Personality Attributes and their Associations with Opioid Use

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Can Five Factor Model personality attributes and the use of other drugs predict opioid use?

Background:

- Opioid-related overdoses reached an all-time high in 2020 with over 70 000 deaths in the USA and 6300 deaths in Canada[1]
- The use of psychoactive drugs can contribute to poor health over time. Along with poverty and social connectedness, the risk of drug consumption can be associated with personality traits described by the Five Factor Model (FFM)[2, 3, 4].
- The current crisis in Canada points to a need to investigate how individual differences in personality contribute to opioid use

Objectives:

1. Construct and validate one predictive model to predict risk of opioid use
2. Construct and validate a second model using a clustering method to identify groups of similar participants

Methods:

Statistical software used: R and R studio

Logistic Regression

- AUC performance comparable with machine learning methods[4]
  - **Model 1**: Backwards elimination
  - **Model 2**: Training (70%)and test (30%) dataset with down-sampling to mitigate overfitting
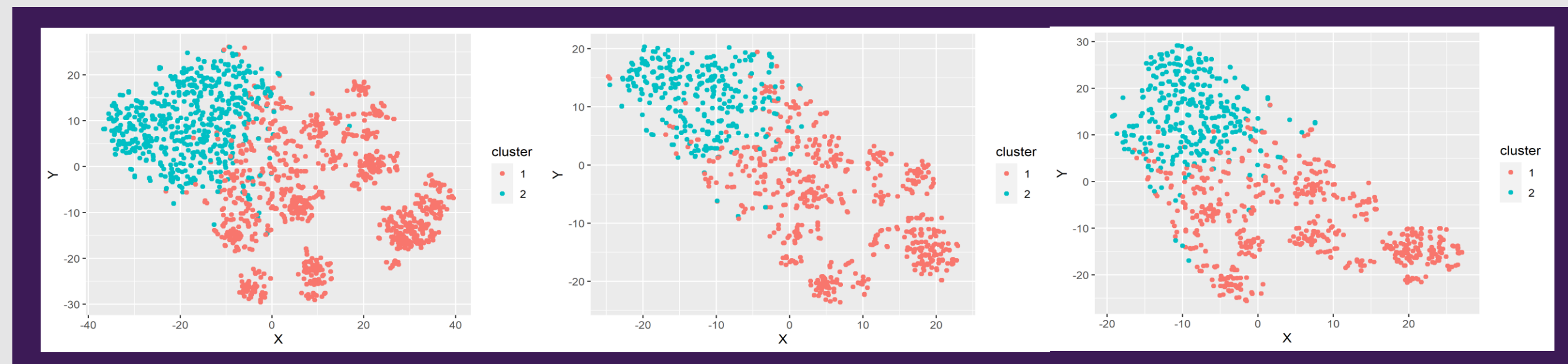
Cluster Analysis: Partitioning around Medoids (PAM)

- Silhouette width and Gower distance which is a commonly used measure of distance for mixed datasets[5]
- Full model vs. clusters after randomly splitting data in half

Dataset: UCI Machine Learning Repository[3]

Online Surveys

Personality Factors
- FFM: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness
- Sensation-seeking (SS)
- Impulsiveness

