data)
adhd_data.dims[[2]]
adhd_data[,c(23:37)]
```

```r
# select categorical columns
cat_cols <- dimnames(adhd_data[,2:53])[[2]]
adhd_fact <-  adhd_data[cat_cols]
# long format
adhd_factm <- melt(adhd_fact, measure.vars = cat_cols, variable.name = 'metric', value.name = 'value')
# plot categorical columns
ggplot(adhd_factm, aes(x = value)) +
  geom_bar(aes(fill = metric)) +
  facet_wrap( ~ metric, nrow = 5L, scales = 'free') + coord_flip() +
  theme(legend.position = "none")
dfSummary(adhd_data, style = 'grid', graph.col = FALSE)
adhds <- sapply(adhd_data[,c(4:21)], as.numeric) %>% cor()
corrplot::corrplot(adhds, method="number")
mds <- sapply(adhd_data[,c(23:37)], as.numeric) %>% cor()
corrplot::corrplot(mds, method="number")
adhd_ques_fa <- factanal(sapply(adhd_data[,c(4:21)], as.numeric),
                         factors = 3,
                         rotation = "promax",
                         scores = "regression")
adhd_ques_fa
fa.diagram(adhd_ques_fa$loadings)
md_ques_fa <- factanal(sapply(adhd_data[,c(23:37)], as.numeric),
                         factors = 3,
                         rotation = "promax",
                         scores = "regression")
md_ques_fa
fa.diagram(md_ques_fa$loadings)
# ADHD question scores dataframe
adhd_ques_fa <- as.data.frame(adhd_ques_fa$scores)
names(adhd_ques_fa) <- c('ADHD_FACT1','ADHD_FACT2','ADHD_FACT3')

# MD questions scores dataframe
md_ques_fa <- as.data.frame(md_ques_fa$scores)
names(md_ques_fa) <- c('MD_FACT1','MD_FACT2','MD_FACT3')

# remove ADHD and MD columns
adhd_newdata <- adhd_data %>% dplyr::select(-c(starts_with('ADHD Q'), starts_with('MD Q')))

# Add new factor columns created
adhd_newdata <- cbind(adhd_newdata, adhd_ques_fa, md_ques_fa)
head(adhd_newdata)
# plot missing values
plot_missing(adhd_newdata)
# rename columns to apply mice
adhd_newdata <- adhd_newdata %>%
  rename('ADHD_Total'='ADHD Total',
         'MD_Total'='MD TOTAL',
         'Sedative_hypnotics'='Sedative-hypnotics',
         'Court_order' = 'Court order',
         'Hx_of_Violence'='Hx of Violence',
         'Disorderly_Conduct'='Disorderly Conduct',
         'Non_subst_Dx'='Non-subst Dx',
         'Subst_Dx'='Subst Dx',
```

```
         'Psych_meds'='Psych meds.') %>%
  dplyr::select(-Psych_meds)
# select columns with non missing values
temp <- adhd_newdata %>% dplyr::select(c(starts_with('ADHD_'), starts_with('MD_'), 'Race', 'Sex', 'Age'

# impute predictors using mice
adhd_impute <- adhd_newdata %>% dplyr::select(-c(starts_with('ADHD_'), starts_with('MD_'), 'Race', 'Sex
adhd_impute <- complete(mice(data=adhd_impute, print=FALSE))
summary(adhd_impute)
# Merged the imputed dataframe with temp
adhd_newdata <- cbind(adhd_impute, temp)
head(adhd_newdata)
# Filter out
#adhd_data <- adhd_data %>% filter(!is.na(Alcohol) &
#                                   !is.na(THC) &
#                                   !is.na(Cocaine) &
#                                   !is.na(Stimulants) &
#                                   !is.na(`Sedative-hypnotics`) &
#                                   !is.na(Opioids) &
#                                   !is.na(`Court order`) &
#                                   !is.na(Education) &
#                                   !is.na(`Hx of Violence`) &
#                                   !is.na(`Disorderly Conduct`) &
#                                   !is.na(Suicide) &
#                                   !is.na(Abuse) &
#                                   !is.na(`Non-subst Dx`) &
#                                   !is.na(`Subst Dx`) &
#                                   !is.na(`Psych meds.`))
# impute numeric predictors using mice
#adhd_data <- complete(mice(data=adhd_data[,:53], method="pmm", print=FALSE))
set.seed(622)

# create dummy variables for categorical features
adhd_dummy <- dummyVars(Suicide ~ ., data = adhd_newdata)
adhd_dummy <- predict(adhd_dummy, newdata=adhd_newdata)

# center and scaling
adhd_transformed <- adhd_dummy %>%
  preProcess(c("center", "scale")) %>%
  predict(adhd_dummy) %>%
  as.data.frame()