Demographics
- Education, age, gender

Psychoactive Drug Use
- 17 Illegal and legal drugs
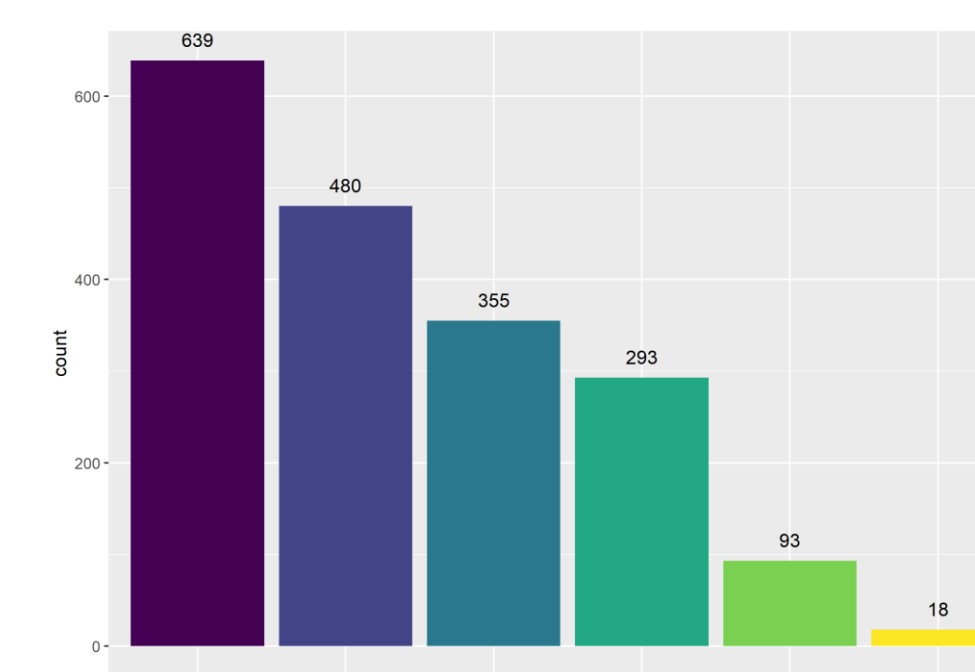- 1 fictitious drug

Composite outcome: Heroin and/or methadone use

Clustering Results:

2 clusters were the most appropriate for all 3 analyses. For the full model:
- The participants in Cluster 1 tended to be young, highly educated, and there were more females than males.
- Cluster 2 included most of the users of heroin and methadone, and across the board, there were more users than non-users for every drug except for caffeine, alcohol, and chocolate.