# add Suicide column
adhd_transformed$Suicide <- adhd_newdata$Suicide

head(adhd_transformed)
set.seed(622)
partition <- createDataPartition(adhd_data$Suicide, p=0.75, list = FALSE)
training <- adhd_data[partition,]
testing <- adhd_data[-partition,]
# training/validation partition for independent variables
#X.train <- ld.clean[partition, ] %>% dplyr::select(-Loan_Status)
#X.test <- ld.clean[-partition, ] %>% dplyr::select(-Loan_Status)
```

```r
# training/validation partition for dependent variable Loan_Status
#y.train <- ld.clean$Loan_Status[partition]
#y.test <- ld.clean$Loan_Status[-partition]
# create subset of ADHD Questions for PCA
adhd_ques_pca <- sapply(adhd_data[,c(4:21)], as.numeric)

# create subset of MD Questions for PCA
md_ques_pca <- sapply(adhd_data[,c(23:37)], as.numeric)

pca_adhd <- prcomp(adhd_ques_pca, scale. = TRUE, center=TRUE)

cor(adhd_ques_pca, pca_adhd$x[,1:10]) %>%
  kableExtra::kbl(booktabs = T, caption ="ADHD Correlations") %>%
  kable_styling(latex_options = c("striped"), full_width = F)
summary(pca_adhd)
fviz_eig(pca_adhd)
#top 10 contributors to the dimension of PC1 and PC2
fviz_contrib(pca_adhd, choice = "var", axes = c(1,2), top = 15)
fviz_pca_var(pca_adhd,
             col.var ="contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE     # Avoid text overlapping
             ,axes=c(1,2)
             )
#top 10 contributors to the dimension of PC1 and PC3
fviz_contrib(pca_adhd, choice = "var", axes = c(1,3), top = 15)
fviz_pca_var(pca_adhd,
             col.var = "contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE     # Avoid text overlapping
             ,axes=c(1,3)
             )
#top 10 contributors to the dimension of PC2 and PC3
fviz_contrib(pca_adhd, choice = "var", axes = c(2,3), top = 15)
fviz_pca_var(pca_adhd,
             col.var = "contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE     # Avoid text overlapping
             ,axes=c(2,3)
             )
pca_md <- prcomp(md_ques_pca, scale. = TRUE, center=TRUE)
cor(md_ques_pca, pca_md$x[,1:10]) %>%
  kableExtra::kbl(booktabs = T, caption ="md Correlations") %>%
  kable_styling(latex_options = c("striped"), full_width = F)
summary(pca_md)
fviz_eig(pca_md)
#top 10 contributors to the dimension of PC1 and PC2
fviz_contrib(pca_md, choice = "var", axes = c(1,2), top = 15)
fviz_pca_var(pca_md,
             col.var ="contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE     # Avoid text overlapping
             ,axes=c(1,2)
```

```
            )
#top 10 contributors to the dimension of PC1 and PC3
fviz_contrib(pca_md, choice = "var", axes = c(1,3), top = 15)
fviz_pca_var(pca_md,
             col.var = "contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE     # Avoid text overlapping
             ,axes=c(1,3)
             )
#top 10 contributors to the dimension of PC2 and PC3
fviz_contrib(pca_md, choice = "var", axes = c(2,3), top = 15)
fviz_pca_var(pca_md,
             col.var = "contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE     # Avoid text overlapping
             ,axes=c(2,3)
             )
gb__train <-subset(training[complete.cases(training$Suicide), ], select= -`Non-subst Dx`)
gb__test <-subset(testing[complete.cases(testing$Suicide), ], select= -`Non-subst Dx`)
y_label_tr <- as.matrix(gb__train$Suicide)
y_label_test <- as.matrix(gb__test$Suicide)
gb__train <- sapply(subset(gb__train, select = -Suicide), as.numeric)
gb_test <- sapply(subset(gb__test, select = -Suicide), as.numeric)
Folds <- list(
    Fold1 = as.integer(seq(1,nrow(gb__train),by = 3))
  , Fold2 = as.integer(seq(2,nrow(gb__train),by = 3))
  , Fold3 = as.integer(seq(3,nrow(gb__train),by = 3))
)

scoringFunction <- function(max_depth, min_child_weight, subsample) {
  dtrain <- xgb.DMatrix(gb__train, label=y_label_tr)
  Pars <- list(
      booster = "gbtree"
    , eta = 0.01
    , max_depth = max_depth
    , min_child_weight = min_child_weight
    , subsample = subsample
    , objective = "binary:logistic"
    , eval_metric = "auc"
  )
  xgbcv <- xgb.cv(
      params = Pars
    , data = dtrain
    , nround = 100
    , folds = Folds
    , prediction = TRUE
    , showsd = TRUE
    , early_stopping_rounds = 5
    , maximize = TRUE
            , verbose = 0)
  return(
    list(
        Score = max(xgbcv$evaluation_log$test_auc_mean)
```