Full Dataset | **Half 1** | **Half 2**

Demographics: N = 1879

Personality

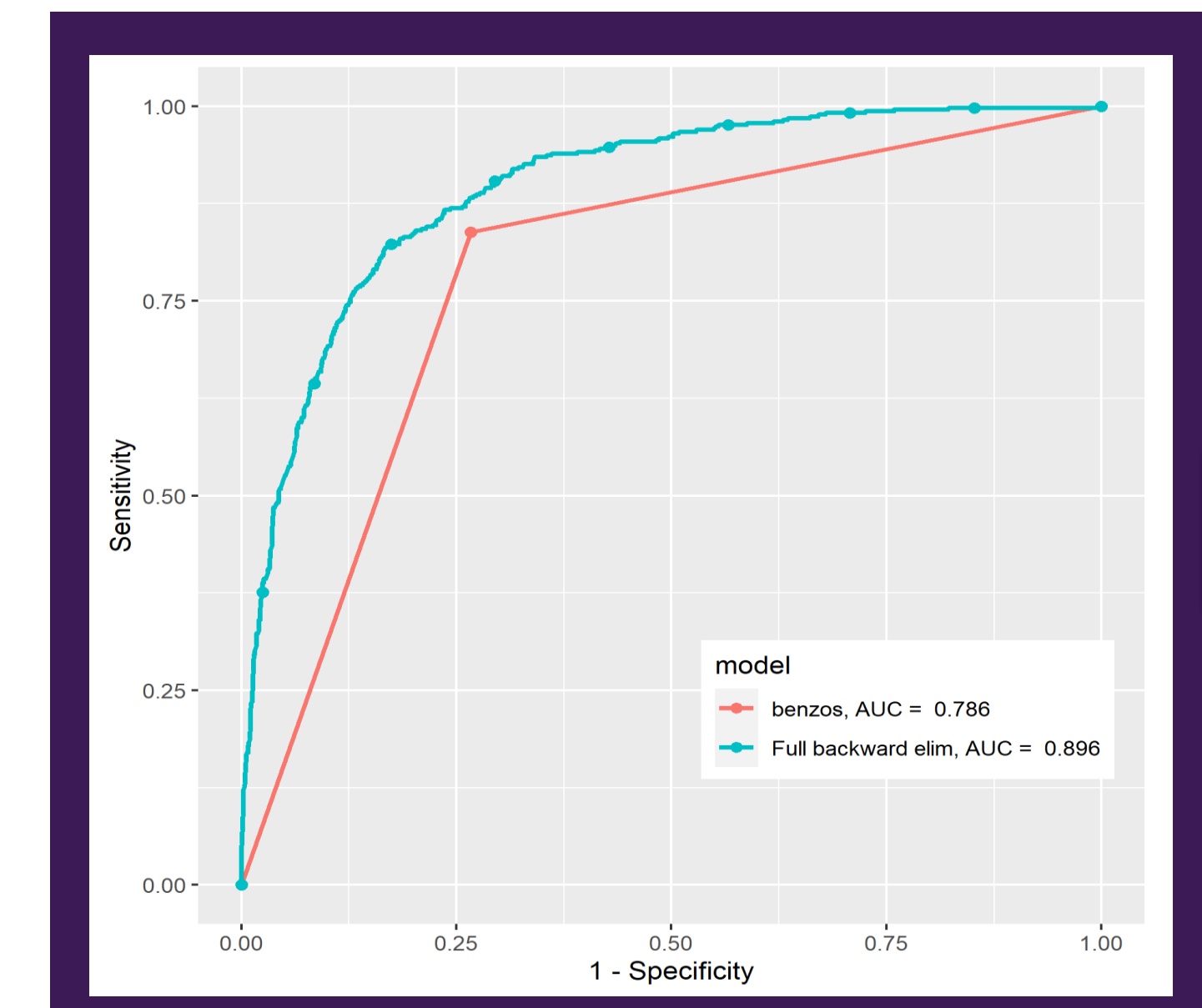| Variable	Mean	SD
nscore	35.92	9.14
escore	39.57	6.77
oscore	45.75	6.58
ascore	42.86	6.43
cscore	41.44	6.96
impulsive	0.01	0.95
ss	-0.01	0.96

Age

Education
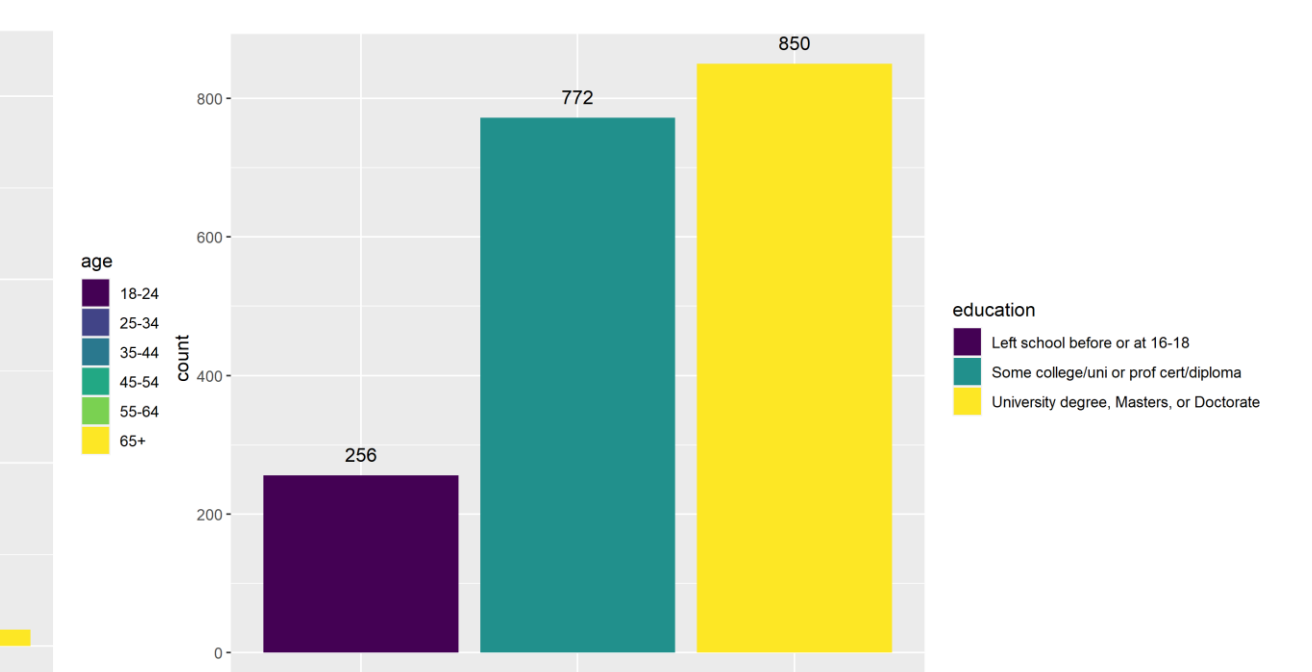
- Demographics after removing participants who claimed to use the fictitious drug semeron.
- Gender was almost equally distributed with 938 females and 941 males.
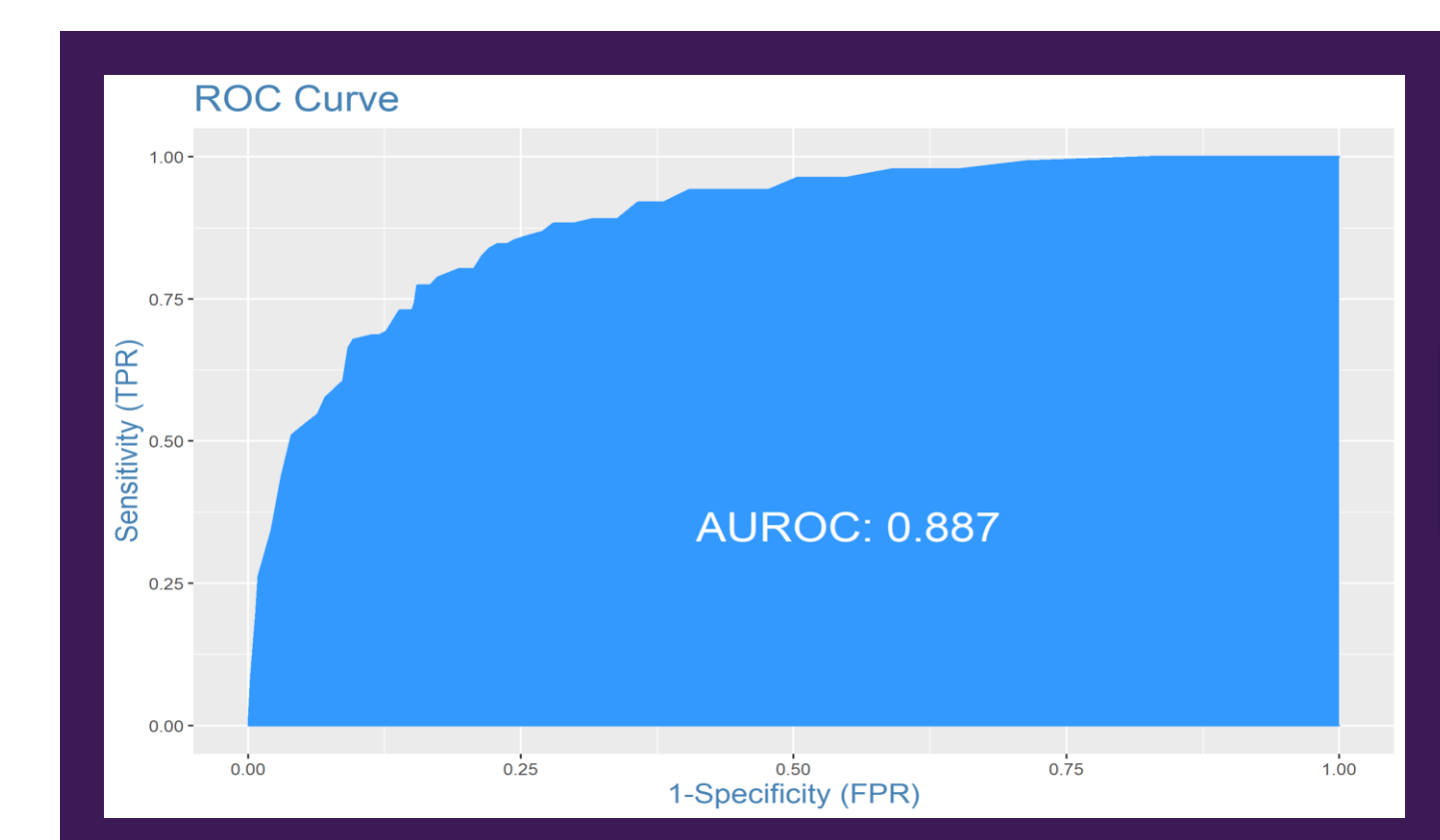- 1 outlier was later removed before running analyses.