```r
      , nrounds = xgbcv$best_iteration
    )
  )
}

set.seed(50)
bounds <- list(
    max_depth = c(2L, 10L)
  , min_child_weight = c(1, 25)
  , subsample = c(0.25, .5)
)

optObj <- bayesOpt(
    FUN = scoringFunction
  , bounds = bounds
  , initPoints = 4
  , iters.n = 3
)
optObj$scoreSummary
print(getBestPars(optObj))
set.seed(622)
mode <- function(x){
  levels <- unique(x)
  indicies <- tabulate(match(x, levels))
  levels[which.max(indicies)]
}
# Clean up training data
training_factors <- training %>%
  dplyr::select(-Age, -`ADHD Total`, `MD TOTAL`)
training_factors <- data.frame(lapply(training_factors, as.factor))
train_knn <- training_factors %>%
  mutate(across(everything(), ~replace_na(., mode(.))))
mode(train_knn$Psych.meds.)
train_knn$Psych.meds.[which(is.na(train_knn$Psych.meds.))] <- 0
sum(is.na(train_knn$Psych.meds.))

# Clean up testing data
testing_factors <- testing %>%
  dplyr::select(-Age, -`ADHD Total`, `MD TOTAL`)
testing_factors <- data.frame(lapply(testing_factors, as.factor))
test_knn <- testing_factors %>%
  mutate(across(everything(), ~replace_na(., mode(.))))
mode(test_knn$Psych.meds.)
test_knn$Psych.meds.[which(is.na(test_knn$Psych.meds.))] <- 0
sum(is.na(test_knn$Psych.meds.))

# Train KNN model
train.knn <- (train_knn[, names(train_knn) != "Suicide"])
prep <- preProcess(x = train.knn, method = c("center", "scale"))
cl <- trainControl(method="repeatedcv", repeats = 5)
knn_model <- train(Suicide ~ ., data = train_knn,
                method = "knn",
                trControl = cl,
```

```r
                preProcess = c("center","scale"),
                tuneLength = 20)
knn_model
# Evaluate Model
plot(knn_model)
knn_predict <- predict(knn_model, newdata = test_knn)
mean(knn_predict == test_knn$Suicide) # accuracy
conf.mat.knn <- confusionMatrix(knn_predict, test_knn$Suicide)
accuracy <- round(conf.mat.knn$overall[[1]], 3)*100
conf.mat.knn
# partitioning for train and test
partition <- createDataPartition(adhd_transformed$Suicide, p=0.75, list = FALSE)
training <- adhd_transformed[partition,]
testing <- adhd_transformed[-partition,]
set.seed(622)

# fit with svmLinear
svm_lin_fit <- train(Suicide ~ .,
                data = training,
                method = "svmLinear",
                preProcess = c("center","scale"),
                tuneLength = 5,
                trControl = trainControl(method = "cv"))

pred_lin_suicide <- predict(svm_lin_fit, testing)
cm_lin <- confusionMatrix(testing$Suicide, pred_lin_suicide)

# fit with svmRadial
svm_rad_fit <- train(Suicide ~ .,
                data = training,
                method = "svmRadial",
                preProcess = c("center","scale"),
                tuneLength = 5,
                trControl = trainControl(method = "cv"))

pred_rad_suicide <- predict(svm_rad_fit, testing)
cm_rad <- confusionMatrix(testing$Suicide, pred_rad_suicide)

# fit with svmPoly
svm_poly_fit <- train(Suicide ~ .,
                data = training,
                method = "svmPoly",
                preProcess = c("center","scale"),
                tuneLength = 5,
                trControl = trainControl(method = "cv"))

pred_poly_suicide <- predict(svm_poly_fit, testing)
cm_poly <- confusionMatrix(testing$Suicide, pred_poly_suicide)

#Compare 3 models:
svm_resamps <- resamples(list(Linear = svm_lin_fit, Radial = svm_rad_fit, Poly = svm_poly_fit))
summary(svm_resamps)
dtrain <- xgb.DMatrix(gb__train, label=y_label_tr)
```

```r
dtest <- xgb.DMatrix(gb_test, label=y_label_test)
xgb <- xgb.train(
      params = list(
                  booster = "gbtree"
                , eta = 0.01
                , max_depth = 10
                , min_child_weight = 1
                , subsample = .5
                , objective = "binary:logistic"
                , eval_metric = "auc"
              )
    , data = dtrain
    , nround = 100
    , maximize = TRUE
            , verbose = 0)

xgbpred <- predict(xgb,dtest)
xgbpred <- ifelse (xgbpred > 0.5,1,0)
y_label_test <- as.numeric(y_label_test)
confusionMatrix(table(xgbpred, y_label_test))
```