Regression Results

The regression table to the left shows the results of Model 2 with *pseudo-R^2*=0.43 compared to *pseudo-R^2*=0.39 for Model 1.

- **User of benzodiazepines** ↑538.2% (95% CI [3.917, 10.525])
- **User of amphetamines** ↑136.9% (95% CI [1.377, 4.079])
- **1-unit increase in neuroticism** ↑3% (95% CI [1.002, 1.060])
- **1-unit increase in openness to experience** ↑3.7% (95% CI [0.995, 1.080])
- **1-unit decrease in agreeableness** ↑4% (95% CI [0.926, 0.995])

ROC: Model 1

ROC: Model 2

Regression Table for Model 2:

Note. Significance levels are '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1. Education, gender, extroversion, alcohol, coke, ecstasy, mushrooms, and VSA were also included in Model 2 but were not significant

Predictor	b (SE)	OR [95%CI]
(Intercept)	-0.68 (1.71)	0.50 [0.02; 14.20]
nscore	**0.03 (0.02)***	1.03 [1.00; 1.06]
oscore	0.04 (0.02).	1.04 [1.00; 1.08]
ascore	**-0.04 (0.02)***	0.96 [0.93; 1.00]
amphetuser	**0.86 (0.28)****	2.37 [1.38; 4.08]
amyluser	-0.72 (0.30)*	0.49 [0.27; 0.87]
benzosuser	**1.85 (0.25)*****	6.38 [3.92; 10.53]
caffuser	-1.25 (0.74).	0.29 [0.07; 1.25]
cannabisuser	**0.75 (0.38)***	2.12 [1.01; 4.54]
crackuser	**0.75 (0.37)***	2.11 [1.04; 4.52]
legalhuser	**0.66 (0.28)***	1.94 [1.12; 3.38]
lsduser	**0.77 (0.31)***	2.17 [1.19; 3.96]

Conclusions:

- Backwards elimination regression model showed better predictive performance than a model using just the use of benzodiazepines as a predictor. Model 2 mitigated overfitting and performed comparably to Model 1.
- Although clusters were stable, they may have been more distinct if different data collection methods other than online recruitment were used. This could have resulted in a more representative sample.
- **Knowledge of distinct personality profiles or characteristics that contribute to opioid use could potentially be used in treatment settings to inform choices that align best with a patient's strengths and weaknesses.**

Opioid Use

↑ **Benzodiazepines**
↑ **Amphetamines**
↑ **Neuroticism**
↑ **Openness to experience**
↓ **Agreeableness**

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